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Article

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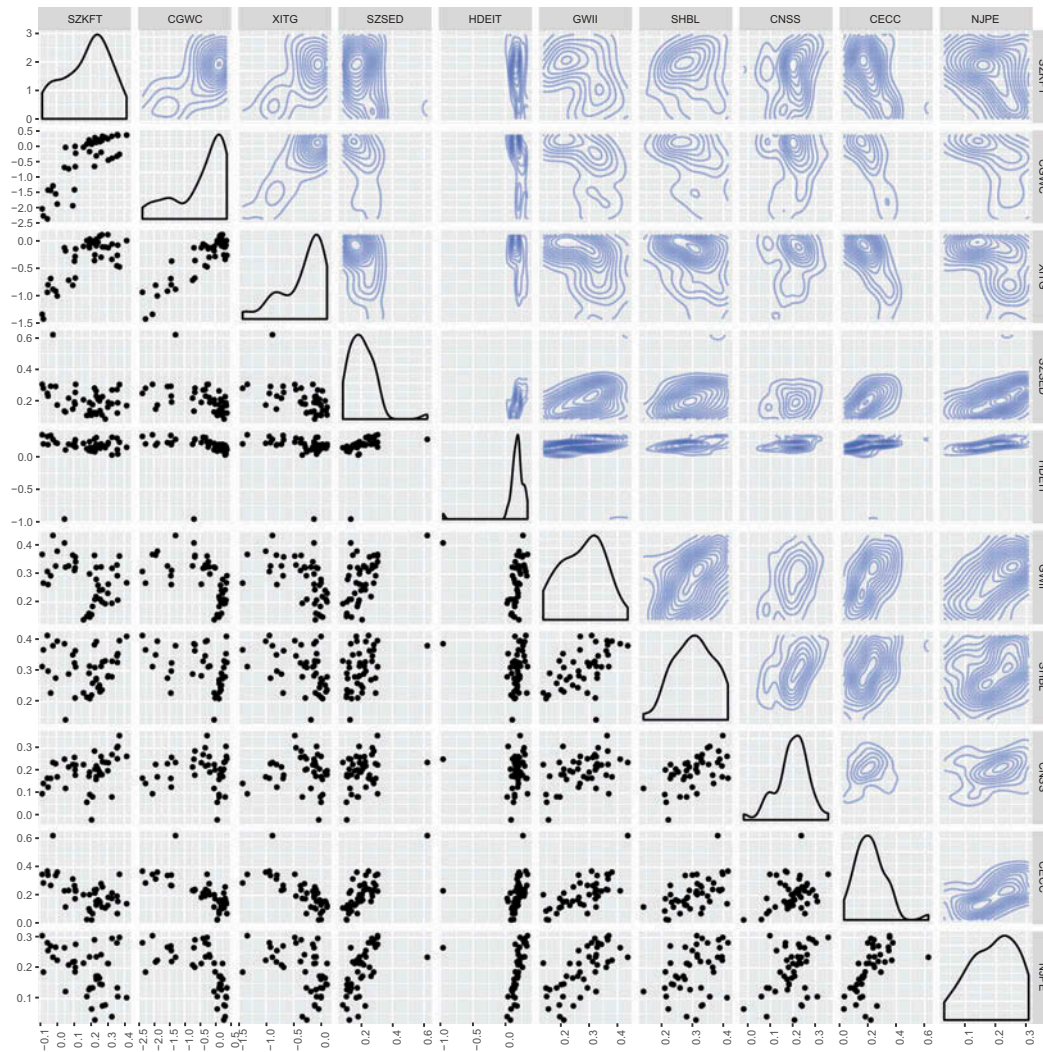
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FINANCIAL ECONOMICS | RESEARCH ARTICLE

Credit risk clustering in a business group: Which matters more, systematic or idiosyncratic risk?

Feng Li¹ and Zhuojing He^{2*†}

Abstract: Understanding how defaults correlate across firms is a persistent concern in risk management. In this paper, we apply covariate-dependent copula models to assess the dynamic nature of credit risk dependence, which we define as “credit risk clustering”. We also study the driving forces of the credit risk clustering in CEC business group in China. Our empirical analysis shows that the credit risk clustering varies over time and exhibits different patterns across firm pairs in a business group. We also investigate the impacts of systematic and idiosyncratic factors on credit risk clustering. We find that the impacts of the money supply and the short-term interest rates are positive, whereas the impacts of exchange rates are negative. The roles of the CPI on credit risk clustering are ambiguous. Idiosyncratic factors are vital for predicting credit risk clustering. From a policy perspective, our results not only strengthen the results of previous research but also provide a possible approach to model and predict the extreme co-movement of credit risk in business groups with financial indicators.

Subjects: Quantitative Finance; Statistics for Business, Finance & Economics; Chinese Economics

Keywords: business groups; credit risk clustering; covariate-dependent copulas; MCMC

JEL classification: C11; C53; C58

1. Introduction

The global financial crisis has dramatic effects on the global financial sector and on default risk. Since then, the domino effects of credit risk have occurred more frequently across inter-connected

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PUBLIC INTEREST STATEMENT

We cluster credit risk in business groups with covariate-dependent copula models. We find time-varying systematic and idiosyncratic factors affect clustering in subsidiaries. M2 and short-term loan rate interest could increase the dependence of credit risk. Idiosyncratic factors in subsidiaries act differently in credit risk clustering. Regulators should remain vigilant of macroeconomic and firm-specific effects. From a policy perspective, our results not only strengthen the results of previous research but also provide a possible approach to model and predict the extreme co-movement of credit risk in business groups with financial indicators.

corporate entities. Nonetheless, the emerging markets are facing histrionic risks in defaults. For example, from Jan 2014 to Nov 2017, we observed an increasing trend of defaults among firms in China, one of the biggest emerging markets. A total of 134 defaults were valued at 841 million Chinese yuan (127.3 million US dollars); state-owned firms were involved in 37 totaling 307 million Chinese yuan (47 million US dollars). During the period of 2014 to 2017, the reported proportion of state-owned firm defaults in terms of both quantity and capital are not negligible anymore.

One may argue that, in many emerging countries, the “state-owned” companies will always be liquidated by the state if they face financial difficulties. But from our observation, the “state-owned” label is not the guarantee for the companies to liquidate. On the contrary, for example in China, we see the evidence that China has experienced its first domestic bond default in 2014 in the recent history after a small Shanghai-based solar power company failed to pay out interest on a security. From then on, the total capital of default is over 840 million Chinese Yuan (120 million US dollars) where over 1/3 are state-owned and this number is increasing. As a result, credit default, especially default of state-owned company, is a crucial problem for financial stability.

The “business group” is a common organizational form in emerging economies because of their weak investor rights protections, communications and information disclosure practices, and capital markets (Cheung, Rau, & Stouraitis, 2006; He, Mao, Rui, & Zha, 2013; Khanna & Palepu, 2000). In such environments, it can be particularly costly for firms to acquire external financing. Therefore, the business group, which comprises several independent firms, serves as an internal financial market with low-cost financing and efficient resource allocation. However, such business groups have negative features. Morck, Wolfenzon, and Yeung (2005) find that a business group with a pyramidal structure provides a feasible way to prop up one large and influential firm at the expense of other weaker firms. Gopalan, Nanda, and Seru (2007) argue that negative spillovers tend to increase for firms with close links to the bankrupt firm in a business group. Emery and Cantor (2005) confirm that the probability of default risk dependence increases across firms with operational and financial linkages. Therefore, if defaults are more heavily clustered than expected among subsidiaries in a business group, then significantly greater capital might be required in order to survive the default losses.

For the purpose of maintaining financial stability, it is critical for financial institutions and regulators to capture the effects of default dependence that arise from business groups, which we refer to as “credit risk clustering”. Thus, in this paper, we intend to examine the following questions:

- (1) Is it possible to cluster credit risk via tail dependence, and how is credit risk clustered in a business group?
- (2) What are the driving forces of credit risk clustering in a business group?

Recently, the risk literature has acknowledged the existence of credit risk clustering among firms (Das, Duffie, Kapadia, & Saita, 2007; Duffie, Eckner, Horel, & Saita, 2009). The existing literature explores two aspects of the dependence of credit risk. On the one hand, default by one firm may be a contagious event that induces other corporate failures. Jorion and Zhang (2007) investigate the contagion effect of financial distress on intra-industry credit default swap (CDS) spreads, and they confirm that this effect depends on the type of credit event. Hertz, Li, Officer, and Rodgers (2008) find evidence that negative effects are transmitted by a firm in the midst of filing for bankruptcy to other firms in the supply chain. Huang and Li (2009) find that negative spillover effects spread from Enron to other firms because of their connection to the same accounting firm. On the other hand, firms may be exposed to common or correlated risk factors, which cause correlated changes in their conditional default probabilities. Oh (2013) concludes that contagion between non-financial institutions occurs during liquidity crises because of learning by the common creditor pool. Manz (2010) shows that external financing constraints may be reinforced, as investors learn that firms in the same industry are affected by common factors. Therefore, the failure of one firm may trigger financial distress in other firms.

