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Xuan Zhang, Minjoo Kim, Cheng Yan, Yang Zhao

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Default dependence in the insurance and banking sectors: A copula approach

Xuan Zhang[a], Minjoo Kim[b], Cheng Yan[c,] , Yang Zhao[d*]

[a] *Nanjing University of Aeronautics and Astronautics, China*

[b] *University of Liverpool, UK*

[c] *University of Essex, UK*

[d] *Central University of Finance and Economics, China*

[*] Yang Zhao, Chinese Academy of Finance and Development, Central University of Finance and Economics, China. Email: yangzhao@cufe.edu.cn
Xuan Zhang, College of Economics and Management, Nanjing University of Aeronautics and Astronautics, China.
Minjoo Kim, Management School, University of Liverpool, United Kingdom.
Cheng Yan, University of Essex, United Kingdom.

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Highlights

- We explore the joint default dependence among firms based on their default probabilities.
- We combine a generalized autoregressive score model with a generalized hyperbolic skewed t copula.
- We identify the term structure of dynamic default dependence between these two sectors.
- We investigate the determinants of the time-series variation in default dependence.
- We find a significant negative correlation between default dependence and global geopolitical risk.

Default dependence in the insurance and banking sectors: A copula approach

ABSTRACT

We employ a time-varying asymmetric copula model that combines the generalized autoregressive score model with the generalized hyperbolic skewed t copula to capture the dynamics and asymmetry of default dependence between insurers and banks. We identify the term structure of default dependence between these two sectors. The short-term and long-term dependence of default risk rise and converge during financial crises. We explore the determinants of the time-series variation in default dependence. While traditional macro variables can explain only a small portion of the variation in default dependence, we find a significant negative correlation between default dependence and global geopolitical risk.

JEL: G22; G33

Keywords: Insurers; probability of default; default dependence; copula; determinants

"In the past, there was no perceived need to specifically address systemic risk in insurance but, given recent developments, it was high time for the insurance industry to engage in the debate on systemic risks and the way they are handled in terms of regulation and supervision."

- Geneva Association (2010)

1. Introduction

The goal of this paper is to empirically model the interrelationship between insurance firms (*i.e.,* insurers) and banks, which has been long neglected until the late 2000s global financial crisis (GFC) (Billio *et al.*, 2012). Perhaps because the GFC is labelled as a banking crisis (e.g., Aiyar, 2012; Cetorelli and Goldberg, 2012; Giannetti and Laeven, 2012; Chodorow-Reich, 2013; De Haas and Van Horen, 2013), the role of insurers has drawn less attention, although the insurers (e.g., American International Group[2]) experience potential insolvency earlier than the banks during the GFC. The traditional view[3] that insurers protect other financial institutions during crises no longer holds as the insurers themselves also need protection during the GFC. As the insurers are no longer systematically irrelevant, it is inappropriate to study either insurers or banks alone without taking the other subsector into account (Billio *et al.*, 2012).

As financial markets worldwide become more tightly integrated, financial conditions within the United States are increasingly influenced from abroad and affecting foreign financial markets. Previous studies show that U.S. financial markets are closely linked to international financial markets. Chan et al. (1992) show that the conditional expected excess return on U.S. stocks is positively related to the conditional covariance of the return of these stocks with the return on a foreign index but is not related to its own conditional variance. Samarakoon (2011) show that there is important bi-directional but asymmetric interdependence and contagion in emerging markets. Interdependence is driven more by shocks in the United States. Frontier markets also exhibit interdependence and contagion to United States shocks.

Using a sample of publicly listed insurers and banks in the U.S. market from March 1991 to February 2021, we study several aspects of the interrelationship between insurers and other banks in this paper. First, we investigate the possible existence of a default correlation/dependence between insurers and other banks[4], because higher default dependence may contribute to higher systemic risk. Second, short-term and long-term default probabilities may contain different information. Therefore, we investigate if the default dependence varies with a default term structure. Third, to understand the determinants of the default dependence, we investigate whether the time-varying default dependence is related to some common risk factors or to the

[2] American International Group Inc. (AIG) was on the brink of collapse in September 2008. The American International Group Financial Products Corporation (AIGFP), a non-insurance entity which was not subject to insurance regulation, held a large portfolio of Credit Default Swaps (CDS) and Collateralized Debt Obligations (CDO). Consequently, it suffered a significant loss during the crisis. To protect the stability of the financial system, the Federal Reserve announced an $85 billion bailout of AIG in 2008.

[3] For instance, insurers reduce the default risk of the policyholders of insurance firms—who are sometimes banks—by mitigating their loss during natural disasters (Lee *et al.*, 2016). Banks are likely to transfer their risk to insurers to reduce their default risk (Lehmann and Hofmann, 2010).

[4] In this paper, default correlation means the interrelationship among PDs captured by pairwise correlations, while default dependence means the interrelationship among PDs captured by copulas.

interactions among firms by regressing the default dependence between insurers and banks on the large set of macro variables[5] proposed by Christoffersen *et al.* (2018).

Previous studies use stock returns and pairwise stock return correlations, which are backwards-looking in nature and only indirectly imply credit risk. Instead, we turn to two direct and forward-looking measures of credit risk: the probability of default (hereafter, PD) and correlations of PD. We find that those correlation coefficients are not able to model the interrelationship between insurers and banks. This is likely because this interrelationship tends to involve tail behavior and systemic risk, which calls for the use of the copula method. Finally, we use a dynamic copula model, which combines the generalized hyperbolic (GH) skewed *t* copula with the Generalized Autoregressive Score (GAS) [6] model to capture the dynamics of default dependence between insurers and banks.

Our main findings are as follows. Firstly, the PD with different term structures of both insurers and banks move in the same direction through the sample period. This implies that risk-based regulations, like Solvency II, applied to the EU insurance sector, are also needed for U.S. insurers.

Secondly, we estimate the joint default dependence of the two sectors based on the dynamic copula model. We also identify a significant dependence between insurers and banks in both short-term (*i.e.,* from 1-month to 6-month) and long-term (*i.e.,* 12-month) horizons. The short-term dependence is low but volatile, while the long-term dependence is high but stable. Both short-term and long-term PD dependence spike and converge during crises. Our study further shows that the default dependence between sectors is both time-varying and asymmetric.

Finally, we identify some underlying determinants of the joint default dependence of the insurance and financial sectors by regressing the variation of default dependence on the large set of financial and macroeconomic variables. We find that short-term correlations are only affected by interest rate level, yield curve slope, and the TED spread. Additionally, we incorporate the global geopolitical risk factor into our analysis. Caldara and Iacoviello (2022) discuss the impact of global geopolitical risk on the economy and analyse it at the firm and industry level, but do not go into depth on the financial sector. While there have been several studies exploring the relationship between global geopolitical risk and banks (Phan et al., 2022), there is a notable scarcity of research from the perspective of systemic default risk within the financial sector. Our findings reveal a significant negative correlation between default dependence and global geopolitical risk, a relationship that substantially differs from those observed in

[5] The early work of Couderc *et al.* (2008) on default probability modeling also shows that non-financial information plays a role in explaining default behavior, as found in the present paper.

