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RESEARCH PAPER

A Simulation Model of Credit Risk in Supply Chain Finance Using a Dynamic Systems Analysis Approach

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Abstract

Objectives: This study aims to identify the key factors influencing credit risk in supply chain finance (SCF), determine the main subsystems, and present a simulation model for credit risk in SCF using a dynamic systems analysis approach.
Method: The research employs a two-tier supply chain financial model, consisting of a buyer company (core company) and a seller company (supplier) in the pharmaceutical industry. The factoring method is used as one of the SCF techniques to construct the supply chain financial model using a dynamic systems analysis approach. Vensim software is utilized for the simulation.
Results: The study identifies the subsystems, key factors influencing credit risk in SCF, causal relationships, delays between these factors, and a systemic view of credit risk in SCF. The findings show that the credit risk of small and medium-sized enterprises (SMEs), decreases when they participate in SCF. A sensitivity analysis of three key variables was conducted by simulating changes in critical parameters over a five-year period. The results highlight that the financial conditions of both the supplier and the main company, macroeconomic and industry risk, supply chain position, the quality of credit risk management by the lending bank, and the effectiveness of risk intermediaries significantly impact credit risk in SCF.
Innovation: This study is the first in the country to develope a simulation model of credit risk in SCF using a dynamic systems analysis approach. It specifically analyzes and evaluates the credit risk of SMEs (supplier companies) within the context of SCF participation.

Keywords:
Causal Loops Diagram, Credit Risk, Dematel, Supply Chain Finance(SCF), Dynamic System Analysis Approach.

Introduction

Supply Chain Management (SCM) has long been defined, conceptualized, and structured. A supply chain consists of three key flows: material, information, and financial. However, in both

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theory and practice, most attention has been given to material and information flows. Until the financial crisis of 2008-2009, the financial flows within supply chains, liquidity issues of companies, and working capital management in supply chains received little focus due to the high market liquidity.

During the financial crisis, credit problems severely affected small and medium-sized enterprises (SMEs), pushing many suppliers to the brink of bankruptcy and threatening the stability of global supply chains. In response, companies began to recognize the benefits of managing financial flows in collaboration with supply chain participants and financial institutions. They also started exploring advanced methods to strengthen financial supply chains. These efforts led to the emergence of the concept of Supply Chain Finance (SCF) (Caniato, et al., 2019).

SCF is a portfolio of management, technological, and financial tools designed to optimize working capital management and unlock liquidity trapped in supply chain processes and transactions. Additionally, SCF operations can resolve financial conflicts between buyers and suppliers. While buyers often prefer to extend payment terms, suppliers seek to expedite payments for goods and services sold. In this financing method, SCF relies on the creditworthiness of the core company within the supply chain and the financial flows from the core company to SMEs. The goal is to provide financing to SMEs, which often have weak credit profiles and face difficulties obtaining loans independently. In this context, not only the creditworthiness of SMEs but also that of the core company becomes crucial.

Supply chain financing is generally considered a high-risk activity due to the complexities inherent in supply chains. A supply chain can include numerous suppliers, distributors, and buyers, where failure to meet financial obligations at any stage may lead to defaults in other stages. Consequently, one of the primary risks in financial supply chains is credit risk. Assessing and measuring this risk can contribute to the healthy performance of a supply chain, and, by extension, the broader industry and economy. Given the complex nature of supply chain finance, adopting a systems approach can be both insightful and beneficial.

Systems thinking is both an art and a science that provides a deep understanding of the underlying structures of systems, enabling logical conclusions about their behavior (Hosseini, et al., 2019). In systems thinking, the problem is viewed as a whole, and the relationships between its components are analyzed over time. This approach acts as a guiding light, clarifying the overall issue and facilitating collaborative discussions using a shared language.

Research Questions

- What are the key subsystems affecting credit risk in supply chain finance?
- What are the influencing factors of credit risk in supply chain finance, and how are they interrelated?
- How do various factors influence credit risk in supply chain finance, and what is their causal hierarchy?
- How can a dynamic systems analysis model be developed to simulate credit risk in supply chain finance based on different factors?

The primary objective of this study is to develop a simulation model for credit risk in supply chain finance using a dynamic systems analysis approach. This research aims to apply a systems approach to create a model that enables a more detailed analysis of the dynamics that contributing to credit risk in supply chain finance.

Theoretical Foundations

Today, as supply chains expand and operating conditions grow more complex, organizations require new and suitable tools and techniques for financial transactions and working capital management. Effective supply chain management demands a different approach to business operations compared to traditional practices. A focus on financial processes provides a comprehensive perspective, enabling companies to view the entire supply chain externally. (Ahmadi, et al., 2021)

One of the primary concerns of any economic entity is ensuring sufficient cash flows to achieve its goals. Various methods exist for securing these cash flows, with bank loans being one of the most common. Companies need liquidity to carry out their operational activities, yet cash inflows and outflows rarely occur simultaneously. This mismatch amplifies the importance of liquidity needs. As traditional financing methods face challenges, businesses have turned to innovative approaches that help mitigate liquidity risks. One of the most effective and modern methods is Supply Chain Finance (SCF). (Ahmadi, et al., 2021)

Research on supply chain finance dates back to the 1970s, before the concept of supply chain management was widely recognized. For instance, Boden and Ippen (1970) studied net cash flows generated during business operations within a cash planning period and how such net inflows are affected by changes in trade credit policies and inventory levels. Healey and Higgins (1973) examined the relationship between inventory policies and trade credit policies using a base accumulation volume model (Xu, 2018). The first formal definition of supply chain finance emerged in 2000 when Stemmler (2000) identified the key features of SCF as the integration of financial flows within the physical supply chain and categorized it as an essential component of supply chain management.

SCF creates a win-win situation for both buyers and suppliers. For example, it provides buyers with deferred payment solutions while allowing suppliers to receive payments more quickly at lower costs by leveraging the buyer's strong credit rating. Consequently, SCF optimizes financial performance across the supply chain. (Caniato, et al., 2019)

Unlike traditional financing methods, SCF covers the entire supply chain continuously, integrating financing tools and risk management strategies. In this ecosystem, financing and risk management models are designed and implemented comprehensively for different supply chain segments.

The development of SCF methods not only supports production but also plays a crucial role in improving the banking system. By reducing non-performing loans, improving cash flow circulation within banks, managing off-balance-sheet items, and utilizing commitment-based financing for production, SCF can enhance banking stability and financial health.

Every financing method involves various risks, and managing these risks is critical to financial system stability. Among these risks, credit risk defined as the inability of a business or individual to meet financial obligations is particularly significant in SCF. Due to the unique characteristics of SCF, credit risk spreads rapidly, potentially impacting the entire supply chain, financial institutions, and even the broader economy

So far, no study has taken a system dynamics approach to credit risk in supply chain finance, with most research focusing on measuring credit risk using statistical, econometric, or artificial intelligence-based approaches. Below, we will review some of the existing articles in the field of credit risk in supply chain financing.

Zhang et al. (2025) in their article titled " Credit Risk Identification in Supply Chains Using Generative Adversarial Networks " explore the application of Generative Adversarial Networks (GANs) to enhance credit risk identification in supply chains. GANs enable the generation of synthetic credit risk scenarios, addressing challenges related to data scarcity and imbalanced datasets. Experimental results demonstrate that the GAN-based model outperforms traditional methods, including logistic regression, decision trees, and neural networks, achieving superior accuracy, recall and F1 scores.

Farajpour Mojdehi et al. (2025) in their article entitled " Novel Hybrid Model for Credit Risk

Assessment of Supply Chain Finance Based on Topological Data Analysis and Graph Neural Network" propose a novel hybrid Topological Data Analysis (TDA) and Graph Neural Network (GNN) to optimize credit risk assessment in SCF. Results demonstrate that the proposed BallMapper- Graph Neural Network (BM-GNN) model achieves higher accuracy and F1-scores, outperforming traditional machine learning approaches. Notably, incorporating network-based features alongside financial ratios yields the most favorable results in credit risk assessment.

Zhou et al. (2025) in their article entitled " Enhancing Credit Risk Decision-Making in Supply Chain Finance with Interpretable Machine Learning Model" evaluate the performance of interpretable machine learning models in assessing credit risks. Specifically, we applied Extreme Gradient Boosting (XGBoost), Random Forest (RF), Least Squares Support Vector Machine (LSSVM) and Convolutional Neural Network (CNN) models for risk assessment. The results indicated that the asset-liability ratio, cash ratio, and quick ratio notably influence credit risk. This study clarified the applicability and limitations of various models, highlighting the superior performance and interpretability of XGBoost through the SHAP algorithm.

Zhang et al (2024) state in their paper titled " Deep reinforcement learning imbalanced credit risk of SMEs in supply chain finance " propose a novel approach called DRL-Risk to address imbalanced credit risk prediction (ICRP) of SMEs in SCF with deep reinforcement learning (DRL). Experimental results demonstrate that the DRL-Risk approach significantly improves the performance of credit risk prediction of SMEs in SCF compared to baseline methods in terms of recall, G-mean, and financial loss.