Regarding the determinants of credit risk clustering, Duffie et al. (2009) find strong evidence that firms are exposed to common dynamic latent factors. Gersbach and Lipponer (2003) examine the impacts of macroeconomic shocks, which are measured as interest shocks, on the default dependences of loan portfolios. They find that macroeconomic shocks increase positive default dependences.

Correctly estimating default dependences is of particular importance for credit risk management because joint default events between obligors determine portfolio losses. Das, Fong, and Geng (2001) find that the default rates on debts in credit portfolios are significantly correlated and that estimated credit losses are substantially biased if the default dependence is ignored. Since the copula model is flexible, it is a popular method for modeling joint default in credit risk management. Giesecke and Weber (2004) use Clayton and Gumbel copula-dependent parameters to measure the default dependence between firms.

In this paper, we provide new insights into the extreme co-movements of default in a business group in emerging markets. Although we only do a study case in a business group in China, our methodology is general and can be applied to any business group where the subsidiary firms are closely connected in finance.

First, we use a structure model to calculate the distance-to-default (DTD) as a measure of credit risk. Then, following the methodology proposed by Li and Kang (2018), we apply the covariate-dependent copula model to investigate the dynamic nature of credit risk clustering across firm pairs in a business group. Finally, we use both systematic and idiosyncratic factors to investigate the driving forces of credit risk clustering. Our finding suggests that credit risk clustering may occur via the tail dependence of default. The tail-dependent coefficients of credit risk in a business group in China are time variant and increase dramatically during the period of financial crisis. The money supply and the short-term interest rate are positively related to credit risk clustering. More importantly, the appreciation of RMB may increase the credit risk clustering in a business group in China. The relationship between the CPI and the credit risk clustering is ambiguous. The idiosyncratic factors are vital for credit risk clustering. However, they exhibit different impacts on credit risk clustering in different firm pairs in a business group.

Our paper contributes to the recent risk literature in three respects. First, we expand on a small number of related studies by providing evidence of credit risk clustering among the subsidiary firms at a business group in China. Second, we incorporate systematic and idiosyncratic factors into a dynamic copula model in order to identify the driving forces of credit risk clustering. In this way, we meet the needs of regulators for risk detection tools and eventual (early) risk warnings. In principle, other information such as guarantee information from off-balance items can be conveniently incorporated into our model if the data are available. Third, our finding of significant credit risk clustering has important implications for regulators, investors and market participants, as tail dependence indicates extreme co-movement and potential for simultaneous large losses in portfolios. Ignoring the credit risk clustering, especially when those portfolios are in a business group, would underestimate the default risk premium.

The remainder of this paper proceeds as follows. Section 2 presents the details of the covariate-dependent copula model. Section 3 describes the data that support our study, the specification of the covariates, and the measures of credit risk, as well as their summary statistics. Section 4 presents model comparisons and examines the structure of tail dependence of credit risk and the covariate effects on credit risk clustering. Section 5 provides conclusions.

2. Credit risk clustering with covariate-dependent copulas

2.1. Copula and dependence concepts

Given two random variables x_1 and x_2 with their marginal distribution functions $u_1 = F(x_1)$ and $u_2 = F(x_2)$, a bivariate copula function $C(u_1, u_2)$ combines the marginal distribution functions to represent the joint distribution function $F(x_1, x_2)$,

$$F(x_1, x_2) = C(u_1, u_2) = C(F(x_1), F(x_2)).$$

The copula function is uniquely determined if the marginal distribution functions are both continuous. The derivation of the copula function yields the copula density $c(u_1, u_2) = \partial^2 C(u_1, u_2) / (\partial u_1 \partial u_2)$. Therefore, the joint density $f(x_1, x_2)$ can be specified as the product of the copula density $c(u_1, u_2)$ and their marginal densities $f(x_1)$ and $f(x_2)$,

$$f(x_1, x_2) = c(u_1, u_2)f(x_1)f(x_2).$$

An appealing feature of a copula is that it provides information on the probability that two variables jointly experience extreme downward or upward movements via the lower tail dependence λ_L and upper tail dependence λ_U coefficients,

$$\lambda_L = \lim_{u \rightarrow 0^+} \Pr[x_1 \leq F_{x_1}^{-1}(u) | x_2 \leq F_{x_2}^{-1}(u)] = \lim_{u \rightarrow 0^+} \frac{C(u, u)}{u},$$

$$\lambda_U = \lim_{u \rightarrow 1^-} \Pr[x_1 > F_{x_1}^{-1}(u) | x_2 > F_{x_2}^{-1}(u)] = \lim_{u \rightarrow 1^-} \frac{1 - 2u + C(u, u)}{1 - u}.$$

Our study uses a diverse family of copula specifications with different dependence structures for model comparisons (see section 4.1), including the Joe-Clayton copula, symmetrized Joe-Clayton copula, Clayton copula and Gumbel copula. Table 1 summarizes the copula specifications. Besides the Archimedean copulas, the class of elliptical copulas is also an option. However, the Gaussian copula does not have any tail-dependence. Despite that the Student's t copula has limited symmetric tail-dependence when the degrees of freedom are very small, modeling the degrees of freedom is very difficult in practice.

2.2. Covariate-dependent copulas

In this section, we describe how to reparameterize the copula functions so that the parameters highlight the features of interest. The parameters in most copula functions do not directly represent the copula features, such as tail dependence. We demonstrate parameterization with the widely used two-parameter Joe-Clayton copula. Other copulas can be reparameterized by following the same procedure.

The Joe-Clayton copula (also known as the BB7 copula), introduced by Joe (1997), is widely used in financial applications. To simplify the interpretation of tail dependence in the copula model, we parameterize it in terms of the lower and upper tail dependence,

$$C_{JC}(u_1, u_2; \lambda_L, \lambda_U) = 1 - [1 - \{1 - (1 - u_1)^{\log 2 / \log(2 - \lambda_U)}\}^{\log 2 / \log \lambda_L} + [1 - (1 - u_2)^{\log 2 / \log(2 - \lambda_U)}] \log 2 / \log \lambda_L - 1]^{\log \lambda_L / \log 2} \log(2 - \lambda_U) / \log 2. \quad (1)$$

The related reparameterized Joe-Clayton copula density is obtained by $\partial^2 C_{JC}(u_1, u_2; \lambda_L, \lambda_U) / (\partial u_1 \partial u_2)$.

Letting the tail-dependent parameters (λ_L and λ_U) be constant is very restrictive in copula modeling, especially in financial time series applications, where time-varying tail dependence is a typical phenomenon (see Patton (2006)). Following Li and Kang (2018), we model lower tail dependence and upper tail dependence for the i -th and j -th margins in a copula as the matrix form

$$\lambda_{Lij} = l_{\lambda_L}^{-1}(x\beta_{Lij}), \lambda_{Uij} = l_{\lambda_U}^{-1}(x\beta_{Uij}), \quad (2)$$

Table 1. Bivariate copula functions and their tail-dependent coefficients			
Copula Name	Formula	Parameter	Tail dependence
Joe-Clayton	$C_{JC}(u_1, u_2; \theta, \delta) = 1 - [1 - ((1 - u_1)^\theta)^{-\delta} + (1 - (1 - u_2)^\theta)^{-\delta} - 1]^{-1/\delta} 1/\theta$	$\theta \geq 1, \delta > 0$	$\lambda_L = 2^{-1/\delta}, \lambda_U = 2 - 2^{1/\theta}$
Symmetrized Joe-Clayton	$C_{SJC}(u_1, u_2; \theta, \delta) = 0.5C_{JC}(u_1, u_2; \theta, \delta) + 0.5C_{JC}(1 - u_1, 1 - u_2; \theta, \delta) + u_1 + u_2$	$\lambda_L, \lambda_U \in (0, 1)$	$\lambda_L = \lambda_U$
Clayton	$C_{CL}(u_1, u_2; \delta) = \max[(u_1^{-\delta} + u_2^{-\delta} - 1)^{-1/\delta}, 0]$	$\delta \in [-1, \infty) \setminus 0$	$\lambda_L = 2^{-1/\delta}, \lambda_U = 0$
Gumbel	$C_G(u_1, u_2; \delta) = \exp(-((-\log u_1)^\delta + (-\log u_2)^\delta)^{1/\delta})$	$\delta \geq 1$	$\lambda_L = 0, \lambda_U = 2 - 2^{1/\delta}$

where x is the $n \times p$ set of the common covariate matrix that determines the dependent structure, $\beta_{L_{ij}}$ and $\beta_{U_{ij}}$ are the $p \times 1$ coefficients vectors, and $l(\cdot)$ is a suitable link function that connects λ_L and λ_U with x . We use the logit function as a natural choice for the link function. With such a covariate-dependent structure, variable selection can be used to select meaningful covariates that influence dependence and prevent overfitting.

