Analysis of Risk Spillover Effect in Internet Financial Market based on Dynamic Factor Coupla Model

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Abstract

This paper employs a Dynamic Factor Copula Model to empirically investigate the risk spillover effects in the internet finance market. Using stock return data from 19 listed companies primarily engaged in internet finance between January 2021 and June 2024, we quantify risk contagion mechanisms across different business modules by constructing metrics such as Joint Probability of Distress (JPD). The results indicate that risk spillover effects in the internet finance market exhibit significant time-varying and sector-heterogeneous characteristics. Policy changes, international conflicts, and economic events are identified as critical factors influencing market volatility and risk contagion. Furthermore, a Shapley value-based feature contribution analysis reveals the driving roles of market sentiment, valuation levels, and liquidity in risk spillovers. This study provides theoretical and empirical support for internet finance risk regulation and offers policy recommendations for categorized supervision and systemic risk prevention.

Keywords

Internet Finance; Risk Spillover Effects; Dynamic Factor Copula Model; Systemic Importance Degree; Joint Probability of Distress.

1. Introduction

Internet finance integrates the advantages of traditional financial institutions and internet enterprises, providing society with diversified financial services such as financing, payment and settlement, investment and wealth management, and information intermediary by virtue of advanced internet technology and information and communication technology. As an innovative financial format, internet finance has become an important part of the financial field.

WIND Database divides the internet financial industry into three modules: P2P model, Third-party payment, and Financial online sales; Peking University Internet Finance Research Center classifies internet finance into six sections according to business attributes, namely Internet payment, Internet money fund, Internet credit, Internet insurance, Internet investment and wealth management, and Internet credit reporting. Yuran Gao (2017) argues that internet finance model, as a new type of financing model, is essentially different from traditional direct financing and indirect financing methods, and introduces several main current internet finance models in China: Online stocks, Third-party payment, P2P model[1]. Zhu Shuying (2022) divides Internet financial market into P2P model, Crowdfunding model, Big data finance model, Third-party payment model, Internet currency, and internet finance model[2]. Chen Yaohui (2015)'s research shows that although Financial online sales holds a place in the internet finance industry, its nature is more inclined to be a marketing method rather than an independent financial business module[3]. Song Xiaorui (2015) argues that although Internet credit reporting plays an important role in the field of internet finance, it does not directly involve financial transactions or capital flows itself, but rather provides credit evaluation services[4]. Therefore, this paper divides the Internet financial market into five modules: Internet bank, Internet investment and wealth management, Internet payment, Internet securities and Internet insurance. Online stocks is not selected here because offline stocks and Online stocks are not currently separated, and traditional stocks involve relatively few internet financial transactions. Natarajan et al. (2014) pointed out that the research on the correlation between financial markets is of great significance for inter-market volatility spillovers, risk transmission, and asset allocation[5]. Following the Global Financial Crisis (GFC) in 2008 and the recent COVID-19 health crisis, research on market spillovers and contagion risks has become increasingly important. Adrian and Brunnermeier (2016) proposed Conditional Value at Risk (ΔCoVaR), which can well measure Risk spillover effect and is one of the effective indicators for measuring systemic risk [6] In addition, Zhao, Xueting et al. (2017) developed a Dynamic ΔCoES model based on the ΔCoVaR model, which can quantify the dynamic risk spillover among financial markets and capture the changes in expected losses of the financial system under risk stress. They also explored the time-varying risk spillovers among China's stock market, exchange, and bond market[7].

