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Research on Industrial Chain Business Credit Risk Assessment Based on the CoVaR Model

Yi Feng[a], Yunqi Zhang[b], Ranchen Geng[b,*]

[a] Higher Education Press, Chaoyang District, Beijing, 100029, China

[b] School of Business, Central University of Finance and Economics, Haidian District, Beijing, 100081, China

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Abstract

In the context of the rapid development of industrial chain finance, traditional static and isolated credit risk assessment methods fail to capture the dynamic and systemic nature of credit risk propagation within industrial chains. This paper focuses on the evaluation and control of credit risk in the business credit value chain. Building on VaR and CoVaR models, it proposes a systemic credit risk quantification framework, further incorporating a LASSO-CoVaR approach to identify credit risk spillovers and marginal effects across interconnected firms. Using the pig industry chain led by Muyuan Foods Co., Ltd as a case study , the paper constructs a credit network and measures topological indicators such as in-degree, out-degree, closeness centrality, betweenness centrality, and eigenvector centrality. Empirical analysis confirms that the structural embeddedness of firms within the credit network significantly influences their risk exposure and systemic transmission potential. Based on the findings, the paper proposes a three-pronged risk mitigation strategy focusing on risk source identification, disruption of transmission paths, and coordinated credit governance. This offers both theoretical insights and practical guidance for financial institutions engaged in credit allocation and risk control within the evolving landscape of industrial chain finance.

Keywords: Business credit; Credit value chain; Industrial chain; CoVaR; Risk management

1. Introduction

In the context of China’s ongoing economic transformation and the advancement of a credit-based society, business credit is playing an increasingly strategic role in resource allocation, risk control, and industrial coordination. Particularly as industrial chains become more networked and complex, traditional credit evaluation methods that focus solely on individual firms can no longer meet the demands of multi-agent and multi-level collaborative risk identification. Credit relations are no longer confined to static lending or transactional behaviors; instead, credit has emerged as a dynamic “carrier of value” and “conduit of risk” that flows along the industrial chain, exerting profound and far-reaching impacts.

In recent years, with the rapid development of industrial chain finance, the concept of the “Business Credit Value Chain”—a nascent research paradigm emphasizing the accumulation, transmission, and

* Correspondence: gengranchen@163.com

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amplification of credit along industrial chains—has attracted increasing attention from both academia and industry. However, existing studies on credit risk still primarily concentrate on financial indicators and the prediction of firm-level default probabilities. There remains a lack of systematic theoretical frameworks and empirical analyses regarding how credit propagates within industrial chain structures, how systemic risk materializes, and how key enterprises may amplify or mitigate such risks. Moreover, prevailing credit risk models often overlook the dynamic and networked nature of inter-firm relationships, making them inadequate for explaining real-world phenomena such as correlated defaults and cascading risk contagion.

In response, this study centers on the Business Credit Value Chain to investigate how credit is embedded within industrial structures and how risk is transmitted across the chain. By introducing complex network analysis and systemic risk metrics—such as CoVaR and LASSO-CoVaR—the paper constructs an integrated research framework that incorporates firms' structural positions, credit behaviors, and risk feedback mechanisms. This approach seeks to address the gap in chain-oriented perspectives within current literature. Based on a case study of the pig supply chain, the study further explores the practical logic of credit risk identification and management within industrial networks, aiming to provide theoretical insights and actionable guidance for optimizing business credit governance the system.

2. Literature Review

With the increasing number and complexity of market participants, credit risk—one of the most systemically impactful risks in the financial system—has become ever more critical to evaluate and quantify. Credit risk assessment and measurement refer to estimating and measuring the likelihood of a risk event, often by using probabilistic methods to more accurately predict the possibility of default. Since the 1960s, academia and industry have shifted from traditional qualitative assessments to quantitative models, promoting systematic and model-based developments in this field.

Early quantitative models primarily relied on statistical methods, such as discriminant analysis (Fisher, 1936), linear regression (Beaver, 1968), and logistic regression (Wiginton, 1980; Fernandes & Artes, 2016; Caigny et al., 2018). While these models improved objectivity and replicability in evaluation, their rigid assumptions regarding variable distribution and linearity limited their applicability in complex credit scenarios.

To overcome the limitations of traditional statistical approaches, researchers began introducing machine learning techniques into credit risk modeling. Representative methods include decision trees (Zhu et al., 2017), neural networks (Angelini et al., 2008), and support vector machines (Kim & Sohn, 2010). Salchenberger et al. (1992) were among the first to apply neural networks in corporate credit risk prediction, initiating widespread use of nonlinear models in credit research. Geng (2015) demonstrated that neural networks outperformed SVM and decision trees in predicting distressed Chinese ST firms. Li et al. (2021) developed a credit risk model for SMEs incorporating soft information, validating the advantage of backpropagation neural networks. However, the "black box" nature of neural networks limits their interpretability, posing challenges in financial regulation and risk communication.

Therefore, models with strong interpretability have regained attention. Abellán et al. (2014) developed a bankruptcy prediction model by combining Bagging with decision trees, achieving the best performance. Since the introduction of Support Vector Machine (SVM) method by Cortes and Vapnik (1995), it has been widely adopted due to its strong generalization ability. Kim (2012) constructed a corporate credit rating system based on multi-layer SVMs, demonstrating superior modeling capability. Maldonado et al. (2017) effectively evaluated corporate credit risk in Chilean banks by integrating profitoriented feature selection with an SVM classifier. Zhang et al. (2018) further improved the SVM structure by proposing a fuzzy approximate SVM model, which addressed the issue of sample imbalance.

In dynamic financial markets, relying solely on expected values may underestimate the impact of extreme events. Hence, Value-at-Risk (VaR) has emerged as a mainstream risk measurement tool. Morgan (1996) first proposed the RiskMetrics framework, quantifying VaR as a specific quantile of the loss distribution. The linear quantile regression model established by Koenker et al. (1978) laid the foundation for VaR estimation. Subsequent studies, such as Taylor (2008) with exponentially weighted quantile models, enriched the empirical foundation of VaR. To model nonlinear structures, White (1992), Taylor (2000), and Feng et al. (2010) used neural networks to capture nonlinear quantile relationships; Takeuchi et al. (2006) developed support vector quantile regression (SVQR) models for greater flexibility.

In addition to machine learning and the VaR framework, mathematical optimization methods have also achieved significant progress in credit risk research. Kwak et al. (2012), using post-crisis data from the Korean financial market, proposed an improved multi-objective optimization approach for bankruptcy prediction, achieving accuracy comparable to that of logistic regression models. Maldonado et al. (2017) designed a mixed-integer linear programming (MILP) model that integrates feature selection and classification capability, and empirically validated its effectiveness. Zhang et al. (2019) further incorporated sparse regularization into the construction of a multi-objective classifier, which performed well across several public datasets.

As research in the field has progressed, the performance improvements of single models have gradually approached a bottleneck, making ensemble learning methods a promising breakthrough direction. Among these, ensemble approaches such as Random Forests (Malekipirbazari et al., 2015) have garnered significant attention. Wang and Ma (2011) proposed the RS-Boosting method, which enhances the accuracy of corporate credit risk identification through collaborative learning across multiple classifiers. Zhu et al. (2019) integrated the Random Subspace method with Multi Boosting, developing the RS-MultiBoosting model, which significantly improved the predictive accuracy of credit risk for small and medium-sized enterprises.

