Supplementary Material for
"Credit risk clustering in a business group: which matters more, systematic or idiosyncratic risk?"

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The following sections show the empirical results of credit risk clustering across 36 pairwise firms. The other 6 pairwise firms of insignificant results are not listed.

1 Model comparisons for other pairwise firms

Figure 2 in the paper suggests that DTDs in CGWC, XITG and CNSS may have bimodal distributions. We apply both the split-t and mixtures of split-t margins to Joe-Clayton copula model for comparison to the pairwise including CGWC, XITG or CNSS. We use Joe-Clayton only in this section, because the comparison results shown in text part Section 4.1 suggest that the Joe-Clayton copula preform the best in our study samples. Different combinations of the covariates are also used for the model comparison in this section. Out-of-sample log predictive score (LPS) is used to select the most adequate model.

Table S1 and Table S2 show that split-t margin distribution is adequate for each pairwise subsidiary in the business group CEC. For different pairwise firms, different covariates should be used to assess the tail dependence of credit risk.

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Table S1: Out-of-sample comparison for Joe-Clayton copula with split-t distribution for unimodal margins. LPS is the Log Predictive Score. The largest LPS values (in bold) indicate the best copula model.

	None	Macro	Specific	Macro+Specific
SZKFT *vs.* SZSED	−60.836	−54.480	−45.824	**-42.447**
SZKFT *vs.* HDEIT	−43.484	−26.442	−57.081	**-5.128**
SZKFT *vs.* GWII	−26.197	**-12.422**	−50.951	−16.311
SZKFT *vs.* SHBL	**-2.282**	−18.546	−41.646	−15.920
SZKFT *vs.* CECC	**-51.168**	−70.712	−70.330	−85.648
SZKFT *vs.* NJPE	−48.611	**-11.464**	−89.704	−86.039
SZSED *vs.* HDEIT	**-25.335**	−56.139	−26.982	−62.701
SZSED *vs.* GWII	−98.763	−69.067	**-20.953**	−104.965
SZSED *vs.* SHBL	−62.114	−75.447	**-16.701**	−44.675
SZSED *vs.* CECC	**-4.340**	−13.852	−91.406	−20.628
SZSED *vs.* NJPE	**-33.936**	−42.823	−82.946	−64.968
HDEIT *vs.* GWII	−26.443	−33.610	**-18.309**	−37.271
HDEIT *vs.* CECC	−36.284	−33.632	**-28.026**	−43.373
GWII *vs.* SHBL	**-10.390**	−12.254	−43.666	−48.521
GWII *vs.* CECC	**-21.033**	−24.950	−85.477	−64.751
GWII *vs.* NJPE	−28.091	−17.364	−104.971	**-9.102**
SHBL *vs.* CECC	−59.096	−43.267	**-39.890**	−85.541
CECC *vs.* NJPE	−74.638	−95.287	**-56.413**	−107.808

Table S2: Out-of-sample comparison for Joe-Clayton copula with both split-t and mixtures of split-t distributions for bimodal margins. LPS is the Log Predictive Score. The largest LPS values (in bold) indicate the best copula model.

	Split-t with Joe-Clayton				Mixture of Split-t with Joe-Clayton			
	None	Macro	Specific	Macro+Specific	None	Macro	Specific	Macro+Specific
SZKFT *vs.* CNSS	−75.794	−56.534	−69.198	**-1.517**	−10.234	−10.365	−62.590	−12.809
SZSED *vs.* CGWC	−54.442	**-20.335**	−101.153	−56.279	−58.902	−58.642	−58.987	−68.008
SZSED *vs.* CNSS	**-6.141**	−38.078	−46.940	−139.944	−21.605	−76.117	−61.973	−63.620
SZSED *vs.* XITG	−89.482	**-2.706**	−97.128	−26.501	−33.877	84.314	−87.297	−37.092
CGWC *vs.* HDEIT	−46.782	**-14.918**	−34.595	−26.131	−48.162	−49.384	−51.001	−61.772
CGWC *vs.* GWII	−69.501	**-6.301**	−19.703	−65.213	−49.769	−56.088	−179.345	−107.433
CGWC *vs.* SHBL	−41.966	−33.612	**-32.399**	−40.518	−50.675	−52.219	−124.892	−125.876
CGWC *vs.* CNSS	−40.571	−104.070	−64.063	**-34.943**	−45.005	−49.836	−45.872	−99.943
CGWC *vs.* CECC	**-9.663**	−38.383	−67.289	−26.406	−54.179	−53.818	−183.762	−165.475
CGWC *vs.* NJPE	−59.689	−56.791	−85.120	**-49.366**	−58.815	−63.108	−147.004	−103.166
HDEIT *vs.* XITG	**-7.348**	−20.619	−22.431	−24.101	−23.463	−48.206	−30.199	−29.615
GWII *vs.* CNSS	−52.453	−20.834	**-11.537**	−61.589	−11.981	−12.214	−19.989	−14.866
GWII *vs.* XITG	−60.400	−30.868	−28.663	**-12.441**	−24.116	−24.143	−83.362	−27.432
SHBL *vs.* XITG	−35.274	−55.308	−56.582	**-19.626**	−25.793	−56.155	−76.096	−92.516
CNSS *vs.* XITG	−42.560	−25.941	−32.258	**-14.676**	−18.879	−47.415	−46.664	−24.637
CNSS *vs.* CECC	**-8.746**	−56.152	−48.034	−43.395	−16.767	−38.101	−68.939	−48.166
XITG *vs.* CECC	−58.550	−32.027	−58.833	**-25.195**	−29.103	−32.539	−121.621	−96.234
XITG *vs.* NJPE	−56.761	−57.415	**-16.049**	−63.275	−33.973	−82.092	−37.237	−82.342

2 Empirical results

2.1 Comparison of SZKFT and SZSED

Section 2.1 presents the empirical results of credit risk clustering between SZKFT and SZSED . Table S3 lists that the mean value of tail-dependence coefficient is 0.015 in the none-covariate Joe-Clayton copula model, 0.211 in the macroeconomic-covariate Joe-Clayton copula model, 0.894 in the specific-covariate Joe-Clayton copula model, and 0.821 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S1 shows the dynamic characteristics of credit risk clustering between SZKFT and SZSED . We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula and macroeconomic-covariate Joe-Clayton copula models are stationary. Whereas, we observe the obvious volatilities of credit risk clustering in the specific-covariate Joe-Clayton and macroeconomic-specific-covariate Joe-Clayton models. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S4 lists the estimated result of covariate effects on the tail dependence of credit risk between SZKFT and SZSED. The model performance criterion LDS is -4.277 in the macroeconomic-specific-covariate Joe-Clayton model while LDS in the none-covariate Joe-Clayton copula model is -669.263. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the macroeconomic-specific-covariate Joe-Clayton copula model is the best model for predicting the cluster of credit risk between SZKFT and SZSED . If we set a threshold for covariate index selection probability of 50%, we would find that SZKFT's solvency capacity, SZKFT's developing capacity, SZSED's developing capacity,and SZSED's profitability are important for estimating the credit risk clustering between SZKFT and SZSED.

Table S3: Estimation of the tail dependence of credit risk between SZKFT and SZSED

	None	Macro	Specific	Macro+Specifi
Mean	0.015	0.211	0.894	0.821
Median	0.016	0.067	0.969	0.990
Std.dev	0.002	0.337	0.226	0.370

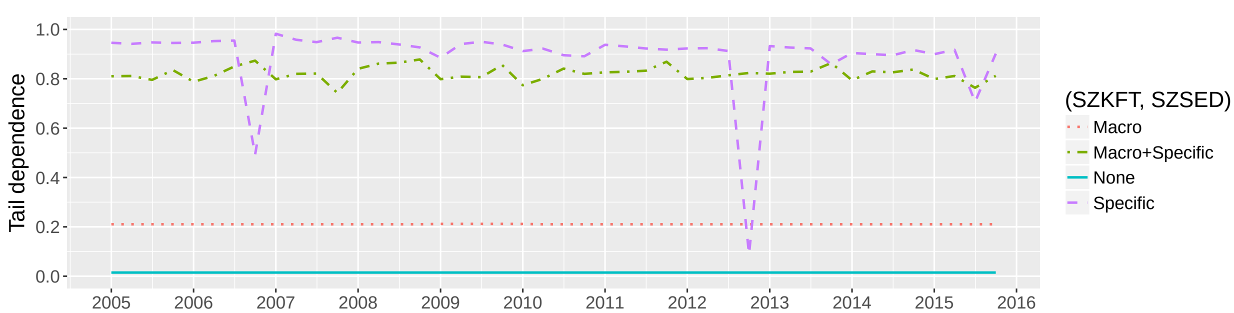

Figure S1: Dynamic of the tail dependence of credit risk between SZKFT and SZSED

Table S4: Covariate effects on the tail dependence of credit risk between SZKFT and SZSED

	None	Macro	Specific	Macro+Specific
Constant	−5.384	1.528	0.060	560.519
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.021		15.502
		(0.998)		(0.406)
M2 growth		0.002		5.617
		(0.817)		(0.372)
Short-term interest rate		−50.114		27.603
		(0.976)		(0.358)
RMB/USD spot rate		−0.314		16.424
		(0.998)		(0.352)
SZKFT's solvency capacity			0.006	0.746
			(0.737)	(0.501)
SZKFT's developing capacity			0.038	−33.884
			(0.823)	(0.562)
SZKFT's profitability			0.181	10.091
			(0.861)	(0.466)
SZKFT's operating capacity			0.017	18.325
			(0.791)	(0.194)
SZSED's solvency capacity			0.018	−60.999
			(0.428)	(0.259)
SZSED's developing capacity			−0.034	−0.722
			(0.926)	(0.758)
SZSED 's profitability			0.106	−2.105
			(0.789)	(0.564)
SZSED 's operating capacity			−0.040	26.142
			0.489	(0.381)
LDS(in-sample)	−669.263	−330.555	−895.344	**-4.277**
LPS(out-of-sample)	−60.836	−54.480	−45.824	**-42.447**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZKFT and SZSED by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicate the criterion of model performance. LPS is Log Predictive Score.

2.2 Comparison of SZKFT and HDEIT

Section 2.2 presents the empirical results of the credit risk clustering between SZKFT and HDEIT. Table S5 lists that the mean value of tail-dependence coefficient is 0.014 in the none-covariate Joe-Clayton copula model, 0.120 in the macroeconomic-covariate Joe-Clayton copula model, 0.640 in the specific-covariate Joe-Clayton copula model, and 0.783 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure 2.2 shows the dynamic characteristics of the credit risk clustering between SZKFT and HDEIT. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, the tail dependence of credit risk uprush dramatically in the macroeconomic-covariate Joe-Clayton copula model, especially during periods of the U.S. subprime mortgage crisis and the European debt crisis. This result means that the probability of credit risk clustering between SZKFT and HDEIT would be enhanced during the periods of global financial crises. However, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and the macroeconomic-specific-covariate Joe-Clayton copula models.

Table S6 lists the estimated result of covariate effects on the tail dependence of credit risk between SZKFT and HDEIT. The model performance criterion LDS is -46.424 in the macroeconomic-specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -357.661. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the macroeconomic-specific-covariate Joe-Clayton copula model is the best model for predicting the cluster of credit risk between SZKFT and HDEIT. If we set a threshold for covariate index selection probabilities of 50%, we would find that all factors except SZKFT's developing capacity are important for estimating the credit risk clustering between SZKFT and HDEIT.

Table S5: Estimation of the tail dependence of credit risk between SZKFT and HDEIT

	None	Macro	Specific	Macro+Specific
Mean	0.014	0.120	0.640	0.783
Median	0.011	0.067	0.753	0.926
Std.dev	0.012	0.186	0.319	0.305

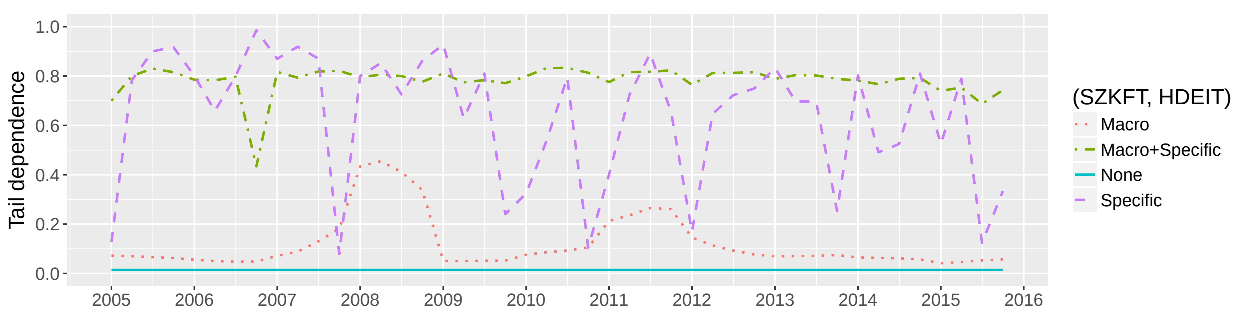

Figure S2: Dynamic of the tail dependence of credit risk between SZKFT and HDEIT

Table S6: Covariate effects on the tail dependence of credit risk between SZKFT and HDEIT

	None	Macro	Specific	Macro+Specific
Constant	−6.796	−4.005	0.174	−1.247
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.024		0.861
		(0.860)		(0.588)
M2 growth		0.013		−2.459
		(0.088)		(0.563)
Short-term interest rate		−0.174		4.425
		(0.488)		(0.588)
RMB/USD spot rate		−0.008		2.842
		(0.074)		(0.694)
SZKFT's solvency capacity		−0.001		0.457
			(0.998)	(0.838)
SZKFT's developing capacity			0.054	3.195
			(0.874)	(0.438)
SZKFT's profitability			−0.008	0.060
			(0.984)	(0.599)
SZKFT's operating capacity			−0.004	−0.102
			(0.133)	(0.644)
HDEIT's solvency capacity			0.262	−3.158
			(0.888)	(0.670)
HDEIT's developing capacity			−0.573	−2.584
			(0.879)	(0.542)
HDEIT's profitability			−0.007	0.293
			(0.138)	(0.509)
HDEIT's operating capacity			−0.053	3.366
			(0.063)	(0.552)
LDS(in-sample)	−357.661	−2373.902	−738.306	**-46.424**
LPS(out-of-sample)	−43.484	−26.442	−57.081	**-5.128**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZKFT and HDEIT by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicate the criterion of model performance. LPS is Log Predictive Score.

2.3 Comparison of SZKFT and GWII

Section 2.3 presents the empirical results of the credit risk clustering between SZKFT and GWII. Table S7 lists that the mean value of tail-dependence coefficient is 0.019 in the none-covariate Joe-Clayton copula model, 0.069 in the macroeconomic-covariate Joe-Clayton copula model, 0.819 in the specific-covariate Joe-Clayton copula model, and 0.802 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S3 shows the dynamic characteristics of the credit risk clustering between SZKFT and GWII. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula and macroeconomic-covariate Joe-Clayton copula models are stationary. Whereas, we observe the obvious volatilities of credit risk clustering in the specific-covariate Joe-Clayton and macroeconomic-specific-covariate Joe-Clayton models. However, we note that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S8 lists the estimated result of covariate effects on the tail dependence of credit risk between SZKFT and GWII. The model performance criterion LDS is -78.253 in the macroeconomic-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -250.435. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the macroeconomic-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZKFT and GWII. If we set a threshold for covariate index selection probabilities of 50%, we would find that all macroeconomic covariates are important for estimating the credit risk clustering between SZKFT and GWII.

Table S7: Estimation of the tail dependence of credit risk between SZKFT and GWII

	None	Macro	Specific	Macro+Specific
Mean	0.019	0.069	0.817	0.802
Median	0.010	0.067	0.990	0.964
Std.dev	0.033	0.051	0.327	0.332

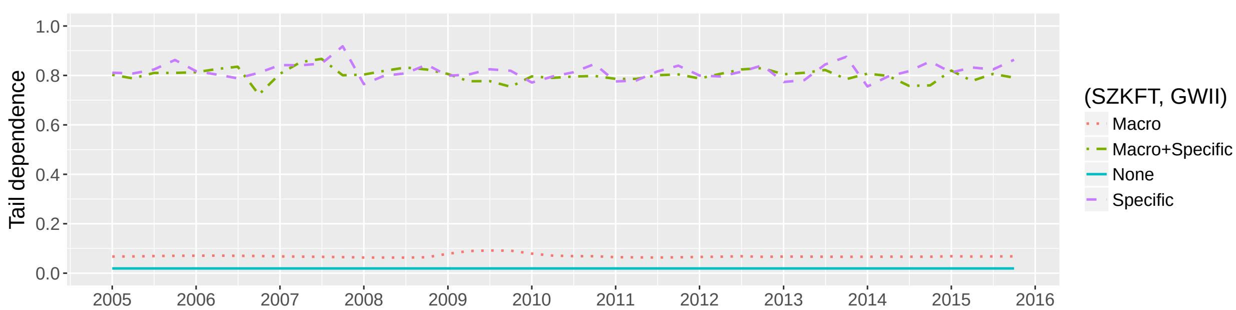

Figure S3: Dynamic of the tail dependence of credit risk between SZKFT and GWII

Table S8: Covariate effects on the tail dependence of credit risk between SZKFT and GWII

	None	Macro	Specific	Macro+Specific
Constant	−6.971	−2.747	13.329	−0.197
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.015		−11.144
		(0.852)		(0.685)
M2 growth		0.010		1.783
		(0.835)		(0.437)
Short-term interest rate		−0.002		−1.693
		(0.858)		(0.773)
RMB/USD spot rate		−0.034		0.157
		(0.965)		(0.460)
SZKFT's solvency capacity			−0.141	−0.024
			(0.294)	(0.944)
SZKFT's developing capacity			0.121	−0.498
			(0.246)	(0.436)
SZKFT's profitability			290.301	1.929
			(0.262)	(0.602)
SZKFT's operating capacity			1.366	0.286
			(0.243)	(0.734)
GWII's solvency capacity			−0.064	0.088
			(0.861)	(0.667)
GWII's developing capacity			5.974	−0.068
			(0.768)	(0.512)
GWII's profitability			0.270	−0.306
			(0.267)	(0.688)
GWII's operating capacity			1313.255	2.844
			(0.251)	(0.574)
LDS(in-sample)	−250.435	**-78.253**	−98.446	−529.368
LPS(out-of-sample)	−26.197	**-12.422**	−50.951	−16.311

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZKFT and GWII by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.4 Comparison of SZKFT and SHBL

Section 2.4 presents the empirical results of the credit risk clustering between SZKFT and SHBL. Table S9 lists that the mean value of tail-dependence coefficient is 0.039 in the none-covariate Joe-Clayton copula model, 0.498 in the macroeconomic-covariate Joe-Clayton copula model, 0.473 in the specific-covariate Joe-Clayton copula model, and 0.980 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S4 shows the dynamic characteristics of the credit risk clustering between SZKFT and SHBL.

