iConVis: Interactive Visual Exploration of the Default Contagion Risk of Networked-Guarantee Loans

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Abstract—Groups of enterprises can serve as guarantees for one another and form complex networks when obtaining loans from commercial banks. During economic slowdowns, corporate default may spread like a virus and lead to large-scale defaults or even systemic financial crises. To help financial regulatory authorities and banks manage the risk associated with networked loans, we identified the default contagion risk, a pivotal issue in developing preventive measures, and established iConVis, an interactive visual analysis tool that facilitates the closed-loop analysis process. A novel financial metric, the contagion effect, was formulated to quantify the infectious consequences of guarantee chains in this type of network. Based on this metric, we designed and implemented a series of novel and coordinated views that address the analysis of financial problems. Experts evaluated the system using real-world financial data. The proposed approach grants practitioners the ability to avoid previous ad hoc analysis methodologies and extend coverage of the conventional Capital Accord to the banking industry.

Index Terms—Networked-guarantee loans, Regtech, Risk management, Visual analytics, Complex network

1 INTRODUCTION

Regulatory technology (RegTech) is designed to enhance transparency and consistency and address the regulatory challenges faced by financial services providers, including monitoring, reporting, and compliance obligations. RegTech development is changing the nature of financial markets and services [2, 3]. The rapid development of FinTech has increased awareness of visual analytics and artificial intelligence in this area. The chief economist for the Bank of England, Andy Haldane, imagined the future of RegTech to be a global map of financial flow that charts spillovers and correlations [46].

Networked-guarantee loans, a unique financial and banking phenomenon in some countries, are attracting increased attention from regulators and banks. When enterprises back one another in loan applications, they form complex directed networks. Highlighted by the multifaceted background of the growth period, the structural adjustment of the pain period, and early stages of the stimulus period, structural and deep-level contradictions have emerged in the economic development system. During economic slowdowns, corporate default 1 financial terminology referring to a business failure to fulfill an obligation, especially to repay a loan or appear in a court of law.

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may spread like a virus and lead to large-scale defaults or even systemic financial crises. Thus, the need for risk management is more urgent than ever before. Monitoring the world’s financial status is so complicated that it is usually only after a capital chain rupture that regulators are able to study cases in depth. Regulators and banks are seeking to utilize data-driven and visual analytics approaches to managing the risk brought about by networked loans. However, the public research output for this problem is still relatively limited.

We worked closely with financial experts to conduct research on the networked-guarantee loan risk management problem. We identified that the default contagion risk for networked loans is an important yet unexplored interdisciplinary research problem. Data-driven and visual analytics-based approaches can provide fresh insights into assessing the contagion risk and preventive measures that can be taken. In this research, we propose iConVis, a novel visual analytics approach, as a means of helping financial experts conduct in-depth analyses of the default contagion risk problem.

The main contributions of this work are as follows:

- **We discover and highlight eight interpretable contagion chain patterns** by analyzing real-world bank loan records. The patterns illustrate different contagion characteristics that lay the basis for quantitative contagion risk assessments (i.e., the contagion effect) and our visualization design.

- **We propose a systematic data-driven and visual analytics approach** to the contagion risk problem within the framework of the closed-loop analysis process. Our approach offers financial experts the ability to avoid previously ad-hoc methodologies.

- **We describe iConVis**, an interactive visual analytics tool we developed to analyze the contagion risk problem with networked loans. Several novel visualization and interaction design are included, such as the guarantee network tessellation layout, flower petal zooming interaction design that overcomes visual clutter, and the contagion effect badge that provides visual symbols for quantifying contagion risk.

The rest of this research is organized as follows. Section 2 describes work involving different aspects related to our problem. Section 3 details the background and requirement analysis used in our approach. Section 4 considers the methods and system. In Section 5, we present the results of case studies and expert feedback on the system. A discussion and conclusions appear in Sections 6 and 7, respectively.

### 2 Related Work

Data and visual analytics technologies are applied extensively in financial risk management problems in domains such as macro-prudential oversight and fraud detection in online transactions and investment [23, 16, 18, 38]. In this section, we first introduce the capital accord, an important risk management framework for the banking industry, and then works on interdisciplinary financial risk management and data visualization analytics.