Meanwhile, hybrid models have also been widely applied in credit risk assessment. Oreski and Oreski (2014) introduced a hybrid genetic algorithm–neural network (HGA-NN) model, which outperformed traditional SVM and ANN approaches on Croatian credit datasets. Yu et al. (2016) constructed an ensemble approach integrating multi-level deep belief networks (DBNs) and extreme learning machines (ELMs), achieving strong results in corporate credit risk evaluation. Zhang et al. (2021) incorporated feature selection mechanisms into ensemble learning frameworks, effectively improving the performance of base classifiers. García et al. (2019) systematically evaluated various ensemble strategies across 14 real-world financial datasets. Niu et al. (2020) proposed a distribution-aware resampling model to tackle class imbalance in credit datasets, and demonstrated its superiority on multiple representative datasets.

Although existing research on credit risk identification and modeling has made considerable progress—ranging from traditional statistical techniques to machine learning, ensemble methods, and hybrid models—most studies remain confined to firm-level financial indicators and overlook the networked nature of firms within industrial chains and the contagion effects of credit. In real-world business contexts, credit risk stems not only from the likelihood of individual firm defaults, but also manifests as systemic risk that propagates and amplifies along the value chain. Particularly in highly coordinated industrial ecosystems, individual credit behaviors often transmit through supply chain relationships to other network nodes, forming feedback loops. Therefore, credit risk assessment must evolve from static financial analysis to dynamic network-based approaches, and from isolated evaluations to holistic measurements across the entire chain. In response, this study adopts the analytical perspective of the "Business Credit Value Chain," aiming to construct an evaluation framework that incorporates structural positions of firms, credit linkage strength, and systemic spillover effects. By integrating VaR, CoVaR, and complex network centrality metrics, the paper explores the causes, pathways and countermeasures of credit risk within industrial chains from both theoretical and empirical dimensions.

3. Methodology

Quantitative evaluation generally requires a relatively high level of assessment techniques. From the perspective of data-driven evaluation models, the extent of data support and the quality of assumptions made by evaluators directly affect the reliability of quantitative evaluation, and are closely related to the accurate prediction of risk exposure. An evaluation method based on Value at Risk (VaR) and Conditional Value at Risk (CoVaR) can, under sufficient data resource support, effectively assess the value of business credit risk.

3.1 Model Overview

The assessment of business credit risk in an industrial chain requires a framework capable of capturing not only the standalone risk of individual firms but also the interdependent nature of their credit exposures. In this study, we adopt a systemic risk perspective based on the Value at Risk (VaR) and Conditional Value at Risk (CoVaR) frameworks. VaR measures the potential loss of a firm over a specified holding period at a given confidence level. Formally, for firm i, VaR at quantile level τ represents the τ-quantile of its return distribution, indicating the maximum expected loss under normal market conditions.

$$\Pr(R_t^i < VaR) = \tau \tag{1}$$

Where R_t^i denotes the logarithmic return of the firm over the holding period $\boldsymbol{i}$.

However, VaR alone fails to capture the spillover of risk among firms in a connected industrial system. To overcome this limitation, CoVaR, proposed by Adrian and Brunnermeier (2008), extends the VaR concept by considering conditional dependence. According to the definition of Tobias and Brunnermeier (2016) , $CoVaR_t^{j|i}$ is the level of risk that a firm $\boldsymbol{j}$ is exposed to when the firm $\boldsymbol{i}$ is in an extreme condition, i.e. the VaR value of the firm $\boldsymbol{j}$ regarding the firm $\boldsymbol{i}$, which can be expressed as:

$$\Pr(R_t^j < CoVaR_t^{j|i} \,\big|\, R_t^i = VaR_t^i) = \tau \tag{2}$$

This framework enables a shift from individual risk evaluation to inter-firm risk transmission analysis, providing a foundation for the LASSO-CoVaR model developed in the next subsection.

3.2 Estimation of LASSO-CoVaR

The traditional estimation of CoVaR considers one-to-one relationships between firms here we expand it to a many-to-one link between firms, and considering the influence of other firms when estimating CoVaR, we include the VaR of other firms as dependent regression variables as well. Thus, CoVaR can be estimated as follows:

$$CoVaR_t^{j|-j} = X_t^{(j)} \hat{\beta}_t^{j|-j} = \hat{\beta}_0^{j|-j} + \hat{\beta}_{VaR}^{j|-j} VaR_t^{-j} + \hat{\beta}_C^{j|-j} C_{t-1}^j \tag{3}$$

Where $\hat{\beta}^{j|-j} \equiv \left\{\hat{\beta}_0^{j|-j}, \hat{\beta}_{VaR}^{j|-j}, \hat{\beta}_C^{j|-j}\right\}$ includes all regression coefficients, $X_t^{-j} \equiv \left\{1, VaR_{1-\tau,t}^{-j}, C_{t-1}^{j}\right\}$ is the vector of regression dependent variables, $VaR_{1-\tau,t}^{-j} = \{VaR_{1-\tau,t}^{1}, VaR_{1-\tau,t}^{2}, \ldots, VaR_{1-\tau,t}^{j-1}, VaR_{1-\tau,t}^{j+1}, \ldots, VaR_{1-\tau,t}^{N}\}$ is the set of VaR of all other firms except firm j, and C_{t-1}^{j} firm j is the firm characteristic at moment $t-1$.

Since not all other firms' VaRs have a significant impact on the CoVaR of a firm j, it is critical to select the other firms that have a significant impact on j in the CoVaR estimation. Drawing on the Least Absolute Shrinkage and Selection Operator- Conditional Value at Risk (LASSO-CoVaR) model of Xu et al. (2019), we utilise the LASSO methodology by adding the L1 penalty to the loss function and estimating the parameters:

$$\beta^{j|-j} = \operatorname{argmin}_{\beta^{j|-j}} \frac{1}{T}\sum_{t=1}^{T} \rho_\tau (R_t^j - X_t^{(j)} \beta^{j|-j}) + \lambda^j \frac{\sqrt{\tau(1-\tau)}}{T} \sum_{i=1, i \neq j}^{N} \hat{\sigma}_i \left|\beta_{VaR^i}^{j|-j}\right| \tag{4}$$

where $\hat{\sigma}_i^{\,2} = \frac{1}{T}\sum_{t=1}^{T}(VaR_t^i)^2$ is the variance of the regressor VaR and λ^j is the data-driven penalty parameter proposed by Belloni and Chernozhukov (2011). When λ^j is relatively large, some coefficients are shrunk toward zero, retaining only a few significant variables; when λ^j is relatively small, the model preserves more tail dependence relationships among firms. This method essentially belongs to a continuous shrinkage process, in which the introduction of the penalty term allows the regression coefficients of irrelevant variables to be compressed to zero during estimation, while simultaneously obtaining coefficient estimates for important variables. In this way, the model achieves variable selection and parameter estimation simultaneously. Compared with traditional subset selection criteria such as AIC and BIC, this continuous shrinkage mechanism effectively avoids the instability and overfitting problems that often arise in high-dimensional data environments, thereby substantially improving the stability and interpretability of the estimation results. By collecting non-zero coefficients across all firms, we can map the risk transmission network within the industrial chain.

