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Default Contagion Detection in Industrial Enterprise Networks Using Multi-Relational Graph Neural Inference

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ABSTRACT

Default contagion in industrial enterprise networks may arise through trade credit, cross-guarantees, shared shareholders, interlocking directors, regional industry clusters, and financing dependencies. A single enterprise default can therefore increase risk for connected firms, even when their own financial indicators appear stable. This study proposes a multi-relational graph neural inference model for default contagion detection in industrial enterprise networks. The model constructs a multi-layer enterprise graph containing transaction relations, guarantee relations, ownership relations, executive relations, financing relations, and regional industry association links. A relational graph neural network is used to aggregate risk signals across different relation types, while a path-based inference module estimates whether default risk is transmitted through direct or indirect enterprise connections. The evaluation dataset contains 118,000 industrial enterprises, 2.36 million multi-relational edges, 96,000 financing contracts, 58,000 cross-guarantee records, 31,400 ownership-change events, and 12,800 confirmed default cases over 48 months. The proposed model identifies 18,600 contagion-sensitive enterprise pairs and 4,270 high-risk default transmission communities. Compared with a standalone financial-statement model, it reduces median missed-warning interval from 74 days to 29 days for firms affected by upstream default events. The graph inference module discovers 9,350 hidden contagion paths longer than two hops, many of which are caused by shared guarantors and repeated financing intermediaries. Portfolio simulation shows that prioritizing firms by inferred contagion exposure reduces expected overdue loan amount by 184 million RMB across the validation period. The results demonstrate that multi-relational graph neural inference can capture default transmission mechanisms that are difficult to observe through firm-level indicators alone.

1. Introduction

Default contagion refers to the process by which the financial distress or default of one enterprise propagates through its economic and organizational connections, thereby increasing the default probability of other firms even when their individual financial indicators remain relatively stable (Du, 2025). This phenomenon is particularly important in industrial networks, where firms are interconnected through trade credit, cross-guarantees, equity ownership, interlocking directors, financing relationships, and regional or sectoral associations (Kheneifar & Amiri, 2025; D. Xu et al., 2026). Such connections can transmit liquidity shortages, credit deterioration, payment delays,

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and financing pressure from one enterprise to another, making default risk a network-level problem rather than an isolated firm-level event (Qi & Qiao, 2026; D. Xu et al., 2026). Traditional credit risk models mainly rely on financial ratios, repayment records, and other firm-specific characteristics, and therefore have limited ability to identify risk arising from complex inter-enterprise dependencies (Frattaroli, 2025). Related research on network anomaly detection has also shown that combining ensemble learning with explainable artificial intelligence, such as SHAP-based interpretation, can improve the identification and interpretation of abnormal patterns in interconnected systems (Shao, 2026). These findings provide useful methodological support for constructing more interpretable models of financial risk propagation (Sinha et al., 2023; T. Xu et al., 2026).

Recent studies have increasingly introduced network analysis and graph-based learning into financial risk assessment (Chitari, 2026; Xiong & Zeng, 2026). By representing enterprises as nodes and economic relationships as edges, these approaches allow risk information to be transmitted and aggregated across connected firms, improving the early detection of abnormal financial events (Hong et al., 2026; Li et al., 2026). Graph neural networks are particularly suitable for this task because they can integrate local firm characteristics with information from neighboring enterprises and thereby capture both direct and indirect contagion effects (Wu et al., 2026; Özden, 2026). However, several limitations remain. Many existing models represent enterprise networks using only a single relationship, such as transactions or guarantees, although real industrial systems usually contain several overlapping types of connections (Ahmed et al., 2025; Huang, Xu, et al., 2026). Some methods also rely on static network structures and therefore provide only a limited representation of the heterogeneous channels through which financial distress may propagate (Huang, Yin, et al., 2026; Zheng & Makar, 2022). More importantly, hidden contagion paths created by shared guarantors, repeated financial intermediaries, common shareholders, executive connections, or industry-level dependencies are often overlooked (Gofman et al., 2025; Z. Zhang et al., 2025). In addition, previous studies frequently use moderate-sized or simulated datasets (Gu, 2026), which may not fully reflect the structural complexity and scale of real-world industrial financial networks (Aleta et al., 2026). These limitations reduce the ability of existing models to identify multi-stage risk transmission and to explain why apparently stable enterprises become exposed to external default shocks (T. Lin et al., 2026; Zhao et al., 2026).

