Integrating Large Language Models and Knowledge Graphs for Causal Reasoning in Financial Risk Contagion Mechanisms

Guanyuan Yu
yuguanyuan@swufe.edu.cn
Southwestern University of Finance and Economics

Xu Wang
222081203024@smail.swufe.edu.cn
Southwestern University of Finance and Economics

Yu Zhao
zhaoyu@swufe.edu.cn
Southwestern University of Finance and Economics

Qing Li
liq_t@swufe.edu.cn
Southwestern University of Finance and Economics

ABSTRACT

A clear and well-documented LaTeX document is presented as an article formatted for publication by ACM in a conference proceedings or journal publication. Based on the "acmart" document class, this article presents and explains many of the common variations, as well as many of the formatting elements an author may use in the preparation of the documentation of their work.

CCS CONCEPTS

• **Computing methodologies** → **Causal reasoning and diagnostics**; • **Applied computing** → *Economics*; • **Social and professional topics** → *Economic impact*.

KEYWORDS

Large Language Models, Financial Knowledge Graphs, Causal Reasoning, Financial Risk Contagion

ACM Reference Format:
Guanyuan Yu, Xu Wang, Yu Zhao, and Qing Li. 2018. Integrating Large Language Models and Knowledge Graphs for Causal Reasoning in Financial Risk Contagion Mechanisms. In *Proceedings of Make sure to enter the correct conference title from your rights confirmation emai (Conference acronym 'XX).* ACM, New York, NY, USA, 8 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

Financial risk contagion refers to the phenomenon where the risk from one financial entity rapidly spreads to other entities [28, 32]. If not properly controlled, financial risk contagion can escalate into systemic risks [14, 27]. For instance, the 2008 financial crisis, which initially stemmed from issues in the U.S. real estate market, quickly spread to the broader financial sector and eventually affected global financial markets, resulting in a worldwide financial crisis. Therefore, identifying and preventing financial risk contagion is crucial for averting financial crises and maintaining economic stability, which has been obtaining widespread attention in both the academic and industrial sectors.

Conference acronym 'XX, June 03–05, 2018, Woodstock, NY

ACM ISBN 978-1-4503-XXXX-X/18/06
https://doi.org/XXXXXXX.XXXXXXX

Recent studies have focused on the issue of financial risk contagion from the perspectives of complex networks [1, 9, 61], statistical correlation [23, 57, 68], statistical causality [8, 41, 83], and deep learning [20, 58, 63]. However, these perspectives have the following limitations,

- **Causal Neglect**. The crucial element in the identification and mitigation of financial risk contagion lies in thoroughly understanding and accurately quantifying the embedded causal logic, which forms the basis of creating effective strategies for risk prevention and management. However, the first approach primarily investigates the influence of network topology on financial risk contagion [5, 15, 54], while the second stresses correlation relationships [12, 33, 71]. Both these methods tend to neglect the examination of causal relationships in financial risk contagion.
- **High Data Dependency**. The third perspective relies on covariance-based causal analysis, which is heavily dependent on high-quality observational data. However, in socio-economic research, it is difficult to obtain high-quality observational data. (a) Ethical and operational constraints render the execution of randomized controlled experiments unfeasible [35]. (b) The incorporation of unobserved confounders in many socio-economic datasets augments the likelihood of estimation errors [78]. (c) The employment of inadequate data collection methodologies and non-representative samples can detract from data quality [65]. (d) Erroneous conclusions can also ensue from poor model construction or inappropriate variable selection [13].
- **Limited Interpretability**. Interpretability is crucial to conducting financial risk contagion analysis. However, the deep learning models remain enigmatic as a black box, posing challenges to the elucidation of its internal mechanisms [18]. Therefore, the fourth approach is primarily centered on risk prediction and can not give insight into cause-and-effect relationships of risk contagion [6].

To address the above challenges, this study attempts to propose a framework called **RiskCausaNet**, integrating the causal reasoning capabilities of large language models (LLMs)[1] [77, 81] with the factual and professional knowledge, and interpretability

[1]In finance, LLMs have been gaining much attention for their exceptional performance [46, 66, 72]. Financial LLMs like FinBERT [42] and Xuanyuan [82] can handle more complex and diverse financial tasks. Notably, LLMs have been proven to possess capabilities in semantic understanding, knowledge generalization, and common sense reasoning, particularly excelling in causal logic reasoning.

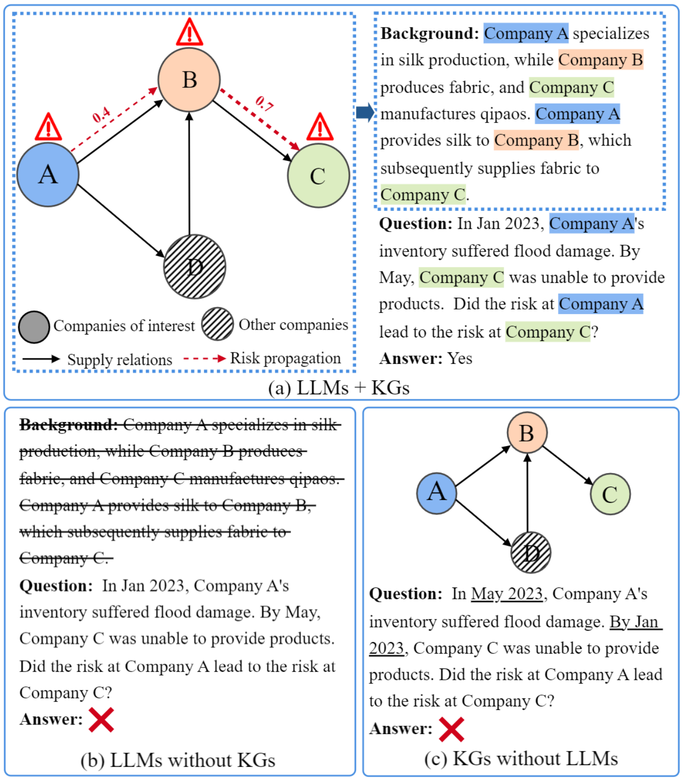

Figure 1: An example of risk contagion.

of financial knowledge graphs (KGs)[2] [51] to deeply analyze the cause-and-effect relationships of financial risk contagion, which is essentially transformed into a causal logic question-answering task via combining LLMs with KGs. For example, Fig. 1(a) demonstrates the identification and quantification of the risk propagation in the supply chain network of garment production. Here, we convert this task into a causal logic reasoning problem based on LLMs, which explain the mechanisms of risk contagion based on the high-level representations of financial KGs. The integration of LLMs and KGs is essential for a thorough analysis of financial risk contagion, with each complementing the other and both are indispensable. In the absence of the factual and professional knowledge provided by KGs, LLMs often struggle to effectively infer the causal mechanisms of risk propagation. As shown in Fig. 1(b), the capabilities of LLMs become limited when background details and graph information are removed. Similarly, without LLMs, KGs also find it difficult to accurately deduce the causal mechanisms. Fig. 1(c) reveals a fallacy of temporal sequence, where the risk event of *Company A* is not the cause of the risk event of *Company C*.