Bao et al (2024) in their paper titled " Research on the Financial Credit Risk Management Model of Real Estate Supply Chain Based on GA-SVM Algorithm: A Comprehensive Evaluation of AI Model and Traditional Model " combine machine learning AI model with traditional credit risk measurement models to more accurately measure the credit default risk of real estate enterprises. By integrating professional credit management knowledge, the hybrid model fills gaps in traditional models outside of financial data and leverages the research experience of traditional models in the financial field to guide machine learning. The research help reduce the information asymmetry in the real estate industry, enhance the credit rating evaluation process for SMEs, and provide references for commercial banks in credit and credit risk management within the real estate supply chain finance sector. offering significant theoretical and practical value.

Peng et al. (2024), in their article titled " Impact of Enterprises Relationship on ML’s Ability to Forecast SME’s Credit Risk in SCF: A Research Based on Complex Network “investigate how incorporating enterprise relationship to train machine learning (ML) algorithms improves their ability to forecast SMEs’ credit risk in SCF. Empirical results indicate that forecasting improves significantly when enterprise transaction relationships are considered, with further enhancement achieved through a weighted one-mode projection approach. Variable importance analysis and binomial logistic regression demonstrate the significant correlation of network attributes with credit risk, while partial dependence plots reveal that SMEs with large degrees are generally non-risky.

Hou et al. (2024), in their study titled "Predicting Credit Risk of Small and Medium Enterprises in Supply Chain Finance Using Machine Learning Algorithms," propose a new framework to predict SME credit risk in SCF with higher accuracy. The proposed framework, named FS-RS-ML, combines feature selection methods, resampling techniques, and machine learning. Experiments based on Chinese SCF data indicate that FS-RS-ML outperforms individual algorithms.Additionally, analysis of empirical results suggests that features derived from SMEs have the most significant impact on credit risk prediction, highlighting the influence of key features in forecasting SME credit risk.

Xie et al. (2023) in their article titled " Financing a dual capital-constrained supply chain:

Profit enhancement and diffusion effect of default risk" examine and compare how various SCF schemes affect participants' profits and the contagion and diffusion effects of default risk in a dual capital-constrained supply chain. This study used a game theoretical approach to investigate a dual capital-constrained supply chain. Using a game theoretical approach, the study finds that while trade credit offered by the manufacturer generates higher profits for supply chain participants compared to bank credit, it increases creditors' expected losses and amplifies the contagion and diffusion effects of default risk.

Liu et al. (2023) in their article titled " Credit Risk Evaluation Model of Supply Chain Finance Based on Deep Dimension Reduction" propose A credit risk assessment model is named SAE_DE_SVM which leverages deep learning dimension reduction to address the challenges of multi-heterogeneous and dynamic high-dimensional characteristics in SCF credit risk assessment. Experimental results show that credit risk assessment model of supply chain finance based on SAE_DE_SVM model performs well in predicting the default probability of SMEs in SCF.

Zhang et al. (2023), in their article titled " Using deep learning to interpolate the missing data in time-series for credit risks along supply chain" introduce approaches for dataset construction and algorithmic model framing. The study tests the interpolation effects of the algorithmic model on three artificial datasets with varying missing rates and compares its predictability before and after the interpolation in a real dataset with the missing data in irregular time-series. The proposed time-decayed long short-term memory (TD-LSTM) model effectively monitors missing data in irregular time-series by capturing more and better time-series information, enabling efficient interpolation. Additionally, the Deep Neural Network (DNN) model can be applied to credit risk prediction (CRP) for datasets with interpolated missing data.

Yi et al. (2023) in their article titled " Financial risk prediction in supply chain finance based on buyer transaction behavior " develop a financial risk prediction model using XGBoost and evaluate it using buyer transaction behavior data. The results show that XGBoost model effectively predicts potential financial risks and provides insight into managers' payment practices. This study is one of the few to empirically examine financial risks in SCF using new models.

Li et al. (2023), in their article titled " Analysis of supply chain finance risk assesment based on numerical analysis algorithm " design a supply chain finance risk assessment and analysis platform to promote coordination, stability, and improved financing environments for SMEs. Combining the characteristics of a large amount of risk assessment data, a numerical analysis algorithm is introduced in the process of platform design, and the extrapolation method in the numerical analysis algorithm is used to calculate the risk assessment related data. To make the calculation faster and the data more accurate, the central difference quotient extrapolation is used to accelerate and a downtime mechanism is introduced. Simulation results show that the platform is as high as 99% and the time required is 17 seconds faster than other assessment models, validating the algorithm's effectiveness in improving accuracy and speed.

Xie et al. (2023) in their article titled " Assessment of associated credit risk in the supply chain based on trade credit risk contagion" propose a novel approach for assessing associated credit risk in the supply chain based on graph theory and fuzzy preference theory. By integrating these methods, the study comprehensively evaluates the credit risk of firms in the supply chain, revealing the contagion effect of trade credit risk. A case study demonstrates that the proposed method enables banks to accurately identify credit risk, helping to curb systemic financial risks.

Feng (2023), in their article entitled " Supply chain financial credit evaluation mechanism under the background of big data " improve the evaluation effect of the supply chain financial credit evaluation mechanism, with the support of big data technology, combines the intelligent evaluation algorithm to analyze the supply chain financial evaluation mechanism, and analyzes the effect of the supply chain financial credit evaluation mechanism by constructing an intelligent evaluation model. The research results show that the supply chain financial credit evaluation system proposed in this paper has good effects in supply chain financial credit evaluation.

Zhang et al. (2023), in their study titled "Predicting Credit Risk of SMEs in Supply Chain Finance Using Bayesian Optimization and XGBoost," used the XGBoost model to assess a constructed risk index, with SVM and Random Forest models serving as comparison benchmarks. Their findings highlight the advantages of Bayesian optimization in enhancing XGBoost's credit risk prediction for SMEs, offering a valuable tool for financial risk management.

Li et al. (2022) in their article titled " Multi-criteria probabilistic dual hesitant fuzzy group decision making for supply chain finance credit risk assessments" propose a Hamming distance measure in a probabilistic dual hesitant fuzzy environment to compare relationships between two probabilistic dual hesitant fuzzy elements and prove some of the properties. Then, to fully consider the DMs' risk preferences, a model is proposed to evaluate supply chain finance credit risk that extends the TODIM method to a probabilistic dual hesitant fuzzy environment based on cumulative prospect theory and the proposed Hamming distance. The TODIM method in a fuzzy environment has proven to be a useful tool for multi-criteria decision-making as it can better reflect the DMs' psychological characteristics.

Xie et al. (2022) in their article titled " Enterprise credit risk portrait and evaluation from the perspective of the supply chain" mine indicators that comprehensively describe the supply chain aspects of credit risk to obtain a precise credit risk portrait of the enterprise. They innovatively design a random forest-weighted naïve Bayes (RF-WNB) model, which offers interpretability and generalization, forming a two-stage process for credit risk evaluation. The model forms an effective two-stage process of enterprise credit risk evaluation that selects key features, quantifies the importance of each, and then evaluates credit risk. The model's effectiveness is verified in selecting key features and quantifying their importance.

Li and Fu (2022), in their paper "Credit Risk Prediction in Supply Chain Finance Based on PCA-GA-SVM Model," propose a credit risk prediction model using PCA-GA-SVM. First, Principal Component Analysis (PCA) is employed to reduce the dimensionality of key index systems. Then, Genetic Algorithm (GA) optimizes the parameters of the Support Vector Machine (SVM). Finally, the principal components selected by PCA are fed into the GA-SVM model for training, leading to the final prediction model. The results indicate that the PCA-GA-SVM model outperforms the SVM and GA-SVM models, demonstrating strong generalization ability. This model could serve as a reference for commercial banks to enhance credit risk management in supply chain finance, contributing to its sustainable development.

Wang et al. (2021) in their article titled " Multiview Graph Learning for Small- and Medium-Sized Enterprises' Credit Risk Assessment in Supply Chain Finance" propose an adaptive heterogenous multiview graph learning method to tackle the small sample size problem in SMEs' credit risk forecasting. three graphs are constructed by using indicators from supply chain operation, SME financial indicator, and nonfinancial indicator individually. All the graphs are integrated in an adaptive manner, providing a quantitative explanation on how the three parts cooperate. Experimental analysis shows that the proposed method has good performance for determining SME credit risk in SCF. From the perspective of SCF, SME financing ability is still the main factor to determine the credit risk of SME.

Hang et al. (2021), in their study titled "Assessing Credit Risk in Supply Chain Finance Using Grey Correlation Model: An Empirical Study in China's Home Appliance Industry," introduce a grey correlation to evaluate credit risk across 15 companies in the Chinese home appliance industry. The model employs 15 performance indicators representing profitability, debt repayment ability, operational capability, and growth potential. Their empirical study demonstrates that the grey correlation model is superior to traditional methods in assessing supply chain finance risk.