2.3. Marginal models

We use balance sheet and stock market data to calculate firms' credit risk with the KMV model, which is extended from Merton (1974) pricing Merton (1974). The detailed calculation is presented in Section 3. The Merton model, which is based on market data, provides a more simple, flexible and useful method of measuring credit risk. Bharath and Shumway (2008) conclude that though the Merton model does not produce statistics to determine the probability of default, but its functional form is useful for forecasting defaults. Afik, Arad, and Galil (2016) examine the sensitivity of the Merton model default prediction performance to its parameter specifications. They find that simplified applications of the model have superior performance compared to more complex and computationally intensive methods. Furthermore, DTD is a measure of default risk derived from observed stock prices and book leverage using the structural credit risk model of Merton (1974). Despite the simplifying assumptions that underlie its derivation, DTD has proven to be an empirically strong predictor of default. Jessen (2015) use simulations to show that the empirical success of DTD may result from its robustness to model misspecification. They consider a number of deviations from the Merton model that involve different asset value dynamics and different default triggering mechanisms. They show that, in general, DTD is successful in ranking firms' default probabilities, even if the underlying model assumptions are altered.

To examine the tail dependences in credit risk, we use the split- t distribution (Li, Villani, & Kohn, 2010) as the marginal distribution for the unimodal DTD of each firm. The split- t is a flexible four-parameter distribution with the Student's- t distribution, the asymmetric and symmetric normal distributions as its special cases. The choice of this model is supported by statistical tests (see the Jarque-Bera test statistics in Table 4 of Section 3.2). We also allow the location parameter μ , the scale parameter ϕ , the degrees of freedom ν , and the skewness parameter κ in the split- t density to be linked to covariates in the matrix form

$$\mu_m = x_m \beta_{\mu_m}, \phi_m = \exp(x_m \beta_{\phi_m}), \nu_m = \exp(x_m \beta_{\nu_m}), \text{ and } \kappa_m = \exp(x_m \beta_{\kappa_m}), \quad (3)$$

where x_m is the covariate matrix for the m -th margin, and the β vectors represent the coefficients of the parameters in the marginal distribution.

For multimodal DTDs, we further allow the marginal distribution to be a finite mixture of the split- t distributions (Li et al., 2010). For simplicity, we keep the skewness parameter $\kappa_m = 1$ in Equation (3) (i.e., no skewness in each mixing density) because skewness in the data is now determined by the location of mixing components (Frühwirth-Schnatter, 2006).

2.4. Model specification and evaluation

We use Bayesian variable selection technique to select important covariates that affect the credit risk clustering. Let \mathcal{I}_j be the variable selection indicator for a given covariate x_j ,

$$\mathcal{I}_j = \begin{cases} 1 & \text{if } \beta_j \neq 0, \\ 0 & \text{if } \beta_j = 0, \end{cases} \quad (4)$$

where β_j is the j -th covariate in the model. We standardize each covariate to mean zero and unit variance and assume prior independence of the intercept β_0 and the slope β . We can decompose the joint prior as follows:

$$p(\beta, \mathcal{I}) = p(\beta_0, \beta_s, \mathcal{I}) = p(\beta_0)p(\beta_s, \mathcal{I}) = p(\beta_0)p(\beta_s|\mathcal{I})p(\mathcal{I}). \quad (5)$$

We will use normal priors for both β_0 and β_s . We also assume that the intercept is always included in each parameter, so the variable selection indicator for β_0 is always one. The complete prior

Table 2. Prior beliefs on features and implied priors for β_0 , β_s , and \mathcal{I} in the covariate-dependent copula models!

Feature	Link function	Prior belief on feature	$p(\beta_0)$
mean μ	identity	$N(\text{mean} = 0, \text{var} = 1)$	$N(\text{mean} = 0, \text{var} = 1)$
scale ϕ	log	$\text{logNorm}(\text{mean} = 1, \text{var} = 1)$	$N(\text{mean} = -0.34, \text{var} = 0.69)$
degrees of freedom ν	log	$\text{logNorm}(\text{mean} = 5, \text{var} = 10)$	$N(\text{mean} = 1.44, \text{var} = 0.34)$
skewness κ	log	$\text{logNorm}(\text{mean} = 1, \text{var} = 1)$	$N(\text{mean} = -0.34, \text{var} = 0.69)$
tail dependences λ_L, λ_U	logit	$\text{Beta}(\text{mean} = 0.2, \text{var} = 0.05)$	$N(\text{mean} = -2.55, \text{var} = 6.91)$
$p(\mathcal{I}_j) \sim \text{Bern}(0.5)$			
$p(\beta_s \mathcal{I}) \sim N(0, \Sigma)$	where $\Sigma = \text{diag}(1, \dots, 1)$		

settings are specified in Table 2. Li and Kang (2018) show that this specification produces robust posterior results.

The posterior in a copula model can be written in terms of the likelihoods from the marginal distributions, the copula likelihood, and the priors for parameters in the copula and marginal distributions,

$$\log p(\{\beta, \mathcal{I}\} | y, x) = \text{constant} + \sum_{j=1}^M \log p(y_j | \{\beta, \mathcal{I}\}_j, x_j) \\ + \log \mathcal{L}_C(u | \{\beta, \mathcal{I}\}_C, y, x) + \log p(\{\beta, \mathcal{I}\}),$$

where $\log p(y_j | \{\beta, \mathcal{I}\}_j, x_j)$ is the log likelihood in the j -th margin, and the sets $\{\beta, \mathcal{I}\}_j$ are the parameter blocks in the j -th margin. Furthermore, $u = (u_1, \dots, u_M)$, where $u_j = (u_{1j}, \dots, u_{nj})$, $u_{ij} = F_j(y_{ij} | \{\beta, \mathcal{I}\}_j)$, $F_j(\cdot)$ is the cumulative distribution function of the j -th marginal distribution, and \mathcal{L}_C is the likelihood for the copula function.

We update the copula features and the marginal features jointly. The joint posterior is not tractable, so we use the Metropolis-Hastings algorithm with a Gibbs sampler, i.e., a Gibbs sampler is used to update the joint parameter components, with each conditional parameter block of covariates and variable selection indicators $\{\beta, \mathcal{I}\}$ updated by the Metropolis-Hastings algorithm. For the complete Markov chain Monte Carlo (MCMC) details, see Li and Kang (2018). The efficiency of MCMC is monitored via the inefficiency factor $IF = 1 + 2 \sum_{i=1}^{\infty} \rho_i$, where ρ_i is the autocorrelation at lag i in the MCMC iterations. The inefficiency factors for all parameters in our analyses are below 40 which indicate high efficiency in MCMC.

We evaluate model performance based on the out-of-sample log predictive score (LPS), defined as $\log p(y_d | y_{-d}, x)$, where y_d is an $n_d \times p$ matrix containing the n_d observations in the d -th testing sample and y_{-d} denotes the training observations used for estimation. If we assume the observations are conditionally independent on $\{\beta, \mathcal{I}\}$, then

$$\text{LPS} = \log p(y_d | y_{-d}, x) = \log \int \prod_{i \in d} p(y_i | \{\beta, \mathcal{I}\}, x_i) p(\{\beta, \mathcal{I}\} | y_{-d}) d\{\beta, \mathcal{I}\}. \quad (6)$$

The LPS is easily calculated by averaging $\prod_{i \in d} p(y_i | \{\beta, \mathcal{I}\}, x_i)$ over the posterior draws from $p(\{\beta, \mathcal{I}\} | y_{-d})$. In our time series application, we calculate the LPS based on posterior estimation of 80% of the historical data and density forecasting of the last 20% of the data. The LPS has three main advantages over other model comparison strategies: i) the LPS is based on out-of-sample probability forecasting, which is the authoritative model evaluation tool for decision makers (Geweke & Amisano, 2010); ii) the LPS is easily calculated based on Monte Carlo simulations that do not require normality assumptions; and iii) the LPS is not sensitive to the choice of priors compared with the marginal likelihood-based criteria (Kass, 1993; Richardson & Green, 1997). If the testing observations are the same as the training observations, Equation (6) functions as the

in-sample goodness-of-fit indicator. We call this the log density score (LDS) in our empirical analyses.