The volatility of credit risk clustering is high and complex when inserting the specific-covariates into the Joe-Clayton copula model.

In Table S10 lists the estimated result of covariate effects on the tail dependence of credit risk between SZKFT and SHBL. We find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZKFT and SHBL, and its Log Density Score (LDS) is −212.239.

Table S9: Estimation of the tail dependence of credit risk between SZKFT and SHBL

	None	Macro	Specific	Macro+Specific
Mean	0.039	0.498	0.473	0.980
Median	0.023	0.324	0.442	0.990
Std.dev	0.026	0.446	0.368	0.096

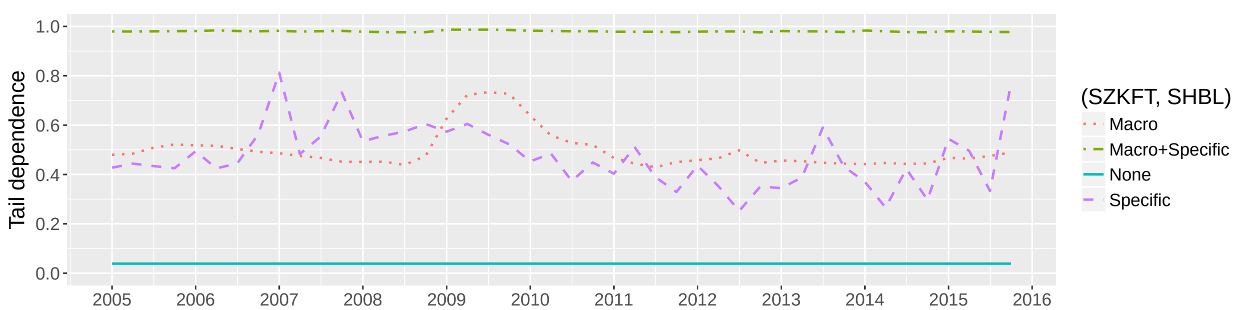

Figure S4: Dynamic of the tail dependence of credit risk between SZKFT and SHBL

Table S10: Covariate effects on the tail dependence of credit risk between SZKFT and SHBL

	None	Macro	Specific	Macro+Specific
Constant	−4.286	−4.162	−0.779	27.596
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.290		3.199
		(0.249)		(0.995)
M2 growth		0.042		−0.091
		(0.904)		(0.007)
Short-term interest rate		0.602		3.908
		(0.883)		(0.998)
RMB/USD spot rate		1.291		3.029
		(0.764)		(0.996)
SZKFT's solvency capacity			0.005	−0.656
			(0.921)	(0.998)
SZKFT's developing capacity			0.636	−0.012
			(0.771)	(0.992)
SZKFT's profitability			−0.292	−0.958
			(0.636)	(0.007)
SZKFT's operating capacity			0.020	−0.037
			(0.784)	(0.993)
SHBL's solvency capacity			0.186	−0.087
			(0.617)	(0.009)
SHBL's developing capacity			0.009	−0.026
			(0.619)	(0.993)
SHBL's profitability			−0.116	0.147
			(0.748)	(0.004)
SHBL's operating capacity			−0.109	−0.000
			(0.765)	(0.989)
LDS(in-sample)	**-212.239**	−2233.640	−343.365	−273.072
LPS(out-of-sample)	**-2.282**	−18.546	−41.646	−15.920

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZKFT and SHBL by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicate the criterion of model performance. LPS is Log Predictive Score.

2.5 Comparison of SZKFT and CNSS

Section 2.5 presents the empirical results of the credit risk clustering between SZKFT and CNSS. Table S11 lists that the mean value of tail-dependence coefficient is 0.014 in the none-covariate Joe-Clayton copula model, 0.101 in the macroeconomic-covariate Joe-Clayton copula model, 0.585 in the specific-covariate Joe-Clayton copula model, and 0.322 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result, we find that tail- dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S5 shows the dynamic characteristics of the credit risk clustering between SZKFT and CNSS. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of tail dependence of credit risk in the macroeconomic-covariate Joe-Clayton copula model. We also identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

In Table S12 lists the estimated result of covariate effects on the tail dependence of credit risk between SZKFT and CNSS. The model performance criterion LDS is −137.359 in the macroeconomic-specific-covariate Joe-Clayton copula model, while LDS in the none-covariate Joe-Clayton copula model is −278.619. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the macroeconomic-specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZKFT and CNSS. If we set a threshold for covariate index selection probabilities of 50%, we would find that CPI, SZKFT's solvency capacity and CNSS's profitability are important for estimating credit risk clustering between SZKFT and CNSS.

Table S11: Estimation of the tail dependence of credit risk between SZKFT and CNSS

	None	Macro	Specific	Macro+Specific
Mean	0.014	0.101	0.585	0.322
Median	0.011	0.067	0.622	0.010
Std.dev	0.009	0.186	0.304	0.451

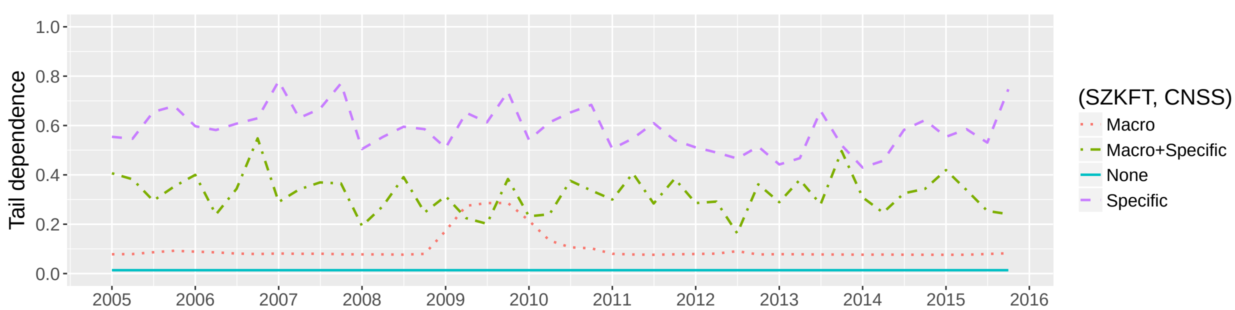

Figure S5: Dynamic of the tail dependence of credit risk between SZKFT and CNSS

Table S12: Covariate effects on the tail dependence of credit risk between SZKFT and CNSS

	None	Macro	Specific	Macro+Specific
Constant	−6.897	−3.262	−0.133	−50.099
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.087		−1.176
		(0.949)		(0.719)
M2 growth		0.134		−0.440
		(0.993)		(0.333)
Short-term interest rate		−0.247		142.076
		(0.944)		(0.383)
RMB/USD spot rate		−0.074		−1.607
		(0.822)		(0.351)
SZKFT's solvency capacity			0.005	−4.640
			(0.927)	(0.583)
SZKFT's developing capacity			0.356	0.328
			(0.528)	(0.299)
SZKFT's profitability			0.212	17.696
			(0.597)	(0.333)
SZKFT's operating capacity			−0.012	1.822
			(0.532)	(0.436)
CNSS's solvency capacity			−0.044	−0.695
			(0.636)	(0.476)
CNSS's developing capacity			−0.084	35.810
			(0.650)	(0.472)
CNSS's profitability			−0.045	−1.597
			(0.808)	(0.684)
CNSS's operating capacity			0.059	31.024
			(0.503)	(0.282)
LDS(in-sample)	−278.619	−210.320	−388.579	**-137.359**
LPS(out-of-sample)	−75.794	−56.534	−69.198	**-1.517**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZKFT and CNSS by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.6 Comparison of SZKFT and CECC

Section 2.6 presents the empirical results of credit risk clustering between SZKFT and CECC. Table S13 lists that the mean value of tail-dependence coefficient is 0.028 in the none-covariate Joe-Clayton copula model, 0.152 in the macroeconomic-covariate Joe-Clayton copula model, 0.707 in the specific-covariate Joe-Clayton copula model, and 0.516 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail- dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S6 shows the dynamic characteristics of the credit risk clustering between SZKFT and CECC.

We see that the time-varying characteristic in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of tail dependence of credit risk in the macroeconomic-covariate Joe-Clayton copula model, especially during the periods of U.S. subprime mortgage crisis and European debt crisis. This result means that the probability of the credit risk clustering between SZKFT and CECC would be enhanced during periods of global financial crises. However, we find that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

In table S14 lists the estimated result of covariate effects on the tail dependence of credit risk between SZKFT and CECC. We find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate BB7 copula model is the best model for predicting the credit risk clustering between SZKFT and CECC, and its Log Density Score (LDS) is −55.518.

Table S13: Estimation of the tail dependence of credit risk between SZKFT and CECC

	None	Macro	Specific	Macro+Specific
Mean	0.028	0.152	0.707	0.516
Median	0.011	0.067	0.963	0.564
Std.dev	0.024	0.238	0.368	0.321

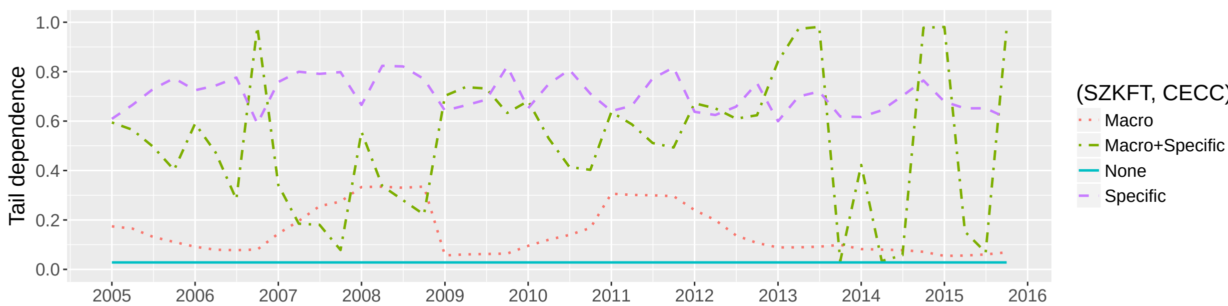

Figure S6: Dynamic of the tail dependence of credit risk between SZKFT and CECC

Table S14: Covariate effects on the tail dependence of credit risk between SZKFT and CECC

	None	Macro	Specific	Macro+Specific
Constant	−5.660	−5.171	0.430	0.039
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		0.517		0.087
		(0.999)		(0.947)
M2 growth		0.011		0.691
		(0.760)		(0.952)
Short-term interest rate		−0.049		0.052
		(0.983)		(0.057)
RMB/USD spot rate		0.224		0.259
		(0.921)		(0.923)
SZKFT's solvency capacity			0.047	−0.027
			(0.905)	(0.998)
SZKFT's developing capacity			−0.106	7.110
			(0.495)	(0.073)
SZKFT's profitability			1.386	0.437
			(0.628)	(0.958)
SZKFT's operating capacity			0.082	0.058
			(0.665)	(0.950)
CECC's solvency capacity			0.278	−2.246
			(0.646)	(0.090)
CECC's developing capacity			0.481	−0.032
			(0.647)	(0.931)
CECC's profitability			−0.366	0.011
			(0.681)	(0.049)
CECC's operating capacity			0.709	−1.334
			(0.702)	(0.972)
LDS(in-sample)	−55.518	−222.213	−301.683	−964.671
LPS(out-of-sample)	−51.168	−70.712	−70.330	−85.648

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZKFT and CECC by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.7 Comparison of SZKFT and NJPE

Section 2.7 presents the empirical results of the credit risk clustering between SZKFT and NJPE. Table S15 lists that the mean value of tail-dependence coefficient is 0.019 in the none-covariate Joe-Clayton copula model, 0.516 in the macroeconomic-covariate Joe-Clayton copula model, 0.663 in the specific-covariate Joe-Clayton copula model, and 0.835 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail dependence-coefficient displays an increasing pattern.

Figure S7 shows the dynamic characteristics of the credit risk clustering between SZKFT and NJPE.

We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of the credit risk clustering in the covariate-dependent Joe-Clayton models. However, we find that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S16 lists the estimated result of covariate effects on the tail dependence of credit risk between SZKFT and NJPE. The model performance criterion LDS is -154.880 in the macroeconomic-covariate Joe-Clayton model while LDS in the none-covariate Joe-Clayton copula model is -520.863 This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the macroeconomic-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZKFT and NJPE. If we set a threshold for covariate index selection probabilities of 50%, we would find that CPI, M2 growth and RMB/USD spot rate are important for estimating the credit risk clustering between SZKFT and NJPE.

Table S15: Estimation of the tail dependence of credit risk between SZKFT and NJPE

	None	Macro	Specific	Macro+Specific
Mean	0.019	0.516	0.663	0.835
Median	0.011	0.575	0.701	0.896
Std.dev	0.023	0.453	0.220	0.185

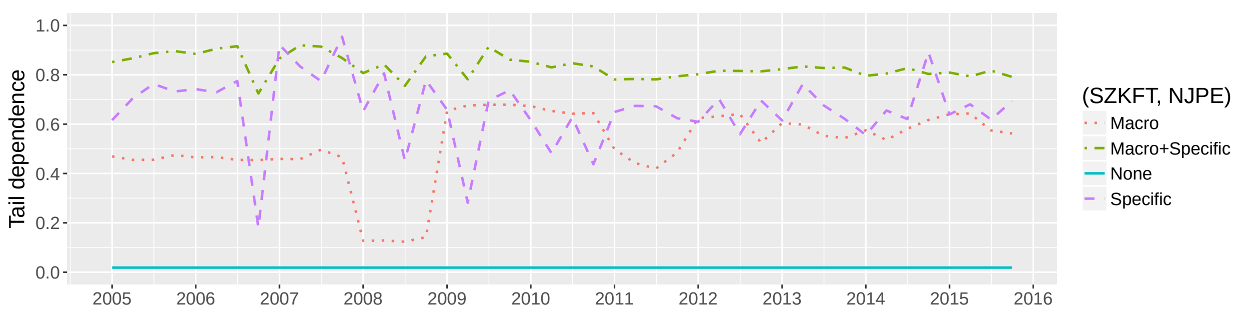

Figure S7: Dynamic of the tail dependence of credit risk between SZKFT and NJPE

Table S16: Covariate effects on the tail dependence of credit risk between SZKFT and NJPE

	None	Macro	Specific	Macro+Specific
Constant	−6.259	20.007	0.020	−0.684
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−2.862		−0.150
		(0.750)		(0.636)
M2 growth		0.123		0.023
		(0.955)		(0.646)
Short-term interest rate		−0.220		0.225
		(0.303)		(0.671)
RMB/USD spot rate		−1.565		0.243
		(0.842)		(0.654)
SZKFT's solvency capacity			0.009	0.000
			(0.951)	(0.917)
SZKFT's developing capacity			0.065	−0.017
			(0.265)	(0.590)
SZKFT's profitability			0.002	0.437
			(0.275)	(0.543)
SZKFT's operating capacity			0.007	0.015
			(0.250)	(0.667)
NJPE's solvency capacity			0.003	0.001
			(0.229)	(0.511)
NJPE's developing capacity			0.160	0.021
			(0.771)	(0.564)
NJPE's profitability			0.015	−0.417
			(0.840)	(0.485)
NJPE's operating capacity			−0.037	−0.033
			(0.784)	(0.503)
LDS(in-sample)	−520.863	**-154.880**	−363.862	−348.292
LPS(out-of-sample)	−48.611	**-11.464**	−89.704	−86.039

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZKFT and NJPE by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.8 Comparison of SZSED and CGWC

Section 2.8 presents the empirical results of the credit risk clustering between SZSED and CGWC. Table S17 lists that the mean value of tail-dependence coefficient is 0.011 in the none-covariate Joe-Clayton copula model, 0.165 in the macroeconomic-covariate Joe-Clayton copula model, 0.739 in the specific-covariate Joe-Clayton copula model, and 0.977 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S8 shows the dynamic characteristics of credit risk clustering between SZSED and CGWC. The volatility of credit risk clustering increases remarkably during the periods of U.S. subprime mortgage crisis and European debt crisis.

Table S18 lists the estimated result of covariate effects on the tail dependence of credit risk between SZSED and CGWC. The model performance criterion LDS is -84.783 in the macroeconomic-covariate Joe-Clayton model while LDS in the none-covariate Joe-Clayton copula model is -546.894. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the macroeconomic-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZSED and CGWC. If we set a threshold for covariate index selection probabilities of 50%, we would find that all macroeconomic covariates are important for estimating the credit risk clustering between SZSED and CGWC.