The Dynamic factor model was initially proposed by Forni and Lippi (2001) to capture common trends in multiple economic time series. These models typically consist of two components: the Observation equation and the State equation[8]. By introducing time factors and dynamic adjustment mechanisms, the Dynamic factor model can update data and parameters in a timely manner to adapt to market changes and the dynamic nature of risks, thereby improving the accuracy of risk management. Gong et al. (2011) and Zhang et al. (2022) argue that financial markets change rapidly due to various influences, especially when responding to major political or economic events. Relying solely on a single structural or parameter copula model is insufficient to describe the dynamic correlations in financial markets. The combination of Dynamic factor model and Copula function can better describe the joint distribution among variables, thereby enhancing the accuracy of Risk spillover effect measurement[9][10]. Wang Peihui et al. (2017) reduced the parameter complexity of the model by utilizing the factor structure of the dynamic factor copula model, converting high-dimensionality into low-dimensionality [[11]]. Specific application cases of dynamic factor models in Risk spillover effect measurement include multiple fields and research directions: Ye Wuyi et al. (2018) analyzed inter-industry systemic risk based on the dynamic factor Copula model, indicating that this model is used to assess Risk spillover effect among different industries [12]. In addition, dynamic factor models have also been applied in the fields of financial engineering and digital finance to calculate China's financial systemic risk measurement indicators Conditional Value at Risk and Marginal expected shortfall, in order to study the Risk spillover effect and time-varying characteristics of the financial system: Fang Yi et al. (2020) extracted factors from five financial markets using a dynamic factor model, solving the problem of limited information sets in the Traditional VAR model due to the restriction on the number of dependent variables [13]; Gong Xiaoli and Xiong Xiong (2020) used the Generalized dynamic factor model to analyze the risk contagion mechanism within the financial system by distinguishing between common volatility components and idiosyncratic volatility components of return fluctuations [14]; Chen et al. (2023) combined the dynamic factor model with the Mean ES (Expected Shortfall) model to construct a comprehensive Dynamic factor copula mean ES model to dynamically capture the dependence structure among various industries[15]. Dynamic factor model has been widely applied in the measurement of Risk spillover effect, covering multiple aspects such as systemic risk analysis among industries, research on Risk spillover effect in international financial markets, and analysis of risk contagion mechanisms within the financial system. Currently, the application of Dynamic factor model in the analysis of Risk spillover effect in the Internet financial market remains blank. However, given that the Internet financial market is continuously consolidating its core position in the financial market under policy support and market accreditation, in-depth analysis of its Risk spillover effect is particularly necessary and of important research value.

2. Model Construction and Metrics Design

2.1. Dynamic Factor Copula Model

By utilizing the Copula function and the respective marginal distributions of random variables, their joint probability distribution can be derived. Basis the conditional Sklar's theorem, assume that the random vector $Y_t = [Y_{1t}, \cdots, Y_{nt}]'$, and F_t is the information set generated by $Y_{t-j}(j = 0,1,2,\cdots)$. Given the information set $\mathcal{F}_{t-1}$, the conditional distribution of the random variable Y_t can be decomposed into its conditional marginal distribution functions and the conditional Copula function. Let$Y_t|\mathcal{F}_{t-1} \sim F_t(\cdot| \mathcal{F}_{t-1}), Y_{it}|\mathcal{F}_{t-1} \sim F_{it}(\cdot| \mathcal{F}_{t-1})$, then for any $y = [y_1, \cdots, y_n]' \in \mathbb{R}^n$ We have

$$F_t(y \mid \mathcal{F}_{t-1}) = C\{ F_{1t}(y_1 \mid \mathcal{F}_{t-1}), \cdots, F_{nt}(y_n \mid \mathcal{F}_{t-1}) \mid \mathcal{F}_{t-1} \} \quad (1)$$

This study adopts the dynamic factor Copula model proposed by Oh and Patton in 2018 to integrate the stock price return distributions of multiple companies, with the model expression shown as follows.

$$X_{it} = \lambda_{it} Z_t + \varepsilon_{it}; Z_t \sim \text{ Skew } t(\nu_Z, \psi_Z); \varepsilon_{it} \sim \text{ iid } t(\nu_\varepsilon) \quad (2)$$

where i represents the i-th stock, taking values in $[1,2,\cdots,N]$, X_{it} is the latent factor variable. The model assumes that the dependence structure of Y_t is determined by its latent factor$X_t = [X_{1t}, \cdots, X_{Nt}]'$ i.e., the Copula function of $Y_t$follows the Copula function of X_t.