3.3 Construction of Value Chain Network

Using LASSO-CoVaR, this paper selects the regressor $\tilde{X}_t^{(j)}$ that has a significant effect on the firm j:

$$CoVaR_{\tau,t}^{j|-j} = \tilde{X}_t^{(j)\prime} \hat{\beta}^{j|-j} \tag{5}$$

where $\tilde{X}_t^{(j)} \equiv \left\{1, VaR_{\tau,t}^{-j|R}, C_{t-1}\right\}$ includes the VaR of other firms that have significant influence. $VaR_{\tau,t}^{-j|R}$ denotes a subset of $VaR_{\tau,t}^{-j}$, corresponding to the coefficient $\hat{\beta}_{VaR_{\tau,t}^{-j|R}}^{j|-j}$.

We construct a value chain network $G = (V, E)$ with a set of nodes $V = \{V_1, V_2, \ldots, V_N\}$ and a set of directed edges E. The weighted adjacency matrix of this value chain network is defined as follows:

$$A_{i,j} = \left\{ \begin{array}{c} \hat{\beta}_{\tau,\ VaR_{\tau,t}^{j|-j}}^{j|-j}, \text{if } VaR_{\tau,t}^{j|-j} \text{ is selected} \\ \\ 0, \text{ otherwise} \end{array} \right\} \tag{6}$$

where $i, j = 1, 2, \cdots, N$. $\hat{\beta}_{\tau, VaR_{\tau,t}^{j|i}}^{j|-j}$ is the i element of $\hat{\beta}_{\tau, VaR_{\tau,t}^{-j|R}}^{j|-j}$ and $\left|\hat{\beta}_{\tau, VaR_{\tau,t}^{j|i}}^{j|-j}\right|$ is the absolute value of $\hat{\beta}_{\tau, VaR_{\tau,t}^{j|i}}^{j|-j}$, which represents the absolute value of edge weights.

In summary, this paper uses a two-stage quantile regression method to measure VaR and CoVaR, constructs a business credit value chain, and then studies the credit risk of the business credit value chain.

4. Empirical Study

This paper takes the pig industry chain of Muyuan Foods Co., Ltd. as a case to conduct empirical research on business credit risk assessment.

4.1 Research Questions and Industrial Context

To identify and objectively evaluate business credit risk, the assessment framework should be designed in line with the specific characteristics of the target firms and the available business credit information. This process involves selecting appropriate indicators and establishing suitable evaluation models and methods. In this study, the empirical analysis is based on data of the pig industry chain of Muyuan Foods Co., Ltd. Given the presence of industry-chain financing in this chain, with Muyuan Foods Co., Ltd. as the core firm, this paper applies business credit risk assessment methods to quantitatively measure the risk of the firms in the chain, as well as the overall risk of the industry chain.

Muyuan Foods Co., Ltd. is a leading firm in China’s pig farming industry and was listed on the stock market in 2014. In 2020, Muyuan Foods Co., Ltd. sold 19.6 million pigs. By developing the pig industry chain, the firm has established 214 pig farms across the country, with plans to reach 40 million pigs by 2025. It has also expanded into upstream and downstream segments of the industry chain, intensifying research into sow breeding technology and pig farming robotics to enhance the technical content of its farming operations and achieve international leadership. In 2020, the firm accelerated the construction of livestock equipment industrial parks and feed processing industrial parks, forming the upstream market of the pig industry. By the second half of 2020, it had completed the extension of the downstream industry, constructing four pig slaughterhouses, with six more under construction. Once fully completed, the annual slaughter capacity could reach 40 million pigs. And a food processing industrial park and a national pork sales network have been established.

Through a “fully self-breeding, large-scale, and integrated” farming model, Muyuan Foods Co., Ltd. has established itself as the dominant and core firm in the pig industry chain. For example, in the construction of pig farms at the upstream end of the industry chain, most projects involve advance payments, and construction firms often find it difficult to obtain loans from banks, resulting in a shortage of funds. Many firms in this industry chain alleviate their financial pressure through industry chain finance. Industry chain finance can be viewed as a financing method where financial institutions conduct a comprehensive credit analysis of the core firm and its upstream and downstream firms, providing more flexible credit support to firms across the supply chain. However, while industry chain finance can address some firms' financing difficulties, it cannot completely eliminate existing credit risks. Especially within the industry chain, firms are interconnected through transactions involving funds and materials, forming an industry chain network, and credit risks can dynamically propagate through this network. This holds significant implications for financing firms, core firms, and banking institutions.

4.2 Data and Variable Description

4.2.1 Data Sources and Sample Selection

In order to assess the credit risk of the pig industry chain with Muyuan Foods Co., Ltd. as the core firm, this paper needs to collect and collate data resources in several fields, of which the data mainly include three categories: the first category , industry chain relationship data; the second category, the financial data of the important node firms in the industry chain; and the third category, the stock market related data of the important node firms in the industry chain.

Considering the completeness of the data, eleven listed firms in the industry chain including Muyuan Foods Co., Ltd. as the core firm are selected as samples in this paper. Since the authors have project cooperation with the local government of the core firm of the industry chain, this paper can obtain the list of five major customers and five major suppliers of Muyuan Foods Co., Ltd. through project cooperation. For the sake of data confidentiality, the names of specific firms in the industry chain are not disclosed. In this study, all firms in the industrial chain are anonymized and represented by capital-letter acronyms (e.g., MYGF, NCP, LDRS), and each acronym denotes a distinct listed firm. The financial data and stock market data of the firms are obtained from CSMAR and Genius Finance Database, respectively. Considering the serious phenomenon of missing data in the characteristics of some listed firms before 2017, the sample period is determined as from 3 January 2017 to 31 December 2020.

4.2.2 Variable Construction and Descriptive Statistics

The variables selected in this paper are divided into two categories: the first category is the response variable (Yield), which is obtained by calculating the daily closing price data of the stock; the second category is the firm-level characteristic variables, including market capitalization, book-to-market ratio and price-earnings ratio, which can also be obtained from the relevant financial reports. See Table 1 for specific definitions.

Table 1. Variables and Definitions

Variable Classification	Variable Name	Frequency	Definition
Response variable	Yield	Day	Obtained by calculating the stock's daily closing price data. $R_t^i = \ln(P_{i,t}/P_{i,t-1})$
Firm Characteristic Variables	Market Capitalisation	Day	Stock price per share multiplied by the total number of shares issued
	Book-to-market ratio	Day	The ratio of the firm's book value to its stock market value.
	P/E ratio	Day	The ratio of the stock price to its earnings per share

In Table 2, the results of descriptive statistics for each variable are reported. It can be seen that five firms have mean yields greater than 0 and six firms have mean yields less than 0; the standard deviations of the yields are all located between 0.02 and 0.04. The mean value of market capitalisation of each firm is relatively balanced, distributed between 21 and 26. The firm with the lowest book-to-market ratio is MYGF, and the highest is HLZC. In addition, the P/E ratio varies widely across firms, with the highest mean P/E ratio at 147.4760 for NCP and the lowest at 4.2093 for STKG.

