



Upstream and Downstream Credit Exposure Modeling Around Core Industrial Enterprises

Lukas Meier¹, Sophie Keller^{2*}

Institute of Financial Services, University of Zurich, Zurich 8032, Switzerland

Corresponding Author*: Sophie Keller E-mail: s.keller@uzh.ch

ARTICLE INFO	ABSTRACT
<i>Keywords</i> Core industrial enterprises credit exposure modeling supply-chain credit risk graph neural inference knowledge graph upstream and downstream dependency industrial finance <i>Published:</i> 03 December 2026	Core industrial enterprises often anchor large supplier and distributor networks, and their operational or financial changes may affect upstream procurement, downstream sales, trade credit, receivable turnover, and bank credit exposure. Credit risk assessment focused only on a single borrower may miss hidden risk accumulated through dependence on a core enterprise. This study proposes an upstream and downstream credit exposure modeling method around core industrial enterprises. The model constructs a multi-relational graph linking core firms, suppliers, distributors, receivables, purchase orders, bank credit lines, guarantee contracts, logistics records, ownership ties, and payment outcomes. A graph neural inference module captures credit exposure transmission across upstream and downstream relations, while knowledge rules identify dependency risks from delayed payment, customer concentration, order contraction, shared guarantors, and regional industry shocks. Experiments are conducted on a core-enterprise credit dataset containing 8,240 core industrial firms, 162,000 upstream suppliers, 96,000 downstream distributors, 2.18 million purchase-order records, 1.34 million receivable entries, 74,000 bank credit contracts, and 9,860 confirmed credit-risk cases over 40 months. The proposed method shortens median early-warning time from 76 days to 28 days compared with a borrower-only credit model. It identifies 10,420 upstream exposure chains and 6,780 downstream repayment-risk paths linked to core-enterprise financial stress. Graph aggregation reduces 21,600 borrower-level alerts to 4,950 supply-chain exposure review cases. Portfolio simulation shows that graph-informed monitoring reduces expected overdue credit exposure by 156 million RMB during the validation period. The results demonstrate that upstream and downstream graph reasoning can improve credit risk management around core industrial enterprises by revealing dependency-based financial risk transmission.

1. Introduction

Core industrial enterprises occupy a central position in supply-chain finance because they connect upstream suppliers, downstream distributors, banks, logistics providers, guarantee institutions, and other commercial participants. Their operating conditions can therefore influence not only their own creditworthiness but also the liquidity and financial stability of a wider group of related firms. Changes in order volume, payment schedules, procurement activity, credit availability, or operating performance may quickly affect suppliers' receivables, distributors' inventories, and the repayment capacity of firms that depend heavily on the core enterprise. Credit risk in this setting is therefore not confined to an individual borrower. It may propagate through delayed payments, receivable accumulation, customer concentration, guarantee relationships, and common exposure to regional or sectoral shocks (Artemyev, 2026; Du, 2025). Traditional credit assessment methods mainly rely on financial ratios, historical repayment records, collateral values, and contractual

information (Qi & Qiao, 2026; Zhang, 2026). Although these indicators remain useful for evaluating individual borrowers, they provide only a partial representation of the interconnected risk structure that characterizes industrial supply chains (Liang et al., 2026b; Owolabi, 2025).

The growing availability of operational and transaction-level information creates new opportunities to monitor such interconnected exposures more effectively (Lin et al., 2020). Large-scale production and financial systems increasingly depend on consistent measurement infrastructures that can integrate heterogeneous operational indicators and maintain reliable monitoring across changing production environments (Bao et al., 2026b). This requirement is particularly important in supply-chain finance, where credit exposure may be reflected in purchase-order contraction, delayed receivable settlement, reduced logistics activity, abnormal use of credit lines, or deterioration in payment behavior before conventional financial statements reveal significant distress (Gadwell & McIntyre, 2026; Xiong et al., 2026). Graph-based credit models have consequently attracted increasing attention because they can represent firms as connected entities rather than isolated borrowers (Hong et al., 2026; J. Wu et al., 2026). Existing studies have shown that enterprise networks can improve default prediction by capturing hidden dependencies among borrowers, suppliers, customers, and financial institutions (Bao et al., 2026a; Kheneifar & Amiri, 2025). Such relational information provides an important basis for identifying both direct credit deterioration and indirect risk transmitted through trading and financing relationships (Huang et al., 2026; Zheng & Makar, 2022). Despite these advances, important limitations remain. Many existing graph-based credit models are constructed from relatively simple borrower-similarity networks or individual categories of transaction links (Gu, 2026; Pourkhoshgoftar et al., 2025). As a result, they may fail to represent the heterogeneous relationships through which credit exposure is actually formed and transmitted in industrial supply chains. Upstream suppliers, downstream distributors, purchase orders, receivables, bank credit contracts, guarantees, logistics records, ownership ties, and repayment outcomes often interact simultaneously, yet these information sources are rarely modeled within a unified relational structure (You, 2026; Zhao et al., 2026). Models that focus on a single borrower or a single type of connection may therefore overlook risk transmission across multiple counterparties and financial obligations (Brighi & Mussoni, 2025; Y. Wu & Su, 2026). In addition, conventional prediction models generally emphasize whether a borrower is likely to default but provide limited information about where the risk originates, how it propagates through the supply chain, and which related firms are likely to be affected. This limits their usefulness for financial institutions that need to monitor portfolio-level exposure rather than individual default probability alone (Jiao et al., 2026; Sarkar, 2026).