3. Business group data

3.1. Sample firm selection

Our modeling strategy is applicable to general business entities. In this paper, we choose to study a typical business group in emerging markets, China Electronics Corporation (CEC), to explain our methodology. CEC is one of the largest business group in China. It ranked third in electronics industry in China in 2016 based on its operating revenues of 198.2 billion Chinese yuan (32.33 billion US dollars) and total profits of 5.09 billion Chinese yuan (0.83 billion US dollars). CEC's main business is electronic information technology devices and services. Competition in the electronics industry is fierce. CEC owns 16 listed subsidiary companies in China. Its organizational structure is complex, and these subsidiary companies form a comprehensive vertical supply chain. Close correlation may in turn increase the probability of credit risk clustering across subsidiaries in the business group through financial and business channels (Emery & Cantor, 2005). Table 3 describes 10 of CEC's 16 listed subsidiaries. We do not present the other six listed subsidiaries because of the missing data for these subsidiaries. The sample period spans from the first quarter of 2005 to the last quarter of 2015, which includes 44 observations for each firm. The balance sheet data are from the China Stock Market and Accounting Research database, and the stock market price and macroeconomic variables data are from the Wind database.

This table describes 10 subsidiaries of the China Electronics Corporation (CEC) and their industry. The abbreviation of each subsidiary is shown in parentheses.

3.2. Measuring credit risk with the distance-to-default index

We use the distance-to-default in Merton model to measure credit risk. In the Merton model, one assumes that the equity value of a firm satisfies

$$V_e = V_a N(d_1) - D e^{-rT} N(d_2), \quad (7)$$

where V_e is the market value of the firm's equity, which equals the market value of tradable shares, V_a is the market value of the firm's assets, and $N(\cdot)$ is the cumulative distribution function of the standard normal density. Furthermore, D is the book value of the firm's debt, which equals

Table 3. Industry of major listed subsidiaries

Listed subsidiary	Industry
Shenzhen Kaifa Technology Co. Ltd. (SZKFT)	Computer communications and other electronic device manufacture
Xiamen ITG Group Co. Ltd. (XITG)	Wholesale and retail
China Great Wall Computer Shenzhen Co. Ltd. (CGWC)	Computer communications and other electronic device manufacture
Shenzhen Sed Industry Co. Ltd. (SZSED)	Wholesale and retail
Nanjing Huadong Electronic Information and Technology Co. Ltd. (HDEIT)	Computer communications and other electronic device manufacture
Great Wall Information Industry Co. Ltd. (GWII)	Computer communications and other electronic device manufacture
Shanghai Belling Co. Ltd. (SHBL)	Computer communications and other electronic device manufacture
China National Software and Service Co. Ltd. (CNSS)	Software and information technology services
Cec Corecast Co. Ltd. (CECC)	Software and information technology services
Nanjing Panda Electronics Co. Ltd. (NJPE)	Computer communications and other electronic device manufacture

the book value of short-term debt plus half of the book value of long-term debt (Duffie, Saita, & Wang, 2007), r is the risk-free rate, and τ is the horizon of the book value of the firm's debt, which equals one year. The parameters d_1 and d_2 are given by

$$d_1 = \frac{\ln(V_a/D) + (r + \sigma_a^2/2)\tau}{\sigma_a\sqrt{\tau}},$$

$$d_2 = \frac{\ln(V_a/D) + (r - \sigma_a^2/2)\tau}{\sigma_a\sqrt{\tau}} = d_1 - \sigma_a\sqrt{\tau},$$

where σ_a is the volatility of the firm's assets. By using Ito's lemma, the relationship between the volatility of the firm's equity (σ_e) and the volatility of its assets (σ_a) is of the form

$$\sigma_e = \frac{V_a N(d_1)}{V_e} \sigma_a. \quad (8)$$

To solve Equations (7)–(8) simultaneously, we set the corresponding period equity value (V_e) and volatility (σ_e) as the initial values. Then, we use Newton's iteration (Duffie et al., 2007; Vassalou & Xing, 2004), Duffie2007 to calculate the market value of the firm's assets (V_a) and its volatility (σ_a). Finally, we calculate the DTD values using

$$DTD = \frac{V_a - D}{V_a \sigma_a}$$

as the measure of each firm's credit risk. In risk management, the probabilities of default are high if the DTD values are small. In other words, the smaller the DTD value is, the higher the probability of default.

The DTDs for CEC's listed subsidiaries are shown in Figure 1. Table 4 reports the descriptive statistics for the DTD of each CEC's subsidiary. On the one hand, SHBL's mean DTD value is the largest among all the subsidiaries, with an average value of 0.304. Its volatility is the lowest, with a standard deviation of 0.065. On the other hand, CGWC has the smallest mean DTD value (– 0.422) and the highest DTD

Figure 1. Distance-to-default (DTD) for 10 subsidiaries in CEC.

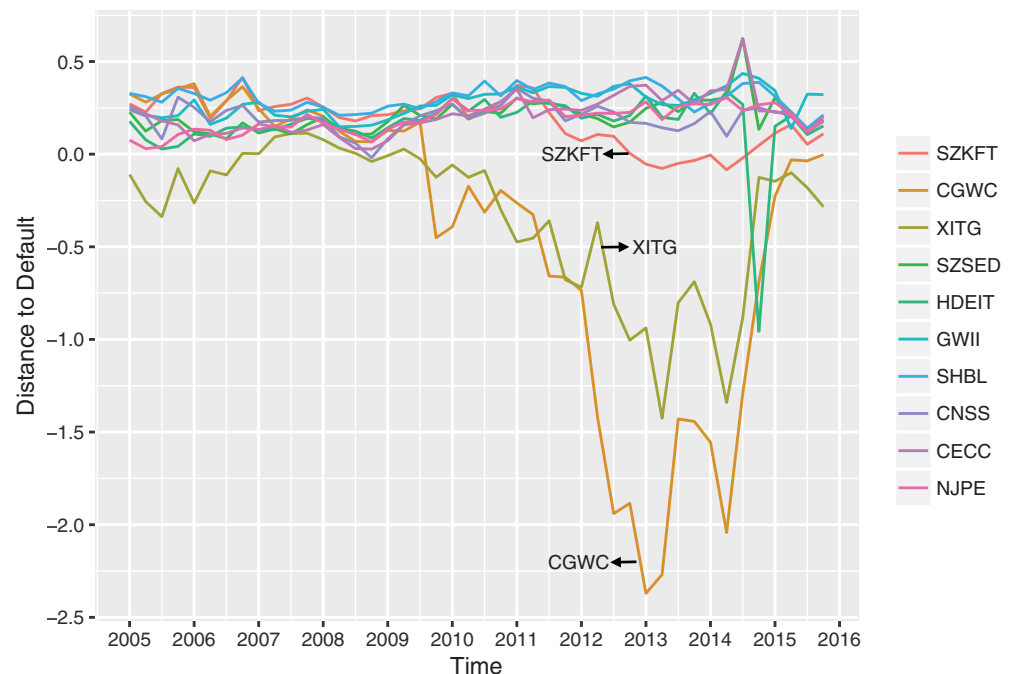


Table 4. Summary of distance-to-default (DTD) index for listed subsidiaries

	SZKFT	SZSED	CGWC	HDEIT	GWII	SHBL	CNSS	XITG	CECC	NJPE
Mean	0.179	0.206	− 0.422	0.161	0.277	0.304	0.196	− 0.324	0.214	0.191
Median	0.210	0.191	− 0.105	0.185	0.287	0.311	0.205	− 0.136	0.206	0.206
Std.dev	0.136	0.091	0.813	0.187	0.076	0.065	0.072	0.397	0.110	0.075
Min	− 0.084	0.083	− 2.370	− 0.956	0.138	0.141	− 0.020	− 1.425	0.027	0.030
Max	0.415	0.622	0.380	0.339	0.436	0.414	0.356	0.113	0.624	0.306
Skewness	− 0.391	2.151	− 1.059	− 4.921	− 0.102	− 0.188	− 0.594	− 1.124	1.087	− 0.324
Kurtosis	2.143	11.022	2.835	30.217	2.147	2.438	3.733	3.368	5.641	2.144
Jarque-Bera statistic	1.571	12.326	2.877	39.187	1.188	0.915	1.889	3.086	4.631	1.453
(p-value)	(0.291)	(0.000)	(0.016)	(0.000)	(0.494)	(0.658)	(0.168)	(0.009)	(0.000)	(0.348)

volatility, with a standard deviation of 0.813. More commonly, we find that a small DTD value is associated with a high volatility value, and vice versa. In other words, a higher probability of default is accompanied by greater volatility among CEC subsidiaries. The distributions of DTD values for some subsidiaries, such as SZSED, HDEIT, XITG, and CECC, do not follow the assumption of normality, as the null hypothesis is rejected by Jarque-Bera test at the 5% significance level.