The GAS model can be expressed as:

$$\begin{gathered} U_\iota \mid \mathcal{F}_{t-1} \sim C\big(\delta_t(\gamma)\big) \\ \delta_t = \omega + B\delta_{t-1} + As_{t-1} \\ s_{t-1} = S_{t-1}\nabla_{t-1} \\ \nabla_{t-1} = \frac{\partial \log \boldsymbol{c}(\boldsymbol{u}_{t-1}; \boldsymbol{\delta}_{t-1})}{\partial \boldsymbol{\delta}_{t-1}} \end{gathered} \quad (3)$$

To less the complexity of estimation, Oh and Patton (2018) combined the factor Copula function with the GAS model proposed by Creal et al. (2013), assuming that λ_t has the following structure:

$$\log \lambda_{it} = \theta_i + \beta \log \lambda_{i,t-1} + \alpha s_{i,t-1}, s_{it} \equiv \frac{\partial \log c(u_t; \lambda_t, \nu_z, \psi_z, \nu_\varepsilon)}{\partial \log \lambda_{i,t}}, i = 1,2,\cdots,N \quad (4)$$

2.2. Joint Probability of Distress

A defining feature of Systemic risk is the simultaneous occurrence of extreme risk events across numerous financial institutions. The frequency of such events directly reflects the accumulated level of Systemic risk. This study adopts the joint probability of distress (JPD) model developed by Oh and Patton (2018) to assess the probability of concurrent tail risk events at different time points, thereby quantifying the overall risk level of the stock market. A risk event is defined as a stock return falling below a specified threshold, expressed as$D_{it} \equiv 1\{R_{it} < c_i\}$, where R_{it}

denotes the return of company i at time t, and c_i represents the established return threshold (set at 5% in this study's empirical analysis).JPD is defined as follows:

$$JPD_{t,k} \equiv P_t\left[\left(\frac{1}{N}\sum_{i=1}^{N} D_{i,t+1}\right) \geqslant \frac{k}{N}\right] \tag{5}$$

where $JPD_{t,k}$ is specifically defined as the probability that at least k internet financial companies will experience risk events at time t+1, based on the information available at time t.

2.3. Expected Proportion of Distress

For each stock i, we calculate the expected proportion of stocks in distress conditional on stock i being in distress:

$$EPD_{i,t} \equiv \mathrm{E}_t\left[\frac{1}{N}\sum_{j=1}^{N} D_{j,t+250}\,\middle|D_{i,t+250} = 1\right] \tag{6}$$

The minimum value it can take is 1/N because we include stock i in the sum. This measure of systemic risk is similar in nature to the CoVaR measure as it focuses on the distress "spillover effect" from an individual stock to the entire market.

3. Data Sources and Processing

This paper selects the stock return data of 19 companies whose main business is internet finance from the internet finance concept stocks in the Wind database and the Guotaian database for empirical analysis.

Table 1 presents the basic statistics of logarithmic returns for 19 stocks. As can be seen from Table 1, the skewness coefficient is positive for 17 stocks, with 89% of the companies exhibiting a right-skewed nature (skewness > 0) in their return distributions. The Jarque-Bera inspection is all significant (p<0.01), indicating that the traditional risk model based on the normal assumption has limitations in this field, which provides an empirical basis for the adoption of the dynamic factor Copula model.

To sum up, internet financial risks have significant business format heterogeneity and policy transmission, and traditional financial risk measurement methods are difficult to accurately capture their dynamic correlation structure, which is the methodological value of adopting the dynamic factor Copula model in this paper.