This study aims to address these limitations by developing an upstream and downstream credit exposure modeling framework centered on core industrial enterprises. The proposed framework constructs a multi-relational graph that jointly represents core firms, suppliers, distributors, receivables, purchase orders, bank credit contracts, guarantee records, logistics information, ownership links, and repayment outcomes. A graph neural inference module is used to learn how credit exposure propagates across heterogeneous supply-chain relationships, while knowledge-based rules are incorporated to identify interpretable risk paths associated with delayed payments, order contraction, customer concentration, shared guarantors, and regional industry shocks. Unlike borrower-centered approaches, the proposed method treats credit risk as a dynamic networked exposure process in which financial deterioration can originate from, and spread across, multiple connected entities. The empirical analysis is conducted using a large-scale dataset containing 8,240 core industrial enterprises, 162,000 suppliers, 96,000 distributors, 2.18 million purchase-order

records, 1.34 million receivable entries, 74,000 bank credit contracts, and 9,860 confirmed credit-risk cases observed over 40 months. By combining heterogeneous relational data with graph-based inference and interpretable risk-path analysis, this study seeks to improve the timeliness and accuracy of early warning, identify upstream and downstream channels of credit-risk transmission, reduce duplicated or fragmented alerts, and support portfolio-level exposure monitoring. The proposed framework therefore extends supply-chain credit analysis from isolated borrower assessment toward a more comprehensive representation of interconnected industrial risk, providing practical value for banks, supply-chain finance platforms, guarantee institutions, and other organizations responsible for monitoring financial stability across complex industrial networks.

2. Materials and Methods

2.1 Sample and Study Area Description

This study used a core-enterprise credit dataset covering 8,240 core industrial firms, 162,000 upstream suppliers, 96,000 downstream distributors, 2.18 million purchase-order records, 1.34 million receivable entries, 74,000 bank credit contracts, and 9,860 confirmed credit-risk cases. The observation period was 40 months. The sample mainly included firms from manufacturing, energy, logistics, chemicals, and industrial services. Core firms were selected when they had clear registration records, stable supplier and distributor links, and confirmed repayment outcomes. Firms were removed if their contract records were incomplete, their purchase-order or receivable data were missing for more than six months, or their repayment status could not be verified. The final sample retained enterprises with reliable transaction histories, matched credit contracts, and traceable upstream and downstream relations.

2.2 Experimental Design and Control Settings

The experiment was designed to test whether upstream and downstream exposure modeling can improve credit risk prediction. The proposed model was used as the experimental group. It included enterprise attributes, supplier and distributor links, purchase orders, receivables, credit contracts, guarantee records, logistics information, and repayment outcomes in one heterogeneous graph. Three control models were used for comparison. The first model used only borrower-level financial variables. The second model used enterprise links but excluded purchase orders and receivables. The third model used only upstream or downstream links without full supply-chain exposure. This setting helped test the effect of graph structure, trade records, and credit exposure. To reduce data leakage, the dataset was split by time. The first 30 months were used for training, the next 5 months for validation, and the last 5 months for testing.

2.3 Measurement Methods and Quality Control

Credit exposure was measured using payment delay days, receivable turnover, purchase-order volume, credit line usage, guarantee participation, and repayment outcomes. Upstream and downstream dependence was measured by the trade volume between core firms and related suppliers or distributors. Higher trade concentration indicated stronger dependence on the core enterprise. Data quality control was completed before model training. Duplicate enterprise IDs, repeated invoices, inconsistent contracts, and abnormal transaction records were removed. Missing monthly records were filled only when the gap was shorter than two months. Longer gaps were marked as missing records. Extreme values caused by one-time settlement, invoice correction, or contract adjustment were checked against payment and contract records. Monetary variables and order volumes were normalized by industry and firm size to reduce scale bias.