Notably, the data foundation for LLMs inference is natural language, whereas financial KGs are structured as graphs, leading to significant disparities in data modality. Here, we seamlessly integrate these two modalities across three dimensions: input data, model architecture, and loss function. **(1) At the input data level**, we transform financial KGs into a dataset tailored for causal question-answering, comprising prompts, contextual narratives, question sets, corresponding answers, and explanations. These transformed features are then fed into both GNNs and LLMs, generating high-level representations for KGs and textual data. **(2) At the model architecture level**, we introduce a joint representation module that incorporates a node attention mechanism from LLMs to KGs, aligning textual nominal and pronominal entities with KG nodes. A risk pathway inference module follows, employing an edge attention mechanism to discern predominant risk pathways. **(3) At the loss function level**, we employ a cross-entropy loss for answer prediction and a novel multi-scale contrastive loss. This additional loss function explicitly coordinates the alignment between textual nominal entities and KG nodes, as well as the alignment between sentences and KGs.

During the inference stage, LLMs leverage concise instructions, eliminating the need for supplementary background details, to adeptly trace the pathways of financial risk contagion via the high-level representations of financial KGs derived from GNNs. Finally, we can utilize network diagrams and Sankey diagrams to visualize the direction and intensity of financial risk contagion. In essence, we employ LLMs as a reasoning engine to explore risk contagion paths within financial KGs. While ensuring high predictive effectiveness, LLMs can provide causal logic reasoning for risk contagion, and can quantify the cause-and-effect relationships. In summary, our study distinguishes itself by making three salient contributions.

- To the best of our knowledge, this study is the first to integrate the reasoning capabilities of LLMs with financial KGs to give insight into the cause-and-effect mechanisms of risk contagion, and explore new methods and perspectives for financial risk research.
- This study explores new territory in fusing LLMs with KGs. It remedies the deficiencies of LLMs regarding factual and professional knowledge, hallucinations, and weak interpretability, and concurrently addresses the limitations of KGs in causal reasoning.
- Our model has demonstrated excellent performance and successfully visualized the pathways of risk contagion. Our corresponding data and code have been shared on GitHub for public access.

2 RELATED WORK

Financial risk contagion, as a key factor that could trigger systemic financial crises, has significantly impacted the socio-economic landscape, garnering widespread attention. Numerous scholars are delving into the phenomenon of financial risk contagion from four main perspectives: complex networks, statistical correlations, statistical causality, and deep learning techniques.

2.1 Complex Networks

Complex networks are mathematical models used to describe and analyze the interactions between various types of entities. In the study of financial risk contagion, complex networks are often employed to reveal the interconnections and influences among financial entities, aiding in the identification and understanding of risk propagation and diffusion [1]. Scholars primarily utilize complex

[2]KGs have significant advantages in representing domain-specific knowledge [51] and can provide clear reasoning pathways by depicting relationships between network entities, enhancing the interpretability of LLMs [74].

networks to study financial risk contagion from the following three perspectives: **(1) Analyzing network topology to study risk propagation**, such as network centrality [5, 9], clustering coefficient [54, 59], small-world properties [10], and connectivity [34, 61]. This approach to network topology helps identify key nodes crucial to network stability, understand the rapid changes in network structure during financial crises, and how these changes accelerate the spread of risk within the network. It also assesses the vulnerability and potential collapse points of the entire financial network system, thereby aiding policymakers and financial regulators in designing effective intervention measures to prevent or mitigate the spread of risk. For example, Daron Acemoglu, a Professor of Economics at MIT, provided a new perspective on the relationship between financial network structure, systemic risk, and financial network stability in a paper published in "American Economic Review" [2], and John Duffy confirmed the significant impact of interbank network structure on financial stability (the likelihood of financial risk contagion) [26]. **(2) Analyzing Complex Network Relationships to Study Risk Propagation**, such as inter-company guarantee networks[47, 53, 76], interbank networks[5, 16], and supply chain networks[10, 11]. These relationships provide important perspectives for analyzing and understanding how financial risks propagate among different financial entities, helping to reveal potential sources of systemic risks and transmission channels. For example, Xin Sui found that dynamic guarantee networks provide channels for risk contagion, exacerbating risk transmission among companies[67]. **(3) Using Network Models to Identify and Analyze Market Behavior Patterns**, such as herding behavior[52, 73], market volatility[3, 19], and investor sentiment[38, 60]. These market behavior patterns are often imitated by other network agents, spreading to alter the network structure, thereby weakening financial market stability[37]. A deeper understanding of these market behavior patterns helps reveal the psychological and social factors behind them, enabling more effective prediction and response to financial crises and providing crucial support for financial regulation and policy formulation. **However, research based on complex network theory for financial risk contagion often heavily relies on historical and observational data. The difficulty in obtaining and processing data frequently limits the construction of complex networks in many studies. Additionally, considering the dynamic nature of financial markets, the network's own dynamics can pose challenges to model stability and predictive capabilities.**