Table S17: Estimation of the tail dependence of credit risk between SZSED and CGWC

	None	Macro	Specific	Macro+Specific
Mean	0.011	0.165	0.739	0.977
Median	0.010	0.067	0.990	0.990
Std.dev	0.002	0.231	0.391	0.113

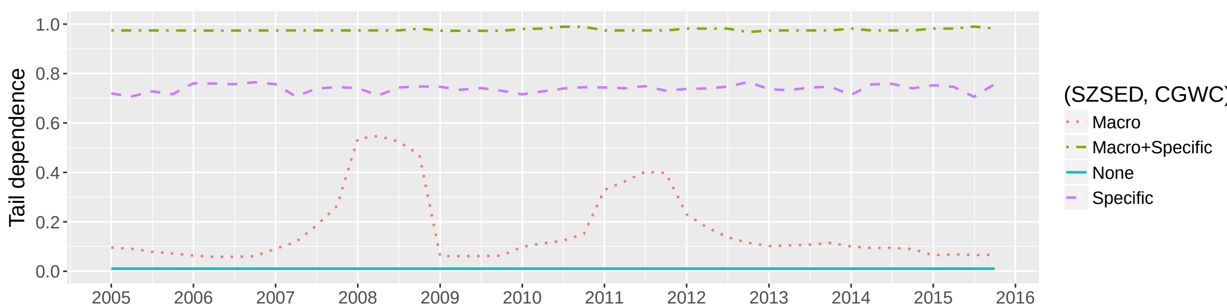

Figure S8: Dynamic of the tail dependence of credit risk between SZSED and CGWC

Table S18: Covariate effects on the tail dependence of credit risk between SZSED and CGWC

	None	Macro	Specific	Macro+Specific
Constant	−7.676	−3.108	418.353	11068.512
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		0.582		−569469.300
		(0.961)		(0.757)
M2 growth		0.010		−79203.440
		(0.526)		(0.124)
Short-term interest rate		−0.064		273.299
		(0.667)		(0.625)
RMB/USD spot rate		−0.112		1229149
		(0.684)		(0.826)
SZSED 's solvency capacity			−162.943	58308.290
			(0.232)	(0.379)
SZSED 's developing capacity			−51.324	−9290.945
			(0.899)	(0.855)
SZSED 's profitability			0.899	684.416
			(0.246)	(0.742)
SZSED 's operating capacity			77.711	−29030.490
			(0.296)	(0.660)
CGWC's solvency capacity			−100.116	52.905
			(0.275)	(0.460)
CGWC's developing capacity			−18.445	−35987.910
			(0.262)	(0.624)
CGWC's profitability			−766.912	6292365.000
			(0.359)	(0.790)
CGWC's operating capacity			27.566	82920.980
			(0.176)	(0.821)
LDS(in-sample)	−546.894	**-84.783**	−3152.373	−1683.696
LPS(out-of-sample)	−54.442	**-20.335**	−101.153	−56.279

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZSED and CGWC by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.9 Comparison of SZSED and HDEIT

Section 2.9 presents the empirical results of the credit risk clustering between SZSED and HDEIT. Table S19 lists that the mean value of tail-dependence coefficient is 0.020 in the none-covariate Joe-Clayton copula model, 0.348 in the macroeconomic-covariate Joe-Clayton copula model, 0.600 in the specific-covariate Joe-Clayton copula model, and 0.453 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail- dependence coefficient in covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S9 shows the dynamic characteristics of the credit risk clustering between SZSED and HDEIT.

We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of the tail dependence of credit risk in the covariate-dependent Joe-Clayton copula model. However, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S20 lists the estimated result of covariate effects on the tail dependence of credit risk between SZSED and HDEIT. We find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZSED and HDEIT, and its Log Density Score (LDS) is −380.349.

Table S19: Estimation of the tail dependence of credit risk between SZSED and HDEIT

	None	Macro	Specific	Macro+Specific
Mean	0.020	0.348	0.600	0.453
Median	0.010	0.310	0.581	0.407
Std.dev	0.018	0.231	0.231	0.414

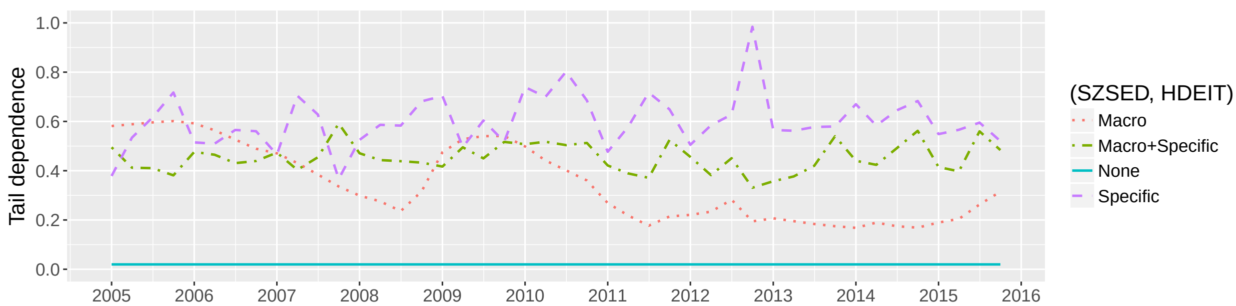

Figure S9: Dynamic of the tail dependence of credit risk between SZSED and HDEIT

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Table S20: Covariate effects on the tail dependence of credit risk between SZSED and HDEIT

	None	Macro	Specific	Macro+Specific
Constant	−6.553	−5.116	0.503	−36.894
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.040		0.063
		(0.242)		(0.599)
M2 growth		0.075		−2.879
		(0.573)		(0.747)
Short-term interest rate		−0.563		0.011
		(0.725)		(0.444)
RMB/USD spot rate		0.895		−1.794
		(0.869)		(0.809)
SZSED 's solvency capacity			0.012	0.012
			(0.647)	(0.752)
SZSED 's developing capacity			0.001	−2.355
			(1.000)	(0.624)
SZSED 's profitability			0.005	0.073
			(0.656)	(0.747)
SZSED 's operating capacity			0.008	0.076
			(0.161)	(0.800)
HDEIT's solvency capacity			0.024	−0.267
			(0.702)	(0.535)
HDEIT's developing capacity			−0.084	0.171
			(0.904)	(0.821)
HDEIT's profitability			−0.014	−22.929
			(0.922)	(0.701)
HDEIT's operating capacity			0.041	0.702
			(0.897)	(0.745)
LDS(in-sample)	**-380.349**	−446.278	−1106.352	−793.033
LPS(out-of-sample)	**-25.335**	−56.139	−26.982	−62.701

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZSED and HDEIT by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.10 Comparison of SZSED and GWII

Section 2.10 presents the empirical results of the credit risk clustering between SZSED and GWII. Table S21 lists that the mean value of tail-dependence coefficient is 0.013 in the none-covariate Joe-Clayton copula model, 0.631 in the macroeconomic-covariate Joe-Clayton copula model, 0.868 in the specific-covariate Joe-Clayton copula model, and 0.702 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S10 shows the dynamic characteristics of the credit risk clustering between SZSED and GWII. The volatility of the credit risk clustering is high and complex when inserting the firm-specific covariates into the

Joe-Clayton copula model.

Table S22 lists the estimated results of covariate effects on the tail dependency of credit risk between SZSED and GWII. The model performance criterion LDS is −84.988 in the specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is −202.136. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZSED and GWII. If we set a threshold for covariate index selection probabilities of 50%, we would find that SZSED 's developing capacity, SZSED 's profitability and GWII's profitability are important for estimating the credit risk clustering between SZSED and GWII.

Table S21: Estimation of the tail dependence of credit risk between SZSED and GWII

	None	Macro	Specific	Macro+Specific
Mean	0.013	0.631	0.868	0.702
Median	0.010	0.841	0.990	0.990
Std.dev	0.011	0.405	0.324	0.440

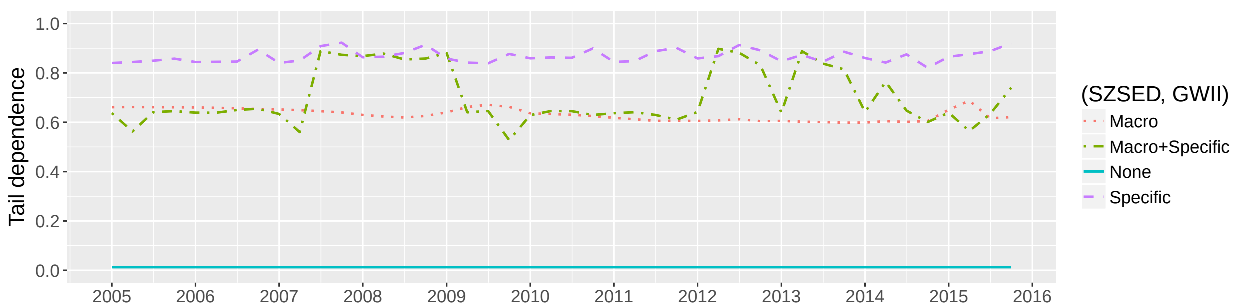

Figure S10: Dynamic of the tail dependence of credit risk between SZSED and GWII

Table S22: Covariate effects on the tail dependence of credit risk between SZSED and GWII

	None	Macro	Specific	Macro+Specific
Constant	−7.166	8.235	896.481	81.551
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.283		−0.554
		(0.231)		(0.449)
M2 growth		−0.171		0.048
		(0.451)		(0.199)
Short-term interest rate		1.005		−1.081
		(0.586)		(0.491)
RMB/USD spot rate		−0.222		−2.723
		(0.878)		(0.327)
SZSED 's solvency capacity			−2.398	−0.373
			(0.182)	(0.110)
SZSED 's developing capacity			−43.723	−0.209
			(0.505)	(0.343)
SZSED 's profitability			59.726	0.304
			(0.649)	(0.713)
SZSED 's operating capacity			889.205	−0.386
			(0.376)	(0.126)
GWII's solvency capacity			759.451	18.573
			(0.310)	(0.436)
GWII's developing capacity			171.343	2.347
			(0.391)	(0.353)
GWII's profitability			−11.322	0.546
			(0.685)	(0.466)
GWII's operating capacity			646.664	−2.596
			(0.423)	(0.361)
LDS(in-sample)	−202.136	−352.010	**-84.988**	−214.629
LPS(out-of-sample)	−98.763	−69.067	**-20.953**	−104.965

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZSED and GWII by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.11 Comparison of SZSED and SHBL

Section 2.11 presents the empirical results of the credit risk clustering between SZSED and SHBL. Table S23 lists that the mean value of tail-dependence coefficient is 0.017 in the none-covariate Joe-Clayton copula model, 0.890 in the macroeconomic-covariate Joe-Clayton copula model, 0.550 in the specific-covariate Joe-Clayton copula model, and 0.850 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in covariate-dependent Joe-Clayton copula model is much higher than that in none-covariate Joe-Clayton copula model.

Figure S11 shows the dynamic characteristics of the credit risk clustering between SZSED and SHBL. We see that the time-varying characteristics in the none-covariate Joe-Clayton copula model and macroeconomic-covariate copula models are stationary. Whereas, we observe an obvious volatility of tail dependence of credit risk in the specific-covariate Joe-Clayton copula model and macroeconomic-specific-covariate copula model. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S24 lists the estimated result of covariate effects on the tail dependency of credit risk between SZSED and SHBL. The model performance criterion LDS is -196.194 in the specific-covariate Joe-Clayton model while LDS in the none-covariate Joe-Clayton copula model is -357.500. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZSED and SHBL. If we set a threshold for covariate index selection probabilities of 50%, we would find that all firm-specific factors are important for estimating the credit risk clustering between SZSED and SHBL.

Table S23: Estimation of the tail dependence of credit risk between SZSED and SHBL

	None	Macro	Specific	Macro+Specific
Mean	0.017	0.890	0.550	0.850
Median	0.010	0.990	0.810	0.990
Std.dev	0.029	0.295	0.449	0.340

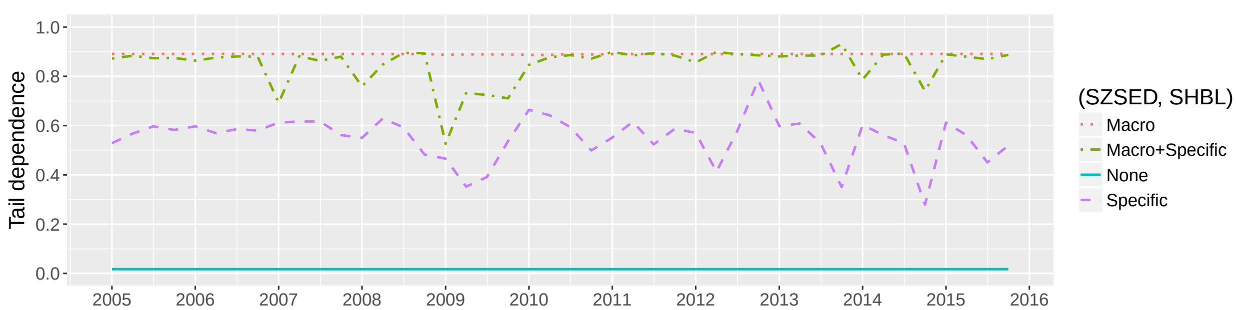

Figure S11: Dynamic of the tail dependence of credit risk between SZSED and SHBL

Table S24: Covariate effects on the tail dependence of credit risk between SZSED and SHBL

	None	Macro	Specific	Macro+Specific
Constant	−7.016	32.386	27.693	254.451
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−33.093		1.281
		(0.912)		(0.473)
M2 growth		13.110		61.946
		(0.868)		(0.285)
Short-term interest rate		5.660		6.549
		(0.839)		(0.592)
RMB/USD spot rate		3.681		8.101
		(0.833)		(0.430)
SZSED 's solvency capacity			−7.259	31.611
			(0.676)	(0.489)
SZSED 's developing capacity			0.324	0.369
			(0.968)	(0.367)
SZSED 's profitability			0.743	−0.264
			(0.727)	(0.477)
SZSED 's operating capacity			0.103	2.044
			(0.513)	(0.433)
SHBL's solvency capacity			−1.142	0.835
			(0.599)	(0.384)
SHBL's developing capacity			0.445	−2.005
			(0.813)	(0.307)
SHBL's profitability			−0.992	1.811
			(0.567)	(0.671)
SHBL's operating capacity			−0.019	−1.107
			(0.577)	(0.358)
LDS(in-sample)	−357.500	−578.632	**-196.194**	−198.684
LPS(out-of-sample)	−62.114	−75.447	**-16.701**	−44.675

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZSED and SHBL by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.12 Comparison of SZSED and CNSS

Section 2.12 presents the empirical results of the credit risk clustering between SZSED and CNSS. Table S25 lists that the mean value of tail-dependence coefficient is 0.015 in the none-covariate Joe-Clayton copula model, 0.133 in the macroeconomic-covariate Joe-Clayton copula model, 0.527 in the specific-covariate Joe-Clayton copula model, and 0.798 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S12 shows the dynamic characteristics of the credit risk clustering between SZSED and CNSS. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary.

Whereas, we observe an obvious volatility of the tail dependence of credit risk in the macroeconomic-covariate Joe-Clayton copula model, especially during the periods of the U.S. subprime mortgage crisis. However, we identify that the time-varying characteristics of the tail dependence of credit risk are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S26 lists the estimated result of covariate effects on the tail dependence of credit risk between SZSED and CNSS. We find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate Joe-Clayton copula model is the best model for predicting credit risk clustering between SZSED and CNSS, and its Log Density Score (LDS) is -120.882.

Table S25: Estimation of the tail dependence of credit risk between SZSED and CNSS

	None	Macro	Specific	Macro+Specific
Mean	0.015	0.133	0.527	0.798
Median	0.011	0.033	0.513	0.897
Std.dev	0.007	0.220	0.311	0.217

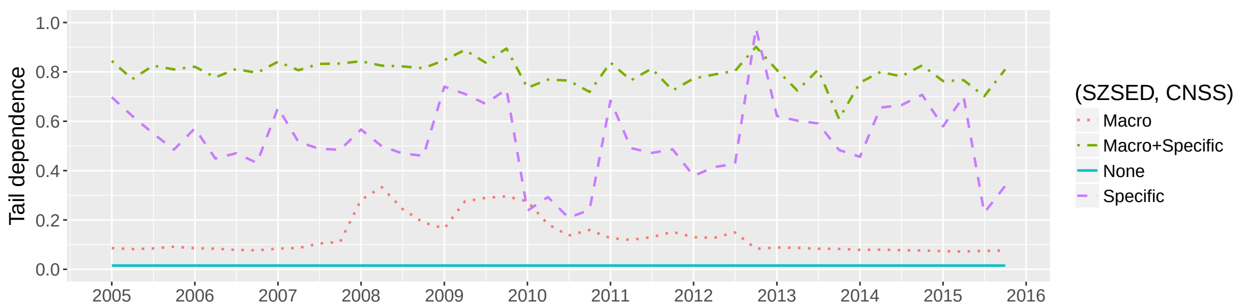

Figure S12: Dynamic of the tail dependence of credit risk between SZSED and CNSS

Table S26: Covariate effects on the tail dependence of credit risk between SZSED and CNSS

	None	Macro	Specific	Macro+Specific
Constant	−6.229	−4.777	0.058	−0.091
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		1.221		0.028
		(0.768)		(0.590)
M2 growth		0.119		0.030
		(0.529)		(0.340)
Short-term interest rate		−0.734		0.058
		(0.682)		(0.601)
RMB/USD spot rate		−0.250		0.162
		(0.679)		(0.776)
SZSED 's solvency capacity			−0.058	−0.007
			(0.846)	(0.562)
SZSED 's developing capacity			0.001	0.001
			(0.994)	(0.980)
SZSED 's profitability			0.024	0.026
			(0.900)	(0.864)
SZSED 's operating capacity			−0.001	0.003
			(0.783)	(0.499)
CNSS's solvency capacity			0.047	0.009
			(0.868)	(0.443)
CNSS's developing capacity			0.022	−0.032
			(0.847)	(0.610)
CNSS's profitability			0.004	0.003
			(0.616)	(0.490)
CNSS's operating capacity			0.015	0.018
			(0.626)	(0.393)
LDS(in-sample)	**-120.882**	−436.132	−593.897	−428.093
LPS(out-of-sample)	**-6.141**	−38.078	−46.940	−139.944

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZSED and CNSS by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.13 Comparison of SZSED and XITG

Section 2.13 presents the empirical results of the credit risk clustering between SZSED and XITG. Table S27 lists that the mean value of tail-dependence coefficient is 0.019 in the none-covariate Joe-Clayton copula model, 0.180 in the macroeconomic-covariate Joe-Clayton copula model, 0.840 in the specific-covariate Joe-Clayton copula model, and 0.825 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in covariate-dependent Joe-Clayton copula model is much higher than that in none-covariate Joe-Clayton copula model.

Figure S13 shows the dynamic characteristics of the credit risk clustering between SZSED and XITG. We see that the volatility of credit risk clustering is high and complex in specific-covariate Joe-Clayton copula model. We also find an obvious increase in the tail dependence of credit risk between SZSED and XITG during the period of U.S. subprime mortgage crisis.

Table S28 lists the estimated result of covariate effects on the tail dependence of credit risk between SZSED and XITG. The model performance criterion LDS is -124.139 in the macroeconomic-covariate Joe-Clayton model while LDS in the none-covariate Joe-Clayton copula model is -141.427. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the macroeconomic-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZSED and XITG. If we set a threshold for covariate index selection probabilities of 50%, we would find that M2 growth and short-term interest rate are important for estimating the credit risk clustering between SZSED and XITG.