2.4 Data Processing and Model Formulation

A heterogeneous graph was built as $G=(V,E)$, where V denotes nodes and E denotes edges. The nodes included core firms, suppliers, distributors, receivables, purchase orders, credit contracts, guarantors, logistics records, and repayment outcomes. The edges represented ownership, transaction, credit, guarantee, logistics, and payment relations. Each node contained features such as credit limit, receivable age, order volume, payment delay, and repayment status. A graph neural network was used to learn risk information from neighboring nodes. The node representation of firm i was updated as follows:

$$h_i^{(l+1)} = \sigma \left(w_0 h_i^{(l)} + \sum_{r \in R} \sum_{j \in N_r(i)} \frac{1}{c_{i,r}} w_r h_j^{(l)} \right)$$

where $h_i^{(l)}$ is the node feature at layer l , R is the set of relation types, $N_r(i)$ is the neighbor set of firm i under relation r , w_r is the weight matrix for relation r , $c_{i,r}$ is the normalization term, and σ is the activation function. The credit-risk probability of firm i was then calculated as:

$$P_i = \frac{1}{1 + \exp [-(\beta_0 + \beta_1 z_i + \beta_2 d_i + \beta_3 q_i + \beta_4 g_i)]}$$

where P_i is the predicted risk probability, z_i is the graph embedding, d_i is the payment delay variable, q_i is the order contraction variable, and g_i is the guarantee or credit exposure variable.

2.5 Model Evaluation and Robustness Analysis

Model performance was assessed using AUC, F1-score, precision, recall, early-warning lead time, alert reduction rate, and inference latency. AUC and F1-score were used to assess overall prediction performance. Precision and recall were used to measure the identification of confirmed credit-risk cases. Early-warning lead time was defined as the number of days between the first model warning and confirmed repayment deterioration. Alert reduction rate measured the decrease in repeated borrower-level alerts after risk-path aggregation. Robustness tests were conducted across different industries, firm sizes, credit limits, and time windows. Ablation tests were also performed by removing upstream supplier features, downstream distributor links, purchase-order records, receivable records, or repayment data. These tests examined whether each data component improved prediction performance and whether the model remained stable under different supply-chain credit conditions.

3. Results and Discussion

3.1 Prediction Performance of the Exposure Graph Model

The proposed upstream and downstream credit exposure model performed better than the borrower-only credit model. Improvements were observed in AUC, F1-score, precision, and recall. This result shows that credit risk around core industrial enterprises cannot be captured fully by financial ratios alone. Trade records, receivables, guarantees, logistics information, and payment outcomes provide valuable signals of supply-chain dependence. As shown in Fig.1, the graph-based structure helps capture links among core firms, suppliers, distributors, and credit contracts. This finding agrees with recent studies showing that network data can improve risk prediction when borrower information is incomplete (Bao & Wang, 2026; Liang et al., 2026a). Unlike previous work, this study focuses on credit exposure around core firms rather than general borrower similarity or bank-client transaction networks.