2.2 Statistical Correlation

Statistical correlation is a measure of the degree of interrelationship between two or more variables. In the study of financial risk contagion, statistical correlation is used to analyze and understand the potential mutual influence and behavioral synchronization among financial entities during crises[24]. Scholars in this field mainly utilize statistical correlation from the following two perspectives to research financial risk contagion: **(1) Analyzing Dynamic Correlation to Study Risk Propagation:** By analyzing the dynamic correlation conditions between the source entity of risk occurrence and other entities, researchers aim to identify whether there is contagion effect among financial entities[57, 68, 75]. For instance, Professor Chiang, a finance expert from Drexel University in the United States, published a paper in the top international finance journal, "Journal of International Money and Finance," where he used dynamic correlation analysis of Asian stock returns data to demonstrate contagion effects during financial crises. This analysis revealed two phases of the Asian crisis: increased correlation (contagion) and sustained high correlation (herding)[23]. This dynamic correlation analysis method is sensitive to the frequency of time series data collection, affecting the observed correlation levels and the understanding of financial risk contagion[71]. **(2) Analyzing Asset Class Correlation to Study Risk Propagation:** Some studies reveal the mechanisms of financial risk contagion by analyzing the correlation between different types of assets, such as contagion between stocks and bonds[33, 55], contagion among bonds, stocks, and currencies[12], and contagion among stocks, real estate, and commodities (e.g., gold)[40]. These studies explore how price fluctuations in one asset class can affect others, especially the strengthening of correlations among assets during crises[64]. **These research methods often overlook the nonlinearity and complexity of financial risk contagion and can introduce uncertainty due to different choices of time windows for analysis. More importantly, these correlation studies tend to focus on the associations among financial entities rather than directly examining causality among them, lacking in-depth interpretability regarding the transmission of risk among financial entities.**

2.3 Statistical Causality

Statistical causality analysis methods are often used to determine whether one variable (such as a risk event of a financial entity) causes a change in another variable (such as the occurrence of risk in another financial entity). In financial risk contagion research, this approach helps to identify and confirm potential causal relationships and transmission pathways between financial entities [36]. Scholars primarily rely on the following four statistical causality analysis methods to study financial risk contagion. **Bayesian Methods**: This statistical approach, based on Bayesian theorem, combines prior knowledge with newly acquired data to update probability estimates and infer causality [83]. It is often used to estimate the association and contagion probability between financial entities [17, 25, 45]. **Structural Equation Modeling**: A multivariate statistical analysis technique for analyzing complex relationships between variables [56], it is used to explore complex interactions between financial entities, such as asset prices [31], relationships between market indices [8], and how they propagate risk across different markets [7]. **Control Variable Method**: This method involves adding additional control variables to the model to fix other potential variables that might affect the outcome, thereby more accurately estimating the causal effect of the main independent variable on the dependent variable [62]. In financial risk contagion research, controlling other potential influencing factors, such as capital controls [29], allows for a more accurate estimation of the impact of specific events (like financial crises) on different financial markets [49]. **Granger Causality Test**: A statistical test method used to determine whether a set of time series data can predict another set of time series data [39], it can be used to detect dynamic associations between financial entities, such as analyzing whether fluctuations in one market can predict those in another [13, 36, 50], thereby revealing potential causalities in financial risk contagion. A representative study by Professor Hong Yongmiao from the University of Chinese Academy of Sciences in the "Journal of Econometrics" demonstrated that the Granger causality model can detect spillover effects in financial markets under extreme risks [41]. **These methods, mainly based on covariance-based causality analysis techniques, rely heavily on observational data [62] and may be affected by issues such as confounding variables, data quality, and model specification errors.**

2.4 Deep Learning

Deep learning is a machine learning method based on artificial neural networks that learns complex patterns through multi-layered data representation. In recent years, given the nonlinear and highly complex nature of financial markets, deep learning has gradually surpassed traditional econometric methods to become an important tool in the research of financial risk contagion. It provides more precise and reliable analytical results by delving into the analysis and understanding of complex interactions among financial entities[58]. The vast amount of financial data poses challenges such as the coexistence of unstructured and structured data, diverse data sources, and imbalanced normal and risk data. Deep learning techniques possess powerful feature extraction and pattern recognition capabilities, enabling effective analysis and handling of data heterogeneity[4, 48, 79], multisource data[44, 80], and data imbalance[6, 43]. This helps in gaining a better understanding of the dynamics and interactions within the financial system[21, 22, 30, 63]. For example, to assist the People's Bank of China in identifying and regulating "gray rhino" events, Associate Professor Cheng Dawei in finance at Tongji University published a paper in the top international data mining journal, "IEEE Transactions on Knowledge and Data Engineering," where he used the graph neural network architecture iConReg to detect risk contagion in loan guarantee networks[20]. **On the one hand, deep learning models are still considered "black boxes," making it challenging to explain their internal workings. On the other hand, these models may perform well on training data but have poor generalization capabilities on new datasets.**

3 OUR APPROACH

Fig. 2 presents the overview of our framework. Initially, financial KGs are converted into causal question-and-answer instructions. Subsequently, KGs and instructions are separately fed into GNNs and LLMs to derive high-level representations. A joint representation module is then responsible for fusing such two representations in a latent space, while the risk pathway reasoning module discerns predominant propagation routes. Finally, network diagrams and Sankey diagrams are used to illustrate the direction and intensity of risk contagion.

3.1 Financial KGs & Causal QA Instructions

Notably, the data foundation for LLMs inference is natural language, whereas financial KGs are structured as graphs, leading to significant disparities in data modality. To bridge this gap, we convert financial KGs into causal question-and-answer instructions, as displayed in Fig. 1. The instructions are then utilized to train and optimize LLMs in a question-and-answer manner, fostering causal reasoning within the context of financial KGs. This process empowers LLMs to more effectively understand and analyze the distinctive mechanisms of risk contagion in the financial domain.