Table S27: Estimation of the tail dependence of credit risk between SZSED and XITG

	None	Macro	Specific	Macro+Specific
Mean	0.019	0.180	0.840	0.825
Median	0.020	0.031	0.990	0.980
Std.dev	0.006	0.308	0.352	0.340

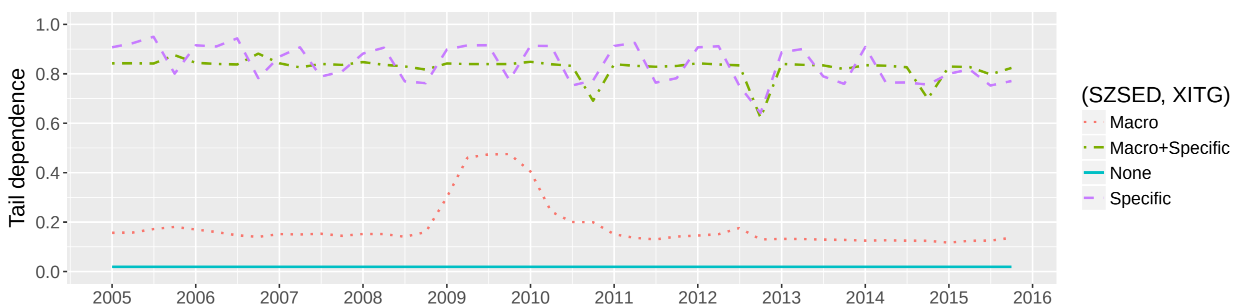

Figure S13: Dynamic of the tail dependence of credit risk between SZSED and XITG

Table S28: Covariate effects on the tail dependence of credit risk between SZSED and XITG

	None	Macro	Specific	Macro+Specific
Constant	−4.982	−5.168	18.161	−3.716
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		2.304		9.958
		(0.216)		(0.533)
M2 growth		0.748		10.909
		(0.589)		(0.502)
Short-term interest rate		−5.644		3.250
		(0.680)		(0.636)
RMB/USD spot rate		0.201		21.955
		(0.377)		(0.538)
SZSED 's solvency capacity			−39.002	−7.940
			(0.709)	(0.734)
SZSED 's developing capacity			−0.175	−6.045
			(0.241)	(0.634)
SZSED 's profitability			17.612	−2.171
			(0.807)	(0.604)
SZSED 's operating capacity			−38.650	−0.577
			(0.782)	(0.527)
XITG's solvency capacity			−0.307	−2.996
			(0.197)	(0.535)
XITG's developing capacity			−49.655	−0.322
			(0.299)	(0.731)
XITG's profitability			−12.280	−226.712
			(0.953)	(0.543)
XITG's operating capacity			15.948	−0.259
			(0.744)	(0.427)
LDS(in-sample)	−141.427	**-124.139**	−194.118	−418.148
LPS(out-of-sample)	−89.482	**-2.706**	−97.128	−26.501

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZSED and XITG by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.14 Comparison of SZSED and CECC

Section 2.14 presents the empirical results of the credit risk clustering between SZSED and CECC. Table S29 lists that the mean value of tail-dependence coefficient is 0.025 in the none-covariate Joe-Clayton copula model, 0.877 in the macroeconomic-covariate Joe-Clayton copula model, 0.787 in the specific-covariate Joe-Clayton copula model, and 0.758 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S14 shows the dynamic characteristics of credit risk clustering between SZSED and CECC. We see that the volatility of credit risk clustering is high and complex in specific-covariate Joe-Clayton copula model.

Table S30 lists the estimated result of covariate effects on the tail dependence of credit risk between SZSED and CECC. We find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZSED and CECC, and its Log Density Score (LDS) is -29.658.

Table S29: Estimation of the tail dependence of credit risk between SZSED and CECC

	None	Macro	Specific	Macro+Specific
Mean	0.025	0.877	0.787	0.758
Median	0.011	0.990	0.842	0.833
Std.dev	0.044	0.307	0.219	0.226

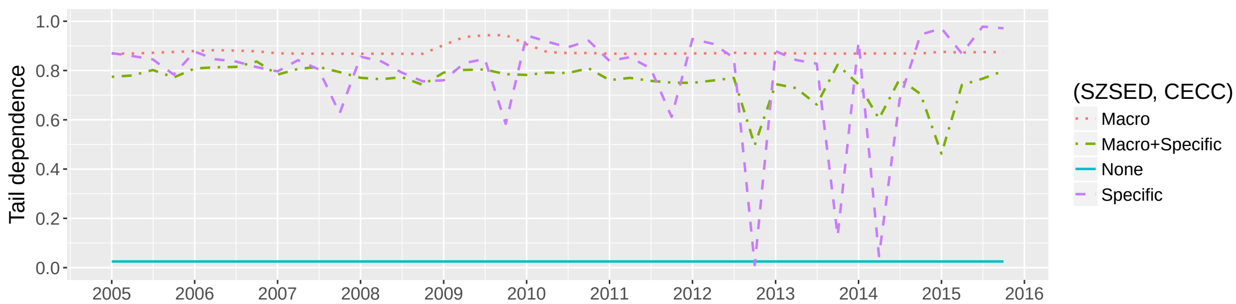

Figure S14: Dynamic of the tail dependence of credit risk between SZSED and CECC

Table S30: Covariate effects on the tail dependence of credit risk of SZSED and CECC

	None	Macro	Specific	Macro+Specific
Constant	−6.387	527.474	−6.880	−1.439
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.119		−0.036
		(0.076)		(0.504)
M2 growth		−2.136		0.017
		(0.079)		(0.487)
Short-term interest rate		−0.049		0.004
		(0.043)		(0.559)
RMB/USD spot rate		−0.245		0.335
		(0.894)		(0.576)
SZSED 's solvency capacity			0.021	−0.000
			(1.000)	(0.555)
SZSED 's developing capacity			−0.088	−0.005
			(1.000)	(0.806)
SZSED 's profitability			−0.006	0.184
			(0.014)	(0.563)
SZSED 's operating capacity			−0.077	0.012
			(0.993)	(0.426)
CECC's solvency capacity			0.007	0.032
			(0.028)	(0.558)
CECC's developing capacity			−0.021	−0.007
			(0.987)	(0.533)
CECC's profitability			0.016	0.174
			(0.005)	(0.566)
CECC's operating capacity			−0.003	0.005
			(0.977)	(0.661)
LDS(in-sample)	**-29.658**	−2474.630	−2967.027	−414.841
LPS(out-of-sample)	**-4.340**	−13.852	−91.406	−20.628

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZSED and CECC by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.15 Comparison of SZSED andNJPE

Section 2.15 presents the empirical results of the credit risk clustering between SZSED and NJPE. Table S31 lists that the mean value of tail-dependence coefficient is 0.099 in the none-covariate Joe-Clayton copula model, 0.335 in the macroeconomic-covariate Joe-Clayton copula model, 0.825 in the specific-covariate Joe-Clayton copula model, and 0.939 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S15 shows the dynamic characteristics of the credit risk clustering between SZSED and NJPE. We see that the volatility of credit risk clustering is high and complex when inserting covariates into the Joe-Clayton copula model.

Table S32 lists the estimated result of covariate effects on the tail dependence of credit risk between SZSED and NJPE. we find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SZSED and NJPE, and its Log Density Score (LDS) is -136.957.

Table S31: Estimation of the tail dependence of credit risk between SZSED and NJPE

	None	Macro	Specific	Macro+Specific
Mean	0.099	0.335	0.825	0.939
Median	0.154	0.300	0.990	0.962
Std.dev	0.067	0.236	0.366	0.088

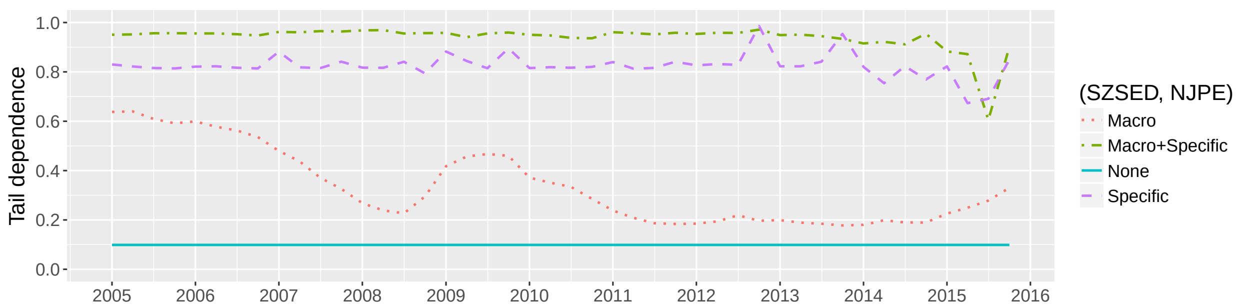

Figure S15: Dynamic of the tail dependence of credit risk between SZSED and NJPE

Table S32: Covariate effects on the tail dependence of credit risk between SZSED and NJPE

	None	Macro	Specific	Macro+Specific
Constant	−3.563	−5.078	900.658	0.022
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.118		0.079
		(0.416)		(0.778)
M2 growth		−0.045		0.114
		(0.203)		(0.714)
Short-term interest rate		−0.524		0.115
		(0.669)		(0.853)
RMB/USD spot rate		1.142		0.091
		(0.990)		(0.762)
SZSED 's solvency capacity		11.931	−0.007	
			(0.345)	(0.847)
SZSED 's developing capacity			3.202	0.0002
			(0.969)	(0.999)
SZSED 's profitability			49.640	0.0004
			(0.788)	(0.774)
SZSED 's operating capacity			18.534	−0.005
			(0.467)	(0.671)
NJPE's solvency capacity			16.927	0.008
			(0.598)	(0.765)
NJPE's developing capacity			82.141	0.010
			(0.495)	(0.212)
NJPE's profitability			4.487	0.0003
			(0.789)	(0.572)
NJPE's operating capacity			−1.391	−0.002
			(0.439)	(0.621)
LDS(in-sample)	**-136.957**	−348.323	−663.390	−678.042
LPS(out-of-sample)	**-33.936**	−42.823	−82.946	−64.968

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SZSED and NJPE by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.16 Comparison of CGWC and HDEIT

Section 2.16 presents the empirical results of the credit risk clustering between CGWC and HDEIT. Table 2.16 lists that the mean value of tail-dependence coefficient is 0.070 in the none-covariate Joe-Clayton copula model, 0.161 in the macroeconomic-covariate Joe-Clayton copula model, 0.301 in the specific-covariate Joe-Clayton copula model, and 0.596 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S16 shows the dynamic characteristics of the credit risk clustering between CGWC and HDEIT. We see that the volatility of credit risk clustering is high and complex when inserting covariates into the

Joe-Clayton copula model.

Table S34 lists the estimated result of covariate effects on the tail dependence of the credit risk between CGWC and HDEIT. The model performance criterion LDS is −8.409 in the macroeconomic-covariate Joe-Clayton model while LDS in the none-covariate Joe-Clayton copula model is −23.947. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the macroeconomic-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between CGWC and HDEIT. If we set a threshold for covariate index selection probabilities of 50%, we would find that CPI and M2 growth are important for estimating the credit risk clustering between CGWC and HDEIT.

Table S33: Estimation of the tail dependence of credit risk between CGWC and HDEIT

	None	Macro	Specific	Macro+Specific
Mean	0.070	0.161	0.301	0.596
Median	0.059	0.060	0.065	0.842
Std.dev	0.054	0.254	0.382	0.426

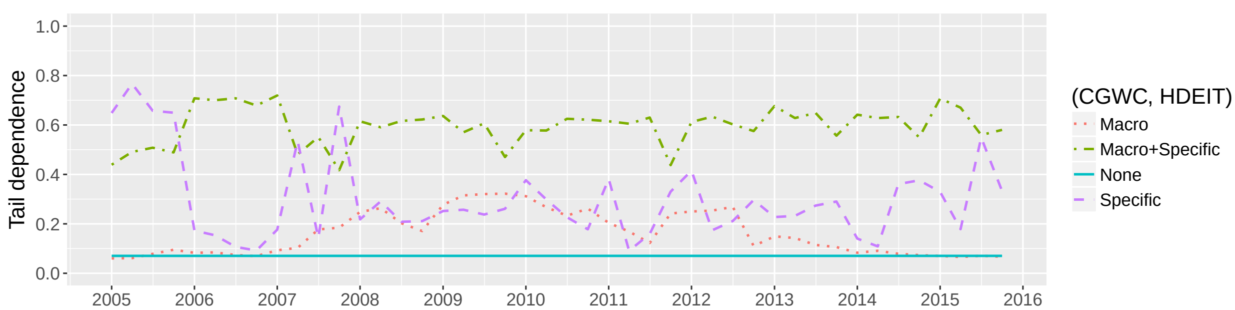

Figure S16: Dynamic of the tail dependence of credit risk between CGWC and HDEIT

Table S34: Covariate effects on the tail dependence of credit risk between CGWC and HDEIT

	None	Macro	Specific	Macro+Specific
Constant	−3.676	−3.520	−3.124	−0.112
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		0.049		−185.379
		(0.781)		(0.683)
M2 growth		0.294		−0.532
		(0.822)		(0.626)
Short-term interest rate		0.088		−12.211
		(0.214)		(0.453)
RMB/USD spot rate		−0.776		104.515
		(0.388)		(0.485)
CGWC's solvency capacity			0.108	−0.521
			(0.771)	(0.711)
CGWC's developing capacity	0.003	14.953		
			(0.764)	(0.509)
CGWC's profitability			0.112	−13.070
			(0.541)	(0.442)
CGWC's operating capacity			0.031	−2.887
			(0.494)	(0.550)
HDEIT's solvency capacity			−0.319	13.444
			(0.846)	(0.576)
HDEIT's developing capacity			0.077	43.064
			(0.728)	(0.458)
HDEIT's profitability			−0.164	15.061
			(0.670)	(0.618)
HDEIT's operating capacity			−0.062	−7.781
			(0.842)	(0.695)
LDS(in-sample)	−23.947	**-8.409**	−64.877	−46.222
LPS(out-of-sample)	−46.782	**-14.918**	−34.595	−26.131

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of CGWC and HDEIT by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.17 Comparison of CGWC and GWII

Section 2.17 presents the empirical results of the credit risk clustering between CGWC and GWII. Table S35 lists that the mean value of tail-dependence coefficient is 0.030 in the none-covariate Joe-Clayton copula model, 0.535 in the macroeconomic-covariate Joe-Clayton copula model, 0.071 in the specific-covariate Joe-Clayton copula model, and 0.572 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S17 shows the dynamic characteristics of the credit risk clustering between CGWC and GWII. We see that the volatility of credit risk clustering in both macroeconomic-covariate Joe-Clayton copula model and macroeconomic-specific-covariate Joe-Clayton copula model are more complex than other models.

Table S36 lists the estimated result of covariate effects on the tail dependence of credit risk between CGWC and GWII. The model performance criterion LDS is -20.028 in the macroeconomic-covariate Joe-Clayton model while LDS in the none-covariate Joe-Clayton copula model is -186.060. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the macroeconomic-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between CGWC and GWII. If we set a threshold for covariate index selection probabilities of 50%, we would find that M2 growth, short-term interest rate and RMB/USD spot rate are important for estimating the credit risk clustering between CGWC and GWII.

Table S35: Estimation of the tail dependence of credit risk between CGWC and GWII

	None	Macro	Specific	Macro+Specific
Mean	0.030	0.535	0.071	0.572
Median	0.011	0.523	0.067	0.712
Std.dev	0.031	0.398	0.083	0.388

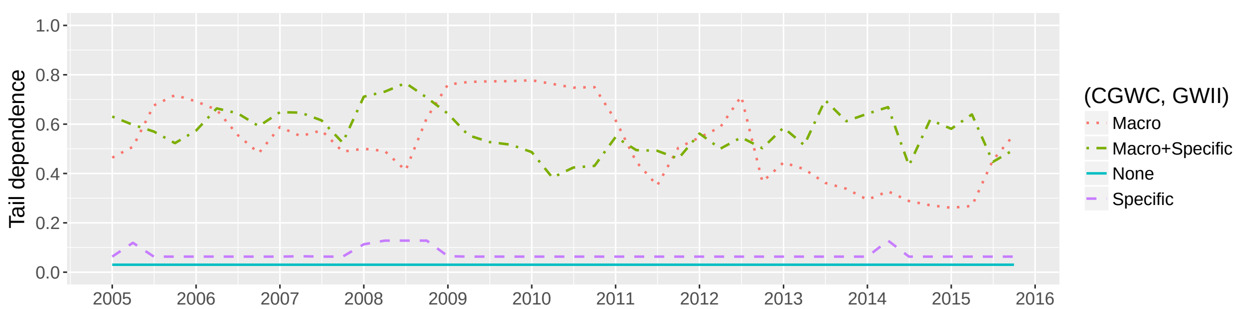

Figure S17: Dynamic of the tail dependence of credit risk between CGWC and GWII

Table S36: Covariate effects on the tail dependence of credit risk between CGWC and GWII

	None	Macro	Specific	Macro+Specific
Constant	−5.648	3.025	−3.514	−0.418
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−11.453		−0.184
		(0.152)		(0.652)
M2 growth		−86.995		−0.078
		(0.819)		(0.763)
Short-term interest rate		−1.148		0.366
		(0.691)		(0.633)
RMB/USD spot rate		−0.078		0.078
		(0.965)		(0.692)
CGWC's solvency capacity			−0.001	0.025
			(1.000)	(0.650)
CGWC's developing capacity			0.012	0.050
			(1.000)	(0.514)
CGWC's profitability			−0.010	0.057
			(1.000)	(0.607)
CGWC's operating capacity			−0.096	−0.132
			(1.000)	(0.732)
GWII's solvency capacity			0.006	0.007
			(1.000)	(0.686)
GWII's developing capacity			−0.037	−0.081
			(1.000)	(0.759)
GWII's profitability			0.203	0.605
			(1.000)	(0.572)
GWII's operating capacity			0.082	−0.029
			(1.000)	(0.516)
LDS(in-sample)	−186.060	**-20.028**	−1635.444	−135.099
LPS(out-of-sample)	−69.501	**-6.301**	−19.703	−65.213

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of CGWC and GWII by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.18 Comparison of CGWC and SHBL

Section 2.18 presents the empirical results of the credit risk clustering between CGWC and SHBL. Table S37 lists that the mean value of tail-dependence coefficient is 0.011 in the none-covariate Joe-Clayton copula model, 0.872 in the macroeconomic-covariate Joe-Clayton copula model, 0.255 in the specific-covariate Joe-Clayton copula model, and 0.553 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S18 shows the dynamic characteristics of the credit risk clustering between CGWC and SHBL. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula and macroeconomic-covariate Joe-Clatyton copula models are stationary. Whereas, we observe an obvious volatility of tail dependence of credit risk in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S38 lists the estimated result of covariate effects on the tail dependence of credit risk between CGWC and SHBL. The model performance criterion LDS is $-6,733$ in the specific-covariate Joe-Clayton model while LDS in the none-covariate Joe-Clayton copula model is -24.566. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between CGWC and SHBL. If we set a threshold for covariate index selection probabilities of 50%, we would find that CGWC's solvency capacity, CGWC's profitability, SHBL's developing capacity and SHBL's operating capacity are important for estimating the credit risk clustering between CGWC and SHBL.