Rishehchi Fayyaz et al. (2020), in their paper "A Data-Driven and Network-Aware Approach for Credit Risk Prediction in Supply Chain Finance," develop a data-driven model to predict credit risk among participants in an automotive supply chain finance network, incorporating a network-based approach. Their findings indicate that a network perspective enhances prediction accuracy.

Zhang et al. (2019), in their paper "Quantifying Credit Risk in Supply Chain Finance," examine credit risk quantification in supply chain finance, focusing on the automotive industry. They utilized the KMV model and the Copula function for risk assessment, also analyzing portfolio credit risk within the supply chain from a top-down perspective. Their model measures both financing company risk and financial portfolio risk within the supply chain.

Research Method

The credit risk of supply chain financing arises from a series of causal relationships within the SCF process. Considering all these factors requires a comprehensive approach and tools capable of accurately explaining the relationships between different elements and analyzing their impact on credit risk in supply chain financing. To this end, this study, for the first time in the country, attempts to identify and analyze the factors influencing credit risk in supply chain financing using the dynamic system analysis modeling approach, which is a powerful method for identifying and analyzing complex systems.

In the dynamic system analysis method, the system boundary is first determined. Dynamic hypotheses are then used to draw causal and flow models, which are modeled and tested using mathematical equations. Finally, various scenarios evaluate the model's explanatory and predictive power, with revisions made as necessary all previous steps are revised.

For this research, a two-tier SCF model in the pharmaceutical industry was developed, including a buyer company (core enterprise) and a supplier company. Factoring was chosen as the SCF method. Given the short-term nature of SCF, the simulation was conducted over a five-year period. The model can be extended to multi-tier supply chains and other SCF methods.

Following a literature review, the subsystems affecting credit risk in SCF were identified. These subsystems include:

1.Internal credit risk of the buyer company
2.Internal credit risk of the supplier company
3.Supply chain position
4.Quality of credit risk management in the lending bank
5.Industry risk
6.Macroeconomic risk

In the next step, to define the relationships between components and determine dynamic hypotheses, an initial model was extracted through literature review. This model was then validated by consulting 14 experts, including four academic experts, seven senior bank executives, and three credit risk specialists. The DEMATEL technique was used to identify key influencing and influenced factors in the model.The DEMATEL technique, is a decision-making method based on pairwise comparisons.

Dynamic hypotheses are structures that reproduce system behavior similar to the reference behavior. These hypotheses play a crucial role in explaining system behavior and are derived from a broad causal framework that includes the most important feedback loops and decision-making components. The causal relationships depicted in the dynamic hypotheses stem from the decision-making rules of system players rather than mere correlations between system variables (Beheshtiseresht, 2021).

To develop a systemic model of credit risk in supply chain financing, we formulate dynamic hypotheses in five key subsystems: Internal credit risk of the supplier company, Internal credit risk of the buyer company, Quality of credit risk management in the lending bank, Industry risk, Macroeconomic risk.

These hypotheses are developed to replicate the mechanisms driving increases or decreases in credit risk within supply chain financing, without necessarily covering all potential behaviors of the subsystems.

Subsystems Analysis

Supplier Company Internal Credit Risk Subsystem

This subsystem identifies financial and non-financial variables affecting the supplier's internal credit risk in a supply chain financing arrangement. Financial variables are derived from the supplier's financial statements and used to calculate key credit risk ratios based on the literature. Non-financial variables originate from internal company information.The key influencing indicators and dynamic hypotheses of the credit risk sub-system for the supplier company are as follows:

Profitability: An increase in the profitability index reduces the supplier company's internal credit risk.Factors affecting the profitability index that lead to its increase include return on equity (ROE), sales return, and profit growth rate.

Short-term Debt Repayment Capability: An increase in this index reduces the supplier company's internal credit risk. Positive factors include the quick ratio and interest coverage ratio, while the debt ratio negatively affects it.

Operational Position: An increase in the operational position index reduces the supplier company's internal credit risk. Positive factors include working capital turnover, inventory turnover, total asset turnover, and cash flow rate, while the accounts receivable collection period negatively affects it.

Default Rate: An increase in the past default rate index reduces the supplier company's internal credit risk.

Business Scale: An increase in the business scale index reduces the supplier company's internal credit risk.

Company Management Quality: An increase in the company management quality index reduces the supplier company's credit risk.

In supply chain finance, the credit risk of the core company influences the credit risk of supply chain finance. Accordingly, the credit risk of the buyer company affects both the interest rate paid by the supplier company for financing and the amount of loans it receives.

Buyer (Core) Company Internal Credit Risk Subsystem:

This subsystem analyzes financial and non-financial variables affecting the credit risk of the buyer company, which serves as the guarantor in the supply chain financing process. Financial variables come from the buyer's financial statements and are used to calculate key credit risk ratios. Non-financial variables originate from internal company information.

According to the literature, the supplier's credit risk is of greater importance, and the core buyer company typically has a higher credit standing. Therefore, fewer variables are used to assess the buyer's internal credit risk.

An increase in the buyer's credit risk leads to an increase in the overall credit risk of supply chain financing.

Lending Bank's Credit Risk Management Quality Subsystem

This subsystem identifies the factors affecting the quality of credit risk management in the lending bank, particularly in supply chain financing. The lending bank, through effective risk assessment techniques, appropriate policies, and monitoring of internal risks, can help reduce credit risk in supply chain financing.better credit risk management in the lending bank reduces supply chain financing credit risk.

Key Indicators and Dynamic Hypotheses of the Credit Risk Management Quality Subsystem of the Lending Bank include:

Credit Assessment and Risk Analysis Quality: This variable is measured by two sub-variables: the quality of assessment methods and the quality of monitoring, supervision, and control. An increase in either of these sub-variables leads to an improvement in the credit assessment and risk analysis quality, which in turn enhances the overall credit risk management quality of the lending bank.

Efficiency of Strategic Planning for Supply Chain Finance Credit Risk Management: This variable is influenced by strategic planning for supply chain finance credit risk management and deviations from this planning. Increasing the efficiency of credit risk management planning for supply chain finance enhances the quality of the lending bank's credit risk management.

Quality of Customer Credit Information Records: A strong and high-quality database of customers' credit history can contribute to improving the credit risk management quality of supply chain finance.

Quality of Oversight on Ethical Risks: In some cases, bank employees may collude with customers, engaging in actions that benefit the customers but harm the bank. Monitoring these ethical risks and implementing preventive measures improve the credit risk management quality of the lending bank.

Collateral Quality: This variable is influenced by vulnerability of collateral, Liquidity potential of collateral, and Price stability of collateral. Enhancing collateral quality leads to an improvement in the credit risk management quality of the lending bank.

Supply Chain Position

the stability of the supply chain reflects the frequency of SME trading with the leading enterprises. Moreover, the stability of the supply chain reflects the durability of these cooperative relationships. A greater frequency of the business activities between SMEs and leading enterprises reveals the strength of the competitiveness of the SMEs, as well as a smaller likelihood of default.

Industry Risk

It consists of present status of supply chain's industry, competitive situation, legal policy and Industry groth rate

Macroeconomic Risk

It consists of Inflation rate, Exchange rate, Groth rate of GDP and Political risk.