Table 2. Descriptive Statistics Results for Each Variable

Firm	Yield		Market Capitalisation		Book-to-market ratio		P/E Ratio	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
MYGF	0.0012	0.0394	25.2526	0.8246	0.1645	0.0619	8.8318	232.4074
NCP	-0.0006	0.0239	23.1700	0.2582	0.4435	0.1080	147.4760	344.2201
LDRS	-0.0003	0.0331	22.7843	0.2152	0.2774	0.0557	35.3310	8.1332
HLZC	-0.0006	0.0251	21.8519	0.2071	0.9017	0.1846	13.8709	35.8627
BLGF	0.0000	0.0253	23.7409	0.2780	0.8696	0.2383	26.6551	10.363
YHCS	0.0004	0.0205	25.0902	0.1821	0.2559	0.0466	45.9613	6.3555
STKG	0.0004	0.0254	22.6556	0.2935	0.4906	0.1429	4.2093	31.8157
JHSW	-0.0006	0.0249	22.1460	0.2277	0.3984	0.0979	28.4029	7.6058

(Table 2. continued)

Firm	Yield		Market Capitalisation		Book-to-market ratio		P/E Ratio	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
SWGF	-0.0004	0.0251	23.8276	0.1683	0.2105	0.0428	52.9084	39.5687
BDH	0.0005	0.0247	23.7495	0.2320	0.3187	0.0656	24.4790	6.6494
ZSKJ	-0.0002	0.0308	22.5133	0.3049	0.2278	0.0562	42.8384	17.687

4.3 Business Credit Risk Assessment Based on VaR and CoVaR

4.3.1 Firm-Level Credit Risk Evaluation

The VaR values of 11 firms the 99% confidence level are given in Fig. 1, where the horizontal coordinate is the time and the vertical coordinate is the earnings. The black line shows the yields of each of the 11 listed firms in the industry chain, and the red line shows the VaR value of each firm. The VaR value reflects the maximum loss that each firm may suffer in the future under a given confidence level (99%) during a given holding period. In the case of Muyuan Foods Co., Ltd. , with the exception of 3 July 2018 and 4 June 2020, MYGF's yields did not exceed its VaR value at a 99% confidence level.

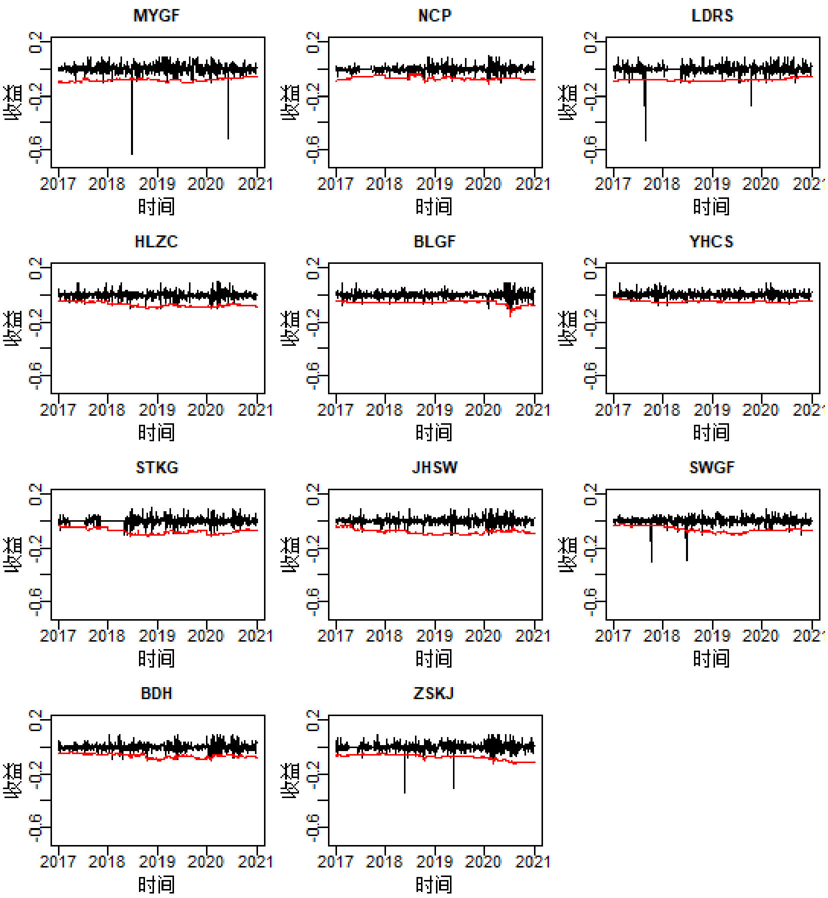

Figure 1. VaR Estimates for the Eleven Listed Firms

4.3.2 Inter-Firm Credit Risk Spillover

To estimate the interaction of credit risk between firms, this paper uses the LASSO-CoVaR method. Due to space constraints, only the estimation results at the 99% confidence level are reported here; estimation results at other confidence levels are similar. The estimation results for 11 firms are reported in Table 3. Taking MYGF as an example, HLZC and JHSW have a significant impact on MYGF. At the same time, MYGF also has a significant impact on NCP, BLGF, YHCS, JHSW, and BDH.

Table 3. LASSO-CoVaR Estimation Results

Variable	MYGF	NCP	LDRS	HLZC	BLGF	YHCS	STKG	JHSW	SWGF	BDH	ZSKJ
Intercept	-0.41	-0.05	0.45	-0.04	0.04	0.56	-0.4	0.26	-0.45	-0.06	1
P/E Ratio											
Market Cap	0.01		-0.02			-0.02	0.02	-0.02	0.02		-0.05
B/M Ratio	0.03			-0.02	-0.03						
MYGF	—	0.03			0.02	0.12		0.10		0.22	
NCP		—		0.11	0.04	0.14	0.18	0.24	0.22	0.09	
LDRS		0.09	—	0.15			0.05				
HLZC	0.13	0.07		—	0.16		0.34			0.12	0.07
BLGF		0.17		0.13	—	0.10		0.36	0.04		
YHCS				0.01		—					
STKG			0.19	0.10			—	0.08			0.03
JHSW	0.31	0.23			0.16			—	0.37	0.01	0.32
SWGF					0.22				—		
BDH		0.21	0.29							—	
ZSKJ				0.15			0.08				—

Next, the results of the table 3 are collated to obtain table 4, which shows more intuitively the interactions among the credit risks of the 11 firms. In the case of LDRS, for example, the influence magnitudes of BDH and STKG on it is 0.29 and 0.19, respectively; and its influence magnitude on NCP, STKG and HLZC is 0.09, 0.05 and 0.15, respectively.