3.3. Covariates for tail dependence

In this paper, we assume that the marginal distributions of the covariate-dependent copula model follow the split-*t* distribution (Li et al., 2010), which is a four-parameter asymmetric Student's-*t* distribution with a location parameter, a scale parameter, a skewness parameter, and a kurtosis parameter. All four parameters of the split-*t* distribution are linked with covariates, as shown in Equation (3). The covariates used in Equations (2) and (3) are systematic and idiosyncratic variables described in Tables 5 and 6. In this paper, we use the CPI (an inflation index), the M2 growth rate (a money supply index), the short-term loan interest rate (a loan cost index), and the RMB/USD spot rate as the systematic factors. We use principal component analysis (PCA) to extract information from the observable indexes (Pu & Zhao, 2012) because the idiosyncratic variables (solvency capacity, operating capacity, developing capacity and profitability) are unobserved. We use the first component of the PCA as the measure of each idiosyncratic variable.

Having off-balance sheet items such as guarantee information in the model could provide more insights into the credit risk clustering problem. Our methodology could conveniently incorporate the information given the data are available. However, this information is usually not publicly available in emerging countries.

4. Empirical results

In this section, we present the empirical results for credit risk clustering for three major subsidiaries (SZKFT, CGWC, and XITG) of CEC. We present the empirical results for credit risk clustering for all other 36 firm pairs in the supplementary materials.

Table 5. Descriptions of macroeconomic covariates

Variable	Description	Mean	Std.dev
CPI	A proxy for the inflation rate	2.797	2.103
M2 growth rate	The supply of money	16.955	4.129
Short-term interest rate	The 6-month loan interest rate	5.504	0.528
RMB/USD spot rate	The RMB to USD exchange rate	6.880	0.711

This table shows the macroeconomic covariates used to estimate the time-varying characteristics of credit risk clustering across firm pairs in CEC. The sample period spans from the first quarter of 2005 to the last quarter of 2015, which includes 44 observations.

Table 6. Descriptions of the firm-specific covariates

First level index	Second level index	Description
Solvency capacity	Current ratio	Current assets/current liabilities
	Quick ratio	Quick assets/current liabilities
	Interest cover ratio	EBIT/financial expenses
	Asset liability ratio	Total liabilities/total assets
Developing capacity	Fixed asset growth ratio	Growth of fixed assets/total fixed assets
	Total asset growth ratio	Growth of total assets/total assets
	Profit growth ratio	Growth of profit/total profit
	Operating revenue growth ratio	Growth of operating revenue/total operating revenue
	Operating profit growth ratio	Growth of operating profit/total operating profit
Profitability	Return on assets	Net profit/average of total assets
	Fixed assets profit margins	Net profit/average of fixed assets
	Net asset return ratio	Net profit/average of equity
	Operating profit ratio	Operating profit/operating revenue
Operating capacity	Accounts receivable turnover ratio	Operating revenue/average of accounts receivable
	Inventory turnover ratio	Operating cost/average of inventory
	Accounts payable turnover ratio	Operating cost/average of accounts payable
	Fixed assets turnover ratio	Operating revenue/average of fixed assets
	Total assets turnover ratio	Operating revenue/average of total assets
	Working capital turnover ratio	Operating revenue/average of working capital

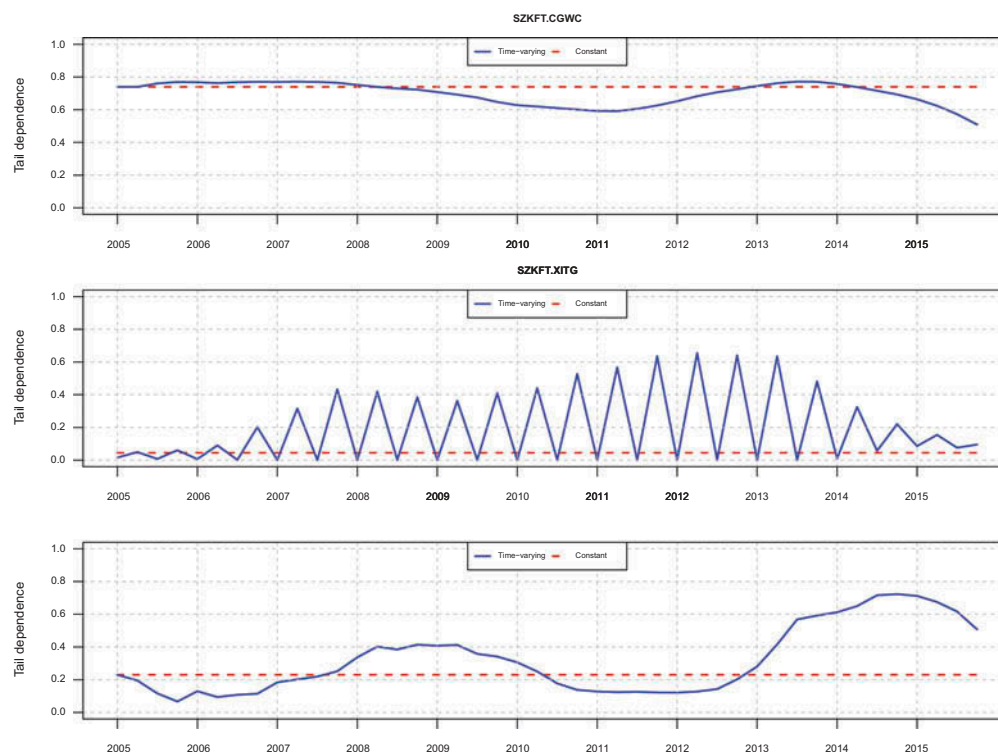
This table shows the firm-specific covariates used in the estimation of the marginal distribution of a firm's credit risk. These firm-specific covariates are also used to model the time-varying characteristics of credit risk clustering across firm pairs in CEC.

SZKFT, CGWC, and XITG are representative firms for investigating credit risk clustering across CEC's subsidiaries. First, SZKFT, CGWC, XITG's DTD decreased considerably from 2011 to 2013 and exhibited an apparent co-movement in Figure 1. Second, SZKFT, CGWC, and XITG have special characteristics which may trigger the credit risk clustering. SZKFT is a core subsidiary of CEC, which has the largest asset scale. The devaluation of its assets may in turn trigger credit risk clustering across subsidiaries in CEC. Collin-Dufresne, Goldstein, and Helwege (2010) conclude that a clustering effect induced by the large company is more significant than that induced by the smaller company. The average DTD value of CGWC is the smallest, and its volatility is the largest (see Table 4). Das, Freed, Geng, and Kapadia (2006) find that dependences in defaults occur during periods of high volatility. XITG's main businesses are in highly competitive industries, and its operational performance is more susceptible to the changes in macroeconomic conditions. Moreover, we find that XITG's DTD does not follow the normality assumption.

4.1. Model comparison

Prior literature has confirmed that correlation or tail dependence between assets in financial market changes over time. Patton (2006) further constructs a series of efficient copula models to estimate the time-varying characteristics among financial market. Using Patton's methodology as a base line, we have evaluated the dynamic tail dependence for the pairs of SZKFT and CGWC, SZKFT and XITG and CGWC and XITG (see Figure 2). The results show strong evidence that tail

Figure 2. Pairwise tail dependence for DTD applying the time-varying copula in Patton (2006). The dashed line is constant tail-dependence, while the solid line is the pairwise time-varying tail-dependence. We have applied the time-varying approach to Gaussian, Student's t, symmetric Joe-Clayton, and Joe-Clayton copulas. According to the criterion of AIC, time-varying Joe-Clayton copula performs the best for SZKFT and CGWC, while the time-varying Student's t copula performs the best for SZKFT and XITG, CGWC and XITG.



dependences among different firm pairs are time-varying. However, there is not enough insight about the drivers for such volatilities with time-varying copulas in Patton (2006).

We now apply the covariate-dependent copulas to compare different types of covariate effects on copula models. Figure 3 suggests that the DTDs of CGWC and XITG have bimodal distributions. Thus, this analysis considers four competing copula models, namely, the Joe-Clayton, the symmetric Joe-Clayton (SJC), Clayton and Gumbel copula models, which all have two different marginal distributions—split- t and mixtures of split- t margins. To select the best copula model for each pair, we also consider different combinations of covariates. The maximum value of the LPS is used to select the most adequate model.