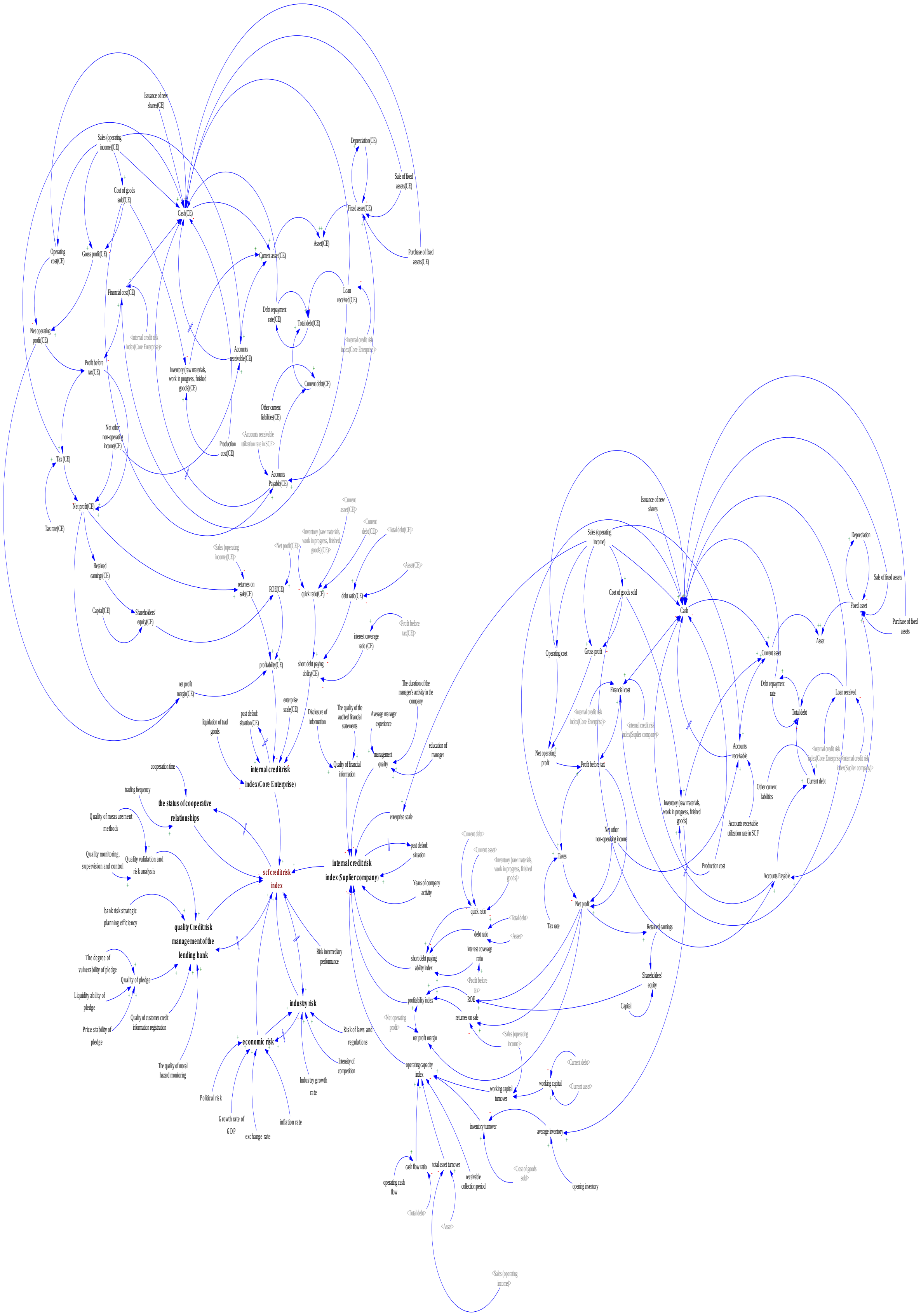


Figure 1. Causal loop diagram of the entire system

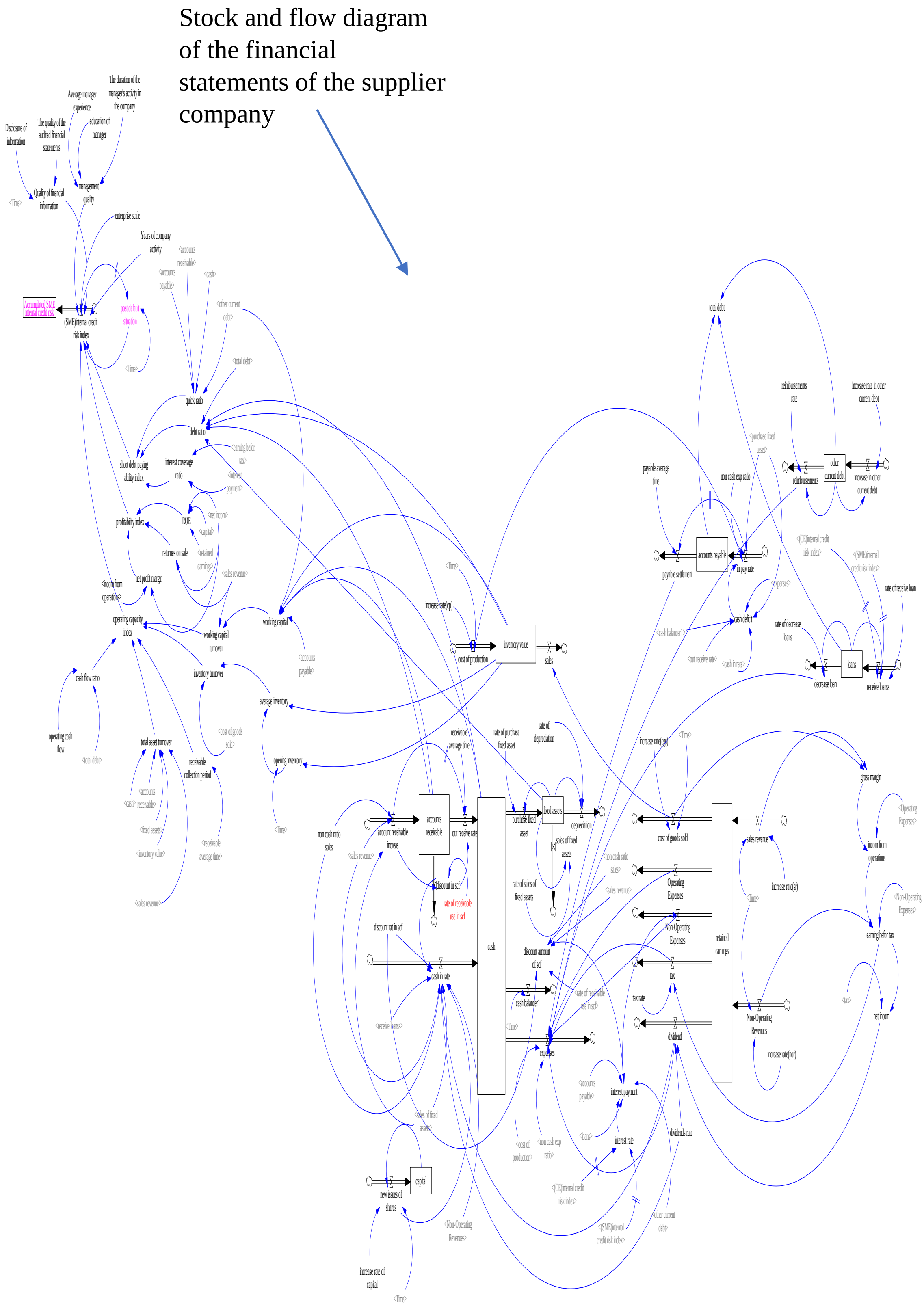


Figure 2. Stock and flow diagram of the supplier company's subsystem

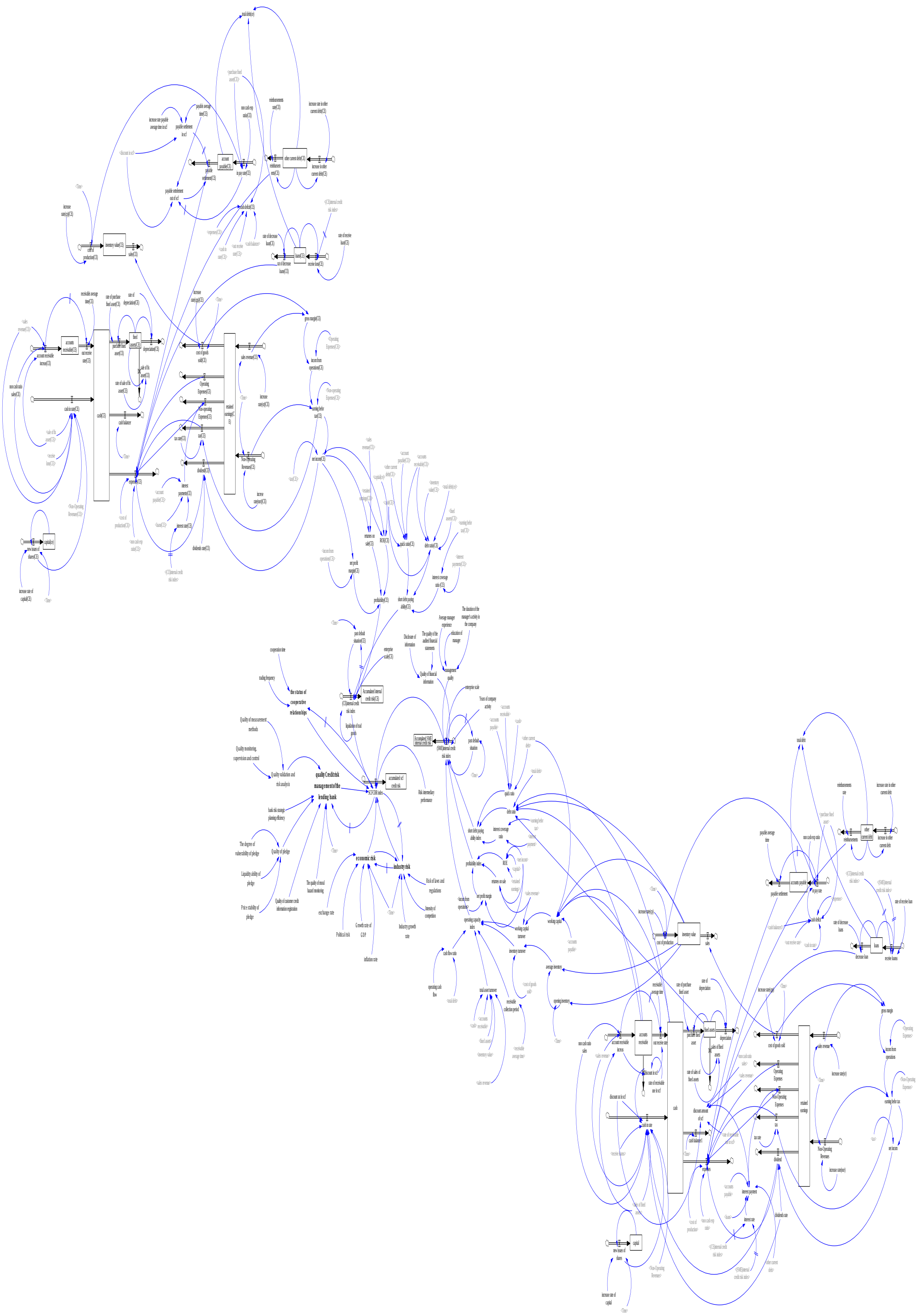


Figure 3. Stock and flow diagram of the entire system

Findings

After expanding the model and before analyzing various scenarios, validation tests were conducted to assess the model’s accuracy and validity under different conditions.