In this study, our textual instructions adhere to the following specifications. (1) The background descriptions align with their corresponding financial KGs. (2) A series of questions are designed around the causal chain of financial risk contagion. (3) Each question is accompanied by an accurate answer, supplemented with an in-depth analysis that elucidates the mechanisms of risk contagion. (4) Their contents cover a broad of risk types, including market volatility, credit events, liquidity crises, and their subsequent chain reactions. (5) Complicated scenarios are constructed to enable our model to discern direct causal relationships and unravel multi-step, indirect risk propagation. Taking risk contagion within supply chain networks as an example, the designed instructions are as follows,

Role: *You are a professional assistant in financial risk contagion causal reasoning, and excel at pinpointing the causality behind risk contagion.*

Background: *Company A specializes in silk production, Company B in fabric manufacturing, and Company C in crafting qipaos. Company A provides silk to Company B, which then supplies fabrics to Company C.*

Q1: *Given the timeline of events, where Company A experienced flooding of their inventory in Jan 2023, leading to Company B's insufficient fabric production in March, and subsequently resulting in Company C's inability to provide products in May. Is it plausible to infer a causal relationship between Company A's risk event and Company C's risk occurrence? Please answer Yes or No.*

Q2: *In Jan 2023, Company A's inventory was flooded. In May, Company C was unable to deliver the products on schedule. Is it plausible to infer a causal relationship between Company A's risk event and Company C's risk occurrence? Please answer Yes or No.*

Q3: *In May 2023, Company A's inventory was flooded. In Jan 2023, Company C was unable to deliver the products on schedule. Please use financial knowledge to analyze whether Company A's risk is the cause of Company C's risk? Please answer Yes or No.*

Q4: *In Jan 2023, Company A's inventory was flooded. In May, Company C was unable to deliver the products on schedule. Please use financial knowledge to analyze whether Company A's risk is the cause of Company C's risk? Please answer Yes or No.*

Q5: *In Jan 2023, Company A's inventory was flooded. In May, Company C was unable to deliver the products on schedule. Please use your financial knowledge to analyze if Company A had not encountered the risk, would Company C still have faced the risk? Please answer Yes or No.*

Role Setting: LLMs typically undergo fine-tuning through prompt learning to enhance their performance in downstream tasks. In this context, endowing the LLMs with the role of "a professional assistant in financial risk contagion causal reasoning" can inspire the model to delve into and interpret core elements of this role, such as personality traits, background stories, motivations, and

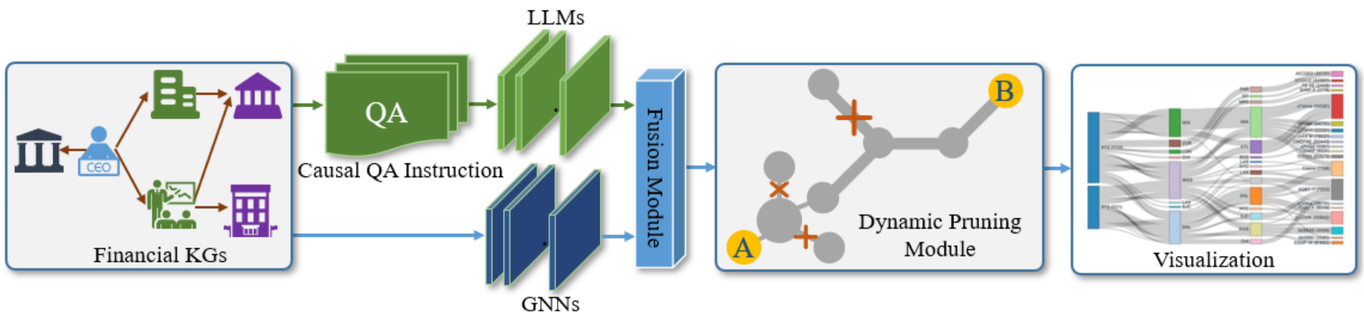

Figure 2: Our whole framework

actions. Through this approach, the model can more effectively simulate various scenarios of causal reasoning, creating dialogues and interactions closely tied to the role, thereby significantly improving its processing and analytical capabilities in the field of causal reasoning.

Background Description: This step aims to effectively transform the information from the knowledge graph into a context that the large language model can understand, while also avoiding semantic confusion that could affect subsequent reasoning accuracy. Specifically, key entities, attributes, and relationships are extracted from the financial knowledge graph using particular search strategies (like breadth-first or depth-first search). Then, this important information is integrated to form a smooth and coherent background description for the question. This approach not only enhances the usability of the information but also provides a clear reasoning foundation for the large language model.

Question Construction: To fully leverage the large model's capabilities in logical reasoning and financial domain knowledge for analyzing causal relationships in risk contagion, the applicant of this project has designed specialized causal question answering instructions: **(1) Considering two important properties in causal reasoning questions—sufficiency and necessity.** Sufficiency means that if the cause event occurs, the result event will also occur; necessity means that if the cause event does not occur, the result event will not happen. The applicant specifically considers these two properties of causal reasoning and meticulously designs for both factual and counterfactual reasoning. In the given example, **Question 2** considers sufficiency, i.e., based on factual reasoning, using the risk occurrence in Company A to predict whether Company C will face risk. **Question 3** in the example considers necessity, i.e., based on counterfactual reasoning, predicting whether Company C will face risk if Company A had not encountered risk. When the results of both **Question 1** and **Question 2** are "Yes," while **Question 3** is "No," it can be strictly determined that the large model has accurately inferred the causal chain of risk contagion, i.e., Company A's risk occurrence led to Company C's risk occurrence, signifying that the risk propagated from Company A to Company C. **(2) Designing the causal question answering instructions as a binary classification task.** A binary classification task involves categorizing the question into two classes for judgment. To enhance the efficiency and judgment capability of the large model in causal reasoning, the applicant has specifically transformed complex causal reasoning questions into binary classification tasks. The above examples **Question 1**, **Question 2**, and **Question 3** all consider this binary nature, i.e., using a simple and direct approach of answering with "Yes" or "No." **(3) Guiding the large model to use financial domain knowledge for causal reasoning through specific prompts.** Specific prompts can effectively guide the large model to focus on utilizing domain-specific knowledge, thereby enhancing its accuracy in causal reasoning within that domain. The applicant has carefully considered the guiding role of specific prompts and meticulously designed them for financial risk contagion causal reasoning. In the aforementioned examples, **Question 1**, **Question 2**, and **Question 3** all consider using these prompts, which is "Please use your knowledge in the field of financial risk to analyze."