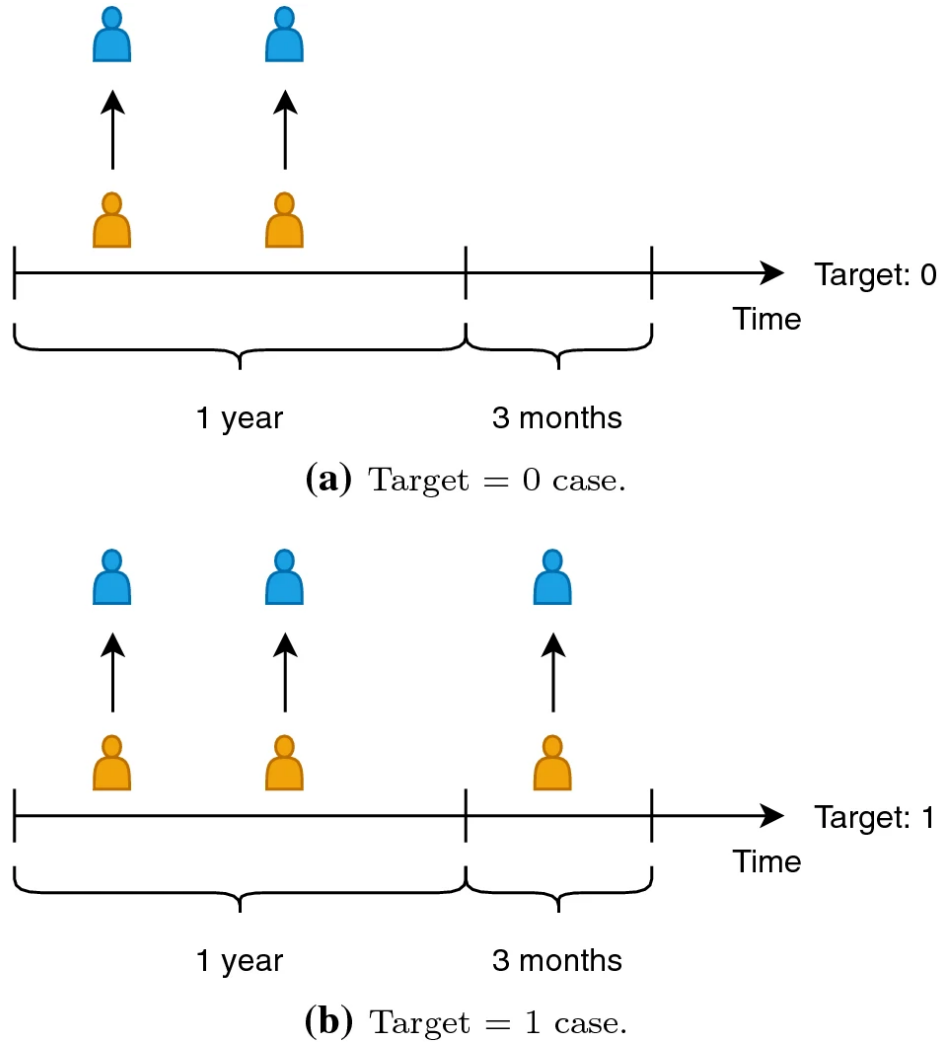


Fig. 1. Graph structure of core firms, suppliers, distributors, and credit links for risk prediction.

3.2 Early Warning Effect of Supply-Chain Signals

The model reduced the median early-warning time from 76 days to 28 days. This indicates that upstream and downstream signals can appear before formal repayment problems occur. In many cases, order reductions or delayed payments by core enterprises happened before suppliers or distributors showed credit stress. Upstream suppliers were more sensitive to receivable delays, while downstream distributors were affected by lower sales and higher inventory pressure. Borrower-only models rely on repayment history and financial ratios, which often lag behind changes in trade activity (Emiris et al., 2026; Wang et al., 2026). By using trade records and credit links, the proposed model detects early exposure changes and hidden risk paths more effectively.

3.3 Risk Path Detection and Alert Reduction

The model identified 10,420 upstream exposure chains and 6,780 downstream repayment-risk paths associated with core-enterprise stress. This shows that credit risk often develops through connected trade events rather than one isolated variable (Sarker, 2025; Yang & Du, 2026). A typical upstream path included delayed payment from a core enterprise, slower receivable collection, supplier cash-flow pressure, and increased bank credit use. A typical downstream path included lower sales orders, weaker distributor turnover, delayed repayment, and higher credit-line usage. As shown in Fig.2, graph aggregation reduced 21,600 borrower-level alerts to 4,950 supply-chain review cases. This reduction is important because repeated alerts increase review costs and slow response. Compared with feature-importance methods, risk-path analysis provides clearer evidence

on how exposure spreads across firms, contracts, and payment events.