First, through multiple meetings with expert consultants and credit risk managers in the bank, the structure and boundaries of the model were discussed and examined. The structure, boundaries, and the appropriateness of the model’s holistic perspective were confirmed.

Next, in order to test the boundary conditions, some of the model’s initial parameters and data were significantly altered. Re-running the model showed that its behavior remained meaningful (Figure (4))

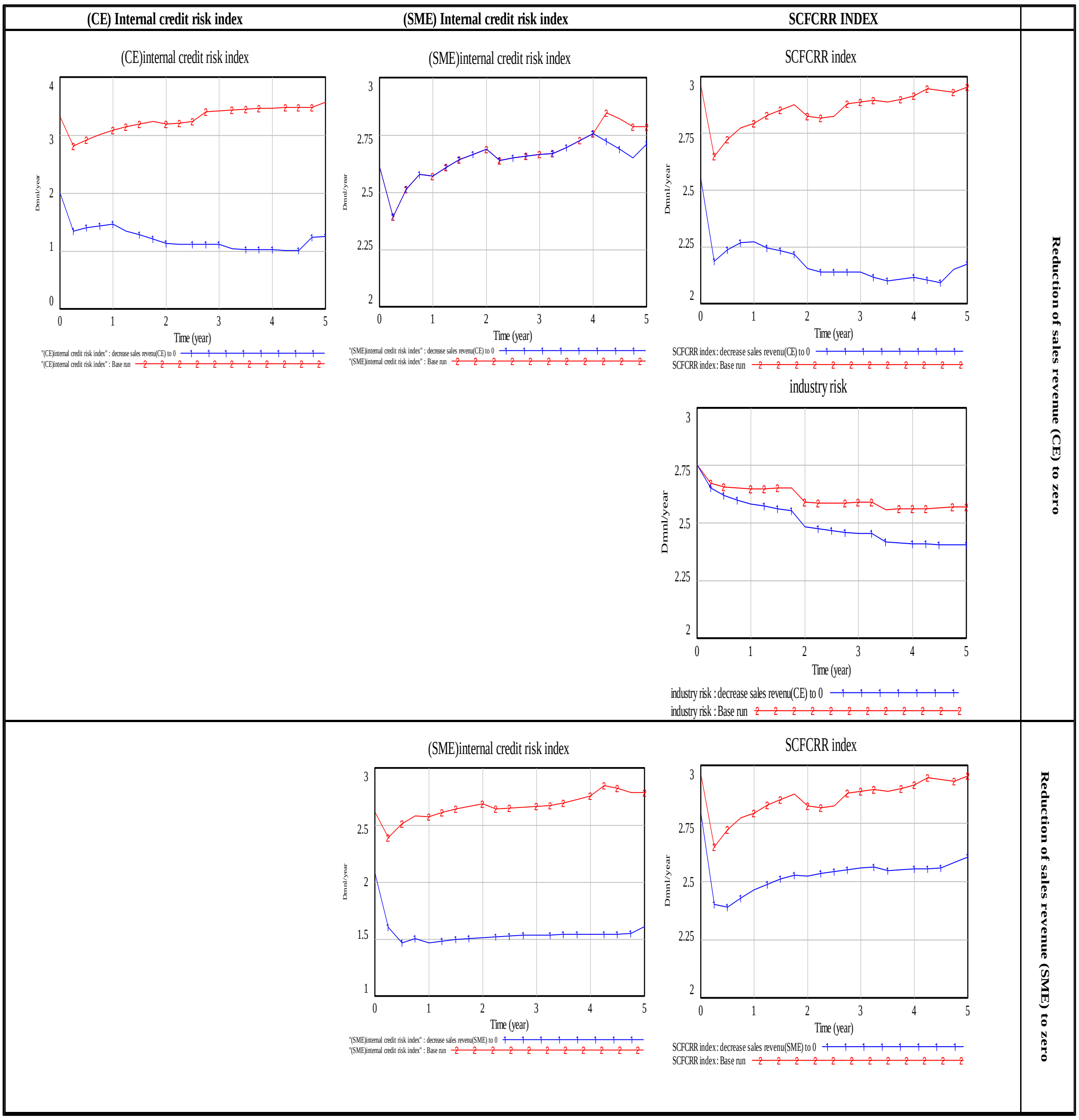


Figure 4. Limit states of some main variables

Finally, to ensure the model’s accuracy in predicting trends, the predicted trends of key model variables were compared with the actual trends. Due to limitations in accessing real data, only three years' worth of data could be compared with the predicted trends. As shown in the charts (Figure (5)), the model has successfully predicted the trends of key variables.

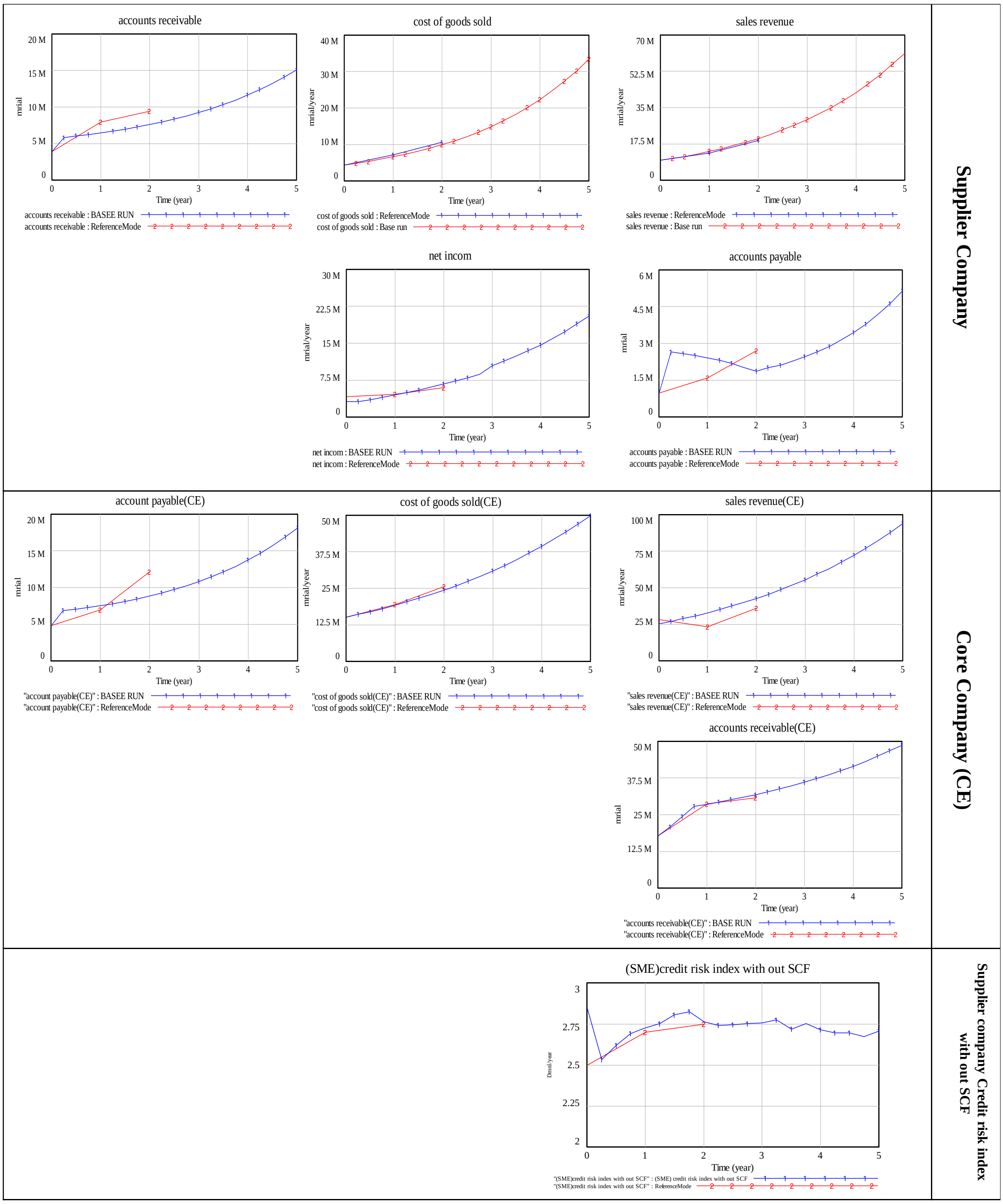


Figure 5. Comparison of the trend predicted by the model with actual data

Simulation Results and Research Findings

In this study, the credit risk index ranges from 1 (very poor credit status) to 5 (highly favorable credit status). Figure (6) presents the initial simulation results. As shown, the credit risk index of the supplier company is lower when it does not participate in supply chain financing compared to when it does. This indicates that the seller company experiences a better credit conditions when involved in supply chain financing. The internal credit risk index of the buyer company is in a better state than that of the seller company. Since the supply chain financing credit risk index is influenced by both the internal credit risk indices of the buyer and seller companies, this leads to an improvement in the supply chain financing credit risk index compared to the seller company's credit risk index alone.