[6] The time-varying copula correlation is captured by the Generalized Autoregressive Score (GAS) model, which is pioneered by Creal *et al.* (2013). The GAS model is widely used in recent empirical research (Creal *et al.,* 2014; Janus *et al.,* 2014; Lucas *et al.,* 2014; Salvatierra and Patton, 2015).

other industries. Although macro variables can explain a small portion of the variation of default dependence, more than half remains unexplained, which is probably due to firm-level characteristics.

This study contributes to the systemic risk literature in the following ways. First, we directly model the correlated default risk by PD, while most studies like Acharya *et al.* (2012), Adrian and Brunnermeier (2018), and Demirer *et al.* (2018) rely on stock returns, which only imply the credit risk indirectly. Second, we propose a time-varying asymmetric copula to model the joint default dependence, while previous studies mainly use CDS data (Lucas *et al.,* 2014; Cerrato *et al*., 2017; Oh and Patton, 2018). One issue of studies using CDS data is that their sample is limited to the firms with CDS contracts, while our PD data cover a larger sample. Third, we further investigate the term structure of default dependence between insurance and other banks using the PD data estimated via the forward-intensity model of Duan *et al.* (2012), and hence provide richer information to regulators and investors to understand the dynamics of default dependence with different horizons. Finally, we use regression analysis to identify financial and macroeconomic variables that may drive the variations of default dependence between insurers and other banks. Our findings are relevant not only for academics, but also for practitioners, because identifying which factors drive joint default risk can help regulators and investors to forecast and mitigate systemic risk.

We also contribute to the small but growing literature on the role of insurers during the GFC. For instance, the Geneva Association (2010) points out that insurers might increase the systemic risk of the financial sector if they heavily engage in derivatives trading, while Billio *et al.* (2012) note that insurers have become more likely to invest in non-core and non-insurance businesses (e.g., credit default swaps, derivatives trading, investment management, and insurance financial products). As default risk can quickly propagate through credit derivatives[7], insurers and banks become increasingly interconnected (e.g., Harrington, 2009; Chen *et al.*, 2013; Cummins and Weiss, 2014; Weiß and Mühlnickel, 2014; Bierth *et al.*, 2015; Mühlnickel and Weiß, 2015).

Our focus on the interrelationship between insurers and banks is not coincidental but motivated by both anecdotal evidence from the late 2000s global financial crisis and the literature (e.g., Billio *et al.*, 2012) which underscores the importance of banks and insurers[8]. We follow the emerging literature (e.g., Acharya *et al.*, 2012; Billio *et*

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[7] For instance, Jorion and Zhang (2007) and Stulz (2010) find that counterparty risk is transferred through financial products like CDS.

[8] Billio *et al.* (2012) note that "*banking and insurance sectors may be even more important sources of connectedness than other parts, which is consistent with the anecdotal evidence from the recent financial crisis. The illiquidity of bank and insurance assets, coupled with the fact that banks and insurers are not designed to withstand rapid and large losses (unlike hedge funds), make these sectors a natural repository for systemic risk. The same feedback effects and dynamics apply to bank and insurance capital requirements and risk management practices based on VaR, which are intended to ensure the soundness of individual financial institutions, but may amplify aggregate fluctuations if they are widely adopted*."

al., 2012; Adrian and Brunnermeier, 2018; Demirer *et al.*, 2018) and focus on the last "L" (*i.e.,* linkage) among the four "L"s of financial crises (*i.e.,* leverage, liquidity, loss, and linkage), given the fact there are already enough studies of the first three (see Billio *et al.,* 2012 and the references therein). In addition, we extend the sample end in Billio *et al.* (2012) from 2008 to the latest COVID-19 pandemic.

The remainder of the paper is structured as follows: In Section 2, we briefly review the development of modeling default risk, and then introduce our methodology. Section 3 presents the summary statistics of the data. Section 4 presents the default dependence analysis. Section 5 concludes. For brevity, we delegate the technical details to the appendices. Appendix A presents the forward intensity model proposed by Duan *et al.* (2012).

2. Systemic Credit Risk

Among several measures of systemic credit risk, we rely on the probability of default (hereafter, PD) correlation as a proxy for systemic credit risk. Albeit its simplicity, the PD correlation preserves the information about the joint default of the insurance and banking sectors. There are three steps to estimate the PD correlation between the insurance sector and the banking sector. First, we obtain the individual PD[9] for each company from the RMI-NUS (National University of Singapore, Risk Management Institute) CRI database, which is estimated following Duan *et al.* (2012). Second, we construct a time series of aggregated PD by the cross-sectional median[10] of individual PDs for each sector. Third, we estimate the time-varying PD correlation between the two sectors using a time-varying asymmetric copula model.

2.1. Probability of Default

Credit risk models have been quickly developed from the credit scoring model to the structural and reduced-form models. Beaver (1966, 1968) and Altman (1968) first proposed the scoring model that calculates firm-level PD by including accounting-based variables in the regression. The structural model, first introduced by Merton (1974), who applies the option theory to evaluate the value of firm-level liabilities in the presence of default (*i.e.,* PD), is embedded in the option-pricing model.

Since the seminal papers of Jarrow and Turnbull (1995) and Duffie and Singleton (1999), the reduced-form model, which assumes that exogenous Poisson random

[9] A key ingredient of this paper is the PD of individual firms, which is incredibly difficult to measure, given the fact that we do not observe many defaults. We take the estimated values from Duan *et al.* (2012) as a proxy of realized default probabilities.

[10] Alternatively, we obtain the qualitatively similar results using weighted average PD. We omit these results for brevity, but they are available upon request.

variables determine firm-level default likelihood, has become very popular.[11] For instance, Duffie *et al.* (2007) propose the doubly stochastic Poisson model with time-varying covariates and forecast the evolution of covariates using Gaussian panel vector autoregressions. Duan *et al.* (2012) further refine it to a measure of the probability of default (PD) by applying the pseudo-likelihood to estimate the forward intensity rate of doubly stochastic Poisson processes with different horizons, "*which captures a firm's likelihood of not fulfilling its financial obligations over some future horizon. It focuses directly on the realization of a rare event of significance, which may trigger cascading defaults and cause widespread distress throughout the financial system*".