3.2 Joint Representation Module

To integrate large model reasoning and knowledge graphs at the model architecture level, the applicant of this project constructs the model architecture as shown in Figure **??**, which includes a large language model, a graph neural network, a joint representation module, and a dynamic pruning module. **(1) Large Language Model for Learning Text Representations:** To stimulate the causal reasoning ability of the large language model in financial risk propagation, the applicant inputs causal reasoning question answering instructions into a pre-trained large language model (e.g., LLAMA2, InternLM) to obtain entity representations (Entity Representations). **(2) Graph Neural Network for Learning Knowledge Graph Representations:** The graph neural network aggregates information transmission between adjacent nodes in the graph through layer operations and updates node representations (Node / Entity Representations). **(3) Joint Representation Module for Aligning Text and Graph Representations:** Considering the modal differences between text and graph representations, the joint representation module employs a bidirectional attention mechanism to capture the fine-grained interactions between the two modalities. Let the input of the l-th layer joint representation module be the entity representations in the text $Q^{l-1} = \{q_i^{l-1}\}_{i=1}^{M}$ and the node representations in the graph $X^l = \{x_i^l\}_{i=1}^{V}$, where M and V represent the number of entities in the text representation and the number of nodes in the knowledge graph representation, respectively, then this module can be specifically represented as:

$$
\begin{aligned}
S_{ij} &= W_S^{\top}[q_i^{l-1}; x_i^l; q_i^{l-1} \circ x_i^l], \\
S_{qi}^l &= softmax(S_{ij}), \\
S_{xj}^l &= softmax(S_{ij}^{\top}), \\
\hat{q}_{ij} &= q_i^{l-1} \otimes S_{qi}^l, \hat{x}_{ij} = x_j^l \otimes S_{xj}^l, \\
q_i^l &= W_Q[q_i^{l-1}; \hat{x}_{ij}; q_i^{l-1} \circ \hat{x}_{ij}; q_i^{l-1} \circ \hat{q}_{ij}], \\
\bar{x}_j^l &= W_X[x_j^l; \hat{q}_{ij}; x_j^l \circ \hat{q}_{ij}; x_j^l \circ \hat{x}_{ij}],
\end{aligned}
$$

In the above formulas, S_{ij} represents the association matrix, $W_S^{\top}$, W_Q, and W_X represent learnable weight matrices, $\circ$ is element-wise multiplication, $\otimes$ represents matrix multiplication, $[;]$ denotes row-wise concatenation, S_{qi}^l represents the KG-to-LM (Knowledge Graph to Large Language Model) attention mechanism, S_{xj}^l represents the LM-to-KG (Large Language Model to Knowledge Graph) attention mechanism, essentially using the large language model to infer key nodes involved in risk contagion on the knowledge graph. With such a design, this module can effectively process and integrate large language model reasoning and knowledge graph information, promoting more precise alignment and fusion between the two. **(4) Dynamic Pruning Module for Capturing Significant Risk Contagion Pathways:** To accurately infer the pathways of financial risk propagation, this module uses the LM-to-KG (Large Language Model to Knowledge Graph) attention scores obtained from the joint representation module, analyzes the importance of each node, and filters out nodes closely related to financial risk propagation. Additionally, these attention scores can further assist in visualizing the financial risk contagion mechanism.

3.3 Risk Pathway Inference Module

3.4 Supervised Fine-tuning & Joint Optimization

To jointly train the overall model, the applicant of this project constructed a training dataset comprising N samples. This dataset encompasses a range of question answering instructions and financial knowledge graphs, along with their corresponding correct answers. Based on this, a binary cross-entropy loss function is constructed for model training:

$$
\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i)]
$$

In this formula, y_i represents the true answer label of the i-th sample, typically taking values 0 or 1; $\hat{y}_i$ is the model's predicted probability that the sample belongs to category 1. Ultimately, the RAdam optimizer is used to minimize the above loss function to achieve optimal model performance.

3.5 Risk Contagion Reasoning & Visualization

Firstly, the financial knowledge graph is converted into question-answering instructions suitable for causal reasoning. Secondly, these question-answering instructions, along with the graph, are input into the model for inferential analysis. Lastly, the attention scores from the LM-to-KG (Large Language Model to Knowledge Graph) selected by the pruning module are visualized for better understanding and analysis of the risk contagion pathways.

4 EXPERIMENTAL EVALUATION

4.1 Our Dataset

4.2 Baseline Models

4.3 Parameter Settings

4.4 Experimental Results & Analysis

4.5 Ablation Study

4.5.1 *How well dose the integration of LLMs with KGs perform?*

LLMs without financial KGs. ***Q2:*** *In Jan 2023, Company A's inventory was flooded. In May, Company C was unable to deliver the products on schedule. Is it plausible to infer a causal relationship between Company A's risk event and Company C's risk occurrence? Please answer Yes or No.*

- **InternLM-20B [70]**
- **InternLM-7B [70]**
- **GEMMA-7b-it [69]**

Financial KGs without LLMs. ***Q4:*** *In May 2023, Company A's inventory was flooded. In Jan 2023, Company C was unable to deliver the products on schedule. Please use financial knowledge to analyze whether Company A's risk is the cause of Company C's risk? Please answer Yes or No.*

- **GAT**
- **GNN**

4.5.2 *How well dose the joint representation module perform?*

Without attention mechanisms.

Visualization of attention weights.

4.5.3 *How well dose the risk pathway inference module perform?*

4.5.4 *How well dose the multi-scale contrastive loss perform?*

5 CONCLUSION

REFERENCES

[1] Kumushoy Abduraimova. 2022. Contagion and tail risk in complex financial networks. *Journal of Banking & Finance* 143 (2022), 106560.
[2] Daron Acemoglu, Asuman Ozdaglar, and Alireza Tahbaz-Salehi. 2015. Systemic risk and stability in financial networks. *American Economic Review* 105, 2 (2015), 564–608.
[3] Daniel Felix Ahelegbey and Paolo Giudici. 2022. NetVIX—A network volatility index of financial markets. *Physica A: Statistical Mechanics and its Applications* 594 (2022), 127017.
[4] Zahra Ahmadi, Peter Martens, Christopher Koch, Thomas Gottron, and Stefan Kramer. 2018. Towards bankruptcy prediction: Deep sentiment mining to detect financial distress from business management reports. In *2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA)*. IEEE, 293–302.
[5] Iñaki Aldasoro, Domenico Delli Gatti, and Ester Faia. 2017. Bank networks: Contagion, systemic risk and prudential policy. *Journal of Economic Behavior & Organization* 142 (2017), 164–188.