Table 1. Descriptive Statistics of Stock Returns for Internet Finance Listed Companies

	Mean	sd	Skewness	Kurtosis		Mean	sd	Skewness	Kurtosis
601166	-0.0002	0.0342	0.2429	1.7073	300773	-0.0010	0.0314	0.4207	6.1852
601998	0.0001	0.0242	0.4651	1.7822	603123	-0.0001	0.0299	0.2445	2.7722
000001	-0.0012	0.0309	0.6086	3.9534	002095	-0.0007	0.0408	0.1407	0.5858
300059	-0.0003	0.0390	0.7036	4.7366	601555	0.0000	0.0346	0.2477	1.6197
300033	-0.0006	0.0302	0.2550	2.0558	600109	-0.0018	0.0303	0.1468	1.9411
000987	0.0002	0.0384	0.3144	0.9533	601519	-0.0007	0.0252	0.4901	3.6134

When a stock's logarithmic return curve exhibits leptokurtic characteristics (sharp peak and thin tails), this typically indicates that its return distribution has higher kurtosis and thinner tails compared to a normal distribution.

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4. Empirical Results and Analysis

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4.1. Marginal Distribution Fitting

Before constructing the dynamic factor Copula model, it is first necessary to determine the marginal distributions of the return series of each company. The ADF test confirmed that all return series are stationary. Based on the results in Table 1 and the Jarque-Bera test, it can be seen that the skewness and kurtosis of different return series vary significantly, and none of them conform to the normal distribution. To more accurately capture the leptokurtic, fat-tailed characteristics and asymmetry of the data, this paper employs the AR(1)-EGARCH(1,1) model, assuming that the residuals follow a skewed t-distribution:

$$R_{it} = \phi_i R_{i,t-1} + \varepsilon_i;\ \ \varepsilon_{it} = \sigma_{it}\eta_{it} \tag{7}$$

$$\ln(\sigma_{it}^2) = \omega_i + \alpha_i\eta_{i,t-1} + \gamma_i\left(|\eta_{i,t-1}| - E|\eta_{i,t-1}|\right) + \beta_i \ln\left(\sigma_{i,t-1}^2\right) \tag{8}$$

here $\eta_{it} \sim iid\ Skew\ t(v_i, \psi_i)$, v_i is the degrees of freedom of the skewed t-distribution, and ψ_i is the skewness of the skewed t-distribution. The parameter results in Table 2 confirm that the AR(1) - EGARCH(1, 1) model is applicable to the data of the Internet market.

Table 2. Estimation Results of Marginal Distribution Parameters

	ϕ_i	ω_i	α_i	β_i	v_i	ψ_i
601166	0.0080	-0.0125	0.0727	0.9985	3.6227	-0.0176
601998	-0.1123	-0.4690	0.1501	0.9449	3.5216	0.2776
000001	0.0084	-0.0014	0.0323	0.9999	4.7769	-0.0194
300059	-0.0569	-0.1378	0.0077	0.9812	3.7787	0.1433
300033	-0.0781	-0.2783	0.0291	0.9586	3.0373	0.1696
000987	-0.0399	-0.1853	-0.0131	0.9756	3.6002	0.1972
002104	-0.0282	-0.2289	-0.0009	0.9683	5.1030	0.1993
300130	-0.0698	-0.1683	0.0171	0.9754	3.9461	0.1338
002537	-0.0501	-0.1324	-0.0129	0.9814	5.5245	0.2172
000997	-0.0116	-0.5909	-0.0362	0.9214	4.6267	0.2063
300773	-0.0613	-1.0479	-0.0976	0.8545	4.5507	0.2488
603123	-0.0049	-0.3326	0.0066	0.9528	4.7253	0.3307
002095	-0.0330	-0.5875	0.0018	0.9172	4.8272	0.4236
601555	-0.0237	-0.2789	0.0342	0.9644	3.6558	0.1581
600109	-0.0416	-0.1439	0.0389	0.9811	3.3494	0.1513
601519	-0.0665	-1.5231	0.0336	0.7904	3.4984	0.4079
601318	-0.0191	-0.4912	0.0048	0.9397	4.9650	0.1185
601319	-0.0701	-0.5713	0.0310	0.9323	4.5679	0.2760
601601	-0.0435	-0.3201	-0.0045	0.9579	4.2594	0.1450