Based on the individual single-period PD data from the RMI-NUS CRI database, we predict the multi-period individual PDs by the forward intensity function suggested by Duan *et al.* (2012).[12] We define the aggregated PD as the cross-section median for each sector:

$$P_t^{(1)}(\ell) := median_{i \in Insurance\ sector}\{P_{i,t}(\ell)\}, \qquad (1)$$

$$P_t^{(2)}(\ell) := median_{i \in financial\ sector}\{P_{i,t}(\ell)\}, \qquad (2)$$

where $P_{i,t}(\ell)$ denotes the ℓ-month PD for company i at time t.

2.2. Default Risk Correlation

Systemic risk measures emphasizing the connectedness among banks include individual capital shortfall (Acharya *et al.,* 2012), stock returns volatility (Demirer *et al.,* 2018), and CoVar (Adrian and Brunnermeier, 2018).[13] However, these measures are backward-looking in nature, and rely on stock returns, which means that they can only imply the credit risk indirectly (Chan-Lau et al., 2016). Alternatively, we prefer a directly relevant and forward-looking measure of credit risk — the probability of default (PD).

The intensity-based modeling of correlated default risk using PD has been well developed. The traditional reduced-form portfolio model relies on either a bottom-up approach (*i.e.,* a portfolio intensity is the aggregate of individual intensities), or a top-down approach (*i.e.,* the portfolio intensity is calculated without individual intensities). The drawback of intensity-based models is their computational complexities.

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[11] A company may default when the exogenous variables (e.g., macroeconomics and company-specific variables) shift from their levels.

[12] The approach suggested by Duan *et al.* (2012) basically follows a doubly stochastic process proposed by Duffie *et al.* (2007). See Appendix A for more details.

[13] Weiß and Mühlnickel (2014) find a very similar magnitude of Marginal Expected Shortfall (MES) and ΔCoVaR among the 20 largest U.S. insurers and the 20 largest U.S. banks in 2007-2009.

We consider a simpler and more flexible approach to estimate the PD correlation between the insurance and financial sectors. We employ copula models among various alternatives due to their statistical advantages. First, copula allows for greater flexibility in modeling the marginal distribution of PD for each sector. Therefore, we model it by ARMA-GJR-GARCH (Glosten *et al.,* 1993) with the skewed student's t-distribution (Hansen, 1994) and the nonparametric empirical distribution.

Second, it allows tail dependence between the two sectors. Since extreme underlying events generate extremely high PDs, tail dependence can capture the default dependence between the two sectors more accurately than traditional correlation measures during a market recession or crisis. We model the tail dependence by the generalized hyperbolic (GH) skewed *t* copula.

Finally, we model the time-varying nature of PD correlation by implementing the Generalized Autoregressive Score (GAS) process into the copula model (e.g., Creal *et al.*, 2013). For brevity, we delegate the technical details to the appendices. Appendix A presents the forward intensity model proposed by Duan *et al.* (2012).

3. Data

Due to data availability, our sample covers all publicly listed insurers and banks in the U.S. market from March 1991 to February 2021: 185 insurers and 507 banks over the period of 360 continuous months. We collect monthly individual PD data from the RMI-NUS CRI database. For each company, the PD data include the term structure of PD over 1-month, 3-month, 6-month, and 12-month horizons.[14] We also collect market data such as the Chicago Fed National Financial Conditions Credit Subindex, VIX, the 10-year Treasury rate, the 3-month Treasury bill, the TED spread, Crude oil price, CPI, and NASDAQ index returns from the Federal Reserve Bank of St. Louis.

[INSERT FIGURE 1 ABOUT HERE]

First, we are interested in how the PD of financial institutions evolves, since the PD with different term structures shows a similar moving pattern (see Figure 1) and only the magnitude is different. The measures of PD in the banking sector are generally higher than in the insurance sector, no matter in short-term or long-term horizons. Moreover, the PD measures in both industries rise sharply during crises/recessions. Finally, the PD in the banking and insurance sectors rises sharply during COVID-19 for the first time since hitting a low in 2013. During the pandemic, the PD rises the most in the 12-month period for both sectors.

[14] In the main analysis, we selectively focus on these horizons as Duan *et al.* (2012) suggest that both in-sample and out-of-sample accuracy ratios are above 85% at these horizons. However, our main results are robust to alternative horizons such as 24-month, 36-month, and 60-month.

4. Dynamic Analysis of Joint Default Dependence

Tumminello *et al*. (2010) and Patro *et al.* (2013) use stock returns to study systemic risk, arguing that daily stock return pairwise correlation is a simple, robust, forward-looking, and timely risk indicator (Patro *et al.*, 2013; Tumminello et al., 2010). However, stock returns are not directly linked to default risk. Hence, we consider the PD correlations (see, e.g., Das *et al.,* 2007). We investigate the dynamic PD correlation between the banking and insurance sectors using the copula model. First, we need to model the marginal distribution of each sector, and then we choose a (either static or dynamic) copula to model the dependence between the banking and insurance sectors.

4.1. Default Probability – Industry Level

To apply the copula model, we transform the PD following the Duan and Miao (2016) method. Then, we calculate the average transformed PD for each sector. Table 1 shows the descriptive statistics for the log difference of transformed PD in different horizons. The average transformed PD of insurers is no higher than that of banks, which suggests that the insurance sector itself is relatively more stable than the banking sector. The variation of the insurance and financial sectors is similar in magnitude, except for the 1-month horizon, where the insurers have a larger standard derivation.

[INSERT TABLE 1 ABOUT HERE]

Descriptive statistics gives us a quick review of the marginal distribution of transformed PD returns. In the next step, we focus on the joint distribution of two sectors. In particular, we are interested in their dependence structure.

4.2. Time-Varying Default Dependence

Patton (2012) suggests that the dependence structure may vary over time, like volatility. Ignoring the time-varying dependence of firms may cause a significant underestimation of their joint credit risk. Figure 1 further shows that PD of the banking and insurance sectors changes in the same trend under different market conditions.

We test the time-varying dependence based on the ARCH-LM test proposed by Engle (1982). The test applies an autoregressive model to $(u_{1,t}u_{2,t})$

$$u_{1,t}u_{2,t} = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{1,t-i}u_{2,t-i} + \epsilon_t, p = 1,5,10. \quad (6)$$

In Table 2, AR (1), AR (5), and AR (10) are rejected for all horizons. This suggests that time-varying dependence exists between the two sectors. Thus, we use the time-varying copula to model default risk dependence between financial and insurers. Unlike parameter-driven models such as the stochastic volatility model and the stochastic intensity model (see, e.g., Bauwens and Hautsch, 2006; Koopman et al., 2008), the GAS model is observation-driven and based on the score function. The scaled score drives the time variation of the parameters.