- [6] Huthaifa Aljawazneh, AM Mora, Pablo García-Sánchez, and PA Castillo-Valdivieso. 2021. Comparing the performance of deep learning methods to predict companies' financial failure. *IEEE Access* 9 (2021), 97010–97038.
- [7] Necmi K Avkiran, CM Ringle, and R Low. 2018. Monitoring transmission of systemic risk: Application of PLS-SEM in financial stress testing. *The Journal of Risk* 20 (2018), 83–115.
- [8] Necmi K Avkiran and Christian M Ringle. 2018. *Partial least squares structural equation modeling: Recent advances in banking and finance*. Vol. 239. Springer.
- [9] Paolo Bartesaghi, Michele Benzi, Gian Paolo Clemente, Rosanna Grassi, and Ernesto Estrada. 2020. Risk-dependent centrality in economic and financial networks. *SIAM Journal on Financial Mathematics* 11, 2 (2020), 526–565.
- [10] Rahul C Basole and Marcus A Bellamy. 2014. Supply network structure, visibility, and risk diffusion: A computational approach. *Decision Sciences* 45, 4 (2014), 753–789.
- [11] Rahul C Basole and Marcus A Bellamy. 2014. Visual analysis of supply network risks: Insights from the electronics industry. *Decision Support Systems* 67 (2014), 109–120.
- [12] John Beirne and Jana Gieck. 2014. Interdependence and contagion in global asset markets. *Review of International Economics* 22, 4 (2014), 639–659.
- [13] Jędrzej Białkowski* and Dobromił Serwa. 2005. Financial contagion, spillovers and causality in the Markov switching framework. *Quantitative Finance* 5, 1 (2005), 123–131.
- [14] Monica Billio, Mila Getmansky, Andrew W Lo, and Loriana Pelizzon. 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of financial economics* 104, 3 (2012), 535–559.
- [15] Michael Boss, Helmut Elsinger, Martin Summer, and Stefan Thurner 4. 2004. Network topology of the interbank market. *Quantitative finance* 4, 6 (2004), 677–684.
- [16] Christian Brownlees, Christina Hans, and Eulalia Nualart. 2021. Bank credit risk networks: Evidence from the Eurozone. *Journal of Monetary Economics* 117 (2021), 585–599.
- [17] Massimiliano Caporin, Rangan Gupta, and Francesco Ravazzolo. 2021. Contagion between real estate and financial markets: A Bayesian quantile-on-quantile approach. *The North American Journal of Economics and Finance* 55 (2021), 101347.
- [18] Davide Castelvecchi. 2016. Can we open the black box of AI? *Nature News* 538, 7623 (2016), 20.
- [19] Muzi Chen, Nan Li, Lifen Zheng, Difang Huang, and Boyao Wu. 2022. Dynamic correlation of market connectivity, risk spillover and abnormal volatility in stock price. *Physica A: Statistical Mechanics and Its Applications* 587 (2022), 126506.
- [20] Dawei Cheng, Zhibin Niu, Jie Li, and Changjun Jiang. 2022. Regulating systemic crises: Stemming the contagion risk in networked-loans through deep graph learning. *IEEE Transactions on Knowledge and Data Engineering* (2022).
- [21] Dawei Cheng, Zhibin Niu, Jianfu Zhang, Yiyi Zhang, and Changjun Jiang. 2023. Critical firms prediction for stemming contagion risk in networked-loans through graph-based deep reinforcement learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, Vol. 37. 14205–14213.
- [22] Dawei Cheng, Zhibin Niu, and Yiyi Zhang. 2020. Contagious chain risk rating for networked-guarantee loans. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 2715–2723.
- [23] Thomas C Chiang, Bang Nam Jeon, and Huimin Li. 2007. Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and finance* 26, 7 (2007), 1206–1228.
- [24] Giancarlo Corsetti, Marcello Pericoli, and Massimo Sbracia. 2001. Correlation analysis of financial contagion: what one should know before running a test. *Available at SSRN 274894* (2001).
- [25] Kingsley E Dogah and Gamini Premaratne. 2021. Dynamic interconnectedness and risk contagion among Asian financial markets. *The Singapore Economic Review* (2021), 1–46.
- [26] John Duffy, Aikaterini Karadimitropoulou, and Melanie Parravano. 2019. Financial contagion in the laboratory: Does network structure matter? *Journal of Money, Credit and Banking* 51, 5 (2019), 1097–1136.
- [27] Larry Eisenberg and Thomas H Noe. 2001. Systemic risk in financial systems. *Management Science* 47, 2 (2001), 236–249.
- [28] Matthew Elliott, Benjamin Golub, and Matthew O Jackson. 2014. Financial networks and contagion. *American Economic Review* 104, 10 (2014), 3115–3153.
- [29] Haichao Fan, Qin Gou, Yuchao Peng, and Wenjing Xie. 2020. Spillover effects of capital controls on capital flows and financial risk contagion. *Journal of International Money and Finance* 105 (2020), 102189.
- [30] Guobin Fang, Yaoxun Deng, Huimin Ma, Jun Zhang, and Li Pan. 2023. Energy Financial Risk Management in China Using Complex Network Analysis. *Journal of Organizational and End User Computing (JOEUC)* 35, 1 (2023), 1–29.
- [31] Emmanuel Senyo Fianu, Daniel Felix Ahelegbey, and Luigi Grossi. 2022. Modeling risk contagion in the Italian zonal electricity market. *European Journal of Operational Research* 298, 2 (2022), 656–679.
- [32] Prasanna Gai and Sujit Kapadia. 2010. Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 466, 2120 (2010), 2401–2423.