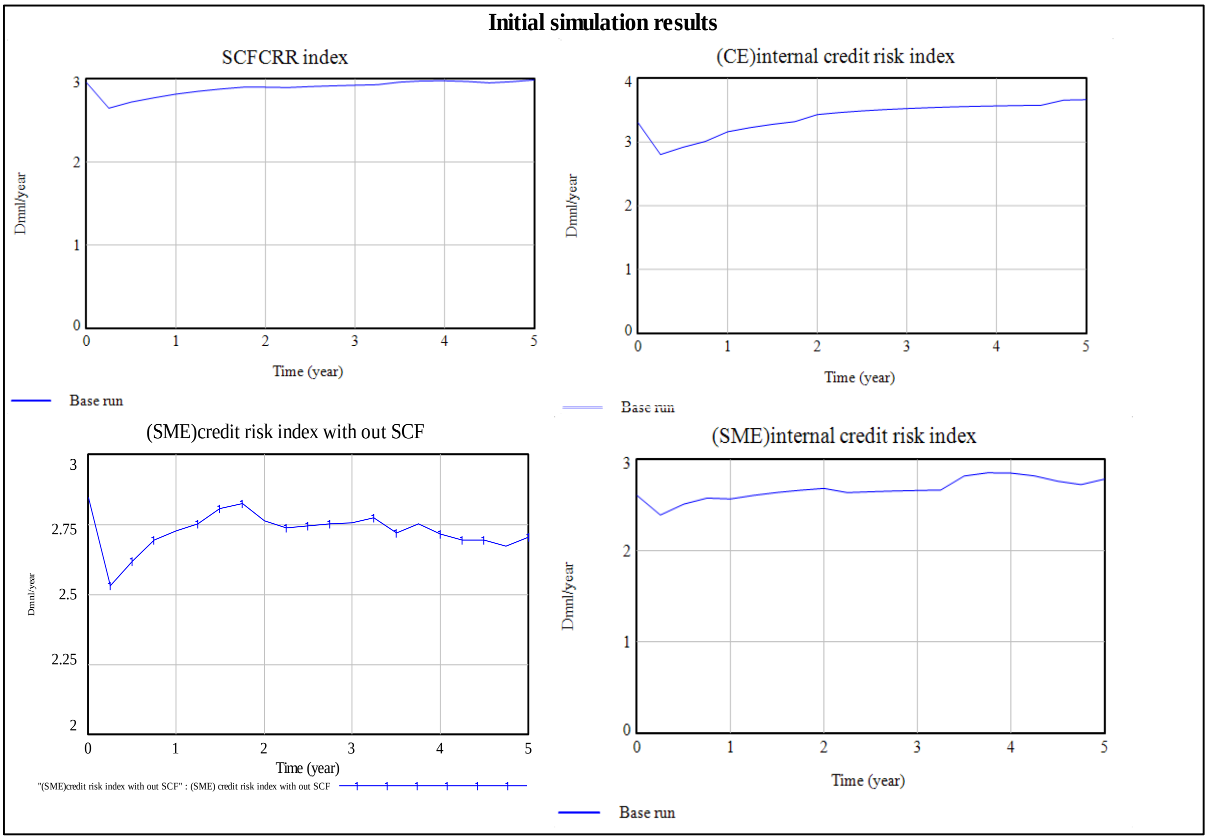


Figure 6. Initial simulation results

Based on the literature, we expect that the supplier company with participating in supply chain financing will experience lower credit risk and achieve a higher index number in terms of credit

Sensitivity Analysis

One of the most important aspects of the system dynamics approach is the sensitivity analysis of the research model. Sensitivity analysis measures how key research variables respond to changes in fixed parameters. For this purpose, the fixed parameters of the research model are altered, and their effects on key variables are examined.

In this study, the key parameters for conducting sensitivity analysis of critical variables include:

- The rate of accounts receivable used in supply chain financing
- The discount rate in supply chain financing
- Changes in the non-cash sales rate of the supplier company
- Changes in the sales growth rate of the main company
- Changes in the sales growth rate of the supplier company
- Changes in the growth rate of the cost of goods sold (COGS) for the main company
- Changes in the growth rate of COGS for the supplier company
- Changes in the initial interest rate
- Changes in the liquidity of the traded goods index
- Changes in the industry and economic risk index
- Changes in the quality of the lending bank’s credit risk management index
- Changes in the supply chain position index

Next, we analyze and evaluate the impact of these parameter changes on three key variables: the internal credit risk of the lender company, the internal credit risk of the main company, and the credit risk of supply chain financing, using Monte Carlo simulation.

- Changes in the rate of accounts receivable used in supply chain financing (10% to 90%) (Supplier Company)

As shown in the charts (Figure (7)), changes in the rate of accounts receivable used in supply chain financing cause greater fluctuations in the internal credit risk index of the supplier company compared to the supply chain financing credit risk index. In other words, based on the chart, an increase in accounts receivable usage in supply chain financing improves the credit risk of the seller company, which in turn improves the supply chain financing credit risk. However, a decrease in this rate does not significantly reduce the supply chain financing credit risk due to the lower financing volume and the buyer company's role as a financial supporter. As observed in the charts, greater fluctuations occur in the second and third years of the simulation, while fluctuations decrease from the fourth year onward.

- Changes in the discount rate in supply chain financing (5% to 30%)

The discount rate in supply chain financing acts as a moderating factor since an increase in financing (or in the rate of accounts receivable used in supply chain financing) leads to a higher discount amount. In the early years of the simulation, greater fluctuations are observed in the seller company's credit risk, which gradually decrease by the fifth year. The fluctuations in the supply chain financing credit risk index are smaller due to the buyer company's presence as a financially strong supporter.

- Changes in the non-cash sales rate (30% to 90%) (Supplier Company)

In the model, the non-cash sales rate is set at 70%. Reducing this rate to 30% improves the internal credit risk of the supplier company, which consequently improves the supply chain financing credit risk. However, according to Figure (7), this improvement is not highly significant, as the supply chain credit risk is influenced by multiple factors.

- Changes in sales growth rate (0% to 30%) (Main Company)

The sales growth rate for the main company is set at 30% in the model. If this rate decreases to 0%, the internal credit risk of the main company increases, leading to a rise in the supply chain financing credit risk. Additionally, from the third year onward, the internal credit risk of the supplier company also increases, as the model assumes that the credit risks of both companies impact the financing rate and borrowing ability of the supplier company. This effect becomes evident from the third year.

- Changes in sales growth rate (0% to 45%) (Supplier Company)

The sales growth rate for the supplier company is set at 45% in the model. If this rate is reduced to 0%, the internal credit risk of the supplier company increases, leading to a rise in the supply chain financing credit risk.

- Changes in COGS growth rate (27% to 60%) (Main Company)

The COGS growth rate for the main company is set at 27% in the model. If this rate increases to 60%, the internal credit risk of both the main and supplier companies, as well as the supply chain financing credit risk, rises.

- Changes in COGS growth rate (50% to 80%) (Supplier Company)

The COGS growth rate for the supplier company is set at 50% in the model. If this rate increases to 80%, the internal credit risk of the supplier company rises significantly, while the supply chain financing credit risk increases to a lesser extent.

- Changes in the initial interest rate (18% to 25%)

Changes in the initial interest rate from 18% to 25% have a minor impact on the credit risks of the supplier and main companies. Ultimately, these changes slightly reduce the supply chain financing credit risk.