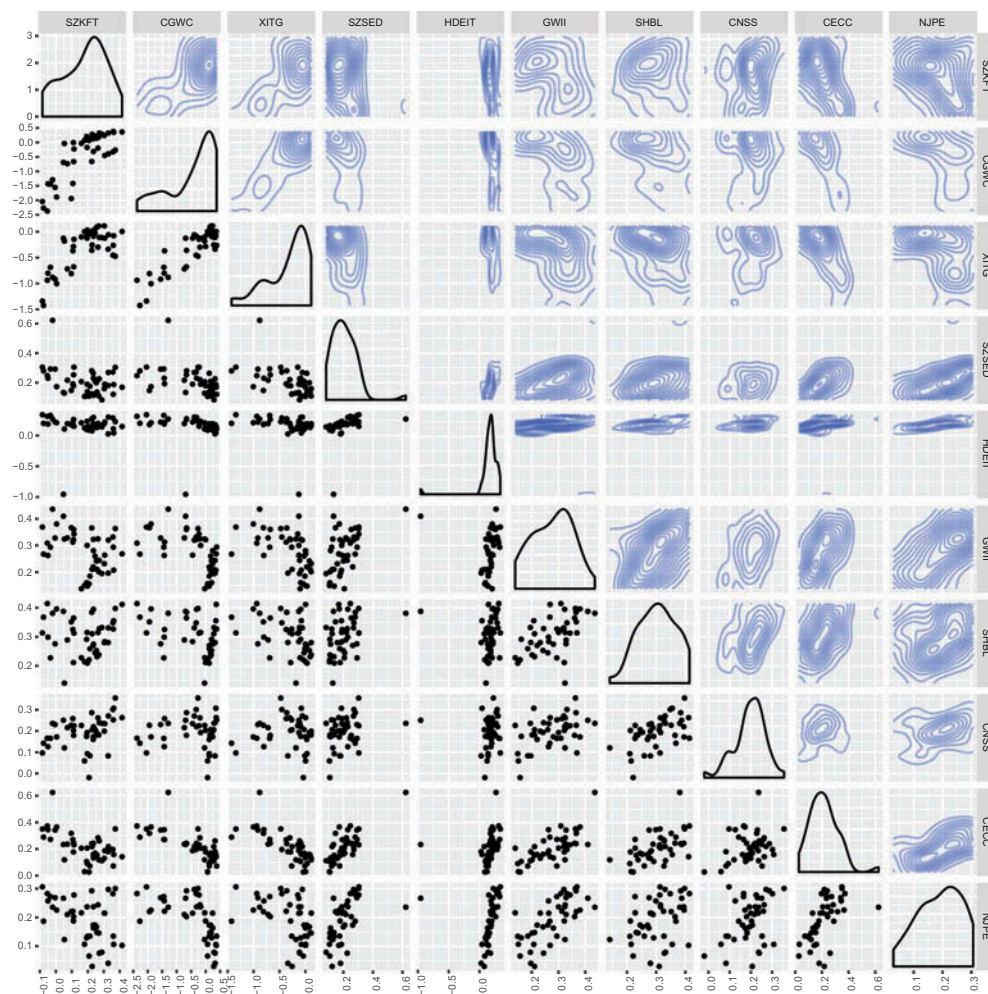
Table 7 presents the estimated results for the different copula models. Note that the split- t with Joe-Clayton copula model with macroeconomic covariates is the best model for the pair of SZKFT and CGWC, while the split- t with Joe-Clayton copula model with macroeconomic and firm-specific covariates is the best model for the pair of CGWC and XITG. As for the pair of SZKFT and XITG, the mixture split- t with Joe-Clayton copula model with firm-specific covariates is an adequate model.

4.2. Tail-dependent structure of credit risk

As the results in Table 7 show, the Joe-Clayton copula model is the best model for each firm pair. The split- t is the adequate margin for the pair SZKFT and CGWC, as well as the pair CGWC and XITG, while a mixture of split- t is the adequate margin for the pair SZKFT and XITG. We include different covariates in the most fitted copula model to identify the dynamic nature of the tail dependence of credit risk. Estimations of the tail dependence of DTD for other firm pairs in CEC are given in the supplementary materials.

Table 8 indicates that the average value of the tail-dependent coefficient in the no-covariate copula model is low for each firm pair. The values are 0.022, 0.067 and 0.027. However, when we import covariates into the copula model, we learn that the tail-dependent coefficient increases

Figure 3. Pairwise plots for the distance-to-default (DTD) indexes. The lower triangular subplots are the pairwise scatterplots for DTD. The upper triangular subplots are the empirical contour densities based on kernel smoothing. The subplots on the diagonal lines are the empirical densities for each firm's DTD.



remarkably. For instance, the tail-dependent coefficient of the pair SZKFT and CGWC is 0.022 in the no-covariate copula model, 0.254 in the macroeconomic-covariate copula model, 0.695 in the specific-covariate copula model, and 0.811 in the macroeconomic-specific-covariate copula model, which demonstrates a pattern of increasing credit risk clustering. These results show that a tail-dependent structure between firms can be captured by considering systematic or idiosyncratic factors. We may underestimate the probability of credit risk clustering if we do not consider common economic circumstances and firms' financial and business situations.

Table 9 shows the summary of the tail dependence of credit risk across different firm pairs. The mean values of tail dependence in the pairs SZKFT and XITG, CGWC and XITG rank in the top 10 among all pairs. The mean of tail dependence for SZKFT and CGWC ranks in the middle. The median values of these three firm pairs also show the similar rank. It is worth mentioning that the empirical results of other firm pairs present the similar characteristics as the representative firm pairs (see the supplementary materials available at the author's homepage).

Furthermore, we can identify different patterns of time-varying features for the credit risk clustering by comparing different types of covariate copula models. Figure 4 presents the time-varying characteristics of the tail dependence of credit risk across firm pairs. We see that the tail dependence in the no-covariate copula model is stationary. One should notice that the tail dependence with no covariates in our model is different from the tail dependence from Patton

Table 7. Out-of-sample model comparison

Margins	Copulas	Covariates	SZKFT vs. CGWC	SZKFT vs. XITG	CGWC vs. XITG
Split-t	Joe-Clayton	None	– 42.841	– 43.155	– 57.275
		Macro	– 21.081	– 41.824	– 45.642
		Specific	– 87.975	– 51.452	– 38.050
		Macro+Specific	– 32.223	– 67.098	– 34.833
	SJC	None	– 89.081	– 94.164	– 82.393
		Macro	– 59.624	– 55.291	– 73.666
		Specific	– 81.088	– 83.210	– 42.509
		Macro+Specific	– 89.829	– 55.448	– 103.649
	Clayton	None	– 59.148	– 58.405	– 58.234
		Macro	– 60.170	– 40.941	– 47.342
		Specific	– 36.735	– 58.737	– 47.272
		Macro+Specific	– 27.758	– 28.883	– 59.565
	Gumbel	None	– 88.839	– 86.930	– 99.706
		Macro	– 49.714	– 68.372	– 57.404
		Specific	– 61.024	– 81.027	– 60.102
		Macro+Specific	– 58.952	– 95.734	– 81.848
Mixtures of split-t	Joe-Clayton	None	– 45.581	– 21.373	– 53.774
		Macro	– 43.975	– 14.065	– 49.258
		Specific	– 45.442	– 9.155	– 52.626
		Macro+Specific	– 43.744	– 13.768	– 51.628
	SJC	None	– 45.427	– 21.220	– 53.711
		Macro	– 42.654	– 11.379	– 51.741
		Specific	– 47.041	– 9.966	– 50.265
		Macro+Specific	– 44.444	– 12.433	– 50.927
	Clayton	None	– 45.764	– 21.560	– 53.960
		Macro	– 45.538	– 16.044	– 50.928
		Specific	– 80.473	– 19.554	– 52.739
		Macro+Specific	– 47.530	– 13.006	– 58.227
	Gumbel	None	– 45.977	– 21.706	– 54.464
		Macro	– 42.641	– 12.441	– 51.032
		Specific	– 67.055	– 24.076	– 55.092
		Macro+Specific	– 71.331	– 15.582	– 61.464

This table shows the comparative results of Joe-Clayton, the symmetric Joe-Clayton, Clayton and Gumbel copula models. Both split-t and two-component mixtures of split-t are used in marginal models.

(2006). This is because we only estimate the constant in our model with no covariates involved. In our empirical results, we observe obvious volatility of tail dependence in the macroeconomic-covariate-dependent copula model, especially during the U.S. subprime mortgage crisis and the European debt crisis. These results mean that the probability of credit risk clustering increases during periods of global financial crisis. Moreover, we also observe that the time-varying characteristics of tail dependence are complicated when considering idiosyncratic variables. This is probably because the roles of firm-specific covariates are different across different firm pairs. From our results, we can conclude that credit risk clustering is affected by both systematic and idiosyncratic factors, but their impacts on credit risk clustering are complex.

