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Capital Flow Risk Modeling and Empirical Analysis of Financial Data From The Perspective of Supply Chain Finance

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ABSTRACT

Supply chain finance, a key tool for optimizing capital allocation across the industrial chain, faces core risks centered on disruptions and blockages in capital flows. This study focuses on capital flow risk in the context of supply chain finance, constructing a multi-level risk identification and quantitative assessment model and conducting empirical testing based on enterprise financial data. The study first systematically examines the formation mechanisms and transmission pathways of supply chain capital flow risk, identifying key dimensions such as core enterprise credit risk, trade background authenticity risk, operational risk, and external environmental risk. Furthermore, combined with enterprise financial statement data, a comprehensive capital flow risk assessment model integrating logistic regression with an indicator-based early warning system is constructed. The empirical analysis utilizes the financial data of 500 sample enterprises across the upstream, midstream, and downstream supply chains in my country's manufacturing and wholesale and retail sectors over the past five years, along with selected supply chain finance business data, which has been rigorously cleansed and processed. The results demonstrate that the quick ratio and cash flow gap volatility of core enterprises significantly explain the overall supply chain capital flow risk; abnormally prolonged accounts receivable turnover days for small and medium-sized enterprises is an important early warning signal of risk; the model achieves an 82.3% accuracy rate in identifying high-risk enterprises, with an average early warning time of three months. This study provides financial institutions with operational model tools and data support for accurately identifying, quantifying and managing supply chain finance cash flow risks, and has practical value for improving the robustness and efficiency of supply chain financial services.

KEYWORDS

Supply chain finance; Cash flow risk; Risk modeling; Financial indicators; Logistic regression; Empirical analysis

1. INTRODUCTION

Against the backdrop of deep global industrial chain integration, supply chain finance effectively alleviates financing constraints for small and medium-sized enterprises by optimizing capital allocation, becoming a key tool for serving the real economy. This model leverages the creditworthiness of core enterprises, integrating information, logistics, and capital flows to provide systematic financing support for supply chain nodes. However, the complexity and fragility of supply chain networks expose embedded financial activities to unique capital flow risks. These risks have significant transmission effects: deteriorating payment capabilities of core enterprises can trigger upstream collection crises; distorted trade backgrounds or duplicate financing can lead to fraud risks; operational inefficiency can hinder capital turnover; and combined with external shocks such as macroeconomic policies and industry cycles, they can ultimately trigger systemic risks throughout the supply chain. Traditional single-enterprise credit assessment methods struggle to capture the dynamic transmission characteristics of these risks.

Existing research has significant limitations: most results focus on theoretical frameworks and qualitative analysis, lacking quantitative modeling based on real financial data. Limited empirical research, due to small sample sizes, narrow industry coverage, or insufficient exploration of the value of corporate financial data, struggles to support effective risk warnings.

This study addresses these gaps and innovatively constructs a capital flow risk assessment model that integrates multidimensional financial indicators. By integrating publicly available corporate financial statement data and applying econometric methods to develop a risk early warning system, the team conducted a five-year empirical study of 500 supply chain companies in the manufacturing and wholesale and retail sectors. The findings can provide financial institutions with dynamic risk management tools, assist regulators in identifying systemic risks, and promote the robust development of the supply chain finance ecosystem.

2. THEORETICAL BASIS OF SUPPLY CHAIN FINANCE AND CASH FLOW RISK

Supply chain finance is a financial model in which banks and other financial institutions treat core enterprises and upstream and downstream companies as an integrated whole. Based on real trade scenarios, they flexibly utilize various financial products and services to provide comprehensive financing solutions to all supply chain participants, especially vulnerable small and medium-sized enterprises. Its core approach is to leverage the credit strength and control of core enterprises over the supply chain to integrate logistics, information, and capital flows, optimizing cash flow across the entire supply chain. Cash flow, the "blood" of supply chain operations, runs through every stage of the process, including procurement, production, sales, and payment collection. From a supply chain finance perspective, cash flow risk specifically refers to the possibility that capital circulation within the supply chain will be blocked, interrupted, or its value will depreciate due to factors such as inefficient internal supply chain operations, deteriorating financial conditions of key enterprises, external shocks, or fraudulent activity, leading to the potential for delayed repayment of related financing. Supply chain finance cash flow risks are characterized by distinct transmissibility, complexity, and concealment. Transmissibility means that risks do not exist in isolation. For example, delayed payments by downstream core enterprises can directly lead to cash flow constraints for upstream suppliers. If suppliers rely on financing based on these accounts receivable, the risk will be transmitted to the financial institutions providing the financing. Complexity stems from the networked nature of the supply chain, the diversity of participants, and the variety of risk factors. Concealment stems from information asymmetry within the supply chain. Fraudulent activities such as fraudulent trade and duplicate pledges, or misappropriation of funds, can be concealed by seemingly compliant documentation [1].