- Changes in the liquidity index of traded goods (1 to 5)

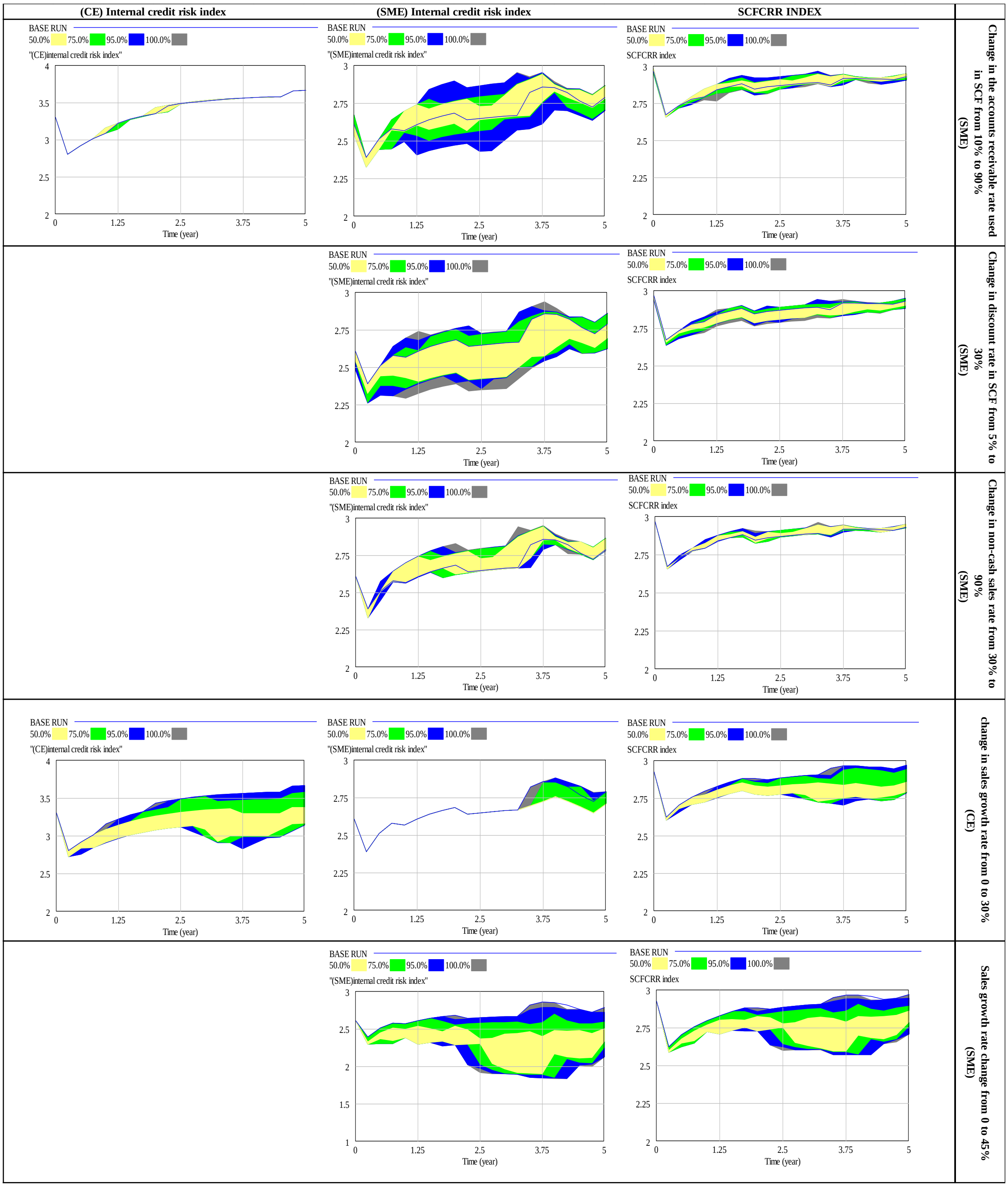
In the model, the liquidity index of the traded goods is set at 5. Reducing this index to 1 increases the credit risk of the main company, as difficulties in selling the produced goods lower the company's ability to repay debts. Consequently, the supply chain financing credit risk also rises. From the third year onward, the internal credit risk of the supplier company also increases, as the model assumes that the credit risks of both companies affect the financing rate and borrowing ability of the supplier company.

- Changes in the industry and economic risk index (1 to 5)

As shown in Figure (7), changes in the industry risk index within the range of 1 to 5 can significantly impact the supply chain financing credit risk.

- Changes in the quality index of the lending bank’s credit risk management (1 to 5)
- Changes in the supply chain position index (1 to 5)

Changes in the quality index of the lending bank’s credit risk management and the supply chain position index within the range of 1 to 5 have a minor impact on the supply chain financing credit risk.



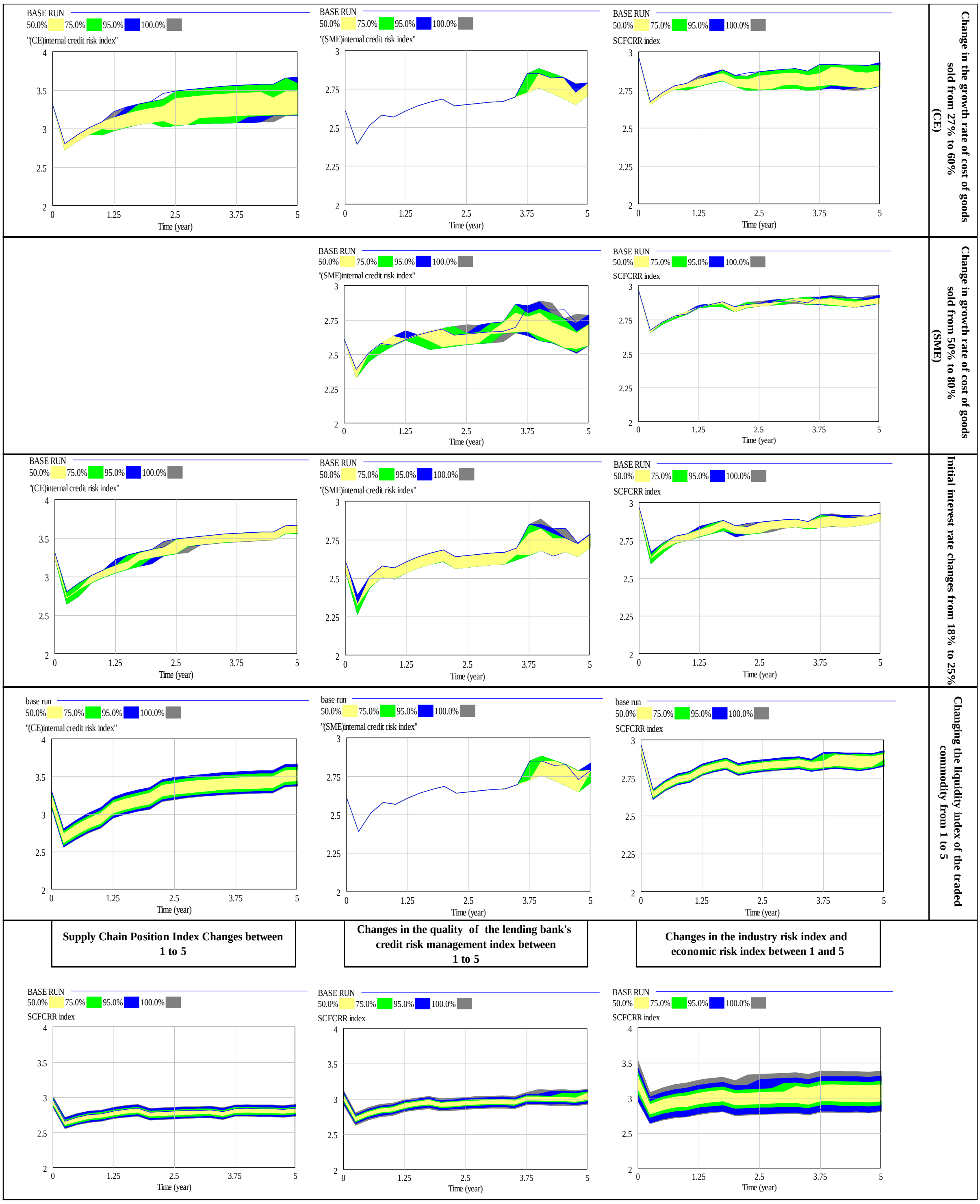


Figure 7. Model sensitivity analysis using Monte Carlo simulation"

Conclusion and Future Work

In this article, an extensive review of the literature and an analysis of previous research on credit risk in supply chain finance were conducted and Using dynamic system modeling, an attempt was made to develop a model that effectively simulates credit risk in supply chain finance. This model aims to enhance understanding of this phenomenon, identify influential factors affecting credit risk in supply chain finance, and analyze the impact of various scenarios on this risk.

To achieve this model, referred to as the Dynamic System Analysis Model for Credit Risk

Simulation in Supply Chain Finance, a two-tier supply chain was considered, financed through the factoring method. The proposed model is extendable to supply chains with more tiers and different financing methods.

Through literature review and expert opinions, the following key subsystems and macro variables were identified:

1.Internal credit risk of the supplier company
2.Internal credit risk of the main company
3.Quality of credit risk management by the lending bank
4.Supply chain position
5.Industry
6.Macroeconomy
7.Quality of the risk intermediary

Dynamic hypotheses for each subsystem were then formulated based on literature studies. The dynamic model was gradually developed, and various structural and behavioral tests were conducted to extract the final model. Next, different scenarios affecting the model were examined, and the model's responses to each scenario were analyzed.