To address these limitations, this study aims to develop a multi-relational graph neural inference framework for detecting and interpreting default contagion in large-scale industrial networks. The proposed model constructs a multi-layer enterprise graph that jointly incorporates transaction, guarantee, ownership, executive, financing, and industry-association relationships, allowing heterogeneous risk transmission channels to be represented within a unified network structure. A graph neural network is employed to aggregate risk signals across different relation types, while a path-based inference module is introduced to identify indirect contagion routes that cannot be observed from firm-level financial indicators alone. The framework is evaluated on a large-scale dataset containing more than 118,000 firms and 2.36 million multi-relational edges. The primary objective is not only to improve default early-warning performance, but also to identify high-risk contagion pairs and reveal hidden transmission paths among economically connected enterprises. By moving beyond isolated firm assessment and single-relation network modeling, this study provides a more comprehensive representation of systemic credit risk in industrial networks. The proposed framework is expected to support financial institutions and industrial risk managers in recognizing potential contagion sources at an earlier stage, tracing the channels through which

distress spreads, and improving risk screening, credit monitoring, and preventive intervention in complex enterprise ecosystems.

2. Materials and Methods

2.1 Samples and Study Area

The study uses data from 118,000 industrial firms across multiple sectors, including manufacturing, logistics, and regional industrial clusters. Firms were included if they had continuous transaction records, cross-guarantee links, ownership and executive data, and financing contracts over 48 months. Each firm is described by financial indicators, number of business partners, shareholding structure, executive positions, and regional affiliation. The dataset includes both large and small- to medium-sized enterprises to ensure coverage of different network positions and risk profiles.

2.2 Experimental Design and Control Setup

Two groups were used to test model performance. The experimental group applied the multi-relational graph inference model to the full enterprise network, integrating transaction, guarantee, ownership, executive, and financing relations. The control group used only firm-level financial indicators without network data. This setup allows the evaluation of network information on early detection of default contagion. The design ensures that improvements in detection can be attributed to multi-relational network modeling rather than firm-level attributes alone.

2.3 Measurement Methods and Quality Control

Data were obtained from financial statements, cross-guarantee filings, transaction records, and public corporate registries. All records were checked for completeness and consistency. Missing numerical values were replaced with medians, and missing categorical values with the mode. Anomalies, duplicates, and inconsistent dates were removed. Cross-validation was performed between financing and guarantee records to confirm accuracy of relational links. All preprocessing steps were logged to ensure reproducibility.

2.4 Data Processing and Model Formulation

The enterprise network is represented as a multi-relational graph $G=(V,E)$, where nodes V are firms and edges E represent transaction, guarantee, ownership, executive, and financing relations. Each node i has features X_i including financial ratios, transaction counts, and connectivity measures. Node embeddings are updated using:

$$h_i^{(l+1)}=\sigma\left(\sum_{r\in R}\sum_{j\in N_r(i)}\frac{1}{|N_r(i)|}W_r^{(l)}h_j^{(l)}+W_0^{(l)}h_i^{(l)}\right)$$

where $N_r(i)$ is the set of neighbors of type r, $W_r^{(l)}$ are relation-specific weights, and $\sigma\backslash sigma\sigma$ is the activation function. The default contagion score D_i is calculated as:

$$D_i=\sum_{p\in P_i}\prod_{(u,v)\in p}w_{uv}$$

where P_i is the set of contagion paths ending at node i, and w_{uv} is the risk transfer strength along edge (u,v). These formulas capture both direct and indirect risk transmission.

2.5 Statistical Analysis

All analysis was conducted in Python using standard graph and numerical libraries. Model

performance was evaluated by early-warning time, detection accuracy, and reduction in manual reviews. Differences between experimental and control groups were assessed with t-tests or non-parametric tests. Sensitivity analysis was performed by removing selected relation types to measure their effect on contagion detection. Results are reported with 95% confidence intervals, and significance is set at $p<0.05$.