4.2. Establishment of Dynamic Factor Copula Function

Basis on the aforementioned theoretical framework, this paper adopts the Generalized Autoregressive Score (GAS) dynamic factor Copula model to capture the time-varying dependence structure of the internet finance system. This model combines the dynamic characteristics of the GAS model and the dependence structure of the Copula function, enabling effective analysis of dynamic correlations and Risk spillover effect among financial markets. Based on the theoretical framework of Patton (2013) and Oh & Patton (2015), the parameter estimates of the dynamic factor Copula model are solved through Formula (3) and Formula (4) combined with the Maximum Likelihood Estimation (MLE) method.

Table 3. parameters of dynamic copula model

	601166	601998	000001	300059	300033	000987	002104	300130	002537	000997
θ_i	-0.004	-0.009	-0.039	0.094	0.147	-0.001	-0.035	-0.027	-0.031	-0.06
	300773	603123	2095	601555	600109	601519	601318	601319	601601	
θ_i	0.062	-0.033	-0.052	0.073	0.291	0.172	-0.055	-0.060	-0.045	
	other parameters									
β		0.983	α	0.086	γ_z	21.47	γ_ε	5.554	ψ_z	0.025

Table 3 presents the estimation results of the model parameters. Among them, the β coefficient is as high as 0.9832, approaching 1, It can be inferred that the estimated loading factors exhibit strong persistence characteristics. The two parameters γ_z and γ_ε respectively reveal the heavy-tailed characteristics of common factors and idiosyncratic factors. The data shows that the value of γ_ε is greater than that of γ_ε, which means that the systemic volatility of internet financial enterprises driven by common factors is more convergent and concentrated, with a relatively smaller fluctuation range compared to the institutional-specific volatility.The ψ_z parameter reveals the skewness property of systemic fluctuations in internet financial enterprises, with a specific value of 0.0258, indicating that in the Internet financial market, the frequency of extreme positive fluctuations is higher than that of extreme negative fluctuations, reflecting the asymmetric characteristics of the market.

Among the 19 stocks examined, the θ_i values of Newland and PICC are the smallest, both below the threshold of -0.005, which indicates that compared with other stocks, the dependence of these two stocks on the overall market is relatively low.

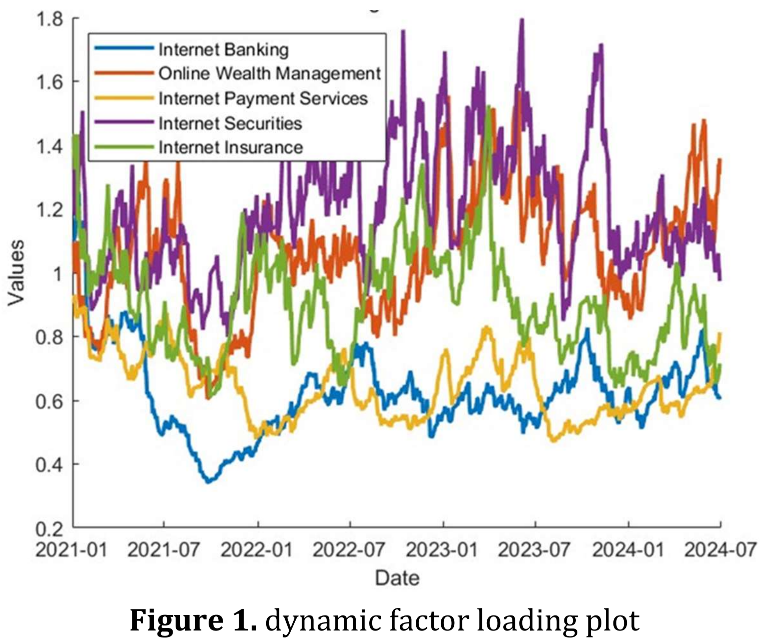

Figure 1. dynamic factor loading plot

Figure 1 shows the time-varying factor loadings implied by the dynamic factor Copula model by averaging the factor loadings of all companies in the same industry. It starts from January