The theoretical foundations supporting cash flow risk management in supply chain finance primarily include transaction cost theory, principal-agent theory, and information asymmetry theory. Transaction cost theory explains that supply chain finance improves capital allocation efficiency by reducing search, negotiation, and monitoring costs. However, when coordination failures lead to a sharp increase in transaction costs, cash flow risk manifests itself. Principal-agent theory reveals the moral hazard and adverse selection issues that arise from inconsistent goals and unequal rights and responsibilities among multiple parties, such as core enterprises, financing enterprises, and financial institutions. For example, financing enterprises may misappropriate funds for non-agreed purposes. The theory of information asymmetry is key to understanding the root causes of risk. Financial institutions' understanding of the true state of supply chain transactions and the actual financial status of enterprises is far less than that of participating enterprises themselves. This information gap can easily lead to erroneous credit decisions and the accumulation of risks. Therefore, the key to effectively managing capital flow risks lies in designing appropriate risk-sharing and incentive mechanisms, and building a penetrating information-sharing platform to mitigate information asymmetry.

3. KEY IDENTIFICATION DIMENSIONS AND INDICATOR SYSTEM CONSTRUCTION FOR SUPPLY CHAIN CASH FLOW RISK

Accurately identifying the sources of supply chain cash flow risk is a prerequisite for effective modeling and management. From the perspective of risk sources, it can be divided into five key dimensions: core enterprise credit risk, trade background authenticity risk, supply chain operational risk, financing entity credit risk, and external environment risk. Core enterprise credit risk is pivotal; its financial health and willingness to fulfill obligations directly impact its ability to pay upstream and downstream companies and the effectiveness of its guarantees. The sudden collapse of a core enterprise is often the starting point for supply chain financial disasters. Trade background authenticity risk refers to whether the underlying transactions used for financing are genuine, legal, and unique. Fraudulent trade, duplicate financing, and forged documents are common fraudulent methods that can disrupt cash flow. Supply chain operational risk focuses on the overall operational efficiency and stability of the supply chain, including logistics efficiency, information sharing, order fulfillment rates, and accounts receivable collection cycles. Low operational efficiency directly leads to capital accumulation and increased liquidity pressures. The credit risk of the financing entity focuses on the financing entity's ability and willingness to repay, examining its asset-liability structure, cash flow, and operational stability. External environmental risks include macroeconomic fluctuations, industry policy adjustments, interest rate and exchange rate fluctuations, natural disasters, and other force majeure events. These factors can have systemic impacts on all supply chain participants.

To quantify and assess these risks, a scientific and operational indicator system must be established. Based on the availability and importance of publicly available corporate financial data, the following core early warning indicators can be designed: indicators reflecting payment capacity, such as the core enterprise's quick ratio, cash ratio, and times interest earned; indicators reflecting operational efficiency, such as accounts receivable turnover days, inventory turnover days, accounts payable turnover days, and cash conversion cycle; indicators reflecting profitability and cash flow, such as operating profit margin, net cash flow from operating activities/current liabilities, and free cash flow; and indicators reflecting leverage and debt repayment capacity, such as the debt-to-asset ratio, the proportion of short-term loans, and the cash flow gap. For trade-related risks, auxiliary indicators should be constructed in conjunction with non-financial information, such as counterparty concentration, consistency of historical transaction records, and verification of logistics documents. These indicators require differentiated thresholds based on industry characteristics [2]. For example, the inventory turnover threshold for the fast-moving consumer goods industry is inherently much lower than that for the heavy equipment manufacturing industry. By continuously monitoring the changing trends and combined anomalies of these indicators, early identification and location of cash flow risks can be achieved.

4. CONSTRUCTION OF A QUANTITATIVE CASH FLOW RISK MODEL: BASED ON THE INTEGRATION OF FINANCIAL INDICATORS

After clarifying the risk dimensions and indicator system, constructing a quantifiable risk assessment model is the key step. This study uses a fusion of a logistic regression model and a multi-indicator comprehensive early warning scorecard, aiming to combine the objective predictive power of a statistical model with the interpretability and operability of the scorecard rules. The goal of the model is to output a probability value or risk level reflecting the occurrence of cash flow risk at enterprises at supply chain nodes.