**Capital Accord** With the goal of enhancing the understanding of key supervisory issues and improving the quality of banking supervision, the Basel Committee on Banking Supervision issued a series of recommendations on banking laws and regulations (Basel I, II, and III) [13]. These principles have been widely accepted by banks around the world. Under Basel II, a series of parameters, also named as internal ratings-based approach [42], are used to calculate the economic or regulatory capital of banking institutions. 1) Probability of default (PD). Default probability can be estimated from historical default data, observable prices of credit default swaps, bonds, and options on the common stock market identified using machine learning algorithms like decision trees, logistic regression, support vector machines, neural networks, genetic programming, ensemble methods, and many other machine learning processes [3, 26]. In credit risk management, the standard assumption is that a loan is considered in default when the client is past due on payment by at least three months. 2) Loss-given default (LGD). This refers to the share of an asset that is lost if a borrower defaults. LGD is facility-specific because such losses may be influenced by key transaction characteristics such as the presence of collateral and the degree of subordination. 3) Exposure at default (EAD). This is defined as the gross exposure of a facility upon the default of an obligor. 4) Expected loss. This can be formulated as the product of PD, LGD, and EAD.

**Micro-prudential oversight** measures systemic risk both timely and accurately [38]. Many studies of visualization for macro-prudential oversight have been conducted for the financial sector. The foremost work is by the Volatility Laboratory of Nobel Laureate Robert Engle. His group provides real-time online measurement, modeling, and forecasting of financial volatility and correlations with systemic risk via classic interactive charts such as bar charts, Box plots, and map charts, and other prime examples [17]. In the cross-sector of machine learning and financial stability, Peter Sarlin published a series of works on visualized systemic risk analytics in cooperation with the European Central Bank, International Monetary Fund, and other international banks [36]. The self-organizing map, a neural network-based unsupervised learning method and visualization tool, can be utilized to evaluate and visualize financial stability with the power of simultaneous clustering and projection [39, 40, 37]. The self-organizing map based on financial stability has also been extended with a novel time dimension to decompose and identify temporal structural changes in macro-financial data around the global during financial crises [38].

**Network visualization** is employed to represent bank interrelations through financial discussion data [11].

**Fraud detection in transactions** is always a primary concern of banks [16]. The Advanced Detection System was one of the earliest risk visualization systems that monitored trades and quotations on the Nasdaq stock index, identifying patterns and practices of behavior of potential regulatory interest [24, 25]. Wireives employs specific coordinated keyword visualization for wire transactions that can be used to detect suspicious accounts, transactions, behaviors [7]. 3D tree maps have been introduced to monitor real-time stock market performance and identify particular stocks that produce unusual trading patterns. Suspect trading pattern matching is used to identify fraud patterns, suspected traders (i.e., attackers), and attack plans [21].

**Network-based visual analysis**. Pienta et al. customized a network query method to help users quickly explore networks by reducing query results and clustering [34]. Major et al. proposed a unit visualization method for large-scale multi-variable relational data, taking into account attributes and network structure [27]. Bach et al. proposed a universal confluent drawings algorithm to bundle edges, simplifying the network but keeping the main skeleton [4]. Chen et al. proposed a structure-based exploratory method to support the effective exploration of large networks [8]. Nocaj proposed a preprocessing method for small-world networks that can automatically select the optimal threshold, filter out the slight edges, and obtain the optimal graph skeleton [32]. Nobre proposed a means of visualizing group networks based on division and hierarchical progression [31].

**Network-based visual analysis in the financial sector** Network algorithms enable the exploration of crucial relationships and associations among a broad set of objects. For example, customers, markets, banks, and global markets connect in a network [3, 22]. Graph-drawing algorithms, as well as financial domain knowledge, are borrowed to visualize and assess. The force-directed layout is perhaps the most extensively utilized in the financial area. Rmnqvist and Sarlin collected text data from online financial forums and generated and visualized a co-mentioned bank network (i.e., interbank network) [35]. Didimo et al. proposed VISFAN, a financial activity network visual exploration tool for discovering financial crimes such as money laundering and fraud [14]. Xu and Chen discussed criminal network analysis and visualization, a very close domain. Their insights included that social network analysis can be used to analyze interaction patterns and criminal networks can be partitioned into subgroups of individuals by the centralities in their network, such as node degree, betweenness, and closeness [47, 15]. Heijmans and others used animation to visualize and analyze the large transaction networks in the daily Dutch overnight money market [20]. Dan used force-directed graph visualization.
tion to analyze Bitcoin transaction activity and explore dynamically generated patterns of algorithmic behavior [28]. We are the first to identify and report a visual analytic framework for the risk management problem with networked loans [30, 10, 9].

3 Problem Statement and Requirement Analysis

In this section, we first present the necessary background of this unique financial phenomenon, and then report major concerns obtained from loan assessment experts; finally, we offer a summary of the analysis tasks and design rationales, based on real-world motivations.