- [33] Konstantinos Gkillas, Athanasios Tsagkanos, and Dimitrios I Vortelinos. 2019. Integration and risk contagion in financial crises: Evidence from international stock markets. *Journal of Business Research* 104 (2019), 350–365.
- [34] Paul Glasserman and H Peyton Young. 2015. How likely is contagion in financial networks? *Journal of Banking & Finance* 50 (2015), 383–399.
- [35] Cory E Goldstein, Charles Weijer, Jamie C Brehaut, Dean A Fergusson, Jeremy M Grimshaw, Austin R Horn, and Monica Taljaard. 2018. Ethical issues in pragmatic randomized controlled trials: a review of the recent literature identifies gaps in ethical argumentation. *BMC medical ethics* 19, 1 (2018), 1–10.
- [36] Marta Gómez-Puig and Simón Sosvilla-Rivero. 2014. Causality and contagion in EMU sovereign debt markets. *International Review of Economics & Finance* 33 (2014), 12–27.
- [37] Qingbin Gong and Xundi Diao. 2023. The impacts of investor network and herd behavior on market stability: Social learning, network structure, and heterogeneity. *European Journal of Operational Research* 306, 3 (2023), 1388–1398.
- [38] Xiao-Li Gong, Jian-Min Liu, Xiong Xiong, and Wei Zhang. 2022. Research on stock volatility risk and investor sentiment contagion from the perspective of multi-layer dynamic network. *International Review of Financial Analysis* 84 (2022), 102359.
- [39] Clive WJ Granger. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society* (1969), 424–438.
- [40] Yingying Han, Pu Gong, and Xiang Zhou. 2016. Correlations and risk contagion between mixed assets and mixed-asset portfolio VaR measurements in a dynamic view: An application based on time varying copula models. *Physica A: Statistical Mechanics and its Applications* 444 (2016), 940–953.
- [41] Yongmiao Hong, Yanhui Liu, and Shouyang Wang. 2009. Granger causality in risk and detection of extreme risk spillover between financial markets. *Journal of Econometrics* 150, 2 (2009), 271–287.
- [42] Allen H Huang, Hui Wang, and Yi Yang. 2023. FinBERT: A large language model for extracting information from financial text. *Contemporary Accounting Research* 40, 2 (2023), 806–841.
- [43] Chyan-Long Jan. 2021. Detection of financial statement fraud using deep learning for sustainable development of capital markets under information asymmetry. *Sustainability* 13, 17 (2021), 9879.
- [44] Alisa Kim, Y Yang, Stefan Lessmann, Tiejun Ma, M-C Sung, and Johnnie EV Johnson. 2020. Can deep learning predict risky retail investors? A case study in financial risk behavior forecasting. *European Journal of Operational Research* 283, 1 (2020), 217–234.
- [45] Hee Soo Lee and Tae Yoon Kim. 2022. A new analytical approach for identifying market contagion. *Financial Innovation* 8, 1 (2022), 39.
- [46] Markus Leippold. 2023. Sentiment spin: Attacking financial sentiment with GPT-3. *Finance Research Letters* (2023), 103957.
- [47] Aolin Leng, Guangyuan Xing, and Weiguo Fan. 2017. Credit risk transfer in SME loan guarantee networks. *Journal of systems science and complexity* 30 (2017), 1084–1096.
- [48] Shixuan Li, Wenxuan Shi, Jiancheng Wang, and Heshen Zhou. 2021. A deep learning-based approach to constructing a domain sentiment lexicon: a case study in financial distress prediction. *Information Processing & Management* 58, 5 (2021), 102673.
- [49] Tangrong Li and Xuchu Sun. 2023. Is controlling shareholders' credit risk contagious to firms?—Evidence from China. *Pacific-Basin Finance Journal* 77 (2023), 101912.
- [50] Ling Lin, Yuanpei Kuang, Yong Jiang, and Xianfang Su. 2019. Assessing risk contagion among the Brent crude oil market, London gold market and stock markets: Evidence based on a new wavelet decomposition approach. *The North American Journal of Economics and Finance* 50 (2019), 101035.
- [51] Michael Loster, Tim Repke, Ralf Krestel, Felix Naumann, Jan Ehmueller, Benjamin Feldmann, and Oliver Maspfuhl. 2018. The challenges of creating, maintaining and exploring graphs of financial entities. In *Proceedings of the Fourth International Workshop on Data Science for Macro-Modeling with Financial and Economic Datasets*. 1–2.
- [52] Shan Lu, Jichang Zhao, Huiwen Wang, and Ruoen Ren. 2018. Herding boosts too-connected-to-fail risk in stock market of China. *Physica A: Statistical Mechanics and its Applications* 505 (2018), 945–964.
- [53] Guojian Ma, Juan Ding, Youqing Lv, et al. 2022. The Credit Risk Contagion Mechanism of Financial Guarantee Network: An Application of the SEIR-Epidemic Model. *Complexity* 2022 (2022).
- [54] Sheri Markose, Simone Giansante, and Ali Rais Shaghaghi. 2012. 'Too interconnected to fail'financial network of US CDS market: Topological fragility and systemic risk. *Journal of Economic Behavior & Organization* 83, 3 (2012), 627–646.
- [55] David G McMillan. 2020. Interrelation and spillover effects between stocks and bonds: cross-market and cross-asset evidence. *Studies in Economics and Finance* 37, 3 (2020), 561–582.
- [56] Shaun McQuitty and Marco Wolf. 2013. Structural equation modeling: A practical introduction. *Journal of African Business* 14, 1 (2013), 58–69.
- [57] Sabur Mollah, AMM Shahiduzzaman Quoreshi, and Goran Zafirov. 2016. Equity market contagion during global financial and Eurozone crises: Evidence