Although the presented model is not claimed to be comprehensive, the applied validation tests and, more importantly, the simulation results indicate that it has successfully achieved the main research objective. The behaviors reproduced from different scenarios stem from the structures and relationships defined within the dynamic hypotheses. While each relationship used in the model is based on scientific and empirical studies, the combination of these relationships and the emergence of complex behaviors could be the subject of numerous future empirical studies.

Thus, this research takes a significant step toward advancing the "Simulation of Credit Risk in Supply Chain Finance Using System Dynamics Analysis." The proposed model can serve as a foundational basis for future research.

In addition to the primary goal, this study pursued several secondary objectives:

•Identifying the main subsystems affecting credit risk in supply chain finance.
•Recognizing the influencing factors and their interrelationships.
•Understanding how different factors interact and their causal relationships in determining credit risk in supply chain finance.
•Exploring the application of system dynamics analysis for credit risk simulation based on various factors.

Regarding credit risk simulation in supply chain finance, the proposed model serves as a suitable foundation. However, the forecast of credit risk trends in supply chain finance has been adjusted to align with the actual firms under study, and its internal relationships have been adapted to the firms' conditions. Nevertheless, since financial statements are integrated into the model and the main relationships between different subsystems are outlined, it allows for the use of Monte Carlo simulation to predict the impact of various scenarios on the credit risk index in supply chain finance.

In supply chain finance, the main company plays a crucial role, as financing is provided based on its creditworthiness. Additionally, the main company, as the buyer, must fulfill its obligations to the supplier on time so that the supplier can, in turn, meet its commitments. A strong main company in the supply chain reassures financial providers that the chain can continue operations and fulfill obligations. However, since the supplier company is responsible for repaying the credit, its financial system and financial indicators are scrutinized in greater detail to assess their impact on the supplier's credit risk.

Based on the literature review, it is expected that a supplier company (SME) participating in supply chain finance will experience lower credit risk and achieve a higher credit quality index. This is due to the presence of influential factors such as the higher creditworthiness of the buyer company (CE) and the risk intermediary, which is confirmed by the model's graphs.

An increase in the internal credit risk of both the supplier and buyer caused by changes in financial statement variables and non-financial factors related to corporate structure leads to higher credit risk in supply chain finance. Moreover, the position of the supply chain significantly affects credit risk. The more transactions occur between the buyer and seller and the longer their business relationship, the lower the credit risk in supply chain finance. However, it is important to note that credit risk in supply chain finance, with a one-period delay, can also impact the position of the supply chain.

The credit risk management of the lending bank plays a crucial role in controlling supply chain finance credit risk. By adopting appropriate risk assessment methods, formulating and implementing effective strategies, obtaining high-quality collateral, monitoring moral hazards to prevent collusion between employees and clients, and establishing a comprehensive credit information database, banks can improve the credit risk index in supply chain finance. Furthermore, credit risk in supply chain finance can, with a one-period delay, influence the quality of credit risk management by the lending bank.

Credit risk in supply chain finance is influenced by industry risk and macroeconomic risk, and in turn, it can impact industry risk and subsequently macroeconomic risk over time. Since supply chains consist of interconnected companies operating within an industry, a crisis in one segment can spread to other segments, the entire industry, or even the broader economy.

The presence of a risk intermediary and the quality of its services, such as providing credit risk insurance for supply chain finance, can help reduce risk.

Given the short-term nature of supply chain finance, a five-year simulation period was considered. Within this timeframe, the effects of various scenarios were examined, and Monte Carlo simulations were conducted. Different scenarios were then tested to analyze the impact of changes in key parameters on supply chain finance credit risk.

As shown in the model’s graphs, any change that simultaneously increases the credit risk of both the buyer and the seller significantly raises supply chain finance risk. However, if only one of the two companies (buyer or supplier) experiences an increase in credit risk, the overall supply chain finance credit risk remains relatively stable, as the other company can absorb the impact.

Finally, based on the results of various scenarios, the impact of changes in key parameters on three critical variables,internal credit risk of the lending bank, the main company, and supply chain finance credit risk was analyzed using Monte Carlo simulation.

As demonstrated in the sensitivity analysis graphs, the Supply Chain Finance Credit Risk Ratio (SCFCRR) is highly sensitive to financial variables affecting the credit conditions of the buyer and supplier. Additionally, it responds in a predictable manner to macroeconomic conditions, industry risk, supply chain position, and the quality of credit risk management by the lending bank.

According to the foregoing results, the following suggestions are summarized for further research:

- The model should be applied to supply chain financing in different industries.
- Use other supply chain financing methods to build and run the model.
- integrating quantitative methods and dynamic system analysis for a more holistic analysis.
- employs a supply chain with more tier to build the model.

Research Gap

So far, no study has employed a system dynamics analysis approach to evaluate credit risk in supply chain finance. Previous research has primarily utilized mathematical, econometric, and artificial intelligence methods to identify the key factors influencing credit risk in supply chain finance and to assign weights to these variables.

In this study, a comprehensive literature review, expert opinions, and the DEMATEL technique were used to identify the most important subsystems and influential variables. Subsequently, a causal loop diagram and flow diagrams were developed, capturing delays, feedback loops, and reinforcing or balancing loops—elements that were not incorporated in prior research due to the limitations of their chosen methodologies. Unlike previous studies, which lacked the ability to model delays, causal relationships, and feedback loops, this research provides a more holistic perspective on credit risk in supply chain finance.

Additionally, Monte Carlo simulation was used to conduct sensitivity analysis on the impact of changes in key variables. Through system dynamics analysis, this research offers a macro-level view of the entire credit risk system in supply chain finance, leading to a relatively comprehensive understanding of the system. This systemic and integrative approach, which enables predictive insights into the evolution of credit risk under different scenarios, has been overlooked in previous research. The absence of a systems perspective in earlier studies could potentially expose the entire supply chain to financial and credit crises.

This study is the first to apply system dynamics modeling for credit risk simulation in supply chain finance. Given its results, it has the potential to open a new chapter in research within this domain. The scientific contribution of this study can be summarized as follows:

- Demonstrating the potential of a holistic approach in examining the complex phenomenon of credit risk in supply chain finance and offering a new direction for further research.
- Providing a clearer picture of the hidden mechanisms influencing credit risk in supply chain finance, contributing to a better and more accurate understanding of this phenomenon.
- Outlining a roadmap for the further development and refinement of credit risk models, allowing for the creation of tailored models for specific supply chains.
- Incorporating delays and feedback relationships among variables, thereby offering a more insightful perspective on the credit risk system in supply chain finance.

Research Limitations

The development of system dynamics models is an iterative process, constantly evolving as new insights emerge and as model behavior is studied in greater detail. Consequently, no real-world phenomenon can be fully and comprehensively modeled, and credit risk in supply chain finance is no exception. The first limitation of this study is, therefore, the incompleteness of the model, which was inevitable given the nature of the methodology and the constraints of time.

Another limitation is the lack of prior research in this specific area. If previous studies had applied system dynamics modeling to credit risk in supply chain finance, this research could have advanced further by refining and expanding upon existing models.

Furthermore, due to the relatively recent emergence of supply chain finance in Iran, this study faced challenges such as limited data availability for model validation and gaps in the implementation and utilization of supply chain finance methods.

Managerial Insights

Since the developed model in this study effectively represents the dynamics of credit risk in supply chain finance, decision-makers in banks can utilize it to analyze the impact of their credit decisions before implementation.

The complexity of credit risk in supply chain finance makes it impossible to fully understand this phenomenon through simplifications or one-sided approaches. The findings suggest that banks, risk intermediaries, and major corporations should adopt a systems-thinking approach and use tools like system dynamics models to assess the potential outcomes of their policies and strategies before execution.

Using system dynamics modeling and refining it based on the characteristics of a specific supply chain finance system can provide a valuable tool for determining credit risk trends in supply chain finance. Achieving this would be a significant and practical contribution to the academic literature on credit risk in supply chain finance, allowing many supply chains to assess and monitor their own credit risk trends effectively.

This study proposes the following strategies to mitigate credit risk in supply chain finance:

1. Improving Creditworthiness:Companies should enhance their credit standing by improving both financial and non-financial variables that influence their credit profile.
2. Strengthening Collaboration:Companies should actively enhance their cooperation within the supply chain to reduce financial vulnerabilities.
3. Enhancing Credit Risk Management:Financial institutions should improve their credit risk management structures and increase risk awareness by adopting appropriate mechanisms.
4. Utilizing Risk Intermediaries:Engaging risk intermediaries to insure risks faced by supply chain finance and activating third-party services for risk assessment, transfer, and mitigation can be highly beneficial.
5. Regulatory Oversight:Stronger monitoring of industry regulations and policies can help prevent cascading financial crises within supply chains and, consequently, in supply chain finance.

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