Table 4. LASSO-CoVaR Estimation Results

Influencing Firm	Affected Firm	Influence Value	Influencing Firm	Affected Firm	Influence Value
LDRS	NCP	0.09	YHCS	HLZC	0.01
HLZC	NCP	0.07	STKG	HLZC	0.10
JHSW	NCP	0.23	NCP	HLZC	0.11
MYGF	NCP	0.03	BLGF	HLZC	0.13
BDH	NCP	0.21	LDRS	HLZC	0.15
BLGF	NCP	0.17	ZSKJ	HLZC	0.15
HLZC	STKG	0.34	HLZC	BDH	0.12
ZSKJ	STKG	0.08	JHSW	BDH	0.01
NCP	STKG	0.18	MYGF	BDH	0.22
LDRS	STKG	0.05	NCP	BDH	0.09
MYGF	JHSW	0.10	NCP	BLGF	0.04
STKG	JHSW	0.08	SWGF	BLGF	0.22
BLGF	JHSW	0.36	JHSW	BLGF	0.16
NCP	JHSW	0.24	HLZC	BLGF	0.16
HLZC	MYGF	0.13	MYGF	BLGF	0.02
JHSW	MYGF	0.31	NCP	YHCS	0.14
BDH	LDRS	0.29	MYGF	YHCS	0.12
STKG	LDRS	0.19	BLGF	YHCS	0.10
NCP	SWGF	0.22	HLZC	ZSKJ	0.07

(Table 4. continued)

Influencing Firm	Affected Firm	Influence Value	Influencing Firm	Affected Firm	Influence Value
JHSW	SWGF	0.37	STKG	ZSKJ	0.03
BLGF	SWGF	0.04	JHSW	ZSKJ	0.32

4.3.3 Systemic Risk Interaction Between Firm and Industry Chain

Let $j = s$ in equation (2), then $CoVaR_t^{s|i}$ denotes the risk spillover effect on the whole industrial chain system when a crisis occurs in the firm i .

$$\Pr(R_t^s < CoVaR_t^{s|i} \mid R_t^i = VaR_t^i) = a \tag{7}$$

where $R_t^s = \sum_{i=1}^{11} R_t^i$. A quantile regression model is built to estimate equation (8), where $R_t^{i|R}$ is the yields of the other firms selected from the LASSO-CoVaR method that have a significant impact on the firm i :

$$R_t^{s|i} = \beta_0^{s|i} + \beta_C^{s|i} C_{t-1} + \beta_R^{s|i} R_t^{i|R} + \varepsilon_t^{s|i} \tag{8}$$

Calculate $CoVaR_t^{s|i}$ using the coefficients obtained from the quantile regression estimation by substituting them into equation (9):

$$CoVaR_t^{s|i} = \hat{\beta}_0^{s|i} + \hat{\beta}_C^{s|i} C_{t-1} + \hat{\beta}_R^{s|i} VaR_t^{i|R} \tag{9}$$

In Fig. 2, the $CoVaR_t^{s|i}$ of 11 firms in the MYGF industry chain is shown, where the black line is the total yield of the whole industry chain, and the red line is the $CoVaR_t^{s|i}$ of the firm. It can be seen that the value at risk of the whole industry chain when a single listed firm in the chain is in trouble reflects the systemic risk of a single listed firm. The results reveal a clear structural pattern aligned with the industrial hierarchy. Upstream suppliers (blue nodes in Figure 4) exhibit higher CoVaR volatility, implying that shocks originating from the supply side have a stronger potential to depress the overall system performance. By contrast, downstream customers (green nodes in Figure 4) generally display lower CoVaR fluctuations, indicating that their individual distress has limited feedback on the upstream system as a whole. Taken together, Figure 2 confirms that upstream shocks dominate systemic risk generation in the MYGF industrial chain.

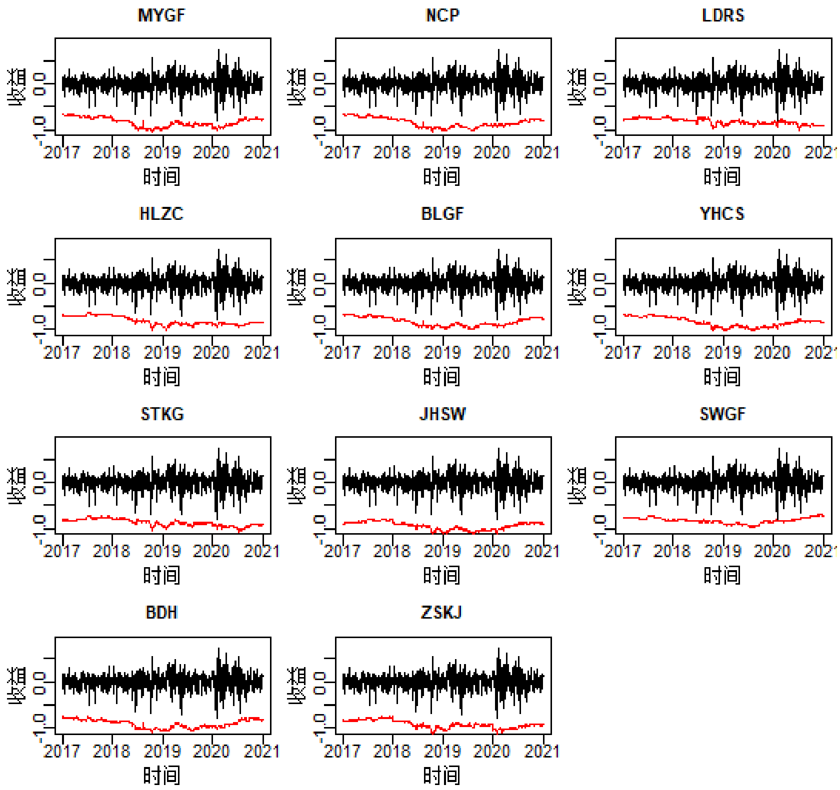

Figure 2. $CoVaR_t^{s|i}$ Estimates for the Eleven Listed Firms

Similarly, by making $i = s$ in Eq. (9), $CoVaR_t^{j|s}$ denotes the risk spillover effect on the firm j when the whole industrial chain system s is in crisis.

$$\Pr(R_t^j < CoVaR_t^{j|s} \mid R_t^s = VaR_t^s) = a \tag{10}$$

A quantile regression model is built to estimate equation (11), where $R_t^{j|R}$ is the yields of other firms selected from LASSO-CoVaR that have a significant effect on firm j :

$$R_t^{j|s} = \beta_0^{j|s} + \beta_C^{j|s} C_{t-1} + \beta_R^{j|s} R_t^{j|R} + \varepsilon_t^{j|s} \tag{11}$$

Calculate $CoVaR_t^{j|s}$ by substituting the coefficients obtained from the quantile regression estimation into equation (12):

$$CoVaR_t^{j|s} = \hat{\beta}_0^{j|s} + \hat{\beta}_C^{j|s} C_{t-1} + \hat{\beta}_R^{j|s} VaR_t^{j|s} \tag{12}$$

In Figure 3, it shows the $CoVaR_t^{j|s}$ of the 11 firms in the MYGF industry chain, where the black line is the individual yield of the 11 firms in the industry chain, and the red line is the corresponding $CoVaR_t^{j|s}$ of the firm. It can be seen that when the entire industrial chain is in trouble, the risk value of individual listed firms increases. Here, downstream customers (green nodes in Figure 4) display stronger sensitivity to system-wide shocks, as their profitability directly depends on upstream supply stability and price fluctuations. In contrast, upstream suppliers appear more resilient, showing smaller deviations of CoVaR under system stress. This may be attributed to their diversified client bases and stronger bargaining positions. MYGF, located at the core, maintains moderate fluctuations, reflecting its dual role as both transmitter and receiver of risk within the chain.