2021 and ends in July 2024, with markers on the timeline at 6-month intervals, specifically in January and July of each year. The figure presents the changes in weighted load factors over time. It can be observed that the load factors range from 0.34 to 1.25, fluctuating over time and showing a certain clustering effect, indicating a continuous increase in the correlation between stocks.

4.3. Joint Distress Probability

Due to the lack of an analytical solution for the dynamic factor Copula function, we adopt a simulation method to estimate the joint distribution of 19 stocks. To shorten the computation time required for simulation, this study sets the estimation frequency to once a month and the number of Monte Carlo simulations to 100. Using the simulated joint distribution function, we calculate the probability that at least k internet finance enterprises are in a risk state at each time point, thereby obtaining the joint risk probability. In terms of the selection of k values, we find that the trends of joint risk probabilities for different k values are roughly the same. For the sake of brevity, this paper only presents the case where k=9 (i.e., more than 50% of internet finance concept stocks are in a risky state). Figure 2 shows the trend chart of the joint risk probability over time.

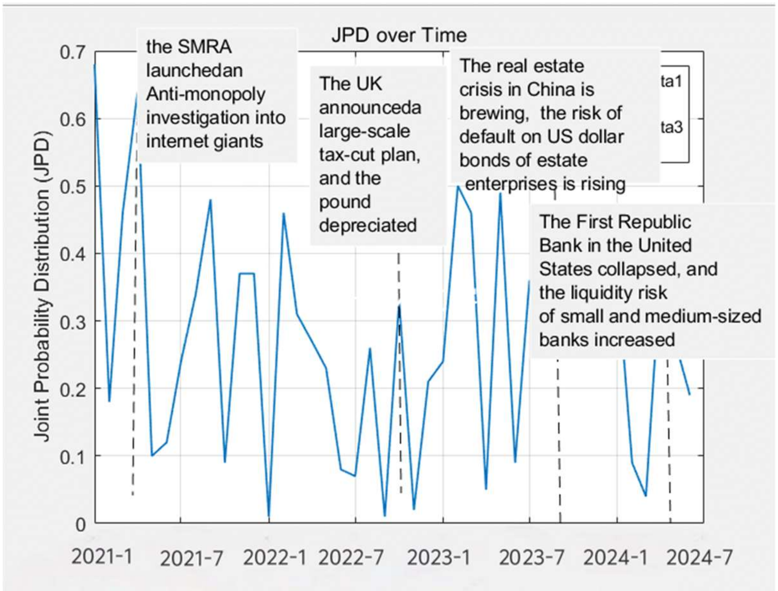

Figure 2. JPD over Time

It can be observed from Figure 2 that major financial events have a significant impact on systemic risk. After the State Administration for Market Regulation of China launched an anti-monopoly investigation into internet giants in April 2021, the JPD value increased significantly, reflecting the impact of sudden changes in regulatory policies on the market. This incident led to a large-scale sell-off of Chinese concept stocks, with sharp declines in the stock prices of internet companies such as Alibaba, and market panic quickly spread to the entire internet finance section. As the business connections between internet platforms and traditional financial institutions have become increasingly close, this regulatory risk has further spread to traditional financial sectors such as banking and securities, resulting in an overall rise in the level of systemic risk.