Table S37: Estimation of the tail dependence of credit risk between CGWC and SHBL

	None	Macro	Specific	Macro+Specific
Mean	0.011	0.872	0.255	0.553
Median	0.010	0.989	0.039	0.896
Std.dev	0.005	0.316	0.345	0.462

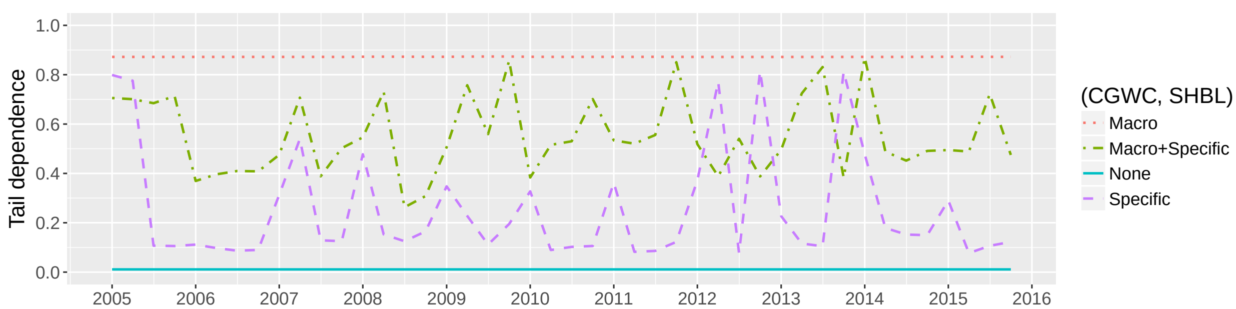

Figure S18: Dynamic of the tail dependence of credit risk between CGWC and SHBL

Table S38: Covariate effects on the tail dependence of credit risk between CGWC and SHBL

	None	Macro	Specific	Macro+Specific
Constant	−7.590	1355.969	−3.966	−4.689
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.006		0.414
		(0.541)		(0.307)
M2 growth		−0.019		0.142
		(0.231)		(0.858)
Short-term interest rate		−14.514		−5.121
		(0.658)		(0.248)
RMB/USD spot rate		12.171		0.469
		(0.612)		(0.439)
CGWC's solvency capacity			0.044	−0.381
			(0.928)	(0.829)
CGWC's developing capacity			0.012	2.076
			(0.187)	(0.615)
CGWC's profitability			0.426	−0.293
			(0.944)	(0.240)
CGWC's operating capacity			−0.005	0.232
			(0.196)	(0.524)
SHBL's solvency capacity			−0.114	0.528
			(0.183)	(0.546)
SHBL's developing capacity			−0.151	0.343
			(0.933)	(0.260)
SHBL's profitability			0.238	−0.012
			(0.194)	(0.110)
SHBL's operating capacity			−0.369	−0.952
			(0.837)	(0.235)
LDS(in-sample)	−24.566	−351.331	**-6.733**	−14.269
LPS(out-of-sample)	−41.966	−33.612	**-32.399**	−40.518

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of CGWC and SHBL by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.19 Comparison of CGWC and CNSS

Section 2.19 presents the empirical results of the credit risk clustering between CGWC and CNSS. Table S39 lists that the mean value of tail-dependence coefficient is 0.021 in the none-covariate Joe-Clayton copula model, 0.056 in the macroeconomic-covariate Joe-Clayton copula model, 0.462 in the specific-covariate Joe-Clayton copula model, and 0.653 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S19 shows the dynamic characteristics of the credit risk clustering between CGWC and CNSS.

We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of tail dependence of credit risk in the macroeconomic-covariate Joe-Clayton copula model. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S40 lists the estimated result of covariate effects on the tail dependence of the credit risk between CGWC and CNSS. The model performance criterion LDS is -32.187 in the macroeconomic-specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -71.794. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the Macroeconomic-specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between CGWC and CNSS. If we set a threshold for covariate index selection probabilities of 50%, we would find that CPI, M2 growth, short-term interest rate, RMB/USD spot rate, CNSS's developing capacity and CNSS's operating capacity are important for estimating credit risk clustering between CGWC and CNSS.

Table S39: Estimation of the tail dependence of credit risk between CGWC and CNSS

	None	Macro	Specific	Macro+Specific
Mean	0.021	0.056	0.462	0.653
Median	0.011	0.010	0.403	0.987
Std.dev	0.030	0.185	0.405	0.436

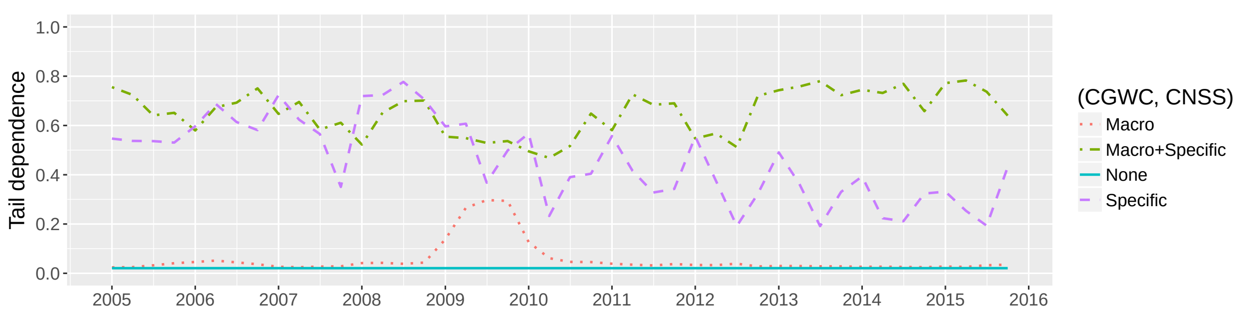

Figure S19: Dynamic of the tail dependence of credit risk between CGWC and CNSS

Table S40: Covariate effects on the tail dependence of credit risk between CGWC and CNSS

	None	Macro	Specific	Macro+Specific
Constant	−6.091	−5.212	−1.428	87.661
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−2.415		−0.779
		(0.312)		(0.517)
M2 growth		0.145		−0.752
		(0.285)		(0.672)
Short-term interest rate		−0.597		−1.531
		(0.970)		(0.528)
RMB/USD spot rate		−0.304		−1.882
		(0.270)		(0.559)
CGWC's solvency capacity			0.007	0.873
			(0.895)	(0.429)
CGWC's developing capacity			0.039	−0.068
			(0.473)	(0.415)
CGWC's profitability			0.629	2.389
			(0.871)	(0.479)
CGWC's operating capacity			−0.170	1.059
			(0.885)	(0.329)
CNSS's solvency capacity			−0.244	−0.378
			(0.759)	(0.349)
CNSS's developing capacity			−0.077	0.012
			(0.611)	(0.591)
CNSS's profitability			0.118	0.092
			(0.693)	(0.395)
CNSS's operating capacity			−0.164	0.785
			(0.972)	(0.568)
LDS(in-sample)	−71.794	−118.116	−67.597	**-32.187**
LPS(out-of-sample)	−40.571	−104.070	−64.063	**-34.943**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of CGWC and CNSS by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.20 Comparison of CGWC and CECC

Section 2.20 presents the empirical results of the credit risk clustering between CGWC and CECC. Table S41 lists that the mean value of tail-dependence coefficient is 0.024 in the none-covariate Joe-Clayton copula model, 0.128 in the macroeconomic-covariate Joe-Clayton copula model, 0.108 in the specific-covariate Joe-Clayton copula model, and 0.635 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S20 shows the dynamic characteristics of the credit risk clustering between CGWC and CECC. We see that the volatility of credit risk clustering is high and complex when inserting covariates into the Joe-Clayton copula model.

Table S42 lists the estimated result of covariate effects on the tail dependence of credit risk between CGWC and CECC. We find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between CGWC and CECC, and its Log Density Score (LDS) is -3.267.

Table S41: Estimation of the tail dependence of credit risk between CGWC and CECC

	None	Macro	Specific	Macro+Specific
Mean	0.024	0.128	0.108	0.635
Median	0.011	0.025	0.010	0.939
Std.dev	0.039	0.242	0.291	0.429

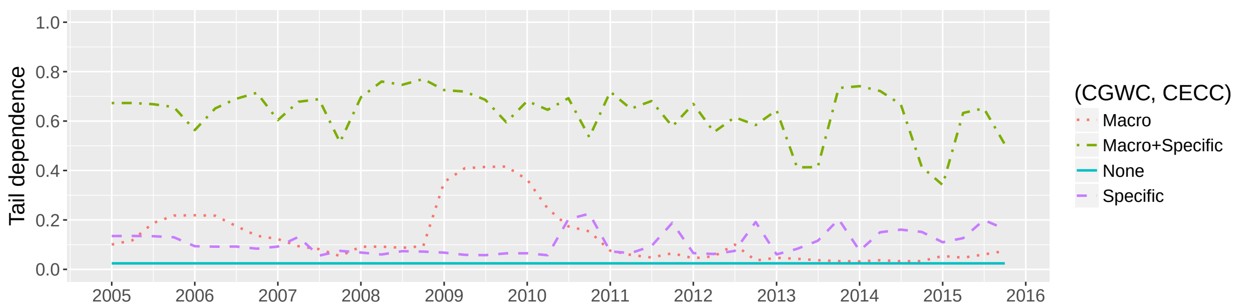

Figure S20: Dynamic of the tail dependence of credit risk between CGWC and CECC

Table S42: Covariate effects on the tail-dependence of credit risk between CGWC and CECC

	None	Macro	Specific	Macro+Specific
Constant	−6.801	−3.622	−121.869	−5.818
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.286		37.905
		(0.648)		(0.345)
M2 growth		−0.122		3.310
		(0.949)		(0.822)
Short-term interest rate		−0.541		2.837
		(0.539)		(0.569)
RMB/USD spot rate		0.620		6.120
		(0.819)		(0.663)
CGWC's solvency capacity			−1.160	−139.237
			(0.571)	(0.691)
CGWC's developing capacity			−3.183	−0.046
			(0.642)	(0.363)
CGWC's profitability			3.174	−0.888
			(0.783)	(0.473)
CGWC's operating capacity			0.081	−0.853
			(0.391)	(0.594)
CECC's solvency capacity			1.221	259.629
			(0.692)	(0.561)
CECC's developing capacity			−0.826	−0.823
			(0.208)	(0.798)
CECC's profitability			1.544	4.735
			(0.764)	(0.625)
CECC's operating capacity			7.516	−0.853
			(0.291)	(0.594)
LDS(in-sample)	**-3.267**	−148.205	−22.148	−41.691
LPS(out-of-sample)	**-9.663**	−38.383	−67.289	−26.406

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of CGWC and CECC by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.21 Comparison of CGWC and NJPE

Section 2.21 presents the empirical results of the credit risk clustering between CGWC and NJPE. Table S43 lists that the mean value of tail-dependence coefficient is 0.016 in the none-covariate Joe-Clayton copula model, 0.101 in the macroeconomic-covariate Joe-Clayton copula model, 0.329 in the specific-covariate Joe-Clayton copula model, and 0.452 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S21 shows the dynamic characteristics of the credit risk clustering between CGWC and NJPE.

We see that the volatility of credit risk clustering is high and complex when inserting covariates into the Joe-Clayton copula model.

Table S44 lists the estimated result of covariate effects on the tail dependence of credit risk between CGWC and NJPE. The model performance criterion LDS is -75.033 in the macroeconomic-specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -147.026, which indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the macroeconomic-specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between CGWC and NJPE. If we set a threshold for covariate index selection probabilities of 50%, we would find that M2 growth, short-term interest rate, RMB/USD spot rate and all firm-specific covariates except NJPE's profitability are important for estimating credit risk clustering between CGWC and NJPE.

Table S43: Estimation of the tail dependence of credit risk between CGWC and NJPE

	None	Macro	Specific	Macro+Specific
Mean	0.016	0.101	0.329	0.452
Median	0.012	0.067	0.224	0.377
Std.dev	0.013	0.149	0.321	0.394

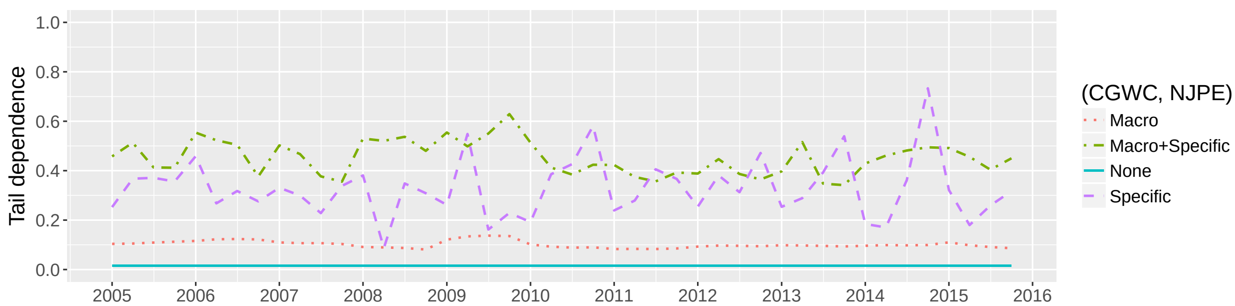

Figure S21: Dynamic of the tail dependence of credit risk between CGWC and NJPE

Table S44: Covariate effects on the tail dependence of credit risk between CGWC and NJPE

	None	Macro	Specific	Macro+Specific
Constant	−6.233	−1.341	−1.986	0.822
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.051		−0.047
		(0.403)		(0.494)
M2 growth		0.004		0.113
		(0.352)		(0.644)
Short-term interest rate		−0.882		−0.264
		(0.913)		(0.602)
RMB/USD spot rate		0.054		−0.362
		(0.713)		(0.719)
CGWC's solvency capacity			−0.006	−0.002
			(0.929)	(0.735)
CGWC's developing capacity			−0.311	−0.017
			(0.867)	(0.756)
CGWC's profitability			−0.763	0.577
			(0.895)	(0.573)
CGWC's operating capacity			−0.043	−0.104
			(0.870)	(0.683)
NJPE's solvency capacity			0.131	−0.017
			(0.933)	(0.599)
NJPE's developing capacity			0.341	0.213
			(0.899)	(0.639)
NJPE's profitability			0.434	0.568
			(0.456)	(0.476)
NJPE's operating capacity			−0.006	−0.091
			(0.924)	(0.614)
LDS(in-sample)	−147.026	−422.016	−282.656	**-75.033**
LPS(out-of-sample)	−59.689	−56.791	−85.120	**-49.366**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of CGWC and NJPE by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.22 Comparison of HDEIT and GWII

Section 2.22 presents the empirical results of the credit risk clustering between HDEIT and GWII. Table S45 lists that the mean value of tail-dependence coefficient is 0.019 in the none-covariate Joe-Clayton copula model, 0.168 in the macroeconomic-covariate Joe-Clayton copula model, 0.391 in the specific-covariate Joe-Clayton copula model, and 0.605 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S22 shows the dynamic characteristics of the credit risk clustering between HDEIT and GWII. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary.

Whereas, we observe an obvious volatility of tail dependence of credit risk in the macroeconomic-covariate Joe-Clayton copula model. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S46 lists the estimated result of covariate effects on the tail dependence of credit risk between HDEIT and GWII. The model performance criterion LDS is -37.708 in the specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -79.853. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between HDEIT and GWII. If we set a threshold for covariate index selection probabilities of 50%, we would find that HDEIT's solvency capacity, HDEIT's operating capacity, GWII's solvency capacity, GWII's developing capacity, GWII's profitability and GWII's operating capacity are important for estimating the credit risk clustering between HDEIT and GWII.

Table S45: Estimation of the tail dependence of credit risk between HDEIT and GWII

	None	Macro	Specific	Macro+Specific
Mean	0.019	0.168	0.391	0.605
Median	0.015	0.083	0.151	0.823
Std.dev	0.011	0.196	0.414	0.406

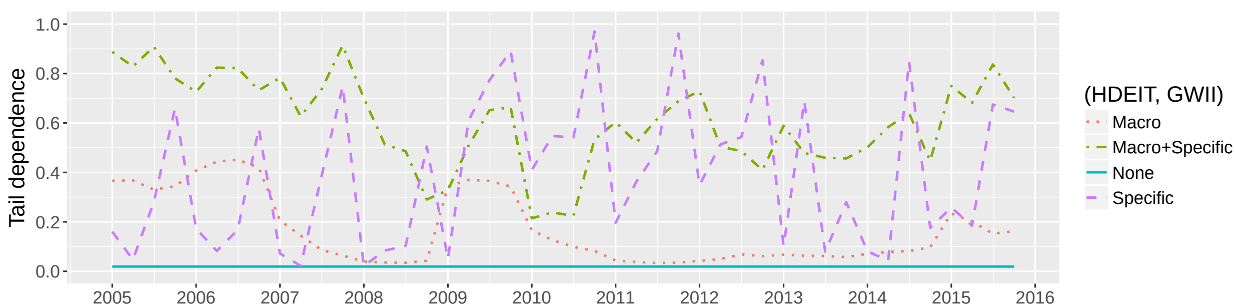

Figure S22: Dynamic of the tail dependence of credit risk between HDEIT and GWII

Table S46: Covariate effects on the tail dependence of credit risk between HDEIT and GWII

	None	Macro	Specific	Macro+Specific
Constant	−5.065	−6.115	−3.188	−14.017
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.799		−0.077
		(0.862)		(0.792)
M2 growth		−0.059		0.009
		(0.590)		(0.734)
Short-term interest rate		−0.142		0.492
		(0.167)		(0.764)
RMB/USD spot rate		1.072		1.855
		(0.978)		(0.370)
HDEIT's solvency capacity			−0.054	−0.099
			(0.652)	(0.377)
HDEIT's developing capacity			0.043	0.324
			(0.443)	(0.417)
HDEIT's profitability			0.275	0.559
			(0.383)	(0.594)
HDEIT's operating capacity			−0.081	−0.761
			(0.941)	(0.804)
GWII's solvency capacity			−0.079	−0.046
			(0.980)	(0.807)
GWII's developing capacity			0.396	−0.358
			(0.817)	(0.792)
GWII's profitability			−0.920	−0.586
			(0.591)	(0.688)
GWII's operating capacity			1.188	0.201
			(0.966)	(0.513)
LDS(in-sample)	−79.853	−279.795	**-37.708**	−95.590
LPS(out-of-sample)	−26.443	−33.610	**-18.309**	−37.271

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of HDEIT and GWII by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.23 Comparison of HDEIT and XITG

Section 2.23 presents the empirical results of the credit risk clustering between HDEIT and XITG. Table S47 lists that the mean value of tail-dependence coefficient is 0.011 in the none-covariate Joe-Clayton copula model, 0.481 in the macroeconomic-covariate Joe-Clayton copula model, 0.290 in the specific-covariate Joe-Clayton copula model, and 0.630 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S23 shows the dynamic characteristics of the credit risk clustering between HDEIT and XITG. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton and macroeconomic-covariate copula models are stationary. However, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S48 lists the estimated result of covariate effects on the tail dependence of credit risk between HDEIT and XITG. We find that comparing with the other covariate-dependent BB7 copula models, the none-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between HDEIT and XITG, and its Log Density Score (LDS) is −11.328.