3.1 Background of Networked Loans

The origin of networked-guarantee loans is illustrated in Figure 2. It is a common scenario in which small businesses that wish to obtain loans from commercial banks usually lack the security required. In this case, they are allowed to seek a guarantee from other businesses. In practice, there can be more than one guarantor per loan transaction, and there may be multiple loan transactions for a single guarantor in a given period. Once the loan is approved, the company can usually immediately obtain the full amount of the loan and begin to repay the bank via a regular instalment plan, until the end of the loan agreement.

![Fig. 2. A typical loan guarantee process includes four major steps.](image)

We worked closely with two loan assessment experts to better understand the real-world challenges inherent in this system. Expert E₁, a senior financial regulatory officer with more than five years of experience with the guaranteed loan problem and had published several important and relevant investigation reports. Expert E₂ came from our partner bank, had ten years of loan approval experience, and could access the complete data set. The financial experts divided the default contagions and corresponding response interventions into four phases (see Figure. 3).

![Fig. 3. Default contagious phases and response interventions. The red nodes refer to the default company and dashed nodes/links are the default contagion chain.](image)

Default contagions are usually triggered by accidental defaults that introduce risks. Since these are obligation contracts, the default contagion may spread to adjacent nodes (those providing guarantees). Anticipating how debt default may spread is critical to introducing the appropriate response interventions. An appropriate guarantee union reduces the risk of default, but in practice, significant damage from contagion can still occur among networked companies. In the case of a down economy, defaults can multiply as large-scale corporate defaults cause side effects in the network. In such cases, the guarantee network can be alienated from the “joint assistance group” as a “breach of contract”. When some companies face operational difficulties, the crisis may set off a domino effect. Default can spread rapidly across the network and put a large number of companies in unfavorable positions. A systemic crisis can result. At this stage, control and mitigation are imperative. After the elimination or eradication stage, the guarantee network may need to be split into several smaller networks, with some companies bankrupted and the transmission risk reduced. Below, we summarize the main concerns of the experts and outline the requirements for mitigation in the following subsection.

Concern 1: Basel accord-based risk management systems may not be well-suited for networked loans, as the network relationship is unique and exceeds the hypothesis [13]. It is urgent and essential to adapt the old or establish new risk measurements for this type of problem.

Concern 2: Particular attention should be paid to contagion risk to prevent the large-scale corporate defaults often brought about by networked loans. Accidental default is usually tolerable, while large-scale defaults or systemic financial crises must absolutely be prevented. However, it is currently unclear how contagion spreads through guarantee networks, how vulnerable the nodes are, or how likely default is to spread. Regulators and banks seek to monitor/assess the status of such spreads via data-driven and visual analytics approaches to resolving risk and ensuring financial stability.

3.2 Summary of Analysis Tasks

Below we summarize our analysis tasks, addressing experts’ most significant concerns, supporting the assessment of crisis levels, and gaining insight into precautions preventing potential financial risks.

T.1 Explore networks at different levels of detail, quickly locating networks of interest. Motivated by expert concerns and technical challenges when analyzing massive bodies of guarantee data, the system should support the quick location of networks of interest and analysis of them according to different levels of detail.

T.2 Understand how default contagion may spread across a guarantee network and extract contagion patterns. The forward approach to understanding the spread of default is to simulate the situation by establishing virus-epidemic models such as in [33]. However, in our case this is impossible, due to a shortage of empirical default data. From a data-driven perspective, identifying the potential contagion chains and extracting their patterns can also provide insights useful to the ultimate goal of precautions that avoid or resolve systemic financial risk.

T.3 Analyze instances of contagion chains. This should support case-by-case risk assessment and evaluation, as there are multiple instances of contagion chains even with the same pattern. Appropriate quantitative indicators are helpful to making careful comparisons.

T.4 Provide novel and objective risk measurements/indicators tailored for networked loans. The classic Basel accord-based risk measurement is not well-suited to the problem, as it is based on the assumption that these are giant independent players in the market. It is necessary to set up a novel objective risk indicator for this type of problem.

T.5 Quantify the amount the risk that will spread and identify key nodes. Inspired by the concept of super-spreaders in epidemiology [41], a few corporations are prone to “superspreading events”, and given the right conditions can ignite explosive epidemics. Moreover, such volatility also means that outbreaks are
more likely to fizzle out relatively quickly. Identifying the super-spreaders (i.e., key nodes) is crucial if a regulator is to take preventive measures.