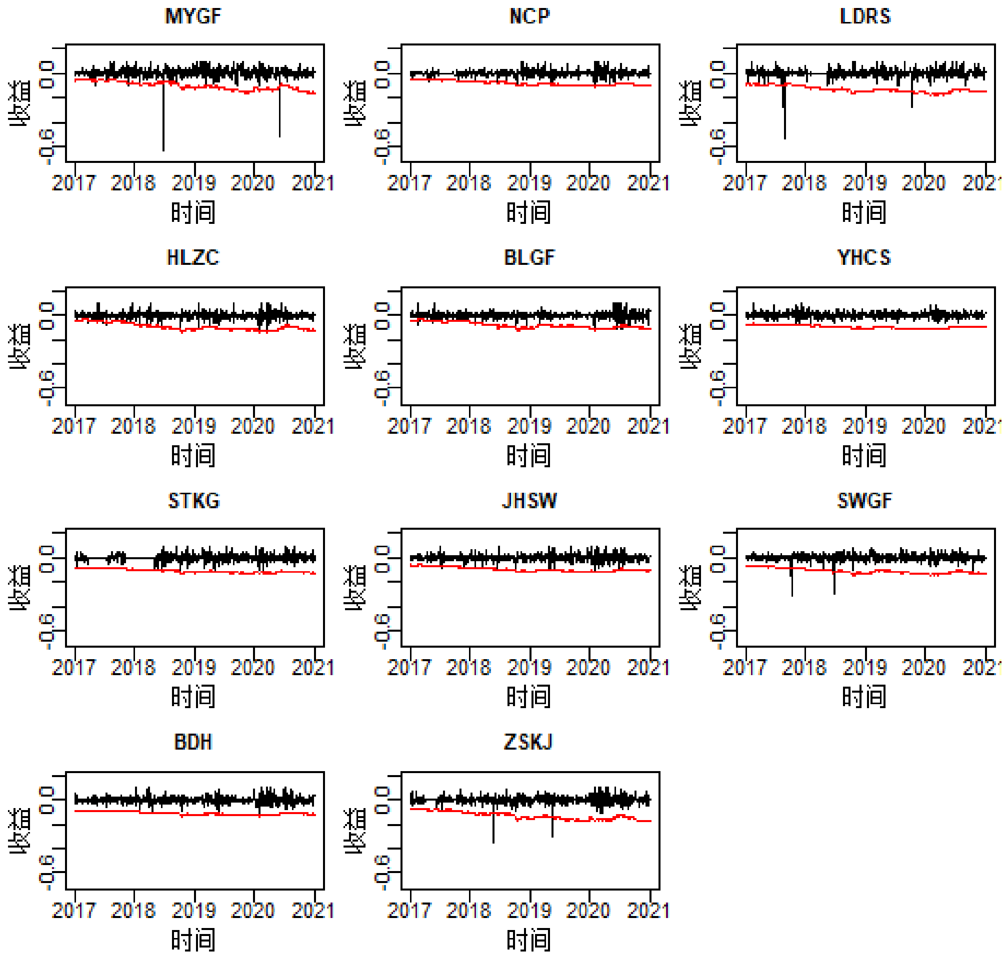

Figure 3. $CoVaR_t^{j|s}$ Estimates for the Eleven Listed Firms

4.4 Industrial Chain Credit Network and Structural Analysis

4.4.1 Industry Chain Network Construction

According to Figure 4 firm impact results, the industry chain network with MYGF as the core firm can be drawn, as shown in Figure 4. The red labels in the centre of the figure is the MYGF, the green labels on the top are the customers of the MYGF, and the blue labels on the bottom are the suppliers of MYGF. It can be seen that except for LDRS, ZSKJ and SWGF, all other firms have established links with MYGF.

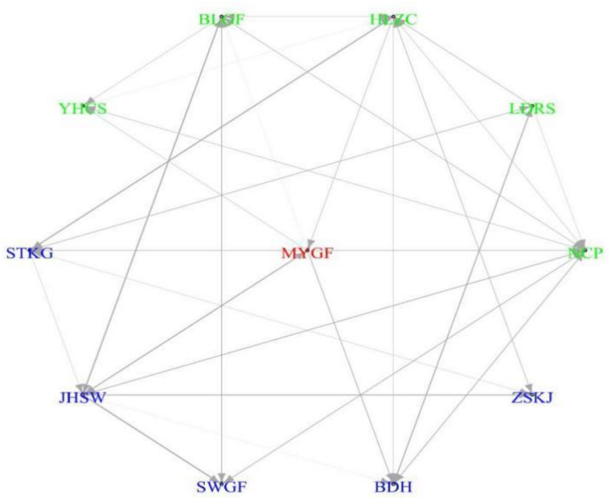

Figure 4. Industrial Chain Network

In order to reflect the importance of nodes within the industrial chain network, we measure several centrality indicators, including in-degree, out-degree, closeness centrality, betweenness centrality, and eigenvector centrality (see Table 5). Specifically, in-degree refers to the number of incoming edges to a node, while out-degree denotes the number of outgoing edges from a node. Closeness centrality reflects a node's overall accessibility within the network — the shorter the average distance from a node to all other nodes, the higher its centrality. Betweenness centrality captures how often a node appears on the shortest paths between other nodes, indicating its role as a bridge or mediator in the network. Additionally, eigenvector centrality considers not only how many connections a node has, but also the centrality of the nodes it is connected to, thereby capturing both direct and indirect influence. As shown in the data, MYGF has an in-degree of 2, an out-degree of 5, a closeness centrality of 0.07, a betweenness centrality of 0.02, and an eigenvector centrality of 0.61. Its out-degree and closeness centrality rank among the highest of the 11 firms in the network.

Table 5. Node Characteristics of Each Firm

Node Characteristics	**MYGF**	**NCP**	**LDRS**	**HLZC**	**BLGF**	**YHCS**	**STKG**	**JHSW**	**SWGF**	**BDH**	**ZSKJ**
In-degree	2	6	2	6	5	3	4	4	3	4	3
Out-degree	5	7	3	6	5	1	4	6	1	2	2
Closeness Centrality	0.07	0.08	0.06	0.07	0.06	0.05	0.06	0.07	0.04	0.05	0.05
Betweenness Centrality	0.02	0.20	0.02	0.29	0.15	0.00	0.08	0.10	0.00	0.05	0.01
Eigenvector Centrality	0.61	1.00	0.43	0.90	0.84	0.39	0.62	0.80	0.40	0.55	0.45