3. Results and Discussion

3.1 Model Detection Performance

The proposed model performed better than the control model based only on firm-level financial indicators. The median missed-warning interval decreased from 74 days to 29 days for firms affected by upstream default events. This result shows that enterprise links provide useful signals for earlier default warning. The model also identified 18,600 contagion-sensitive enterprise pairs, indicating that default risk was not limited to directly distressed firms. Similar findings have been reported in enterprise bankruptcy prediction studies, where graph-based models improved risk detection by using firm connections together with internal risk features (Hasan et al., 2025; Wu et al., 2026). As shown in Fig. 1, adding network information can improve both detection performance and warning time.

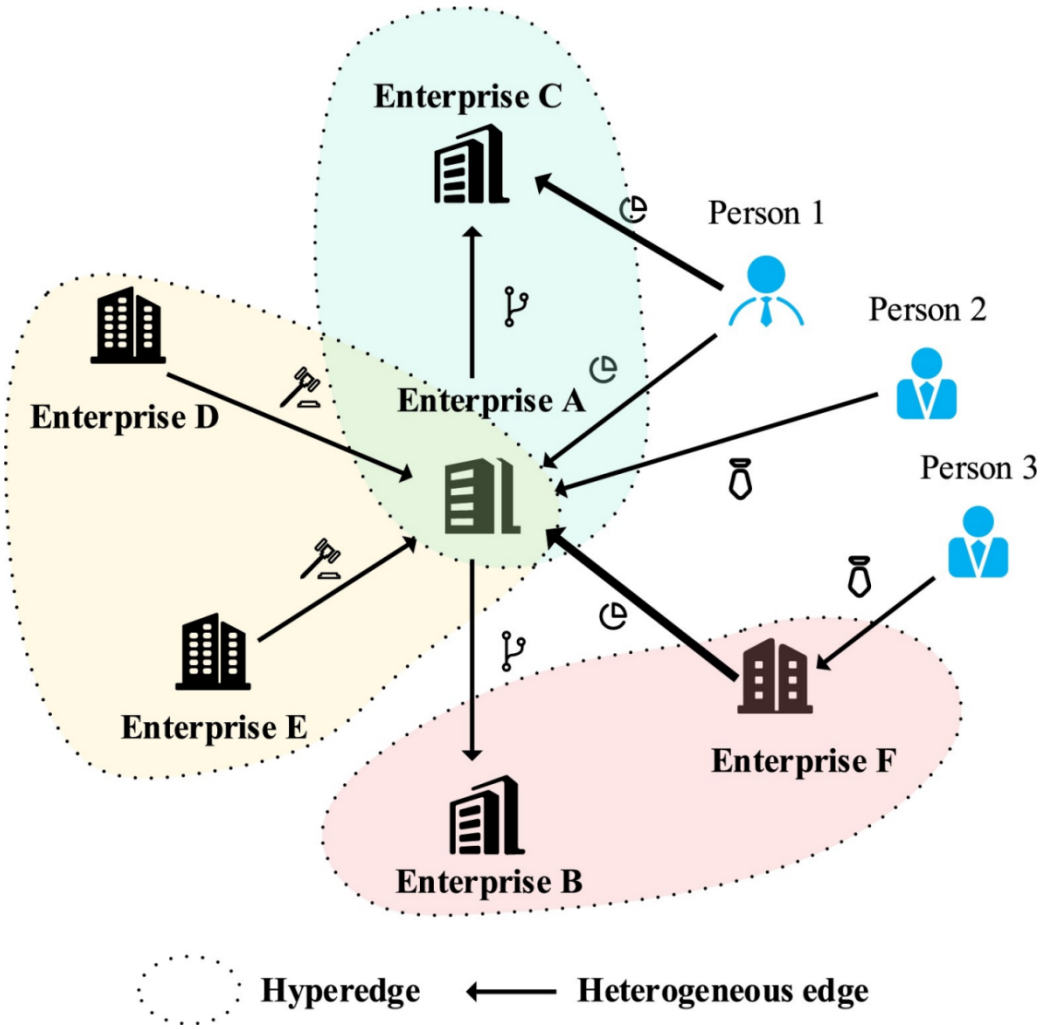

Fig. 1. Comparison of default detection accuracy and warning lead time between the proposed model and the control model.