Table 8. Estimations of tail dependence

	No covariates	Macroeconomic covariates	Specific covariates	Macroeconomic and specific covariates
Panel A: SZKFT vs. CGWC				
Mean	0.022	0.254	0.695	0.811
Median	0.011	0.154	0.824	0.990
Std.dev	0.037	0.265	0.308	0.353
Panel B: SZKFT vs. XITG				
Mean	0.067	0.726	0.642	0.634
Median	0.067	0.859	0.990	0.970
Std.dev	0.000	0.282	0.458	0.440
Panel C: CGWC vs. XITG				
Mean	0.027	0.196	0.309	0.578
Median	0.011	0.122	0.077	0.726
Std.dev	0.025	0.208	0.376	0.388

This table describes the estimations of the dynamic characteristics of the tail dependence in credit risk for the pairs SZKFT and CGWC, SZKFT and XITG, and CGWC and XITG. The split-t with Joe-Clayton copula model is the best model for the pairs SZKFT and CGWC, as well as the pair CGWC and XITG, and the mixture of split-t with Joe-Clayton copula model is used for the pair SZKFT and XITG.

4.3. Covariate effects on the credit risk clustering

Based on the results in Section 4.1, we use different copula models for the covariate effect estimations. To investigate the driving forces for credit risk clustering, we include different covariates in the copula models. In this section, we use the LDS (see Section 2.4) as the full sample fitted model criterion.

Table 10 lists the results of the estimated covariate effects on the credit risk clustering for the pair SZKFT and CGWC. The split-t with Joe-Clayton with macroeconomic variables is the best model for the pair SZKFT and CGWC. Its LDS is -36.277 , which is the maximum value of the covariate copula models. This result indicates that the credit risk clustering for the pair SZKFT and CGWC can be captured by systematic factors. We identify the importance of systematic variables in the credit risk clustering using the value of the selective probability. The CPI and the short-term interest rate are more important. The selective probabilities of the CPI and the short-term interest rate are 0.821 and 0.546, which are higher than those of the M2 growth rate and the RMB/USD spot rate. On the other hand, systematic factors play different roles in the credit risk clustering. Our empirical results indicate that the CPI, M2 growth rate and short-term interest rate are positively associated with the credit risk clustering for the pair SZKFT and CGWC. However, the RMB/USD spot rate's role is negative. This indicates that RMB appreciation would increase the credit risk clustering for the pair SZKFT and CGWC.

Table 11 lists the estimated results of covariate effects on the credit risk clustering for the pair SZKFT and XITG. We use the mixture of split-t with Joe-Clayton copula model with firm-specific covariates to investigate the covariate effects on the credit risk clustering. The LDS is -151.243 . We find that firm-specific factors, such as SZKFT's solvency capacity, SZKFT's developing capacity, SZKFT's profitability, XITG's profitability, and XITG's operating capacity are more significant than other covariates, with index selective probabilities are all above 50%. Other firm-specific covariate index selective probabilities are around 40%, which cannot be ignored either. Furthermore, SZKFT's solvency capacity, SZKFT's developing capacity, SZKFT's operating capacity, XITG's developing capacity and XITG's profitability are negatively related to the credit risk clustering for the pair SZKFT and XITG. Other firm-specific variables, such as SZKFT's profitability, XITG's solvency capacity, and XITG's operating capacity, play the positive roles on the credit risk clustering.

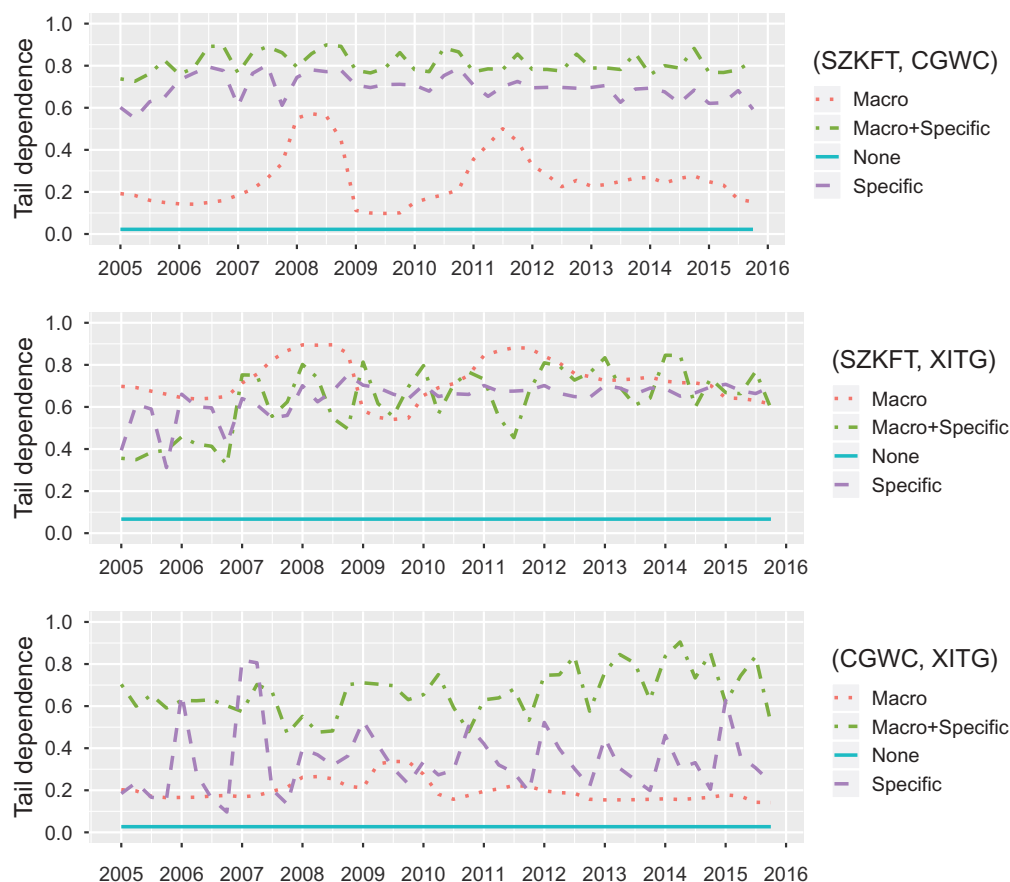
Table 9. Tail-dependent comparison

Pair Group	Mean	Rank	Median	Rank	Std.Dev	Rank
SZSED vs. GWII	0.868	1	0.990	1	0.324	19
SZKFT vs. SZSED	0.821	2	0.990	1	0.370	14
GWII vs. XITG	0.787	3	0.990	1	0.383	13
SZKFT vs. HDEIT	0.783	4	0.926	5	0.305	22
SHBL vs. XITG	0.699	5	0.989	2	0.443	5
CGWC vs. CNSS	0.653	6	0.987	3	0.436	6
SZKFT vs. XITG	0.642	7	0.990	1	0.458	1
CNSS vs. XITG	0.642	7	0.906	6	0.409	8
XITG vs. CECC	0.631	8	0.973	4	0.449	4
CGWC vs. XITG	0.578	9	0.726	8	0.388	11
GWII vs. NJPE	0.556	10	0.642	9	0.363	15
SZSED vs. SHBL	0.550	11	0.810	7	0.449	4
CGWC vs. GWII	0.535	12	0.523	11	0.398	9
SZKFT vs. NJPE	0.516	13	0.575	10	0.453	2
CECC vs. NJPE	0.485	14	0.489	12	0.308	20
CGWC vs. NJPE	0.452	15	0.377	13	0.394	10
GWII vs. CNSS	0.432	16	0.342	14	0.394	10
HDEIT vs. GWII	0.391	17	0.151	18	0.414	7
XITG vs. NJPE	0.383	18	0.226	16	0.386	12
SHBL vs. CECC	0.380	19	0.250	15	0.362	16
SZKFT vs. CNSS	0.322	20	0.010	28	0.451	3
HDEIT vs. CECC	0.291	21	0.074	19	0.360	17
CGWC vs. SHBL	0.255	22	0.039	23	0.345	18
SZKFT vs. CGWC	0.254	23	0.154	17	0.265	23
SZSED vs. XITG	0.180	24	0.031	24	0.308	21
SZSED vs. CGWC	0.165	25	0.067	21	0.231	25
CGWC vs. HDEIT	0.161	26	0.060	22	0.254	24
CNSS vs. CECC	0.119	27	0.071	20	0.142	26
SZSED vs. NJPE	0.099	28	0.154	17	0.067	27
GWII vs. SHBL	0.081	29	0.067	21	0.039	31
SZKFT vs. GWII	0.069	30	0.067	21	0.051	28
SZKFT vs. SHBL	0.039	31	0.023	25	0.026	33
SZKFT vs. CECC	0.028	32	0.011	27	0.024	34
SZSED vs. CECC	0.025	33	0.011	27	0.044	29
CGWC vs. CECC	0.024	34	0.011	27	0.039	32
GWII vs. CECC	0.023	35	0.014	26	0.041	30
SZSED vs. HDEIT	0.020	36	0.010	28	0.018	35
SZSED vs. CNSS	0.015	37	0.011	27	0.007	36
HDEIT vs. XITG	0.011	38	0.010	28	0.003	37

The table presents the descriptive statistics of tail dependence of credit risk across all firm pairs in CEC. All descriptive statistics are computed based on the best fitted covariate-dependent copula model. The firm pairs with boldfaces are representative firms defined in Figure 1. The empirical results of credit risk clustering across other paired firms not listed in the paper are available in the supplementary material at <https://feng.li/credit-risk/>.