4.3. Asymmetric Default Dependence

Tail dependence can provide insight into the potential for simultaneous defaults of multiple firms under extreme circumstances. We investigate if the default intensity of their dependence is statistically equivalent at both lower and upper tails. This is useful for the choice of copulas and the analysis of systemic risk. For the symmetric dependence,

$$\lambda^{q} = \lambda^{1-q} \text{ for } q \in [0,1], \qquad (3)$$

where λ^{q} is the dependence at the qth quantile and is defined as

$$\lambda^{q} = \begin{cases} P[u_{1,t} \leq q \mid u_{2t} \leq q], 0 < q \leq 0.5 \\ P[u_{1,t} > q \mid u_{2t} > q], 0.5 < q < 1 \end{cases}. \qquad (4)$$

Following Patton (2012), we test the symmetric dependence between the two sectors:

$$H_0: \begin{bmatrix} \lambda^{0.025} - \lambda^{0.975} \\ \lambda^{0.050} - \lambda^{0.950} \\ \lambda^{0.100} - \lambda^{0.900} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} vs.\ H_{\alpha}: \begin{bmatrix} \lambda^{0.025} - \lambda^{0.975} \\ \lambda^{0.050} - \lambda^{0.950} \\ \lambda^{0.100} - \lambda^{0.900} \end{bmatrix} \neq \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \qquad (5)$$

Table 2 shows that at the 5% significance level, we can reject the null hypothesis that the dependence between the two sectors is symmetric in three out of four cases (*i.e.,* 1-month, 6-month, and 12-month horizon), and the same null hypothesis is rejected at 10% statistical level for the 3-month horizon case, which suggests that asymmetric copulas (such as skewed *t* copula) would be more suitable as they can treat upper and lower tails differently. To capture this asymmetric default dependence, we model the dependence structure of the two sectors in the following subsection using a time-varying asymmetric copula method.

[INSERT TABLE 2 ABOUT HERE]

4.4. Modeling Marginal Distribution of Default Probability

The forward intensity function of Duan *et al.* (2012) is the exponential of a linear combination of some firm-specific and macroeconomic variables. Then PD is equal to one minus the exponential of the product of default intensity and horizon.

We make the transformation of PDs, which takes them back to the linear combinations of default attributes (Duan and Miao, 2016):

$$g_{k,t}(\ell) = \ln\left\{-\ln\left[1 - P_t^{(k)}(\ell)\right]\right\}, k = 1,2 \qquad (6)$$

so that $g_{k,t}(\ell) \in (-\infty,\infty)$.

Next, we assume that the change of transformed PD follows the stochastic process:

$$\Delta g_{k,t} = \mu_{k,t}(X_{t-1}) + \sigma_{k,t}(X_{t-1}) z_{k,t}, k = 1,2 \qquad (7)$$

where X_{t-1} denotes the latent underlying state vector and $z_{k,t}$ the standardized random variable.[15] First, we specify the condition mean and volatility in (4) by ARMA (m, n) and GJR-GARCH (1,1,1) (Glosten *et al.*, 1993).

$$\Delta g_{k,t} = c_k + \varepsilon_{k,t} + \sum_{i=1}^{m} \varphi_{k,i} \Delta g_{k,t-i} + \sum_{j=1}^{n} \theta_{k,j} \varepsilon_{k,t-j} \qquad (8)$$

$$\sigma_{k,t}^2 = \omega_k + \alpha_k \varepsilon_{k,t-1}^2 + \beta_k \sigma_{k,t-1}^2 + \gamma_k \varepsilon_{k,t-1}^2 I_{k,t-1} \qquad (9)$$

where $I_{k,t-1}$ takes the value of either 1 if $\varepsilon_{k,t-1} < 0$ or 0 if $\varepsilon_{k,t-1} > 0$. Second, we consider both parametric and nonparametric marginal distributions for $z_{k,t}$. For the parametric marginal one, we assume that $z_{k,t}$ follows the skewed student's *t* distribution from Hansen (1994):

$$z_{k,t} \sim F_{k,skew-t}(v_k, \lambda_k),\ v_k \in (2,\infty], \lambda_k \in (-1,1). \qquad (10)$$

where v_i is the degree of freedom, and λ_i the skewness parameter. For the nonparametric marginal one, we assume that the Empirical Distribution Function (EDF) is the consistent estimate of probability distribution:

$$z_{k,t} \sim F_k(z) \approx \frac{1}{T+1} \sum_{t=1}^{T} 1\{\hat{z}_{k,t} \le z\}. \qquad (11)$$

[15] Note that we remove the survival time-length, l, for simplicity without loss of generality.

4.5. Joint Distribution of Default Probability

The Sklar (1959) theorem demonstrates that the joint probability distribution can be decomposed into marginal distributions and a copula. Thus, the joint probability distribution of default probabilities can be expressed in terms of its marginals u and a copula function C:

$$F(z_{1,t}, z_{2,t}) = C(u_{1,t}, u_{2,t}), \qquad (12)$$

where $u_{k,t} = F_k(z_{k,t})$ and $C\ [0,1]^2 \rightarrow [0,1]$ is a 2-dimensional copula. We choose the multivariate skewed *t* copula to model the default dependence:

$$\mathbf{c}_{skt}\left(\mathbf{z};\gamma,\nu,\Sigma_t\right) = \frac{2^{\frac{(\nu-2)(n-1)}{2}} K_{(\nu+n)/2}\left(\sqrt{\left(\nu+\mathbf{z}^{*'}\Sigma_t^{-1}\mathbf{z}^{*}\right)\gamma'\Sigma_t^{-1}\gamma}\right)e^{\mathbf{z}^{*'}\Sigma_t^{-1}\gamma}}{\Gamma\left(\frac{\nu}{2}\right)\left|\Sigma\right|^{\frac{1}{2}}\left(\nu+\mathbf{z}^{*'}\Sigma_t^{-1}\mathbf{z}^{*}\right)^{\frac{-\nu+n}{2}}\left(1+\frac{1}{\nu}\mathbf{z}^{*'}\Sigma_t^{-1}\mathbf{z}^{*}\right)^{\frac{-\nu+n}{2}}} \times \prod_{i=1}^{n}\frac{\left(\sqrt{\left(\nu+\left(z_i^{*}\right)^2\right)\gamma_i^2}\right)^{-\frac{\nu+1}{2}}\left(1+\frac{1}{\nu}\left(z_i^{*}\right)^2\right)^{\frac{\nu+1}{2}}}{K_{(\nu+1)/2}\left(\sqrt{\left(\nu+\left(z_i^{*}\right)^2\right)\gamma_i^2}\right)e^{z_i^{*}\gamma_i}} \qquad (13)$$

where *K* is the modified Bessel function of the second kind, υ is the degree of freedom, and γ is the asymmetric parameter. Σ_t is the time-varying covariance matrix, such that $\sum_t = D_t R_t D_t$, where D_t is an identity matrix in the copula modeling and R_t is the time-varying correlation matrix.

$$R_t = \begin{bmatrix} 1 & \delta_t \\ \delta_t & 1 \end{bmatrix}. \qquad (14)$$

The time-varying correlation is driven by the GAS model of Creal *et al.* (2013). First, we follow Patton (2012) and transform the correlation parameter δ_t to be (-1,1):

$$f_t = h(\delta_t) \Leftrightarrow \delta_t = h^{-1}(f_t) \qquad (15)$$

where $\delta_t = (1 - \exp\{-f_t\})/(1 + \exp\{-f_t\})$. Next, the transformed parameter is updated by the dynamic specification:

$$f_{t+1} = \omega + \beta f_t + \alpha I_t^{-1/2} s_t \qquad (16)$$

where ω denotes a constant, $I_t^{-1/2} s_t$ the score of copula likelihood, $I_t := E_{t-1}[s_t s_t']$ and $s_t := \frac{\partial \ln c(u_{1,t}, u_{2,t}; \delta_t)}{\partial \delta_t}$.