Table S47: Estimation of the tail dependence of credit risk between HDEIT and XITG

	None	Macro	Specific	Macro+Specific
Mean	0.011	0.481	0.290	0.630
Median	0.010	0.067	0.023	0.857
Std.dev	0.003	0.460	0.381	0.396

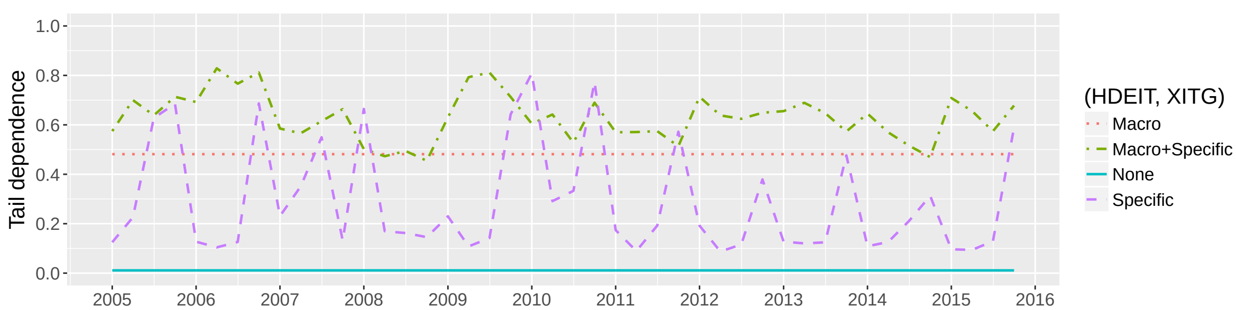

Figure S23: Dynamic of the tail dependence of credit risk between HDEIT and XITG

Table S48: Covariate effects on the tail dependence of credit risk between HDEIT and XITG

	None	Macro	Specific	Macro+Specific
Constant	−7.440	11.159	−3.675	−2.450
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−20.886		−0.887
		(0.997)		(0.740)
M2 growth		−0.046		0.031
		(0.999)		(0.534)
Short-term interest rate		−50.019		0.906
		(0.997)		(0.798)
RMB/USD spot rate		−0.007		0.060
		(0.536)		(0.578)
HDEIT's solvency capacity			−0.023	−0.163
			(0.830)	(0.706)
HDEIT's developing capacity			−0.417	0.345
			(0.817)	(0.799)
HDEIT's profitability			0.085	−0.608
			0.441	(0.793)
HDEIT's operating capacity			0.606	0.022
			(0.856)	(0.576)
XITG's solvency capacity			−0.657	0.008
			(0.750)	(0.640)
XITG's developing capacity			−1.558	−0.232
			(0.836)	(0.411)
XITG's profitability			0.188	−0.006
			(0.717)	(0.596)
XITG's operating capacity			0.033	0.005
			(0.880)	(0.867)
LDS(in-sample)	**-11.328**	−17.473	−123.325	−138.924
LPS(out-of-sample)	**-7.348**	−20.619	−22.431	−24.101

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of HDEIT and XITG by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.24 Comparison of HDEIT and CECC

Section 2.24 presents the empirical results of the credit risk clustering between HDEIT and CECC. Table S49 lists that the mean value of tail-dependence coefficient is 0.027 in the none-covariate Joe-Clayton copula model, 0.083 in the macroeconomic-covariate Joe-Clayton copula model, 0.291 in the specific-covariate Joe-Clayton copula model, and 0.550 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S24 shows the dynamic characteristics of the credit risk clustering between HDEIT and CECC.

We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of tail dependence of credit risk in the macroeconomic-covariate Joe-Clayton copula model. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S50 lists the estimated result of covariate effects on the tail dependence of credit risk between HDEIT and CECC. The model performance criterion LDS is -1.916 in the specific-covariate Joe-Clayton model while LDS in the none-covariate Joe-Clayton copula model is -30.803. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the specific-covariate Joe-Clayton copula model is the best model for predicting credit risk clustering between HDEIT and CECC. If we set a threshold for covariate index selection probabilities of 50%, we would find that all firm-specific covariates except CECC's profitability are important for estimating the credit risk clustering between HDEIT and CECC.

Table S49: Estimation of the tail dependence of credit risk between HDEIT and CECC

	None	Macro	Specific	Macro+Specific
Mean	0.027	0.083	0.291	0.550
Median	0.011	0.013	0.074	0.622
Std.dev	0.027	0.210	0.360	0.353

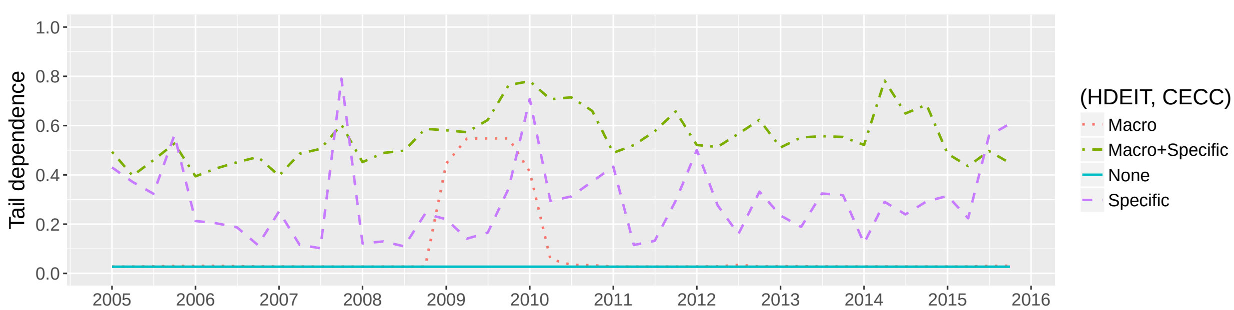

Figure S24: Dynamic of the tail dependence of credit risk between HDEIT and CECC

Table S50: Covariate effects on the tail dependence of credit risk between HDEIT and CECC

	None	Macro	Specific	Macro+Specific
Constant	−6.143	−1.798	−3.254	−0.194
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.875		−0.019
		(1.000)		(0.566)
M2 growth		0.041		0.065
		(1.000)		(0.620)
Short-term interest rate		−1.521		0.072
		(1.000)		(0.680)
RMB/USD spot rate		−1.447		−0.180
		(1.000)		(0.494)
HDEIT's solvency capacity			−0.568	−0.018
			(0.552)	(0.409)
HDEIT's developing capacity			0.057	−0.000
			(0.960)	(0.693)
HDEIT's profitability			0.158	0.247
			(0.593)	(0.592)
HDEIT's operating capacity			0.151	0.179
			(0.976)	(0.729)
CECC's solvency capacity			−0.424	0.002
			(0.967)	(0.578)
CECC's developing capacity			0.033	0.001
			(0.963)	(0.894)
CECC's profitability			0.057	−0.318
			(0.454)	(0.583)
CECC's operating capacity			0.026	−0.010
			(0.560)	(0.748)
LDS(in-sample)	−30.803	−162.256	**-1.916**	−173.487
LPS(out-of-sample)	−36.284	−33.632	**-28.026**	−43.373

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of HDEIT and CECC by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.25 Comparison of GWII and SHBL

Section 2.25 presents the empirical results of the credit risk clustering between GWII and SHBL. Table 2.25 lists that the mean value of tail-dependence coefficient is 0.081 in the none-covariate Joe-Clayton copula model, 0.608 in the macroeconomic-covariate Joe-Clayton copula model, 0.251 in the specific-covariate Joe-Clayton copula model, and 0.531 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S25 shows the dynamic characteristics of the credit risk clustering between GWII and SHBL. We see that the volatility of the credit risk clustering is high and complex when inserting covariates into the Joe-Clayton copula model.

Table S52 lists the estimated result of covariate effects on the tail dependence of credit risk between GWII and SHBL. We find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between GWII and SHBL, and its Log Density Score (LDS) is -46.568.

Table S51: Estimation of the tail dependence of credit risk between GWII and SHBL

	None	Macro	Specific	Macro+Specific
Mean	0.081	0.608	0.251	0.531
Median	0.067	0.990	0.098	0.631
Std.dev	0.039	0.451	0.314	0.401

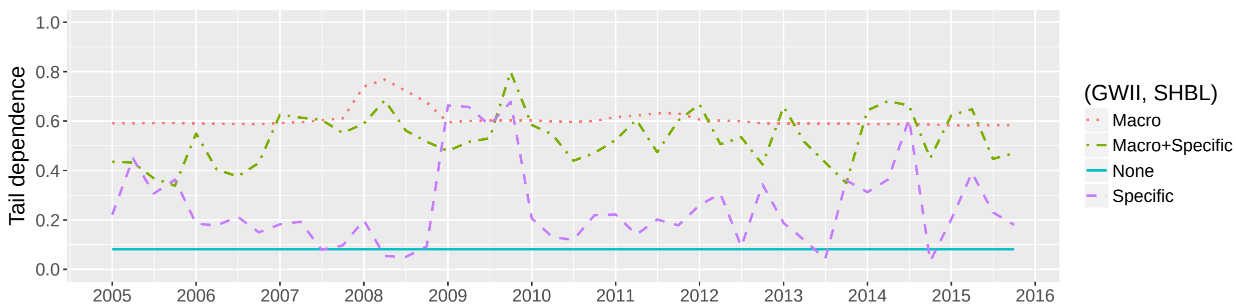

Figure S25: Dynamic of the tail dependence of credit risk between GWII and SHBL

Table S52: Covariate effects on the tail dependence of credit risk between GWII and SHBL

	None	Macro	Specific	Macro+Specific
Constant	−2.698	3751.493	−2.382	−1.566
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−5.626		−0.029
		(0.855)		(0.671)
M2 growth		−0.063		1.620
		(0.169)		(0.801)
Short-term interest rate		−0.140		1.850
		(0.229)		(0.764)
RMB/USD spot rate		8.611		−0.795
		(0.222)		(0.606)
GWII's solvency capacity			−0.033	−0.116
			(0.844)	(0.671)
GWII's developing capacity			−0.093	2.166
			(0.555)	(0.528)
GWII's profitability			−0.670	0.187
			(0.621)	(0.589)
GWII's operating capacity			−0.161	0.264
			(0.445)	(0.681)
SHBL's solvency capacity			0.153	−0.557
			(0.772)	(0.701)
SHBL's developing capacity			−0.064	−0.074
			(0.527)	(0.644)
SHBL's profitability			−0.313	0.238
			(0.659)	(0.749)
SHBL's operating capacity			0.091	−0.591
			(0.648)	(0.673)
LDS(in-sample)	**-46.568**	−5645.198	−280.791	−165.301
LPS(out-of-sample)	**-10.390**	−12.254	−43.666	−48.521

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of GWII and SHBL by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.26 Comparison of GWII and CNSS

Section 2.26 presents the empirical results of the credit risk clustering between GWII and CNSS. Table S53 lists that the mean value of tail-dependence coefficient is 0.017 in the none-covariate Joe-Clayton copula model, 0.104 in the macroeconomic-covariate Joe-Clayton copula model, 0.432 in the specific-covariate Joe-Clayton copula model, and 0.541 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S26 shows the dynamic characteristics of the credit risk clustering between GWII and CNSS. We see that the volatility of credit risk clustering is high and complex when inserting covariates into the Joe-Clayton copula model.

Table 2.26 lists the estimated result of covariate effects on the tail dependence of credit risk between GWII and CNSS. The model performance criterion LDS is −43.907 in the specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is −231.520. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between GWII and CNSS. If we set a threshold for covariate index selection probabilities of 50%, we would find that all firm-specific covariates are important for estimating the credit risk clustering between GWII and CNSS.

Table S53: Estimation of the tail dependence of credit risk between GWII and CNSS

	None	Macro	Specific	Macro+Specific
Mean	0.017	0.104	0.432	0.541
Median	0.011	0.018	0.342	0.653
Std.dev	0.019	0.204	0.376	0.410

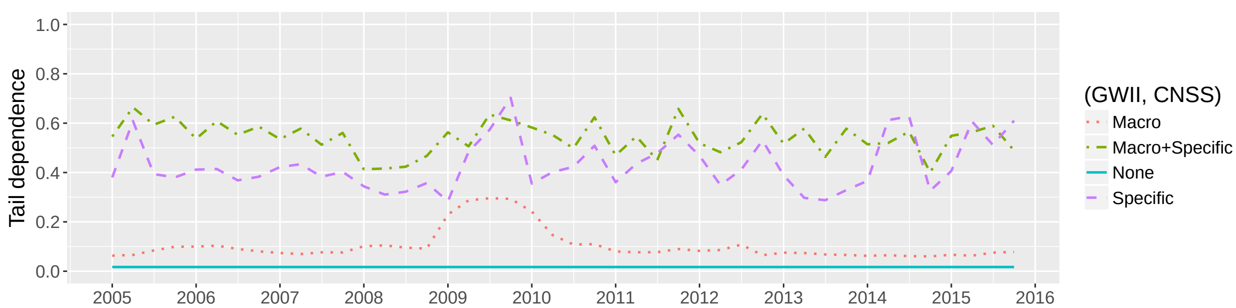

Figure S26: Dynamic of the tail dependence of credit risk between GWII and CNSS

Table S54: Covariate effects on the tail dependence of credit risk between GWII and CNSS

	None	Macro	Specific	Macro+Specific
Constant	−6.662	−2.029	−1.741	−1.626
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.581		−0.165
		(0.644)		(0.656)
M2 growth		5.846		0.016
		(0.317)		(0.776)
Short-term interest rate		6.100		0.182
		(0.464)		(0.599)
RMB/USD spot rate		−0.266		0.091
		(0.302)		(0.672)
GWII's solvency capacity			0.038	−0.048
			(0.790)	(0.639)
GWII's developing capacity			−0.001	0.005
			(0.743)	(0.610)
GWII's profitability			0.359	0.199
			(0.686)	(0.596)
GWII's operating capacity			0.233	0.003
			(0.529)	(0.638)
CNSS's solvency capacity			−0.233	0.063
			(0.595)	(0.663)
CNSS's developing capacity			0.129	0.163
			(0.729)	(0.608)
CNSS's profitability			−0.191	−0.008
			(0.700)	(0.483)
CNSS's operating capacity			−0.137	−0.021
			(0.676)	(0.654)
LDS(in-sample)	−231.520	−77.736	**-43.907**	−147.812
LPS(out-of-sample)	−52.453	−20.834	**-11.537**	−61.589

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of GWII and CNSS by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.27 Comparison of GWII and XITG

Section 2.27 presents the empirical results of the credit risk clustering between GWII and XITG. Table S55 lists that the mean value of tail-dependence coefficient is 0.013 in the none-covariate Joe-Clayton copula model, 0.097 in the macroeconomic-covariate Joe-Clayton copula model, 0.403 in the specific-covariate Joe-Clayton copula model, and 0.787 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S27 shows the dynamic characteristics of the credit risk clustering between GWII and XITG. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of tail dependence of credit risk in the macroeconomic-covariate Joe-Clayton copula model. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table 2.27 lists the estimated result of covariate effects on the tail dependency of credit risk between GWII and XITG. The model performance criterion LDS is −41.696 in the specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is −234.996. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between GWII and XITG. If we set a threshold for covariate index selection probabilities of 50%, we would find that all firm-specific factors except XITG's developing capacity and XITG's operating capacity are important for estimating credit risk clustering between GWII and XITG.