4.4.2 Influence of Industry Chain Structure

In order to test the impact of the network structure characteristics of the industry chain in which the firm is located on the risk spillover of this industry chain, the following four linear regression models are estimated separately:

$$MeanCoVaR^{s|i} = \alpha_1 \mathrm{Mean}firmfeartures + \alpha_2 networkfeatures + \varepsilon \tag{13}$$

$$\mathrm{Median}CoVaR^{s|i} = \alpha_1 \mathrm{Median}firmfeartures + \alpha_2 networkfeatures + \varepsilon \tag{14}$$

$$MeanCoVaR^{j|s} = \alpha_1 Meanfirmfeartures + \alpha_2 networkfeatures + \varepsilon \tag{15}$$

$$MedianCoVaR^{j|s} = \alpha_1 Medianfirmfeartures + \alpha_2 networkfeatures + \varepsilon \tag{16}$$

In Eq. (13), $MeanCoVaR^{s|i}$ represents the mean value of $CoVaR^{s|i}$, $Meanfirmfeartures$ represents the mean value of each firm-level characteristic variable, and $networkfeatures$ represents each network characteristic variable; in Eq. (14), $MedianCoVaR^{s|i}$ represents the median value of $CoVaR^{s|i}$, and $Medianfirmfeartures$ represents the median value of each firm-level characteristic variable. Similarly, in Eqs. (15) and (16), $MeanCoVaR^{j|s}$ and $MedianCoVaR^{j|s}$ represent the mean and median of $CoVaR^{j|s}$, respectively. Due to the serious multicollinearity among the explanatory variables, the stepwise regression method was chosen to estimate the above four equations.

M1 to M4 correspond to the estimation results of Eqs. (13) to (16), respectively. In M1, proximity centrality and eigenvector centrality are significantly and negatively correlated with the mean of $CoVaR^{s|i}$, and mediator centrality and out-degree are significantly correlated with the mean of $CoVaR^{s|i}$. In M2, mediator centrality and eigenvector centrality are also shown to be significantly correlated with the median of $CoVaR^{s|i}$. In M3 and M4, it can be found that out-degree is significantly negatively correlated with the mean and median of $CoVaR^{j|s}$, while eigenvector centrality is significantly positively correlated with the mean and median of $CoVaR^{j|s}$. All the above results show that the characteristics of industrial chain network structure have a significant impact on the risk spillover in the industrial chain, which needs to be given enough attention in the credit risk evaluation.

Table 6. Regression Analysis Results

Variable	M1	M2	M3	M4
Yield			-36.4800*	-25.0800*
			(11.8700)	(2.8040)
Market Cap	0.0387***	0.0560***	0.0243**	0.0092*
	(0.0069)	(0.0100)	(0.0057)	(0.0011)
P/E Ratio	0.0005*		-0.0003*	-0.0007*
	(0.0002)		(0.0001)	(0.0001)
Book-to-market ratio				-0.0509
				(0.0120)
Closeness Centrality	-8.5283*		3.7650	2.3410
	(3.8028)		(1.7940)	(0.5861)
Betweenness Centrality	1.1392***	0.9596***	-0.1458	0.1622
	(0.2116)	(0.2430)	(0.0836)	(0.0621)
Out-degree	0.0643*		-0.0344*	-0.0493*
	(0.0299)		(0.0133)	(0.0078)
In-degree				-0.0334
				(0.0067)
Eigenvector Centrality	-0.5488**	-0.2285**	0.2789**	0.5914*
	(0.1786)	(0.0962)	(0.0719)	(0.0801)
Coefficient	-1.2643***	-2.1086***	-0.9192**	-0.4914**
	(0.2276)	(0.2334)	(0.1925)	(0.0346)
Adjusted R-squared	0.8212	0.7618	0.8660	0.9829

Note: (1) The yield, market capitalisation, P/E ratio, and book-to-market ratio are chosen as the mean in M1 and M3, and their medians in M2 and M4; (2) *, **, and * indicate significant at the 10%, 5%, and 1% levels, respectively; (3) The values in parentheses indicate the Z-statistics.

5. Business Credit Value Chain Risk Response Strategies

In practicing business credit risk management, it is essential to first accurately identify the type of risk. If the risk stems from an individual firm, it can be handled independently. However, if it is a systemic or environmental credit risk, it must be taken seriously. Accordingly, business credit risk response strategies should be divided into two categories: individual risk treatment and overall risk response within the business credit value chain. For risks at the individual firm level, traditional credit management provides relatively mature methods. However, effective strategies for addressing the overall credit risk of the business credit value chain remain relatively underdeveloped. This paper proposes the establishment of a targeted risk response strategy for the business credit value chain, which includes identifying the sources of business credit risk, blocking the transmission of business credit risk across the value chain, strengthening effective management of business credit risk, and dynamically adjusting business credit risk management strategies based on the outcomes of implementation.

5.1 Identify the Source of Business Credit Risk

The premise of effective management of business credit risk is to find out the reasons for the formation of business credit risk. Business credit risk is a complex social and economic phenomenon, and the understanding of its causes is a difficult problem in the response to business credit risk. The causes of business credit risk can be explored from three aspects: business credit environment, business credit system and business credit management. Only when the source is found can effective methods be adopted. Among them, the most crucial factor is the failure of business credit management. In a complex and ever-changing market environment, parties involved in business transactions often lack sufficient experience and capabilities to fully understand and manage business credit risk, including its origins, development, and potential consequences. This lack of understanding further exacerbates the inherent uncertainty of business credit activities. In such circumstances, business entities are prone to making mistakes or failing to take effective preventive measures in a timely manner in such activities, resulting in various losses. Common causes include mistakes made by personnel responsible for managing business credit activities or insufficient control of business credit risk. Participants in business credit activities should enhance their efficiency in managing business credit activities and associated risks, clarify the objectives of management, improve risk control effectiveness and activity management efficiency, thereby achieving the overall benefits of credit activities. In management practice, business credit activities have both positive and negative mechanisms, which reflect the successful or failed credit activity trajectories of the entities involved. Therefore, identifying, evaluating, warning, controlling, and monitoring are business credit activity management is ineffective is the top priority of business credit risk management.

5.2 Blocking the Transmission of Business Credit Risk Across the Value Chain

5.2.1 Mechanism of Business Credit Risk Formation

In a highly volatile and uncertain business credit environment, the credit system is prone to uncontrollable and irregular fluctuations. If risk-management measures fail at the same time, these irregular fluctuations may further slip out of control, causing the system to become unstable or even suffer systemic failure, and eventually to evolve into persistent irregular oscillations. Such developments can trigger more severe risk events and ultimately manifest as heightened business credit risk. Based on the above analysis, several conclusions can be drawn. First, the environment in which business credit operates cannot be altered by credit participants; they can only adapt to it. Second, the business credit system is constrained and influenced by numerous external factors that are likewise difficult to eliminate.

Therefore, throughout the formation process of business credit risk, the decisive influence lies in the willingness and initiative of credit-participating subjects to improve their business-credit behaviour and enhance the effectiveness of credit management, thereby reducing risks at their source and preventing their occurrence.

5.2.2 Business Credit Risk Management Concept

There are three causes of business credit risk: the first one is the deterioration of business credit environment; the second one is the damage of business credit system; and the third one is the failure of business credit management. In order to effectively manage and avoid business credit risk, industry chain players must clarify the interrelationship between them. The three causes of risk are both independent of each other and interact with each other. By analysing the degree of suitability of the business credit environment, the degree of security of the business credit system and the degree of effectiveness of business credit management, the preliminary idea of improving the "degree" of these three aspects can help business credit subjects adapt to changes in the business credit environment, weaken the fluctuations brought about by the business credit system, and ensure the effectiveness of business credit management, with a view to improving the reliability of business credit. The three causes are interrelated and interact with each other.