4.6. Estimating Time-Varying and Asymmetric Joint Default Dependence

We first estimate the parameters of the time-varying skewed *t* copula[16] for each time horizon using both parametric and semiparametric methods. For parametric estimation, we model the univariate distribution using the skewed *t* distribution function. For semiparametric estimation, we model it using the empirical distribution function. The log-likelihoods in Table 3 suggest that the parametric model outperforms the semiparametric model across different horizons, and hence we focus on the parametrically estimated default dependence hereafter.

[INSERT TABLE 3 ABOUT HERE]

Table 4 reports the descriptive statistics of default dependence between the insurance and financial sectors for different horizons. The long-term default dependences (i.e., 6-month, 12-month ones) are of a larger magnitude than short-term ones (i.e., 1-month, 3-month ones).

[INSERT TABLE 4 ABOUT HERE]

Figure 2 shows the estimated joint default dependence of the insurance and banking sectors from March 1991 to February 2021 by the time-varying skewed *t* copula. The joint default dependencies are estimated based on 1-month, 3-month, 6-month, and 12-month horizons, respectively. The arrows indicate several major events in the global financial market.

The joint default dependence across all horizons shows a similar moving trend in our 20-year period. The longer the time horizon is, the higher the joint default dependence will be.

In addition, we find that the joint default dependence between the insurance and banking sectors is very sensitive to the global financial market. From 1997 to 1998, the dependence slightly rises during the Asian financial crisis. Later, we spot a big increase

[16] This time-varying skewed *t* copula has been used in empirical studies such as Christoffersen *et al.* (2012), Lucas *et al.* (2014) and Oh and Patton (2018), among many others.

during the Argentine and Russian financial crises and further note that the joint PDs peak around 2000 when the dot-com bubble burst. During the GFC, the joint PDs grew dramatically and then decline gently until the end of 2009. We identify two upward slopes in the next two years, when the European debt crisis and the S&P downgrading of U.S. sovereign debt ratings occurred. During the COVID-19 outbreak, the short-term and long-term default correlations rise dramatically.

Consistent with previous results, Figure 2 suggests that the two sectors have a high positive default dependence in the long term, but the default dependence fluctuates more in the short term. The default dependence between the two sectors is more likely to increase during global financial events or economic recessions, noting that the default dependence with different horizons normally diverges, especially for the 1-month correlation. For example, although default risk correlations remain high, they show heterogeneous patterns for different term structures after 2012. Notably, the 1-month default risk correlation moves in the opposite direction from 2014 to 2015. However, all the default risk correlations show the same trend and converge during times of distress in general (*i.e.,* the dot-com bubble, global financial crisis, S&P downgrading U.S. sovereign debt, the European debt crisis, and the COVID-19 pandemic).

The financial systemic risk proxied by our estimated default dependence suggests that financial regulatory reform is needed to prevent unexpected loss. For the U.S. market, insurers should follow more stringent risk-based regulations like *Solvency II* (which has been implemented in the EU), given their close relations with banks. For the entire financial industry, capital requirements should be increased to limit risk-taking. Higher capital requirements should be imposed on systemically significant organizations with progressively increasing requirements as an entity's default dependence grows.

[INSERT FIGURE 2 ABOUT HERE]

4.7. Determinants for the Default Dependence

The different behaviors from short- and long-term correlations between the two sectors motivate us to investigate the underlying determinants behind them. To understand the underlying determinants of the default dependence in the different horizons, we run the regression of the default dependence (the dependent variable) with macro variables (the independent variables). This analysis is also motivated by whether the time-varying movement of dependence between the two sectors comes from economic conditions or the interactions among insurance and other banks.

We select the following macroeconomic factors based on Christoffersen *et al.* (2018): (1) The change of the Chicago Fed National Financial Conditions Credit Subindex is used to measure the credit conditions in the market. It is composed of indexes of credit conditions. Increasing risk, tighter credit conditions, and declining leverage suggest tightening financial conditions. Therefore, a positive coefficient indicates that the corresponding credit conditions are tighter than on average, while a negative one indicates the opposite. (2) The log of the VIX index is used to model the equity market risk. It measures the market expectation of near-term volatility conveyed by stock index option prices. (3) Financial stress indicator: the spread between the 10-year Treasury rate and the 3-month Treasury bill is used to capture the term structure, and the 3-month Treasury bill is used as a level variable. (4) The TED spread, the difference between the Libor rate and short-term government debt rate, is used to capture liquidity in fixed-income markets. It is measured as the spread between the 3-month Libor based on U.S. Dollars and the 3-month Treasury Bill. (5) Commodities Market: The log of Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma. (6) Inflation: The log of CPI to measure inflation. (7) The log return of the NASDAQ Composite Index. (8) The global geopolitical risk (GPR) by Caldara and Iacoviello (2022).

Compared to the paper by Christoffersen et al. (2018), we introduce the global geopolitical risk factor. Caldara and Iacoviello (2022) demonstrate that increased geopolitical risk is linked to reduced investment and employment, as well as an elevated probability of disasters and increased downside risk. Industries that are more exposed to geopolitical risk experience more pronounced declines in investment. Additionally, higher firm-level geopolitical risk is correlated with reduced firm-level investment. Adverse geopolitical events and threats can influence macroeconomic variables through various channels, such as capital stock destruction, increased military spending, or heightened precautionary behaviors.

[INSERT TABLE 5 ABOUT HERE]

Table 5 reports the regression results for different horizons. The adjusted R^2 of 1-month correlation is 0.2122, and it first declines (3-month) and then continues to rise as the time horizon expands. It peaks at the 12-month time horizon with an adjusted R^2 of 0.2096. Low adjusted R^2 indicates that, although macro variables can explain a small portion of the variation of default dependence, more than half remains unexplained, which is probably due to firm-level characteristics.