Through the analysis of the time series chart of joint distress probability, it can be found that the rise of systemic risks in recent years is often closely related to major policy adjustments or industry crises. Therefore, regulatory authorities need to establish a more sensitive risk monitoring system, focusing on policy changes and industry trends that may trigger systemic risks.

4.4. Measurement Results of Expected Proportion of Default (EPD)

EPD is the expected proportion that other enterprises will also fall into risk under the condition that a certain internet financial enterprise is known to be in risk, which is calculated by formula (6). EPD provides a quantitative indicator to assess how the risk of an individual internet financial enterprise spills over to the entire market. A high EPD value indicates that when a specific enterprise faces risk, it may significantly increase the systemic risk of the entire market. In Figure 3, we summarize the results of EPD estimation and provide the average value, 20% and 80% quantiles of 19 stocks in our sample.

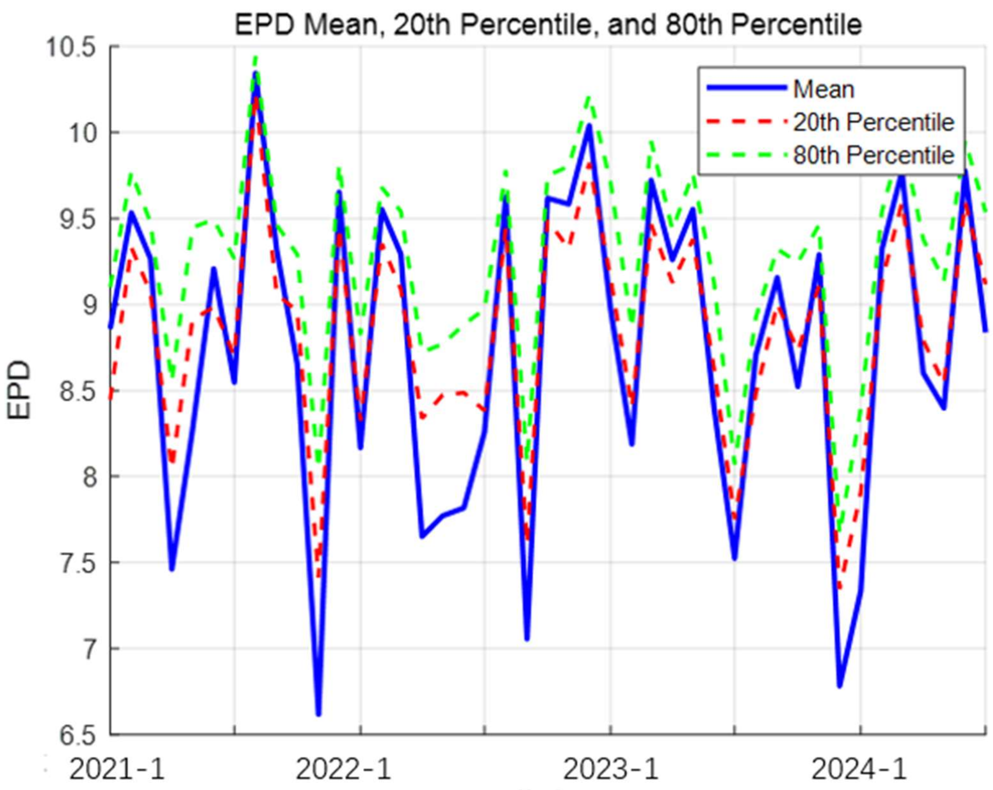

Figure 3. average EDP plot

As can be observed from Figure 2, starting from April 2021, the EPD value also showed an upward trend. The upward trend of the EPD value indicates that with the enhancement of correlation among Internet finance sector, the risk spillover effect of individual stocks increased accordingly, leading to a rise in the overall market risk level. This is related to the profound impact of the UK government's Large - scale tax cut plan on the global economy, including factors such as supply chains disruptions, declining demand and rising unemployment rate, which may all lead to increased market volatility and investor uncertainty. In February 2022, the EPD value also reached a peak, indicating that in a high-correlation environment, the risk of individual stocks is more likely to spread to the entire market, increasing Systemic risk.