from a dynamic correlation analysis. *Journal of International Financial Markets, Institutions and Money* 41 (2016), 151–167.

[58] Mojtaba Nabipour, Pooyan Nayyeri, Hamed Jabani, Amir Mosavi, and Ely Salwana. 2020. Deep learning for stock market prediction. *Entropy* 22, 8 (2020), 840.

[59] J-P Onnela, Kimmo Kaski, and Janos Kertész. 2004. Clustering and information in correlation based financial networks. *The European Physical Journal B* 38 (2004), 353–362.

[60] Xingzhi Qiao, Huiming Zhu, Zhongqingyang Zhang, and Weifang Mao. 2022. Time-frequency transmission mechanism of EPU, investor sentiment and financial assets: A multiscale TVP-VAR connectedness analysis. *The North American Journal of Economics and Finance* 63 (2022), 101843.

[61] Natalia Restrepo, Jorge M Uribe, and Diego Manotas. 2018. Financial risk network architecture of energy firms. *Applied Energy* 215 (2018), 630–642.

[62] Julia M Rohrer. 2018. Thinking clearly about correlations and causation: Graphical causal models for observational data. *Advances in methods and practices in psychological science* 1, 1 (2018), 27–42.

[63] Mehmet Sahiner. 2023. Volatility Spillovers and Contagion During Major Crises: An Early Warning Approach Based on a Deep Learning Model. *Computational Economics* (2023), 1–65.

[64] Garry J Schinasi and R Todd Smith. 2000. Portfolio diversification, leverage, and financial contagion. *IMF staff papers* 47, 2 (2000), 159–176.

[65] Scott M Smith, Catherine A Roster, Linda L Golden, and Gerald S Albaum. 2016. A multi-group analysis of online survey respondent data quality: Comparing a regular USA consumer panel to MTurk samples. *Journal of Business Research* 69, 8 (2016), 3139–3148.

[66] Matheus Gomes Sousa, Kenzo Sakiyama, Lucas de Souza Rodrigues, Pedro Henrique Moraes, Eraldo Rezende Fernandes, and Edson Takashi Matsubara. 2019. BERT for stock market sentiment analysis. In *2019 IEEE 31st international conference on tools with artificial intelligence (ICTAI)*. IEEE, 1597–1601.

[67] Xin Sui and Liang Li. 2018. Guarantee network model and risk contagion. *Chaos, Solitons & Fractals* 106 (2018), 323–329.

[68] Manolis N Syllignakis and Georgios P Kouretas. 2011. Dynamic correlation analysis of financial contagion: Evidence from the Central and Eastern European markets. *International Review of Economics & Finance* 20, 4 (2011), 717–732.

[69] Gemma Team, Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, Pouya Tafti, and et al. 2024. Gemma. (2024). https://doi.org/10.34740/KAGGLE/M/3301

[70] InternLM Team. 2023. Internlm: A multilingual language model with progressively enhanced capabilities.

[71] Haytem Troug and Matt Murray. 2021. Crisis determination and financial contagion: an analysis of the Hong Kong and Tokyo stock markets using an MSBVAR approach. *Journal of Economic Studies* 48, 8 (2021), 1548–1572.

[72] Chaojie Wang, Yuanyuan Chen, Shuqi Zhang, and Qiuhui Zhang. 2022. Stock market index prediction using deep Transformer model. *Expert Systems with Applications* 208 (2022), 118128.

[73] Guocheng Wang and Yanyi Wang. 2018. Herding, social network and volatility. *Economic Modelling* 68 (2018), 74–81.

[74] Junxing Wang, Xinyi Li, Zhen Tan, Xiang Zhao, and Weidong Xiao. 2021. Relation-aware Bidirectional Path Reasoning for Commonsense Question Answering. In *Proceedings of the 25th Conference on Computational Natural Language Learning*. 445–453.

[75] Kuan-Min Wang. 2013. Did Vietnam stock market avoid the "contagion risk" from China and the US? The contagion effect test with dynamic correlation coefficients. *Quality & quantity* 47 (2013), 2143–2161.

[76] Lei Wang, Shouwei Li, and Chaoqun Wu. 2019. Risk contagion in inter-firm credit guarantee network. *Physica A: Statistical Mechanics and its Applications* 526 (2019), 120842.

[77] Taylor Webb, Keith J Holyoak, and Hongjing Lu. 2023. Emergent analogical reasoning in large language models. *Nature Human Behaviour* 7, 9 (2023), 1526–1541.

[78] Takashi Yanagawa. 1984. Case-control studies: assessing the effect of a confounding factor. *Biometrika* 71, 1 (1984), 191–194.

[79] Xiaoxian Yang, Shunyi Mao, Honghao Gao, Yucong Duan, and Qiming Zou. 2019. Novel financial capital flow forecast framework using time series theory and deep learning: a case study analysis of Yu'e Bao transaction data. *Ieee Access* 7 (2019), 70662–70672.

[80] ShuiLing Yu and Zhe Li. 2018. Forecasting stock price index volatility with LSTM deep neural network. In *Recent Developments in Data Science and Business Analytics: Proceedings of the International Conference on Data Science and Business Analytics (ICDSBA-2017)*. Springer, 265–272.

[81] Cheng Zhang, Stefan Bauer, Paul Bennett, Jiangfeng Gao, Wenbo Gong, Agrin Hilmkil, Joel Jennings, Chao Ma, Tom Minka, Nick Pawlowski, et al. 2023. Understanding causality with large language models: Feasibility and opportunities. *arXiv preprint arXiv:2304.05524* (2023).

[82] Xuanyu Zhang and Qing Yang. 2023. Xuanyuan 2.0: A large chinese financial chat model with hundreds of billions parameters. In *Proceedings of the 32nd ACM International Conference on Information and Knowledge Management*. 4435–4439.

[83] Michael J Zyphur and Frederick L Oswald. 2015. Bayesian estimation and inference: A user's guide. *Journal of Management* 41, 2 (2015), 390–420.

A RESEARCH METHODS

A.1 Part One

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Morbi malesuada, quam in pulvinar varius, metus nunc fermentum urna, id sollicitudin purus odio sit amet enim. Aliquam ullamcorper eu ipsum vel mollis. Curabitur quis dictum nisl. Phasellus vel semper risus, et lacinia dolor. Integer ultricies commodo sem nec semper.

A.2 Part Two

Etiam commodo feugiat nisl pulvinar pellentesque. Etiam auctor sodales ligula, non varius nibh pulvinar semper. Suspendisse nec lectus non ipsum convallis congue hendrerit vitae sapien. Donec at laoreet eros. Vivamus non purus placerat, scelerisque diam eu, cursus ante. Etiam aliquam tortor auctor efficitur mattis.

B ONLINE RESOURCES

Nam id fermentum dui. Suspendisse sagittis tortor a nulla mollis, in pulvinar ex pretium. Sed interdum orci quis metus euismod, et sagittis enim maximus. Vestibulum gravida massa ut felis suscipit congue. Quisque mattis elit a risus ultrices commodo venenatis eget dui. Etiam sagittis eleifend elementum.

Nam interdum magna at lectus dignissim, ac dignissim lorem rhoncus. Maecenas eu arcu ac neque placerat aliquam. Nunc pulvinar massa et mattis lacinia.

Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009