The interest rate level and the geopolitical risk are significant at conventional statistical levels across different horizons while the credit index, VIX, and crude oil are statistically insignificantly different from zero. Since asset prices are affected by interest rates, this suggests that financial institutions hold similar assets, leading to increased systemic risk. Also, the financial systemic risk is more likely driven by fundamental economic factors, such as interest rate level, yield curve slope, the TED spread, and inflation. When the financial condition is tighter than average, the two sectors become more correlated. In addition, the index return is statistically significant on the long-term horizon, suggesting that the default correlation rises as the stock market booms.

It is evident that global geopolitical risks have a substantial impact on the macroeconomic environment. Financial markets are highly sensitive to changes in the macro environment. In previous research on systemic risk in financial markets, macroeconomic factors have been found to significantly influence systemic risk. The global geopolitical risk factor contributes unique and additional information not captured by other macroeconomic factors, making its relationship with systemic risk a valuable area of investigation. Earlier studies suggest that geopolitical risk is a form of economy-wide uncertainty that plays a pivotal role in investment decisions (Feng et al., 2023). Moreover, global geopolitical risk has been shown to reduce bank stability (Phan et al., 2022). Remarkably, our findings reveal a significant negative correlation between default dependence and geopolitical risk. This suggests that an increase in geopolitical risk has not led to an escalation of future default correlation in financial markets. One possible explanation is that central banks and policymakers may intervene to stabilize financial markets during times of geopolitical turmoil. They can provide liquidity, implement monetary policies, and take measures to prevent widespread defaults across financial institutions.

5. Concluding Remarks

In this paper, we investigate the linkage between the insurance and banking sectors from the perspective of their default dependence. First, we model the dependence of default risk between the two sectors using a time-varying asymmetric copula. Both parametric and semiparametric approaches are implemented. We identify the asymmetric correlations between the two sectors in both short-term and long-term horizons. The PD correlation spikes before the late 2000s global financial crisis and rises dramatically again during the COVID-19 pandemic.

Second, we identify the time-varying PD correlations between these two sectors, highlighting the importance of using a time-varying tail dependence in risk modeling. Moreover, the PD correlations vary widely in different horizons. Short-term PD correlations are relatively lower but fluctuate more, while long-term PD correlations are higher but more stable. The short-term and long-term PD correlations between these two sectors spike and converge during crises.

Third, we identify some underlying determinants of the co-movement of the insurance and financial sectors by regressing the default dependence with macroeconomic variables. Across all horizons, interest rate level and geopolitical risk always remain significant while the credit index, VIX, and crude oil remain insignificant. In general, short-term correlations are affected by interest rate level, yield curve slope, and the TED spread. The index return is only significant in long-term correlation, suggesting that the default correlation rises as the stock market booms. However, macro variables can explain a small portion of the variation of default dependence, more than half remains unexplained, which is probably due to firm-level characteristics.

Our results suggest that financial regulatory reform is needed to prevent unexpected losses. The insurance industry should follow more stringent risk-based regulations like *Solvency II*. For the banking industry, higher capital requirements should be imposed on systemically significant organizations with progressively increasing requirements as an entity's default dependence grows.

Our study is one of the first steps in the literature toward improving our understanding of the relationship between insurers, banks, regulators, and the real economy. From the macro-prudential view, it calls for closer monitoring of interactions among banks and to what extent, a single firm contributes to the stability of the overall financial system. Other dynamic high-dimensional copulas, such as dynamic vine copulas or factor copulas, could be used for firm-level studies in the future.

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Appendix

A. Forward Intensity by Duan et al. (2012)

In this appendix, we briefly introduce the forward intensity model in Duan *et al.* (2012). This model is based on a doubly-stochastic formulation of the point process for default proposed by Duffie *et al.* (2007). The conditional probability of default within τ years is

$$q(X_t,\tau) = E\left(\int_t^{t+\tau} e^{-\int_t^z (\lambda(u)+\varphi(u))du} \lambda(z)dz \,\middle|\, X_t\right) \qquad (1)$$

where X_t is the Markov state vector of company-specific and macroeconomic covariates. λ_t (*i.e.,* the conditional mean arrival rate of default measured in events per year) is firm-level default intensity. The firm may exit for other reasons like mergers or acquisitions. The intensity is defined as φ_t, and the total exit intensity is $\varphi_t + \lambda_t$.

The doubly-stochastic model allows combining two decouple estimators β and γ to obtain the maximum likelihood estimator of the PD: $q(X_t,\tau)$. In the default estimation models, given the path of state-vector *X*, the merger or acquisition and default times of the company are conditionally independent. We present a detailed log-likelihood function and forward intensity below.

Likelihood Function

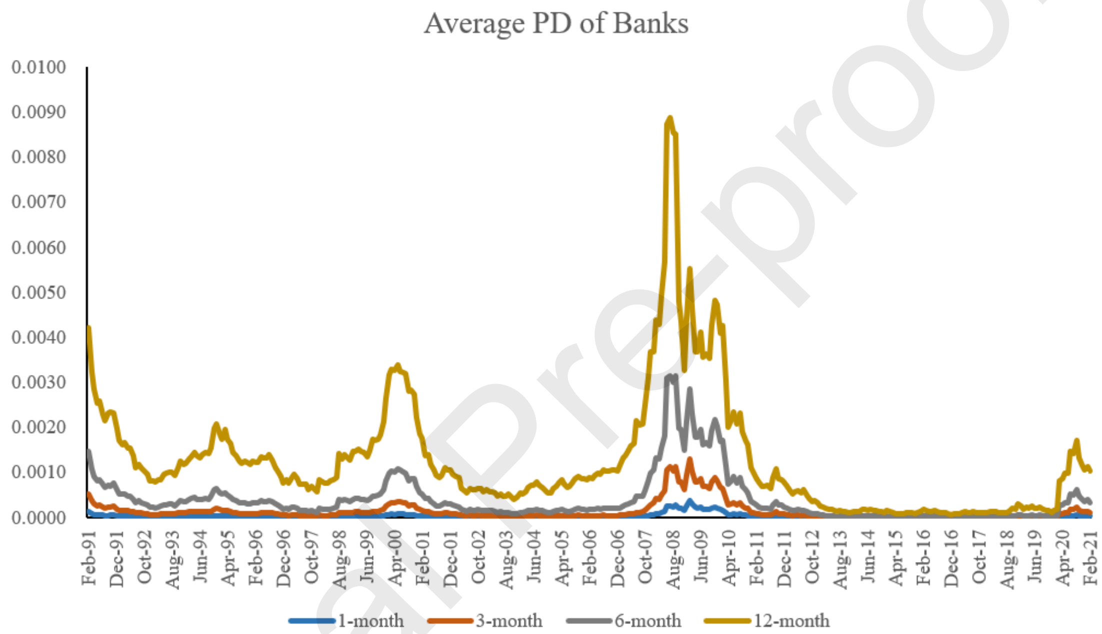
Instead of modeling the time-varying covariates to calculate the PD, Duan *et al.* (2012) use the forward intensity rate to calculate the default rate. The model needs to derive the forward intensity rate at time τ.