Table S55: Estimation of the tail dependence of credit risk between GWII and XITG

	None	Macro	Specific	Macro+Specific
Mean	0.013	0.097	0.403	0.787
Median	0.014	0.011	0.162	0.990
Std.dev	0.002	0.211	0.424	0.383

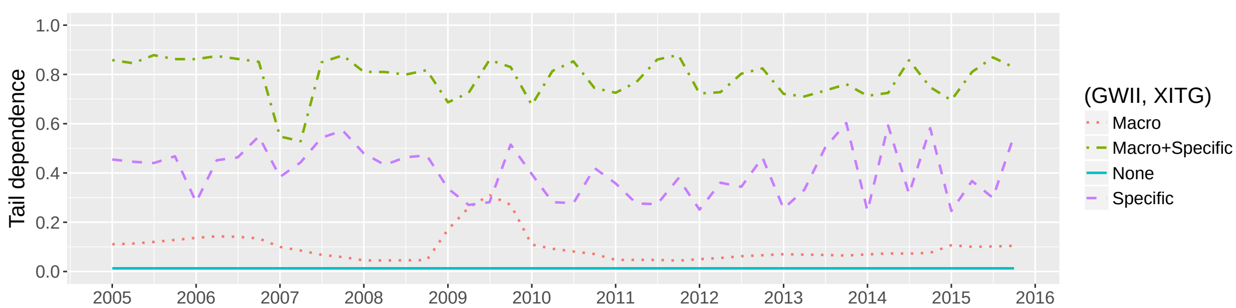

Figure S27: Dynamic of the tail dependence of credit risk between GWII and XITG

Table S56: Covariate effects on the tail dependence of credit risk between GWII and XITG

	None	Macro	Specific	Macro+Specific
Constant	−6.080	−4.628	4.025	134.336
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.994		0.043
		(0.954)		(0.497)
M2 growth		−1.031		14.842
		0.698		(0.416)
Short-term interest rate		−8.963		−3.241
		(0.050)		(0.461)
RMB/USD spot rate		10.164		−41.003
		(0.159)		(0.504)
GWII's solvency capacity			−3.868	−0.891
			(0.732)	(0.335)
GWII's developing capacity			−2.538	1.051
			(0.609)	(0.365)
GWII's profitability			−2.972	3.359
			(0.560)	(0.431)
GWII's operating capacity			2.416	−17.101
			(0.661)	(0.280)
XITG's solvency capacity			0.419	1.302
			(0.723)	(0.263)
XITG's developing capacity			1.845	−26.483
			(0.414)	(0.517)
XITG's profitability			−2.984	−1.583
			(0.479)	(0.464)
XITG's operating capacity			1.355	1.511
			(0.641)	(0.540)
LDS(in-sample)	−234.996	−158.511	−41.696	**-35.633**
LPS(out-of-sample)	−60.400	−30.868	−28.663	**-12.441**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of GWII and XITG by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.28 Comparison of GWII and CECC

Section 2.28 presents the empirical results of the credit risk clustering between GWII and CECC. Table S57 lists that the mean value of tail-dependence coefficient is 0.023 in the none-covariate Joe-Clayton copula model, 0.716 in the macroeconomic-covariate Joe-Clayton copula model, 0.601 in the specific-covariate Joe-Clayton copula model, and 0.675 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S28 shows the dynamic characteristics of the credit risk clustering between GWII and CECC. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of credit risk clustering in the covariate-dependent Joe-Clayton copula model. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S58 lists the estimated result of covariate effects on the tail dependence of credit risk between GWII and CECC. We find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between GWII and CECC, and its Log Density Score (LDS) is -105.400.

Table S57: Estimation of the tail dependence of credit risk between GWII and CECC

	None	Macro	Specific	Macro+Specific
Mean	0.023	0.716	0.601	0.675
Median	0.014	0.990	0.674	0.871
Std.dev	0.041	0.437	0.268	0.363

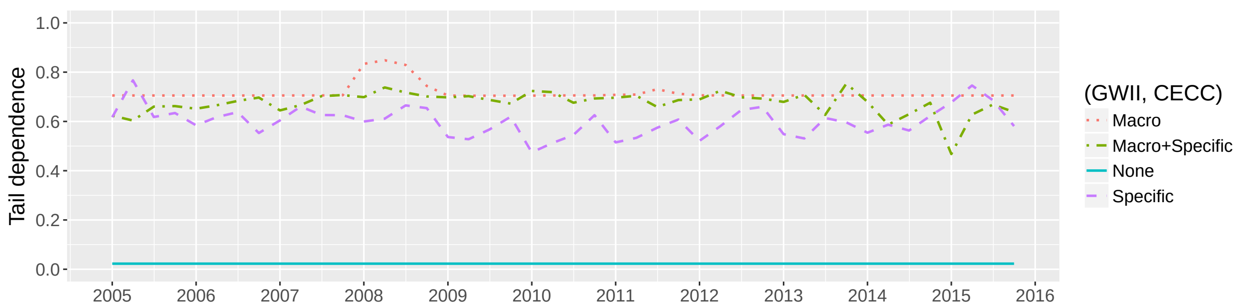

Figure S28: Dynamic of the tail dependence of credit risk between GWII and CECC

Table S58: Covariate effects on the tail dependence of credit risk between GWII and CECC

	None	Macro	Specific	Macro+Specific
Constant	−5.839	244.695	0.097	−2.291
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		0.614		−0.034
		(0.292)		(0.543)
M2 growth		−0.832		0.024
		(0.170)		(0.425)
Short-term interest rate		−0.073		0.231
		(0.183)		(0.588)
RMB/USD spot rate		2.176		0.121
		(0.680)		(0.707)
GWII's solvency capacity			0.0124	0.009
			(0.666)	(0.670)
GWII's developing capacity			−0.042	0.059
			(0.636)	(0.501)
GWII's profitability			−0.018	0.304
			(0.513)	(0.540)
GWII's operating capacity			0.063	−0.045
			(0.556)	(0.496)
CECC's solvency capacity			−0.143	0.179
			(0.539)	(0.596)
CECC's developing capacity			−0.004	0.001
			(0.586)	(0.630)
CECC's profitability			−0.159	−0.250
			(0.679)	(0.725)
CECC's operating capacity			0.033	0.007
			(0.818)	(0.578)
LDS(in-sample)	**-105.400**	−1603.458	−268.740	−338.377
LPS(out-of-sample)	**-21.033**	−24.950	−85.477	−64.751

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of GWII and CECC by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.29 Comparison of GWII and NJPE

Section 2.29 presents the empirical results of the credit risk clustering between GWII and NJPE. Table S59 lists that the mean value of tail-dependence coefficient is 0.015 in the none-covariate Joe-Clayton copula model, 0.900 in the macroeconomic-covariate Joe-Clayton copula model, 0.282 in the specific-covariate Joe-Clayton copula model, and 0.556 in the macroeconomic-specific-covariate Joe-Clayton copula model. In this result we find that tail-dependence coefficient in the covariate-dependent Joe-Clayton copula model is much higher than that in the none-covariate Joe-Clayton copula model.

Figure S29 shows the dynamic characteristics of the credit risk clustering between GWII and NJPE. We see that the volatility of credit risk clustering is high and complex when inserting covariates into the Joe-Clayton copula model.

Table 2.29 lists the estimated result of covariate effects on the tail dependence of credit risk between GWII and NJPE. The model performance criterion LDS is −71.630 in the macroeconomic-specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is −86.875. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the macroeconomic-specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between GWII and NJPE. If we set a threshold for covariate index selection probabilities of 50%, we would find that all factors are important for estimating credit risk clustering between GWII and NJPE.

Table S59: Estimation of the tail dependence of credit risk between GWII and NJPE

	None	Macro	Specific	Macro+Specific
Mean	0.015	0.900	0.282	0.556
Median	0.011	0.990	0.070	0.642
Std.dev	0.020	0.263	0.359	0.363

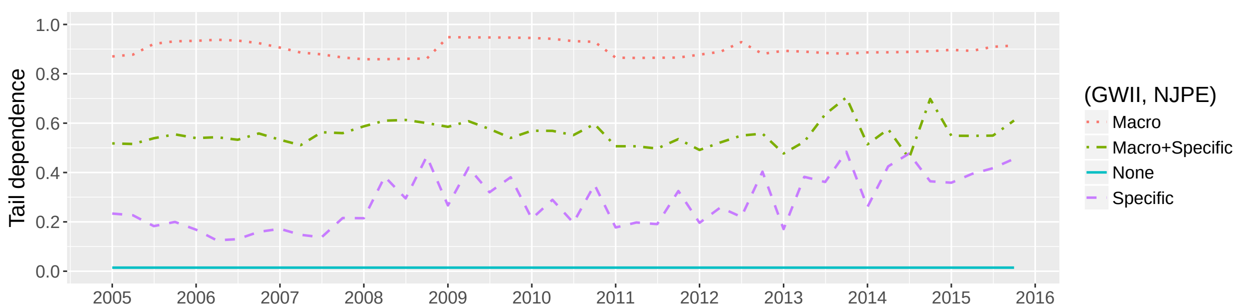

Figure S29: Dynamic of the tail dependence of credit risk between GWII and NJPE

Table S60: Covariate effects on the tail dependence of credit risk between GWII and NJPE

	None	Macro	Specific	Macro+Specific
Constant	−6.798	278.016	−3.673	−1.813
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−1.987		−0.000
		(0.112)		(0.593)
M2 growth		0.726		0.063
		0.903		(0.705)
Short-term interest rate		−0.041		−0.004
		(0.131)		(0.624)
RMB/USD spot rate		−0.024		0.111
		(0.115)		(0.662)
GWII's solvency capacity			0.008	0.003
			(0.910)	(0.766)
GWII's developing capacity			0.115	0.031
			(0.734)	(0.634)
GWII's profitability			−0.371	−0.119
			(0.549)	(0.607)
GWII's operating capacity			0.091	0.046
			(0.733)	(0.562)
NJPE's solvency capacity			−0.052	−0.068
			(0.700)	(0.692)
NJPE's developing capacity			−0.033	−0.034
			(0.645)	(0.595)
NJPE's profitability			−0.064	−0.066
			(0.700)	(0.600)
NJPE's operating capacity			−0.011	0.005
			(0.557)	(0.598)
LDS(in-sample)	−86.875	−109.261	−261.820	**-71.630**
LPS(out-of-sample)	−28.091	−17.364	−104.971	**-9.102**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of GWII and NJPE by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.30 Comparison of SHBL and XITG

Section 2.30 presents the empirical results of the credit risk clustering between SHBL and XITG. Table S61 lists that the mean value of tail-dependence coefficient is 0.014 in the none-covariate Joe-Clayton copula model, 0.074 in the macroeconomic-covariate Joe-Clayton copula model, 0.295 in the specific-covariate Joe-Clayton copula model, and 0.699 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S30 shows the dynamic characteristics of the credit risk clustering between SHBL and XITG.

We see that the volatility of credit risk clustering is high and complex when inserting covariates into the Joe-Clayton copula model.

Table S62 lists the estimated result of covariate effects on the tail dependence of credit risk between SHBL and XITG. The model performance criterion LDS is -2.860 in the macroeconomic-specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -20.060. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the macroeconomic-specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SHBL and XITG. If we set a threshold for covariate index selection probabilities of 50%, we would find that SHBL's profitability, XITG's solvency capacity, and XITG's profitability are important for estimating credit risk clustering between SHBL and XITG.

Table S61: Estimation of the tail dependence of credit between SHBL and XITG

	None	Macro	Specific	Macro+Specific
Mean	0.014	0.074	0.295	0.699
Median	0.011	0.011	0.064	0.989
Std.dev	0.019	0.189	0.371	0.443

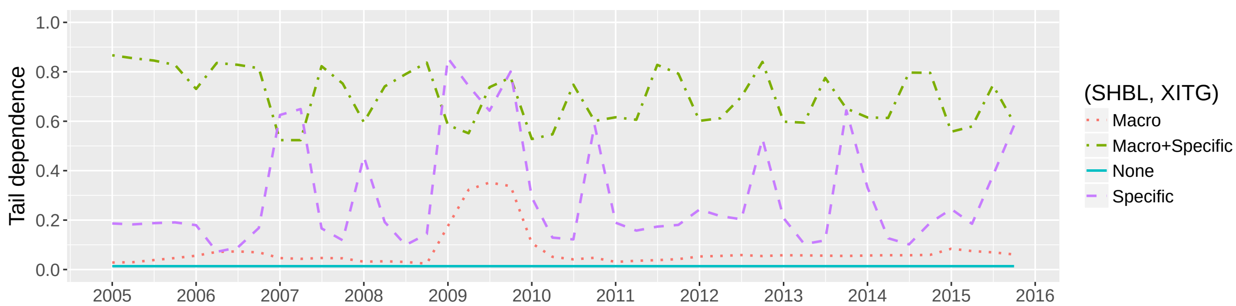

Figure S30: Dynamic of the tail dependence of credit risk between SHBL and XITG

Table S62: Covariate effects on the tail dependence of credit risk between SHBL and XITG

	None	Macro	Specific	Macro+Specific
Constant	−7.160	−3.232	−4.115	83.526
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−1.030		0.300
		(0.975)		(0.218)
M2 growth		0.077		−0.765
		(0.211)		(0.319)
Short-term interest rate		−0.067		−1.446
		(0.228)		(0.263)
RMB/USD spot rate		−0.211		−7.934
		(0.236)		(0.365)
SHBL's solvency capacity			0.336	1.826
			(0.896)	(0.275)
SHBL's developing capacity			0.019	−1.725
			(0.827)	(0.458)
SHBL's profitability			0.193	−1.599
			(0.662)	(0.523)
SHBL's operating capacity			0.377	−1.887
			(0.688)	(0.315)
XITG's solvency capacity			−0.062	−0.446
			(0.728)	(0.742)
XITG's developing capacity			0.039	0.938
			(0.592)	(0.425)
XITG's profitability			0.288	−0.098
			(0.484)	(0.506)
XITG's operating capacity			−0.100	9.451
			(0.871)	(0.379)
LDS(in-sample)	−20.060	−21.888	−273.223	**-2.860**
LPS(out-of-sample)	−35.274	−55.308	−56.582	**-19.626**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SHBL and XITG by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.31 Comparison of SHBL and CECC

Section 2.31 presents the empirical results of the credit risk clustering between SHBL and CECC. Table S63 lists that the mean value of tail-dependence coefficient is 0.039 in the none-covariate Joe-Clayton copula model, 0.197 in the macroeconomic-covariate Joe-Clayton copula model, 0.380 in the specific-covariate Joe-Clayton copula model, and 0.705 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S31 shows the dynamic characteristics of the credit risk clustering between SHBL and CECC. We see that the volatility of credit risk clustering is high and complex when inserting covariates into the Joe-Clayton copula model.

Table S64 lists the estimated result of covariate effects on the tail dependence of credit risk between SHBL and CECC. The model performance criterion LDS is -6.737 in the specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -143.049. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between SHBL and CECC. If we set a threshold for covariate index selection probabilities of 50%, we would find that all firm-specific covariates are important for estimating credit risk clustering between SHBL and CECC.

Table S63: Estimation of the tail dependence of credit risk between SHBL and CECC

	None	Macro	Specific	Macro+Specific
Mean	0.039	0.197	0.380	0.705
Median	0.013	0.012	0.250	0.967
Std.dev	0.046	0.360	0.362	0.396

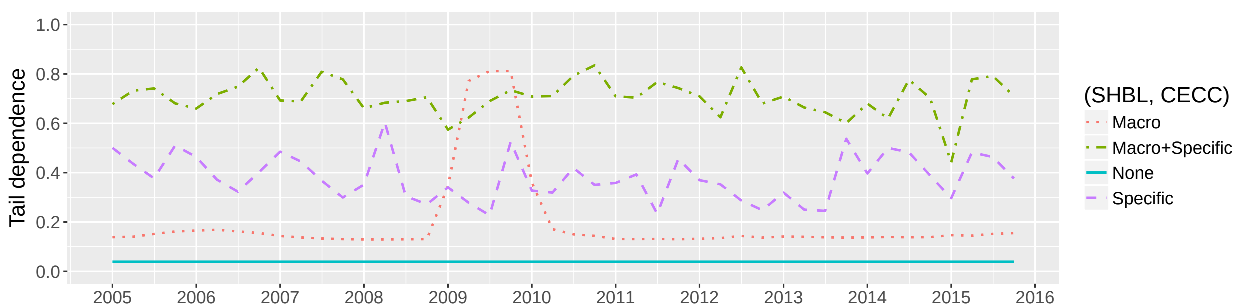

Figure S31: Dynamic of the tail dependence of credit risk between SHBL and CECC

Table S64: Covariate effects on the tail dependence of credit risk between SHBL and CECC

	None	Macro	Specific	Macro+Specific
Constant	−5.370	21.728	−3.191	−1.273
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.572		−7.141
		(0.714)		(0.506)
M2 growth		0.329		1.199
		(0.893)		(0.441)
Short-term interest rate		−1.257		−70.424
		(0.718)		(0.416)
RMB/USD spot rate		31.586		108.295
		(0.100)		(0.343)
SHBL's solvency capacity			−0.240	0.126
			(0.571)	(0.493)
SHBL's developing capacity			0.183	−0.191
			(0.777)	(0.701)
SHBL's profitability			−0.680	−2.868
			(0.639)	(0.369)
SHBL's operating capacity			0.092	343.252
			(0.718)	(0.585)
CECC's solvency capacity			0.106	−144.342
			(0.576)	(0.533)
CECC's developing capacity			0.088	23.136
			(0.704)	(0.386)
CECC's profitability			−0.748	0.126
			(0.624)	(0.531)
CECC's operating capacity			0.054	0.512
			(0.837)	(0.738)
LDS(in-sample)	−143.049	−143.749	**-6.737**	−163.993
LPS(out-of-sample)	−59.096	−43.267	**-39.890**	−85.541

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of SHBL and CECC by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.32 Comparison of CNSS and XITG

Section 2.32 presents the empirical results of the credit risk clustering between CNSS and XITG. Table S65 lists that the mean value of tail-dependence coefficient is 0.012 in the none-covariate Joe-Clayton copula model, 0.077 in the macroeconomic-covariate Joe-Clayton copula model, 0.485 in the specific-covariate Joe-Clayton copula model, and 0.642 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S32 shows the dynamic characteristics of the credit risk clustering between CNSS and XITG. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula and macroeconomic-covariate Joe-Clayton copula models are stationary. However, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table 2.32 lists the estimated result of covariate effects on the tail dependence of credit risk between CNSS and XITG. The model performance criterion LDS is -1.834 in the macroeconomic-specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -39.294. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the macroeconomic-specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between CNSS and XITG. If we set a threshold for covariate index selection probabilities of 50%, we would find that all macroeconomic covariates and some of the firm-specific covariates including CNSS's solvency capacity, CNSS's developing capacity, XITG's solvency capacity and XITG's operating capacity are important for estimating credit risk clustering between CNSS and XITG.