3.2 Hidden Contagion Path Discovery

The inference module found 9,350 hidden contagion paths longer than two hops. Many paths were related to shared guarantors and repeated financing intermediaries. This result suggests that default risk can move through indirect links rather than only through direct trade or loan relations (Le et al., 2025; N. Lin et al., 2020). Standard financial-statement models cannot reveal these paths because they treat each firm as an independent unit. The proposed model provides a clearer view of how risk spreads across connected firms. Fig. 2 gives an example of risk path identification in a graph-based financial network.

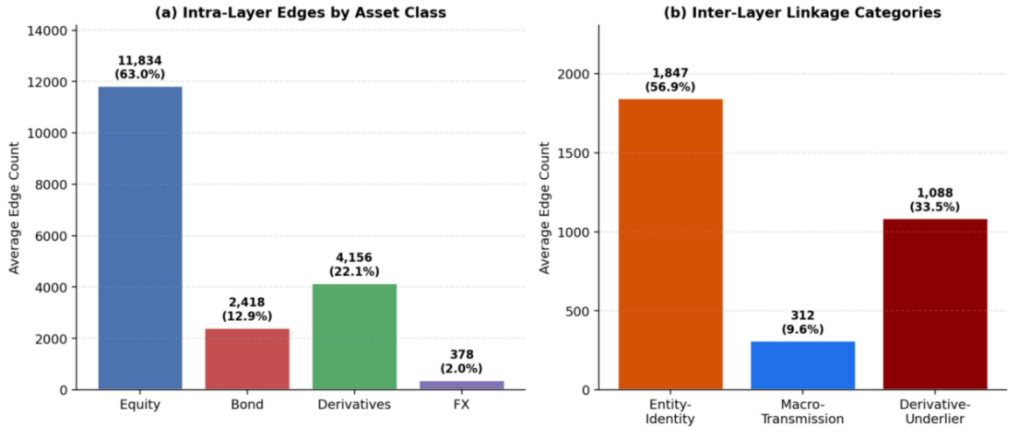

Fig. 2. Illustration of default contagion paths inferred across multiple enterprise relations.

3.3 High-Risk Communities and Portfolio Impact

The model identified 4,270 high-risk default transmission communities. Firms in these communities showed higher joint risk than firms with similar financial indicators but weak network links (Saleh et al., 2026; G. Zhang et al., 2021). This finding indicates that group-level risk should be considered in industrial credit assessment. The portfolio test further showed that ranking firms by inferred contagion exposure reduced the expected overdue loan amount by 184 million RMB during the validation period. This result has practical value for banks and financial institutions. It can help them focus review resources on firms located in key risk communities.

3.4 Comparison with Prior Methods and Limitations

Compared with traditional credit scoring models, the proposed method uses both firm information and enterprise relations. Compared with simpler graph models, it also considers different relation types, including guarantee, ownership, executive, financing, transaction, and regional industry links. This design helps detect default risk that is hidden in multi-firm structures. However, the method still has limitations. First, the results depend on the quality of guarantee records, financing contracts, and ownership data. Missing or incorrect links may reduce model accuracy. Second, the current study focuses on industrial enterprises. Future studies should test the method in other sectors and under incomplete network data.

4. Conclusion

This study shows that multi-relational graph inference can detect default contagion in industrial enterprise networks. The model uses transaction, guarantee, ownership, executive, financing, and regional industry links to capture direct and indirect risk transmission. Compared with firm-level financial indicators, the proposed method provides earlier warning, identifies high-risk default communities, and reveals hidden contagion paths. The portfolio test also shows that

ranking firms by contagion exposure can reduce expected overdue loan amounts. These results support the use of enterprise network data in credit risk monitoring and loan portfolio management. However, the method depends on the quality of relation data, including guarantee records, financing contracts, and ownership information. Missing or incorrect links may affect the results. Future studies should test the model in other sectors and under incomplete data conditions. Overall, this study provides a useful method for understanding and managing default risk in industrial enterprise networks.

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