In risk assessment, the Expected Probability of Distress (EPD) provides us with a key indicator to identify stocks that are closely linked to overall market crises. If an enterprise has a low risk measurement value, this usually indicates that the stock's distress does not signal widespread market problems, but rather reflects more of its specific risk characteristics.

Table 4. Distribution of EPD values

	Nov-21		Jan-23		Jun-24	
	company	EPD	company	EPD	company	EPD
1	601319	8.297	300033	9.827	601319	10.222
2	000001	8.104	300773	9.813	601519	10.114
3	000987	8.064	601998	9.732	000987	10.049
4	002537	8	601166	9.717	601166	9.964
16	601601	7.711	002104	9.208	600109	9.588
17	002095	7.667	601319	9.05	002537	9.488
19	600109	7.5	601601	9.0	002104	9.433
Min	601555	7.375	300059	0	603123	9.404

Table 4 lists the top four and bottom four companies for three dates during the sample period: the first month (August 2021), the middle month (January 2023), and the final month (July 2024). We observe that as the sample period progresses, the EPD distribution for the middle month (June 2023) reveals the median EPD value of stocks with the lowest Systemic risk has increased from 7.58 to 9.025. This indicates that even among stocks with lower Systemic risk, a certain degree of risk interconnectedness exists-specifically, the mutual influence between these stocks gradually strengthens when they face distress.

Overall, the risk correlation among stocks showed an upward trend during the sample period, suggesting that the market's overall Systemic risk has increased over time, posing certain challenges to market stability. For companies with higher Systemic risk, their distress may more easily trigger market-wide chain reactions. Therefore, special attention should be paid to their risk profiles and potential market impacts.

5. Conclusion and Recommendations

Based on the research findings of this paper, we can draw the following conclusions: The dynamic factor Copula model, as an effective tool, can capture the risk spillover effect among different modules in the internet finance market and reveal how risk events in a single module can quickly spread to other modules, thereby posing a threat to the stability of the entire market. Through empirical analysis, we find that the volatility of the internet finance market is related to multiple factors, including policy changes, international conflicts, and economic events. These factors affect market volatility by influencing market expectations and investor behavior.

Regulatory authorities should pay attention to internet finance companies with a high degree of systemic importance, as their risk events may pose a threat to the stability of the entire financial market. When making investment decisions, investors should consider the spillover effect of risks in the internet finance market, especially during periods when the market is under pressure or uncertainty increases. When formulating policies related to internet finance, policymakers should take into account market volatility and risk spillover effects to promote the healthy development of the market and prevent Systemic risk. This study provides new perspectives and tools for understanding and managing risks in the internet finance market, and holds significant reference value for financial regulation and investment practices.

In summary, the research in this paper shouldprovides new theoretical support and empirical evidence for the risk management of the internet financial market, but also offers valuable references for financial regulation and investment practices. Through the application of the dynamic factor Copula model, we can more accurately identify and assess the intensity and path of risk transmission among different markets, thereby providing a scientific basis for the healthy development of the internet finance market. Based on the above conclusions, Regulatory authorities should establish an EPD early warning mechanism; use the Joint Probability of Distress (JPD) time - series chart (Figure 4) to demonstrate the law of risk aggregation to market participants, helping identify crisis precursors; the contribution of the common factor (γ_z =21.47) to Systemic risk far exceeds that of the idiosyncratic factor (γ_ε=5.554), and its driving mechanism can be analyzed in combination with macroeconomic data in the future. When formulating policies related to internet finance, policymakers should take into account market volatility and spillover effects to promote the healthy development of the market and prevent Systemic risk. The research in this paper provides a new perspective and tools for understanding and managing the risks of the internet financial market, and has important reference value for financial regulation and investment practice.

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