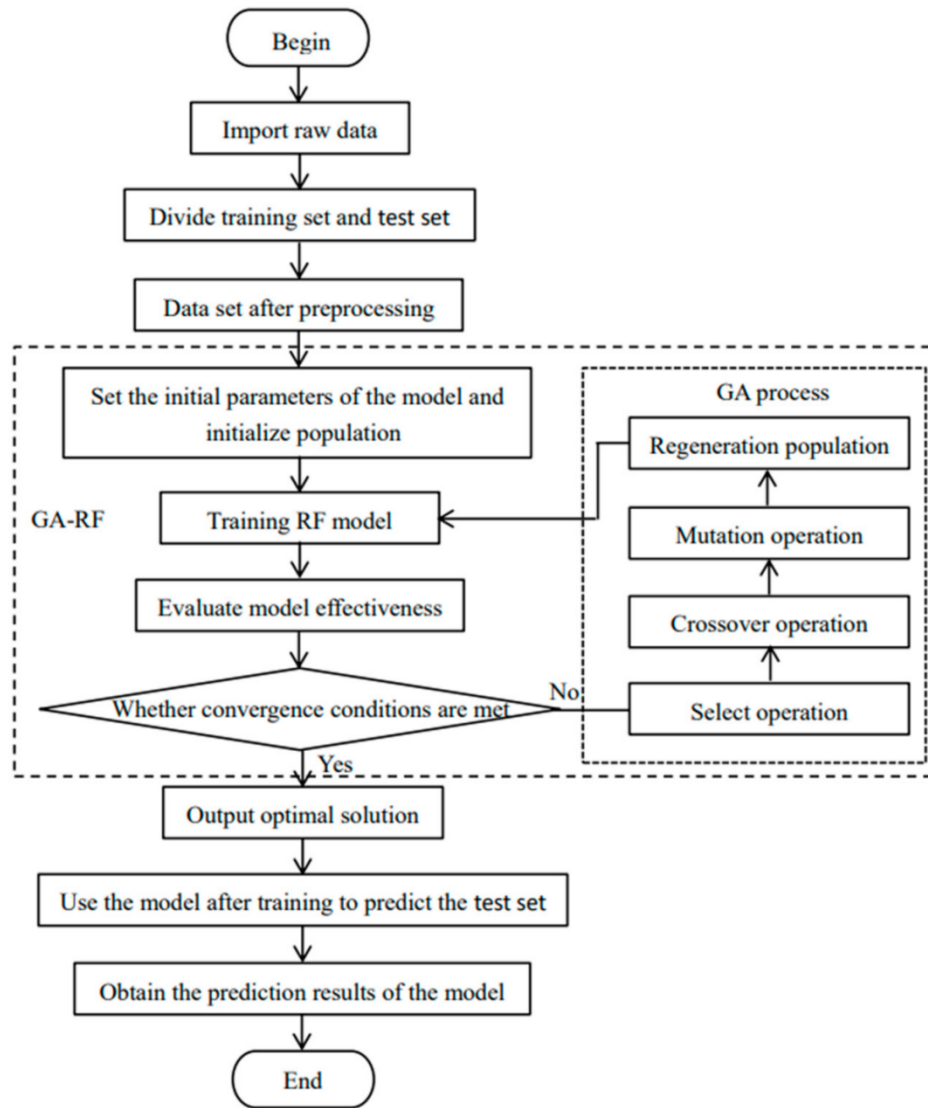


Fig. 2. Process of risk path detection and alert reduction in industrial finance.

3.4 Comparison with Existing Studies and Practical Implications

The results extend existing supply-chain credit research in three ways. First, prior studies mainly used financial indicators, expert scores, or single-firm variables. This study uses a multi-relational graph including core firms, suppliers, distributors, purchase orders, receivables, credit contracts, guarantees, logistics records, ownership links, and payment outcomes. Second, most prior studies focused on prediction accuracy. Here, early-warning time, exposure-path detection, alert reduction, and portfolio loss control were also evaluated. Third, portfolio simulation showed that graph-informed monitoring reduced expected overdue credit exposure by 156 million RMB during the validation period. This suggests that the model can support credit review, exposure monitoring, and early intervention for banks and industrial finance platforms. Limitations remain: missing purchase orders, delayed receivables, and incomplete logistics records may reduce stability. Future studies should test the model in other industrial clusters, credit products, and economic conditions.

4. Conclusion

This study developed a credit exposure model for core industrial enterprises that considers both upstream suppliers and downstream distributors. The results show that trade records, receivables, guarantees, and payment outcomes provide early signals of credit risk beyond borrower-level financial data. Compared with a borrower-only model, the proposed approach reduced the median early-warning time from 76 days to 28 days, identified more than 10,000 upstream exposure chains and nearly 7,000 downstream risk paths, and decreased 21,600 raw alerts to 4,950 review cases. The main contribution is the construction of a multi-relational graph linking core firms, suppliers, distributors, purchase orders, receivables, credit contracts, guarantees, logistics records, ownership, and repayment outcomes, which allows risk to be traced across the supply chain. This method offers early warning and interpretable risk paths, supporting banks, industrial finance platforms, and regulators in monitoring portfolio exposure. Limitations include reliance on complete trade, receivable, and logistics records, as missing or delayed data can reduce prediction reliability. Future work should test the model in different industries, integrate real-time transaction monitoring, and enhance stability under varying economic conditions.

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