Table S65: Estimation of the tail dependence of credit risk between CNSS and XITG

	None	Macro	Specific	Macro+Specific
Mean	0.012	0.077	0.485	0.642
Median	0.010	0.067	0.579	0.906
Std.dev	0.011	0.081	0.321	0.409

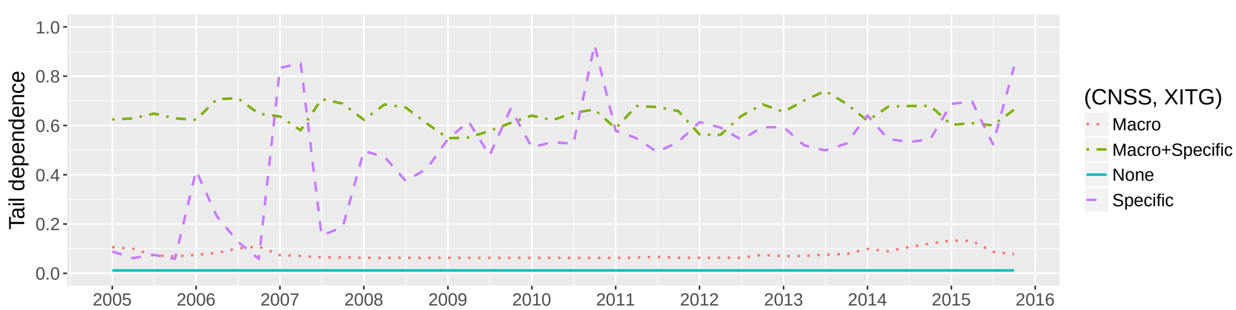

Figure S32: Dynamic of the tail dependence of credit risk between CNSS and XITG

Table S66: Covariate effects on the tail dependence of credit risk between CNSS and XITG

	None	Macro	Specific	Macro+Specific
Constant	−7.592	−2.771	−1.108	19.435
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.076		−2.726
		(1.000)		(0.532)
M2 growth		−0.065		−0.0578
		(1.000)		(0.607)
Short-term interest rate		0.124		1.209
		(1.000)		(0.521)
RMB/USD spot rate		0.084		1.124
		(1.000)		(0.584)
CNSS's solvency capacity			0.050	−2.401
			(0.366)	(0.538)
CNSS's developing capacity			−0.041	0.132
			(0.561)	(0.615)
CNSS's profitability			0.329	1.362
			(0.540)	(0.499)
CNSS's operating capacity			0.014	0.119
			(0.557)	(0.414)
XITG's solvency capacity			0.034	−0.346
			(0.439)	(0.607)
XITG's developing capacity			−0.208	0.184
			(0.941)	(0.407)
XITG's profitability			0.329	−0.258
			(0.446)	(0.356)
XITG's operating capacity			−0.070	0.052
			(1.000)	(0.758)
LDS(in-sample)	−39.294	−62.937	−312.566	**-1.834**
LPS(out-of-sample)	−42.560	−25.941	−32.258	**-14.676**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of CNSS and XITG by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

2.33 Comparison of CNSS and CECC

Section 2.33 presents the empirical results of the credit risk clustering between CNSS and CECC. Table S67 lists that the mean value of tail-dependence coefficient is 0.119 in the none-covariate Joe-Clayton copula model, 0.241 in the macroeconomic-covariate Joe-Clayton copula model, 0.613 in the specific-covariate Joe-Clayton copula model, and 0.612 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S33 shows the dynamic characteristics of the credit risk clustering between CNSS and CECC. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of tail dependence of credit risk in the macroeconomic-covariate Joe-Clayton copula model, especially during periods of the U.S. subprime mortgage crisis and the European debt crisis. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table 2.33 lists the estimated result of covariate effects on the tail dependence of credit risk between CNSS and CECC. We find that comparing with the other covariate-dependent Joe-Clayton copula models, the none-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between CNSS and CECC, and its Log Density Score (LDS) is -3.517.

Table S67: Estimation of the tail dependence of credit risk between CNSS and CECC

	None	Macro	Specific	Macro+Specific
Mean	0.119	0.241	0.613	0.612
Median	0.071	0.102	0.819	0.828
Std.dev	0.142	0.288	0.371	0.407

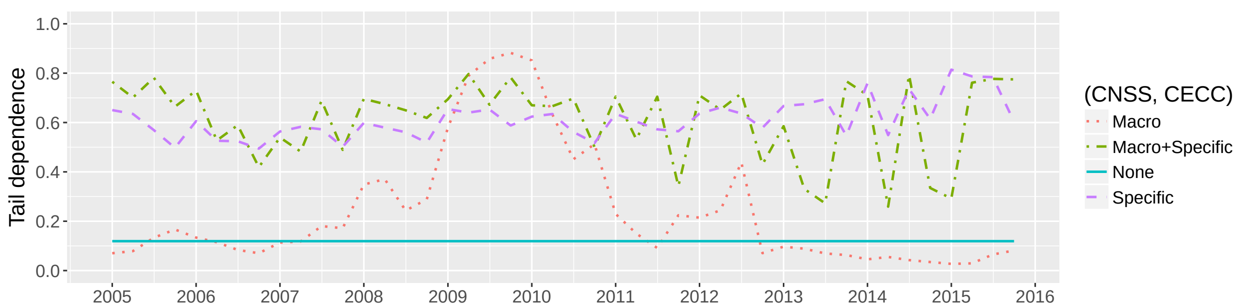

Figure S33: Dynamic of the tail dependence of credit risk between CNSS and CECC

2.34 Comparison of XITG and CECC

Section 2.34 presents the empirical results of the credit risk clustering between XITG and CECC. Table S69 lists that the mean value of tail-dependence coefficient is 0.026 in the none-covariate Joe-Clayton copula model, 0.185 in the macroeconomic-covariate Joe-Clayton copula model, 0.338 in the specific-covariate Joe-Clayton copula model, and 0.631 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S34 shows the dynamic characteristics of the credit risk clustering between XITG and CECC. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula model is stationary. Whereas, we observe an obvious volatility of tail dependence of credit risk in the macroeconomic-covariate Joe-Clayton copula model, especially during the periods of the U.S. subprime mortgage crisis and the European debt crisis. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S70 lists the estimated result of covariate effects on the tail dependence of credit risk between XITG and CECC. The model performance criterion LDS is -40.186 in the macroeconomic-specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -59.681. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models, the macroeconomic-specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between XITG and CECC. If we set a threshold for covariate index selection probabilities of 50%, we would find that XITG's operating capacity, CECC's developing capacity and CECC's operating capacity are important for estimating credit risk clustering between XITG and CECC.

Table S68: Covariate effects on the tail dependence of credit risk between CNSS and CECC

	None	Macro	Specific	Macro+Specific
Constant	−2.728	−4.513	0.577	−4.428
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		0.233		0.027
		(0.877)		(0.810)
M2 growth		0.684		0.140
		(0.983)		(0.577)
Short-term interest rate		−0.938		0.175
		(0.901)		(0.876)
RMB/USD spot rate		−0.671		−0.018
		(0.431)		(0.751)
CNSS's solvency capacity			0.104	0.412
			(0.919)	(0.631)
CNSS's developing capacity			0.012	−0.340
			(0.600)	(0.802)
CNSS's profitability			−0.119	2.135
			(0.811)	(0.662)
CNSS's operating capacity			−0.085	0.079
			(0.792)	(0.421)
CECC's solvency capacity			−0.036	−0.218
			(0.381)	(0.638)
CECC's developing capacity			−0.009	−0.045
			(0.844)	(0.919)
CECC's profitability			0.130	−1.653
			(0.803)	(0.734)
CECC's operating capacity			0.001	0.255
			(0.952)	(0.727)
LDS(in-sample)	**-3.517**	−37.433	−461.350	−1405.178
LPS(out-of-sample)	**-8.746**	−56.152	−48.034	−43.395

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of CNSS and CECC by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

Table S69: Estimation of the tail dependence of credit risk between XITG and CECC

	None	Macro	Specific	Macro+Specific
Mean	0.026	0.185	0.338	0.631
Median	0.011	0.082	0.066	0.973
Std.dev	0.024	0.244	0.402	0.449

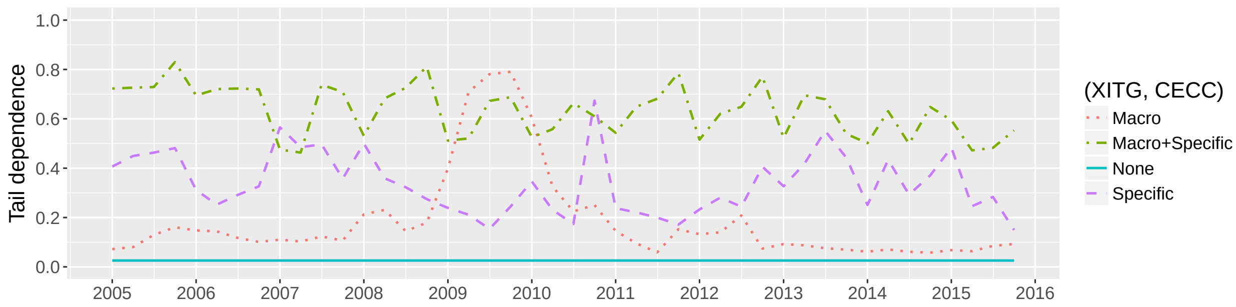

Figure S34: Dynamic of the tail dependence of credit risk between XITG and CECC

2.35 Comparison of XITG and NJPE

Section 2.35 presents the empirical results of the credit risk clustering between XITG and NJPE. Table S71 lists that the mean value of tail-dependence coefficient is 0.015 in the none-covariate Joe-Clayton copula model, 0.049 in the macroeconomic-covariate Joe-Clayton copula model, 0.383 in the specific-covariate Joe-Clayton copula model, and 0.507 in the macroeconomic-specific-covariate Joe-Clayton copula model. The tail-dependence coefficient displays an increasing pattern.

Figure S35 shows the dynamic characteristics of the credit risk clustering between XITG and NJPE. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula and macroeconomic-covariate Joe-Clayton copula models are stationary. Moreover, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table 2.35 lists the estimated result of covariate effects on the tail dependence of credit risk between XITG and NJPE. The model performance criterion LDS is -62.718 in the specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -313.788. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between XITG and NJPE. If we set a threshold for covariate index selection probabilities of 50%, we would find that all firm-specific covariates except XITG's solvency capacity are important for estimating credit risk clustering between XITG and NJPE.

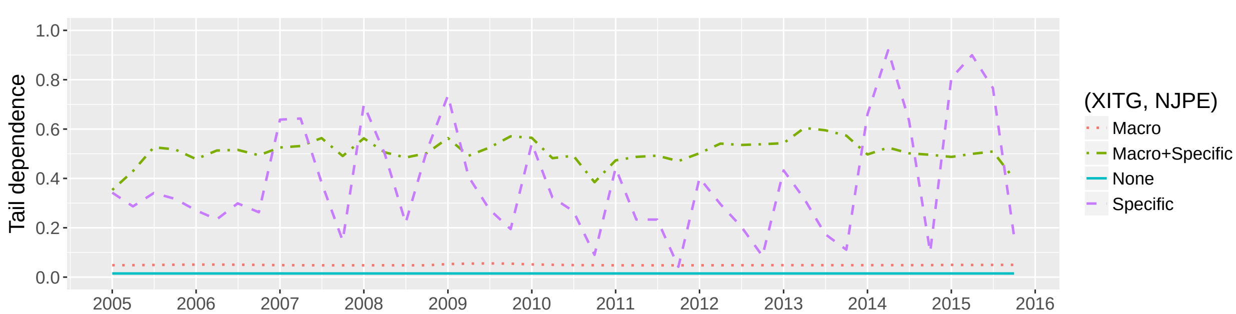

Figure S35: Dynamic of the tail dependence of credit risk between XITG and NJPE

2.36 Comparison of CECC and NJPE

Section 2.36 presents the empirical results of the credit risk clustering between CECC and NJPE. Table S73 lists that the mean value of tail-dependence coefficient is 0.026 in the none-covariate Joe-Clayton copula model, 0.040 in the macroeconomic-covariate Joe-Clayton copula model, 0.485 in the specific-covariate Joe-Clayton copula model, and 0.508 in the macroeconomic-specific-covariate Joe-Clayton copula model. The

Table S70: Covariate effects on the tail dependence of credit risk between XITG and CECC

	None	Macro	Specific	Macro+Specific
Constant	−5.758	−3.803	−3.077	26.632
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		0.036		5.240
		(0.623)		(0.340)
M2 growth		0.375		−1.292
		(0.984)		(0.330)
Short-term interest rate		−0.590		−0.502
		(0.649)		(0.354)
RMB/USD spot rate		−0.302		−1.398
		(0.450)		(0.445)
XITG's solvency capacity			−0.264	3.235
			(0.784)	(0.378)
XITG's developing capacity			0.050	2.330
			(0.881)	(0.269)
XITG's profitability			0.661	−16.638
			(0.673)	(0.354)
XITG's operating capacity			−0.024	5.228
			(0.830)	(0.530)
CECC's solvency capacity			−0.976	0.410
			(0.799)	(0.438)
CECC's developing capacity			0.001	0.487
			(0.540)	(0.655)
CECC's profitability			−0.912	−11.276
			(0.890)	(0.360)
CECC's operating capacity			−0.005	−0.344
			0.746	(0.615)
LDS(in-sample)	−59.681	−56.392	−1506.056	**-40.186**
LPS(out-of-sample)	−58.550	−32.027	−58.833	**-25.195**

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of XITG and CECC by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

Table S71: Estimation of the tail dependence of credit risk between XITG and NJPE

	None	Macro	Specific	Macro+Specific
Mean	0.015	0.049	0.383	0.507
Median	0.011	0.067	0.226	0.586
Std.dev	0.017	0.038	0.386	0.410

Table S72: Covariate effects on the tail dependence of credit risk between XITG and NJPE

	None	Macro	Specific	Macro+Specific
Constant	−6.586	−4.301	−4.823	0.503
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.687		−0.137
		(1.000)		(0.568)
M2 growth		0.002		0.011
		(0.660)		(0.720)
Short-term interest rate		−0.007		0.277
		(0.659)		(0.796)
RMB/USD spot rate		0.002		−0.250
		(0.659)		(0.756)
XITG's solvency capacity			−0.215	−0.029
			(0.418)	(0.769)
XITG's developing capacity			0.511	0.056
			(0.658)	(0.708)
XITG's profitability			−0.414	0.310
			(0.807)	(0.466)
XITG's operating capacity			−0.146	0.018
			(0.790)	(0.738)
NJPE's solvency capacity			−0.186	−0.007
			(0.976)	(0.783)
NJPE's developing capacity			0.300	0.021
			(0.601)	(0.669)
NJPE's profitability			−0.432	−0.036
			(0.838)	(0.788)
NJPE's operating capacity			−0.095	0.006
			(0.533)	(0.648)
LDS(in-sample)	−313.788	−124.563	**-62.718**	−66.387
LPS(out-of-sample)	−56.761	−57.415	**-16.049**	−63.275

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of XITG and NJPE by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.

tail-dependence coefficient displays an increasing pattern.

Figure S36 shows the dynamic characteristics of the credit risk clustering between CECC and NJPE. We see that the tail dependence of credit risk in the none-covariate Joe-Clayton copula and macroeconomic-covariate Joe-Clayton copula models are stationary. However, we identify that the time-varying characteristics of tail dependence are complicated in the specific-covariate Joe-Clayton copula and macroeconomic-specific-covariate Joe-Clayton copula models.

Table S74 lists the estimated result of covariate effects on the tail dependence of credit risk between

CECC and NJPE. The model performance criterion LDS is -1.700 in the specific-covariate Joe-Clayton copula model while LDS in the none-covariate Joe-Clayton copula model is -171.990. This indicates that by comparing with the other covariate-dependent Joe-Clayton copula models the specific-covariate Joe-Clayton copula model is the best model for predicting the credit risk clustering between CECC and NJPE. If we set a threshold for covariate index selection probabilities of 50%, we would find that CECC's developing capacity, CECC's operating capacity, NJPE's solvency capacity, NJPE's developing capacity, NJPE's profitability and NJPE's operating capacity are important for estimating credit risk clustering between CECC and NJPE.

Table S73: Estimation of the tail dependence of credit risk between CECC and NJPE

	None	Macro	Specific	Macro+Specific
Mean	0.026	0.040	0.485	0.508
Median	0.037	0.010	0.489	0.571
Std.dev	0.012	0.156	0.308	0.386

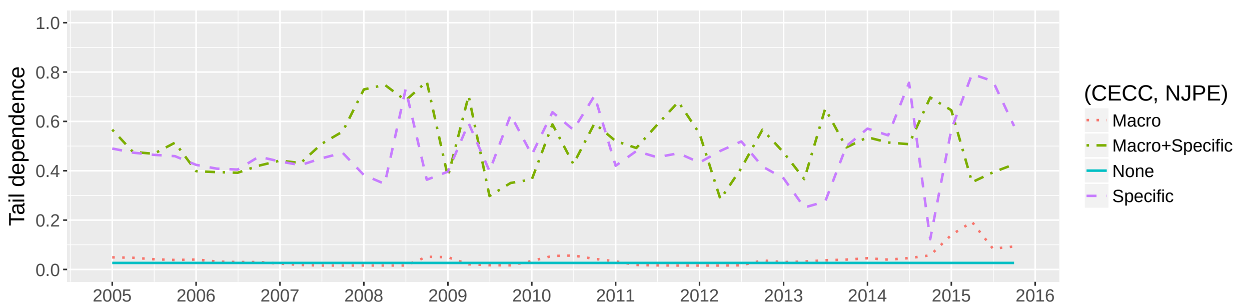

Figure S36: Dynamic of the tail dependence of credit risk between CECC and NJPE

Table S74: Covariate effects on the tail dependence of credit risk between CECC and NJPE

	None	Macro	Specific	Macro+Specific
Constant	−4.961	16.980	−0.886	−1.719
	(1.000)	(1.000)	(1.000)	(1.000)
CPI		−0.661		0.318
		(0.767)		(0.548)
M2 growth		−0.399		−0.091
		(0.333)		(0.804)
Short-term interest rate		−1.152		0.309
		(0.156)		(0.779)
RMB/USD spot rate		−1.322		0.117
		(0.313)		(0.890)
CECC's solvency capacity			−0.055	0.117
			(0.274)	(0.418)
CECC's developing capacity			−0.061	0.100
			(0.577)	(0.743)
CECC's profitability			−0.264	−0.560
			(0.390)	(0.586)
CECC's operating capacity			0.018	−0.021
			(0.587)	(0.636)
NJPE's solvency capacity			−0.062	0.032
			(0.845)	0.690
NJPE's developing capacity			−0.086	−0.314
			(0.731)	(0.748)
NJPE's profitability			−0.337	−0.055
			(0.673)	(0.545)
NJPE's operating capacity			0.131	−0.025
			(0.820)	(0.653)
LDS(in-sample)	−171.990	−99.828	**-1.700**	−88.895
LPS(out-of-sample)	−71.638	−95.287	**-56.413**	−107.808

This table shows the estimated results of covariate effects on the tail dependence of credit risk for the pair of CECC and NJPE by using split-t with Joe-Clayton copula. The covariate index selection probabilities are shown in parenthesis. LDS is Log Density Score, which indicates the criterion of model performance. LPS is Log Predictive Score.