The above three forces are interrelated and interact with each other, and we believe that the reliability of business credit is measured by the product of the appropriateness of the business credit environment, the security of the business credit system, and the effectiveness of business credit management, as shown in Equation 24.

$$K_t = E_t S_t M_t \tag{24}$$

The degree of unreliability in the system (i.e., business credit risk incident) can also be expressed by the degree of unreliability. Meanwhile, the degree of risk of business credit is represented by using the risk coefficient p, then the degree of business credit risk is the product of the business credit risk coefficient and the degree of unreliability of business credit activitiesF_t, as shown in Equation 25.

$$R_t = pF_t = p(1 - K_t) \tag{25}$$

5.3 Strengthening Effective Management of Business Credit Risk

Failure of business credit management is the main cause of business credit risk. The reasons for the failure of management of business credit activities are various, and the management of the business credit value chain entities is a cross-organisational management, which is very difficult to manage. Cross-organisational, long-term management requires not only the efforts of the main body of business credit activities, but also the joint efforts of business credit value as a whole. Therefore, to eliminate the occurrence of business credit management failure and improve the effectiveness of business credit activity management is an important way to prevent business credit risk. To solve these problems, we should start from the fundamental problems of business credit management and try to do well in the following aspects.

5.3.1 Strengthen the Construction of Business Credit Culture

In the process of improving business credit risk management, the role of business credit culture must be emphasised. Business credit culture is an important soft environment for business credit risk management. As a participant in market economic activities, the main body of business credit activities is not only the producer of business credit risk, but also the bearer of business credit risk. Therefore, each subject in the industrial chain should pay attention to the management of business credit risk and improve the knowledge of the law of business credit risk, so as to continuously improve the level of business credit risk management and eliminate the hidden danger of business credit risk.

5.3.2 Improve Business Credit Risk Management Mechanism

In terms of business credit risk management mechanism, the focus should be to improve the business credit management methods and approaches. In the process of business credit management, business credit activity owners should carefully analyse the credit environment, identify the relevant risk factors, formulate preventive measures in advance, and standardize management behaviors. At the same time, they should study the application of modern risk management technology in business credit risk management, and control and disperse the risk through professional risk management technology. The most important thing is to improve the overall industrial chain credit level and enhance the ability to resist various risks, so as to reduce the risk level.

5.3.3 Reasonable Application of Business Credit Risk Management Tools

Business credit risk management is a long-term and complex management activity that needs to be carried out by firms within organisations. The main body of business credit activities should make use of diversified ways to make reasonable use of all kinds of business credit risk management tools. In this way, they can prevent potential risks, ensure the relative stability of the business credit environment and the sustainable development of the business credit value chain, and ultimately realise the value addition in the business credit value chain.

6. Conclusion

6.1 Theoretical Contributions

This paper makes four theoretical contributions. First, by introducing the VaR, CoVaR, and LASSO-CoVaR models, it expands the research perspective on systemic credit risk, enabling a transition from individual firm-level to industrial chain-level risk measurement and enriching the theoretical toolbox for credit risk assessment. Second, by employing indicators such as in-degree, out-degree, closeness centrality, betweenness centrality, and eigenvector centrality, it is the first time to portray how a firm's structural position within the industrial chain influences risk spillover, thereby enhancing the explanatory capacity of credit contagion pathways. Third, by integrating financial data with industrial relational data, the study proposes a dual-dimensional credit risk evaluation method that improves both the breadth and precision of credit risk identification for small and medium-sized enterprises. Finally, through an empirical analysis of a regional pig farming industrial chain, the study validates the applicability and explanatory power of the theoretical model, offering practical support and a methodological paradigm for applying the "Business Credit Value Chain" theory in complex industrial contexts such as agriculture and manufacturing.

6.2 Managerial Implications

This paper provides multifaceted managerial implications for enterprise managers, financial institutions, and policymakers. First, core enterprises should actively strengthen their credit management functions. As the "credit hub" of the industrial chain, they can enhance the overall credit stability of upstream and downstream firms by improving their own credit quality and information transparency, thereby reducing systemic credit risk across the entire chain. Second, financial institutions engaged in industrial chain finance should move beyond a sole reliance on traditional financial statements. Instead, they should incorporate structural positions and inter-firm relationships within the industrial network, using systemic risk assessment tools such as CoVaR to enable more precise credit decisions and risk management. Third, small and medium-sized enterprises (SMEs) should emphasize credit interaction with core enterprises, enhancing their value as credit nodes in the industrial chain by improving transaction stability and contract fulfillment, thereby increasing access to financing. Fourth, at the policy level, it is essential to promote the development of integrated platforms for heterogeneous data sources, enabling the interconnection and sharing of administrative, transactional, financial, and credit data to support dynamic monitoring and early warning of risks within the credit value chain. Fifth, regulatory authorities are advised to foster a risk governance framework centered on "credit transmission chains," guiding the evolution of credit systems from individual evaluations to systemic management and enhancing the overall resilience of industrial economies.

6.3 Limitation and Future Research

Despite achieving certain theoretical and empirical advancements in the identification and evaluation of credit risk within the business credit value chain, this study still has limitations that open avenues for further research. First, in terms of data acquisition, the study takes the pig industry chain as a case example; however, due to constraints in data availability and time span, it fails to capture a complete industrial cycle. In particular, the dynamic effects of industry-specific factors such as the "pig cycle" have not been thoroughly explored. Future studies could incorporate longer time series data and cross-industry diversified samples for validation. Second, although the study adopts advanced models such as VaR, CoVaR, and quantile regression, it does not integrate higher-order nonlinear approaches such as deep learning or graph neural networks. This results in insufficient dynamic simulation of risk spillover paths. Subsequent research may consider incorporating artificial intelligence methods to enhance the intelligent level of risk prediction and early warning systems. Third, while this study analyzes the propagation mechanism of credit risk from the perspective of network centrality, it lacks systematic investigation into chain-based feedback loops and potential asymmetric contagion effects. Future work may construct more complex dynamic evolutionary network models and simulate heterogeneous agent behaviors at the micro level. Furthermore, from a theoretical standpoint, the business credit value chain remains an emerging paradigm without a unified conceptual framework or classification system. Future research could deepen exploration in areas such as theoretical system construction, indicator integration, and institutional response mechanisms.

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The data are not publicly available due to privacy or ethical restrictions.

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The authors declare no conflicts of interest.

Conflicts of Interest

The authors declare no conflicts of interest.

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About Author(s)

Feng Yi is an editor at the Center for Economics, Management, and Law of Higher Education Press. She holds a Ph.D. in Management, and her research and editorial work primarily focus on marketing, economics, and management.

Zhang Yunqi is a Professor and Ph.D. advisor at the School of Business, Central University of Finance and Economics. He holds a Ph.D. in Management and specializes in marketing risk management and business credit management.

Geng Ranchen is a doctoral student at the School of Business, Central University of Finance and Economics. His primary research interest lies in business credit management.