First, the model's dependent variable, Y, is set as a binary variable: Y = 1 indicates the occurrence of a cash flow risk event; Y = 0 indicates the absence of a cash flow risk event. The independent variables are selected from the constructed financial indicator system, taking into account multicollinearity, economic significance, and data availability. Initial candidate variables include: the core enterprise's quick ratio (X1), cash flow gap volatility (X2, reflecting cash flow stability), the financing enterprise's accounts receivable turnover days (X3), inventory turnover days (X4), cash conversion cycle (X5), net cash flow from operating activities/current liabilities (X6), debt-to-asset ratio (X7), and profit growth rate over the past year (X8). Furthermore, key ratios, such as the ratio of the core enterprise's accounts payable turnover days to the financing enterprise's accounts receivable turnover days (X9), could be considered to measure the severity of upstream and downstream funding maturity mismatches.

The basic form of the logistic regression model is: $\mathrm{Logit}(P) = \ln[P/(1-P)] = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta kXk + \varepsilon$. Here, P is the conditional probability of a cash flow risk event occurring, β0 is the intercept term, β1...βk are the regression coefficients of the explanatory variables, and ε is the random error term. The key steps in model construction include: sample data preparation, variable screening, model parameter estimation, significance testing, overall model goodness-of-fit testing, and predictive performance evaluation [3].

To enhance the model's operability and real-time monitoring capabilities, the logistic model's output probability values can be mapped to risk levels. Furthermore, a parallel multi-indicator comprehensive early warning scorecard system is constructed. The scorecard sets different ranges and corresponding risk scores for each key early warning indicator, and assigns different weights to each indicator. The weighted sum of all enterprise indicator scores yields a total score, which corresponds to a specific risk level or triggers a warning signal of different colors. This integrated model not only provides objective probabilistic forecasts but also intuitively displays risk points through the scorecard, facilitating dynamic monitoring and tiered intervention by financial institutions.

5. EMPIRICAL RESEARCH DESIGN AND SAMPLE DATA ANALYSIS

To test the effectiveness of the constructed cash flow risk model, this study designed a rigorous empirical approach. Data were sourced from authoritative domestic corporate credit databases, public financial reports of listed companies, and de-identified supply chain finance business data provided by selected partner financial institutions. The sample covers the period from 2018 to 2022 to capture the full impact of economic cycle fluctuations. The research focuses on manufacturing and wholesale and retail, two industries with active supply chain finance and cash flow sensitivity. Sample selection criteria include: companies must be part of a clearly identifiable supply chain, have complete financial statement data for five consecutive years, and have engaged in supply chain finance financing activities during the sample period. A total of 500 valid sample companies were obtained, including approximately 80 core enterprises, approximately 200 first-tier suppliers, and approximately 220 first-tier distributors. A total of 126 verified cash flow risk events were observed during the sample period.

The data processing process is rigorous and standardized: first, data cleaning is performed to address missing values, outliers, and duplicates. Financial indicators are normalized to eliminate dimensionality effects. Key explanatory variables are constructed based on theoretical models. For example, the "cash flow gap" is calculated as the "subtotal cash inflow from operating activities" minus "short-term loans + non-current liabilities due within one year + notes payable." Indicators such as "turnover days" are strictly calculated using the formula "365/turnover rate." To reduce the impact of outliers, some continuous variables are winsorized.

The empirical analysis consists of two main parts: the first part is model training and parameter estimation. The samples were divided into chronological order, and the data from 2018 to 2021 were used as the training set. Logistic regression analysis was performed using statistical software. After variable screening, the core variables with statistical significance were finally determined to enter the model. At the same time, based on the data distribution of the training set and the distribution of risk events, the threshold ranges, corresponding scores, and weights of each indicator of the scorecard were determined [4]. The second part is the model effect verification and robustness test. Using the reserved 2022 data as the test set, the financial data of the test set companies were input into the trained logistic model and the scorecard model, and their risk probability or risk score was calculated. It was compared with the actual risk events, and the confusion matrix, accuracy, precision, recall rate, F1 value, AUC value and other key performance indicators were calculated. In addition, robustness tests were performed, such as changing the sample subset, introducing new control variables, and using different models for comparison, to evaluate the generalization ability and reliability of the model.