We use the Joe-Clayton copula model with split-t margins to study the covariate effects on the credit risk clustering for the pair CGWC and XITG. Table 12 presents the empirical results for the covariate impacts on the credit risk clustering. Based on the LDS, we find that the copula model with both systematic and idiosyncratic factors is the best model for the pair CGWC and

Figure 4. Pairwise time-varying tail dependence for DTD. The three figures show the dynamic nature of tail dependence in the Joe-Clayton copula model with i) no covariates, ii) macro-economic covariates, iii) specific covariates and iv) macroeconomic and specific covariates.



XITG. Its LDS is -108.374 . The index selective probabilities of all macroeconomic variables are above 50%, which indicates that systematic factors are important for the credit risk clustering between CGWC and XITG. However, their impacts on the credit risk clustering are different. The CPI and RMB/USD spot rate are negatively associated with the credit risk clustering, while the M2 growth rate and the short-term interest rate play positive roles. On the other hand, firm-specific covariates' index selective probabilities are also above 50%, except for CGWC's profitability and XITG's solvency capacity. All firm-specific variables, except XITG's solvency capacity and XITG's profitability, play the negative roles on the credit risk clustering.

5. Conclusions

The co-movement of credit risk between portfolios has attracted a great deal of attention from researchers and practitioners, particularly in the wake of the global financial crises. However, discussions about extreme co-movements in credit risk between subsidiaries in business groups are still limited. In this paper, we shed light on this topic in China, as the business group is a common organizational structure in China. This study examines the dynamic nature of credit risk clustering, which is defined as tail dependence of credit risk, and its driving forces across subsidiaries in a business group. We propose a covariate-dependent copula model, which is a flexible method of modeling tail-dependent structures. We compare different copula models to select the best model for our study. Then, by including covariates in the copula model, we can identify different patterns of the time-varying nature in the credit risk clustering and investigate the roles of systematic and idiosyncratic factors.

The empirical results provide strong evidence of dynamic nature of credit risk clustering across subsidiaries in business group. We observe a considerable surge during the U.S. subprime

Table 10. Covariate effects on the credit risk clustering in the pair SZKFT and CGWC!

	No covariates	Macroeconomic covariates	Specific covariates	Macroeconomic and specific covariates
Constant	– 6.159 (1.000)	– 3.477 (1.000)	1.632 (1.000)	68.095 (1.000)
CPI		0.337 (0.821)		– 0.342 (0.764)
M2 growth rate		0.225 (0.460)		0.024 (0.233)
Short-term interest rate		0.420 (0.546)		0.297 (0.794)
RMB/USD spot rate		– 0.751 (0.396)		– 0.278 (0.181)
SZKFT's solvency capacity			– 0.004 (0.824)	– 0.226 (0.944)
SZKFT's developing capacity			– 0.328 (0.778)	– 0.368 (0.238)
SZKFT's profitability			0.363 (0.630)	1.577 (0.816)
SZKFT's operating capacity			0.019 (0.612)	1.529 (0.325)
CGWC's solvency capacity			– 0.010 (0.638)	– 0.361 (0.244)
CGWC's developing capacity			0.058 (0.680)	– 0.191 (0.836)
CGWC's profitability			– 0.376 (0.784)	0.016 (0.809)
CGWC's operating capacity			– 0.019 (0.447)	0.102 (0.756)
LDS (in-sample)	– 74.357	– 36.277	– 159.406	– 125.909
LPS (out-of-sample)	– 42.841	– 21.081	– 87.975	– 68.693

This table shows the results for the estimated covariate effects on the credit risk clustering for the pair SZKFT and CGWC using the split-t with Joe-Clayton copula. The covariate index selective probabilities are shown in parentheses. LDS is the log density score, which is a criterion of model performance. LPS is the log predictive score.

mortgage crisis and the European debt crisis by considering systematic factors in the dynamic nature of credit risk clustering. The volatility of the credit risk clustering is dramatic when idiosyncratic factors are included in the copula model. This indicates that the credit risk clustering among subsidiaries in business group in China is impacted by global financial crises. Moreover, credit risk clustering is sensitive to idiosyncratic factors. We further explore the roles of systematic and idiosyncratic factors on the credit risk clustering. We find that both macroeconomic and firm-specific covariates are important for the credit risk clustering. However, for different pairwise portfolios, these systematic and idiosyncratic factors would have different effects. We find that the money supply and the short-term loan interest rate are positively associated with the credit

Table 11. Covariate effects on the credit risk clustering in the pair SZKFT and XITG

	No covariates	Macroeconomic covariates	Specific covariates	Macroeconomic and specific covariates
Constant	– 2.788 (1.000)	– 1.235 (1.000)	21.285 (1.000)	– 0.933 (1.000)
CPI		0.310 (0.754)		– 7.574 (0.470)
M2 growth rate		0.010 (0.187)		0.799 (0.563)
Short-term interest rate		0.420 (0.803)		1.115 (0.761)
RMB/USD spot rate		– 0.023 (0.226)		– 0.534 (0.562)
SZKFT's solvency capacity			– 0.331 (0.699)	0.165 (0.907)
SZKFT's developing capacity			– 1.978 (0.642)	– 3.308 (0.550)
SZKFT's profitability			2.927 (0.562)	– 22.722 (0.708)
SZKFT's operating capacity			– 0.087 (0.44)	– 0.587 (0.790)
XITG's solvency capacity			0.279 (0.479)	– 0.590 (0.572)
XITG's developing capacity			– 3.975 (0.424)	– 0.125 (0.334)
XITG's profitability			– 0.282 (0.568)	1.683 (0.152)
XITG's operating capacity			4.155 (0.760)	– 0.563 (0.727)
LDS (in-sample)	– 169.833	– 156.437	– 151.243	– 153.360
LPS (out-of-sample)	– 21.373	– 14.065	– 9.966	– 12.433

This table shows the results for the covariate effects on the credit risk clustering for the pair SZKFT and XITG using the mixture split-t with Joe-Clayton copula model. The covariate index selective probabilities are shown in parentheses. LDS is the log density score, which is a criterion of model performance. LPS is log predictive score.

risk clustering, whereas the exchange rate has the negative impacts. The roles played by the CPI are ambiguous. As for the firm-specific covariates, their effects on credit risk clustering depend on the firm's operational and financial situations.

These findings have several important implications for investors, risk managers and policy-makers: They should realize that extreme co-movements in credit risk are dynamic and affected by the international financial market. The evaluation of credit risk in a single portfolio should not ignore its relationship with other portfolios. Policymakers should remain vigilant of the effects of

Table 12. Covariate effects on the credit risk clustering in the pair CGWC and XITG

	No covariates	Macroeconomic covariates	Specific covariates	Macroeconomic and specific covariates
Constant	– 5.977 (1.000)	– 3.370 (1.000)	– 3.010 (1.000)	– 1.239 (1.000)
CPI		0.019 (0.378)		– 0.166 (0.654)
M2 growth rate		0.150 (0.442)		0.102 (0.627)
Short-term interest rate		– 0.014 (0.436)		0.124 (0.780)
RMB/USD spot rate		– 0.255 (0.546)		– 0.058 (0.551)
CGWC's solvency capacity			0.056 (0.423)	– 0.035 (0.597)
CGWC's developing capacity			– 0.205 (0.750)	– 0.028 (0.550)
CGWC's profitability			1.700 (0.853)	– 0.201 (0.481)
CGWC's operating capacity			– 0.041 (0.581)	– 0.055 (0.638)
XITG's solvency capacity			– 0.355 (0.836)	0.093 (0.361)
XITG's developing capacity			0.182 (0.857)	– 0.166 (0.523)
XITG's profitability			– 1.957 (0.766)	1.689 (0.523)
XITG's operating capacity			0.041 (0.732)	– 0.027 (0.662)
LDS (in-sample)	– 114.033	– 109.464	– 123.074	– 108.374
LPS (out-of-sample)	– 57.275	– 45.642	– 38.050	– 34.833

This table shows the results for the estimated covariate effects on the credit risk clustering for the pair CGWC and XITG. The covariate index selective probabilities are shown in parentheses. LDS is the log density score, which is a criterion of model performance. LPS is the log predictive score.

macroeconomic policy on extreme co-movement of credit risk to keep financial markets and the economy stable and less risky.

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