The pseudo-likelihood function for the prediction time τ is defined as

$$\mathcal{L}_\tau(\alpha,\beta;\tau_C,\tau_D,X) = \prod_{i=1}^{N}\prod_{t=0}^{T-1}\mathcal{L}_{\tau,i,t}(\alpha,\beta), \qquad (2)$$

where α and β are estimated parameters of the intensity model. The likelihood function $\mathcal{L}_{\tau,i,t}(\alpha,\beta)$ for the company *i* consists of five situations: the first is the company *i* survives in the prediction period, the second is the company *i* defaults in the prediction period, the third is the company *i* exits for other reasons (*i.e.,* like merger and acquisition), the fourth is the company *i* exits after this prediction period and the last is the company *i* exits before the start of this time interval:

$$\mathcal{L}_{\tau,i,t}(\alpha,\beta) = 1_{\{t_{0i} \le t,\, \tau_{Ci} \ge t+\tau\}} P_t(\tau_{Ci} > t+\tau) + 1_{\{t_{0i} \le t, \tau_{Di} = \tau_{Ci} \le t+\tau\}} P_t(\tau_{Di} = \tau_{Ci} \le t+\tau) + 1_{\{t_{0i} \le t, \tau_{Di} \ne \tau_{Ci}, \tau_{Ci} \le t+\tau\}} P_t(\tau_{Di} \ne \tau_{Ci}, \tau_{Ci} \le t+\tau) + 1_{\{t_{0i} > t\}} + 1_{\{t_{Ci} < t\}}. \tag{3}$$



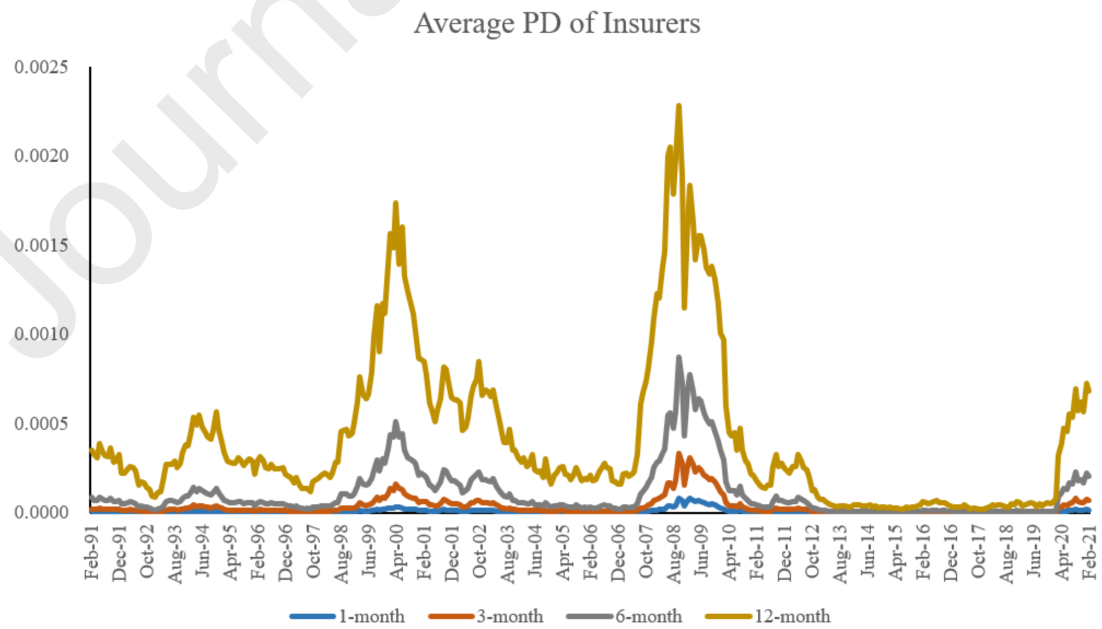


Figure 1. Average PD of banking and insurance sectors

Notes: This figure plots the average PD of banking and insurance sectors with 1-month, 3-month, 6-month, and 12-month horizons, respectively.

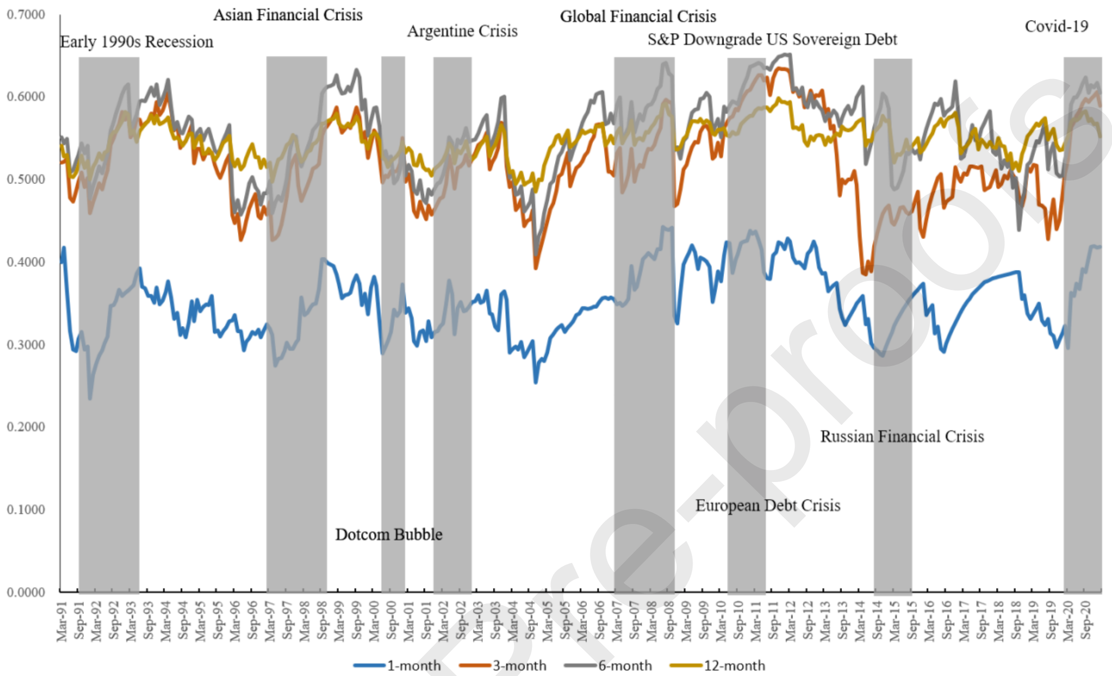


Figure 2. Joint default dependence for insurance and finance sectors

Notes: This figure plots the estimated time-varying joint default dependence of insurance and financial sectors from March 1991 to February 2021 by the time-varying skewed t copula. The joint default probabilities are estimated based on 1-month, 3-month, 6-month, and 12-month horizons respectively. The arrows indicate several major events in the financial market.