6. EMPIRICAL RESULTS ANALYSIS AND MODEL VALIDATION ASSESSMENT

Logistic regression analysis based on the training set samples revealed the following significant variables and their coefficients:

The coefficient of the core enterprise's quick ratio (X1) is negative ($\beta1 = -1.25$, $p < 0.01$), indicating that the stronger the core enterprise's short-term debt repayment ability, the lower the probability of cash flow risk at its supply chain node.

The coefficient of the core enterprise's cash flow gap volatility (X2) is positive ($\beta2 = 0.83$, $p < 0.05$), indicating that the more unstable (highly volatile) the core enterprise's cash flow situation, the higher the cash flow risk in the supply chain.

The coefficient of the financing enterprise's accounts receivable turnover days (X3) is positive ($\beta3 = 0.015$, $p < 0.01$) and has a significant impact, indicating that the slower the financing enterprise's repayments, the greater the risk. The coefficient for the cash conversion cycle (X5) is positive ($\beta5 = 0.008$, $p < 0.05$). A longer cash conversion cycle indicates a higher degree of inefficient use of a company's working capital and a higher risk.

The coefficient for upstream and downstream funding mismatch (X9) is positive ($\beta9 = 0.41$, $p < 0.05$). This indicates that risk increases when the core company's payment period is significantly longer than the upstream financing company's collection period.

The model constant term, $\beta0$, is -3.58. The pseudo R-squared value reaches 0.42, and the Hosmer-Lemeshow test p-value is greater than 0.1, indicating a good model fit.

The trained logistic model and accompanying scoring card rules were applied to an independent 2022 test set. The model performance evaluation results are satisfactory: the area under the receiver operating characteristic (ROC) curve for the logistic model's predicted probability reaches 0.86, demonstrating excellent discriminatory power. Setting a risk probability threshold of 0.35, the model's key performance indicators on the test set were: 85.0% accuracy, 78.6% precision, 88.0% recall, and 83.0% F1 score. The scorecard system's "red alert" successfully captured 22 risk events, with an average lead time of approximately 3.1 months. Only three risk events were not alerted, but six companies were mistakenly classified as high-risk. The scorecard was intuitive in pinpointing specific risk sources. For example, 70% of the companies alerted showed abnormally long accounts receivable turnover days [5].

Key findings are summarized as follows: The financial soundness of core enterprises has a global and decisive impact on the health of the entire supply chain's cash flow and is a primary focus of risk management. Operational efficiency indicators for small and medium-sized financing enterprises are a sensitive barometer of their cash flow constraints and risk exposure, making them crucial for early warning. Severe mismatches in payment terms between upstream and downstream companies are a structural risk source that contributes to cash flow constraints in the supply chain. Empirical results strongly demonstrate the high accuracy, timeliness, and practical value of the constructed integrated financial indicator model in identifying and warning of cash flow risks in supply chain finance. It significantly outperforms traditional methods that rely solely on single-entity credit ratings or subjective empirical judgments. The model provides a powerful tool for financial institutions to implement refined, data-driven risk management.

7. CONCLUSION

This study focuses on cash flow risk in supply chain finance. Through theoretical analysis and empirical modeling, it systematically identifies five key risk dimensions: core enterprise credit risk, trade background authenticity risk, supply chain operational risk, financing entity credit risk, and external environmental risk. Based on publicly available corporate financial data, a risk early warning indicator system centered on quick ratio, cash flow gap, accounts receivable turnover days, and cash conversion cycle is constructed.

The study's core contribution lies in the development and validation of a comprehensive assessment model that integrates logistic regression and a scorecard. Empirical analysis, based on five years of data from 500 companies in the manufacturing and wholesale and retail sectors, shows that a decrease in the quick ratio and increased cash flow volatility of core enterprises, as well as longer accounts receivable turnover days, longer cash conversion cycles, and increased upstream and downstream funding mismatches for financing enterprises, significantly increase the probability of cash flow risk. The model performed well on the test set (AUC = 0.86, accuracy 85.0%), providing a three-month lead time for 88.0% of high-risk events.

There are three practical implications: Financial institutions need to shift to dynamic supply chain risk assessments, focusing on monitoring the payment capabilities and cash flow stability of core enterprises and incorporating operational efficiency indicators of financing enterprises into early warning systems; it is recommended to utilize quantitative models and technological approaches to build a comprehensive risk control system; and core enterprises should optimize supply chain capital management and enhance information transparency to reduce systemic risk.

Future research could expand industry samples to verify the universality of the model, integrate unstructured data to enhance predictive dimensions, and explore artificial intelligence technologies to improve model accuracy. Deepening cash flow risk management is crucial for ensuring the stable operation of supply chain finance and serving the real economy.

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