Table 1. Summary Statistics of the Log Difference of Transformed PDs

Month	Sector	Mean	Max.	Min	Std
1	*Insurers*	-0.0003	0.0578	-0.1239	0.0207
	Banks	0.0004	0.0541	-0.1975	0.0222
3	*Insurers*	-0.0003	0.0666	-0.1861	0.0250
	Banks	0.0005	0.0571	-0.2058	0.0233
6	*Insurers*	-0.0003	0.0716	-0.1785	0.0245
	Banks	0.0006	0.0772	-0.2050	0.0233
12	*Insurers*	-0.0002	0.0768	-0.1593	0.0234
	Banks	0.0006	0.1137	-0.1865	0.0231

Note: This table shows the summary statistics of the log differences of transformed PDs from the insurers and banks in 1-month, 3-month, 6-month, and 12-month horizons. The original historical individual PDs are from the RMI-CRI database with the sample period from March 1991 to February 2021. 'Std' stands for standard derivation.

Table 2. Tests for Time-varying and Asymmetric Dependence

Month	AR (1)	AR (5)	AR (10)	Symmetric test
1	0.080	0.000	0.004	0.008
3	0.006	0.000	0.000	0.071
6	0.056	0.000	0.001	0.000

12	0.052	0.002	0.001	0.002

Note: Table 2 shows the results for the time-varying dependence 'ARCH LM' test and symmetric dependence test. P-values of AR (1), AR (5), AR (10), and symmetric dependence test are presented here with 1-month, 3-month, 6-month, and 12-month horizons, respectively.

Table 3. Parameter Estimations of GAS Skewed Copulas

		1-month	3-month	6-month	12-month
Skewed t	$\hat{\omega}$	0.0694	0.0869	0.1387	0.1406
		(0.0096)	(0.0053)	(0.0114)	(0.0205)
	$\hat{\alpha}$	0.0334	0.1236	0.0135	0.0250
		(0.0186)	(0.0264)	(0.0077)	(0.0047)
	$\hat{\beta}$	0.9178	0.9247	0.8930	0.8862
		(0.0127)	(0.0061)	(0.0875)	(0.0166)
	$\hat{\eta}^{-1}$	0.1635	0.2570	0.2719	0.2485
		(0.1280)	(0.0088)	(0.1304)	(0.0919)
	λ	0.0135	0.0155	0.0171	0.0840
		(0.0041)	(0.0235)	(0.0412)	(0.0140)
	$log\mathcal{L}$	44.0710	66.1121	78.6004	68.0749
EDF	$\hat{\omega}$	0.1057	0.0786	0.1707	0.1827
		(0.0028)	(0.0088)	(0.0101)	(0.0369)
	$\hat{\alpha}$	0.0599	0.1070	0.0142	0.0372
		(0.0169)	(0.0011)	(0.0137)	(0.0182)

$\hat{\beta}$	0.8797	0.9304	0.8685	0.8510
	(0.0229)	(0.0104)	(0.0794)	(0.0299)
$\hat{\eta}^{-1}$	0.0795	0.2020	0.2638	0.2470
	(0.0333)	(0.0329)	(0.0748)	(0.1287)
λ	0.0150	0.0102	0.0092	0.0840
	(0.0047)	(0.0214)	(0.0301)	(0.0131)
$log\mathcal{L}$	45.7451	66.9093	81.4679	69.4305

Note: Table 3 presents the estimated parameters of the GH skewed *t* copula and GAS model for the insurance and financial sectors with 1-month, 3-month, 6-month, and 12-month horizons respectively. The marginal distributions are estimated by parametric (Hansen's skewed *t* distribution) and nonparametric (empirical distribution function, EDF) models, respectively. Standard errors and log-likelihood for both parametric and semiparametric models are reported.

Table 4. Time-varying Joint Default Dependence via GH Skewed *t* GAS Copula

Month	Mean	Std.	Median	Max	Min
1	0.3507	0.0403	0.3490	0.4425	0.2350
3	0.5198	0.0525	0.5157	0.6342	0.3845

6	0.5565	0.0475	0.5599	0.6510	0.4093
12	0.5478	0.0218	0.5487	0.5981	0.4847

Note: Table 4 presents the average, standard derivation, median, maximum, and minimum of time-varying default dependence for 1-month, 3-month, 6-month, and 12-month horizons, respectively.

Table 5. Potential Determinants of Default Correlations

	1-month		3-month		6-month		12-month	
Constant	0.3757	***	0.5327	***	0.5817	***	0.5717	***
	(0.0078)		(0.0113)		(0.0097)		(0.0042)	
Credit Index (-1)	-0.0001		-0.0001		-0.0001		-0.0001	
	(0.0001)		(0.0001)		(0.0001)		(0.0000)	
VIX (-1)	0.0060		0.0130		0.0252		0.0110	
	(0.0148)		(0.0213)		(0.0183)		(0.0080)	
Interest rate level (-1)	-0.0100	***	-0.0042	***	-0.0090	***	-0.0052	***
	(0.0011)		(0.0015)		(0.0013)		(0.0006)	
Yield curve slope (-1)	-0.0032		0.0040		-0.0010		-0.0024	**
	(0.0020)		(0.0028)		(0.0024)		(0.0011)	

TED (-1)	0.0307	***	0.0145		0.0254	***	0.0090	***
	(0.0062)		(0.0089)		(0.0076)		(0.0033)	
Crude oil (-1)	0.0314		0.0271		0.0186		0.0002	
	(0.0240)		(0.0347)		(0.0298)		(0.0130)	
Inflation (-1)	1.6314	**	1.2946		1.0359		0.6305	
	(0.7053)		(1.0166)		(0.8735)		(0.3821)	
Index return (-1)	0.0495		0.0944		0.1454	**	0.0574	**
	(0.0456)		(0.0657)		(0.0564)		(0.0247)	
GPR(-1)	-0.0002	**	-0.0002	**	-0.0002	**	-0.0002	***
	(0.0001)		(0.0001)		(0.0001)		(0.0000)	
Adjusted R^2	0.2122		0.0398		0.1329		0.2096	

Note: Table 5 shows the full-sample regression results of default correlations on credit risk index, VIX, interest rate level yield curve slope, TED spread, crude oil, inflation, NASDAQ, Composite index return and GPR; standard errors in parentheses, *, ** and *** indicates significant coefficient at the 10%, 5%, and 1% level, respectively.