### 3.3 Design Rationale

Based on these analysis tasks, a series of design decisions was made, as outlined below.

**DR 1 Scalable and appropriate network layout visualization.** The networks, constructed from real-world datasets, should be composed of massive nodes. The system requires a scalable massive node network layout to avoid severe visual clutter and sufficient performance to enable sophisticated interactions. The experts were familiar with the force-directed layout, as in our previous work [30]. It avoids excessive occlusion and visual clutter caused by unnecessary node coverage with expensive computational resources. In practice, target users may wish to analyze networks of interest on various levels of detail; thus, we need a compact arrangement incorporating over 3,000 independent networks via interactions such as magnify, filter, and select (T.1-T.5).

**DR 2 Focus on contagion chains.** Identify and discover the default contagion patterns in a guarantee network (T.2) and propose appropriate contagion risk indicators/measurements based on the patterns (T.4), as well as intuitive visualization to help with efficient evaluation of the assignment of priorities.

**DR 3 Appropriate symbols and color mapping for intuitive metaphors.** Intuitive representation is an essential element of most visualization systems. Proper visual metaphors help experts reduce the visual burden and improve their understanding of the actual situation (T.1).

### 4 Method

This section describes the method used to develop the visual analytic system.

### 4.1 Overview of the Approach

Motivated by the analytical tasks outlined above, we designed and implemented iConVis to support financial experts interactively exploring the contagion risk associated with networked loans. Figure 4 gives an overview of the approach.

The process mainly included three steps. 1) Data preprocessing. Raw bank loan records have been cleaned and reorganized into the node table (corporation profiles), edge table (guarantee relations), and contagion chain table. 2) Contagion pattern analysis. We employed an unsupervised learning-based approach to extract contagion chain structure patterns, and here propose a novel financial metric for quantifying the contagion risk of the chains and networks. The patterns and metrics formed the basis of our visual design and support this type of financial analysis. 3) Visual analysis loop. We designed a visual interface that is closely coupled with financial risk management tasks and knowledge to support closed-loop analysis processing and an iterative level of detailed exploration. We describe the details of the data and contagion pattern analysis in the subsequent subsection and the visualization design and interaction in the section after that.

### 4.2 Data

In this work, we collected ten-year loan data from cooperating commercial banks and built a guarantee network. The names of the customers in the records were encrypted. In the record preprocessing phase, by joining the tables, we obtained records related to the corporation ID and guarantee contract. We then constructed the guarantee network.

As Figure 4 shows, at the data preprocessing step, we cleaned and reorganized the record data into three main tables. 1) The node table included the corporation profiles (business type, size, and registered capital); the primary key was the corporation ID. 2) The edge table was the directed guarantee relations between corporations (i.e., the nodes in the node table). It also included the guarantee amounts between them as weights of the edges. Figure 5 gives an overview of the real-world data set, with each node representing an enterprise and the link direction representing the guarantee relationship. More than 20,000 businesses and more than 3,000 independent networks are visualized. It is clear that the networks overlap, but few insights can be drawn. Zooming in, there is a significant directed subgraph microstructure. Some prime aspects may be familiar to loan assessment domain experts [30, 9, 10], but the collective financial properties of those microstructures are unclear and need to be explored.

3) Contagion chain table. We defined the contagion chain (i.e., the chain of contagion) as the subgraph of where the default might spread. If we can obtain and understand the contagion risk pattern, we may be able to determine how the default risk might spread across the guarantee network and thus implement measures to prevent any potential occurrence of large-scale defaults (T.1). The contagion chain table was reconstructed from the node and edge tables and used repeatedly throughout this work. The contagion chain, different from the guarantee chain, worked in the direction opposite to the arrows. In practice, the guarantee network was split into several subgraphs of contagiousness (noted as contagion chains) when we reversed the directions of the arrows. We applied a breadth-first traversal algorithm and generated a series of subgraphs, storing them as contagion chain files in the JSON format. Figure 6 includes an example where (a) is the guarantee network, (b) is the contagion chain when Node A defaults and spreads the risk, and (c) gives all possible contagion chains. It should be noted that though some of the chain were subgraphs of other chains, all were...
analyzed equally because each node could have been the first default and thus spread the risk.

4.3 Contagion Chain Pattern Analysis

The contagion chain pattern analysis is the basis of our approach and critical to understanding the contagion properties of a network. In this section, we apply the unsupervised learning approach to extract the patterns, interpret their financial meaning, and quantify the risk brought by each kind of contagion pattern.

The contagion chains were subgraphs, so we extracted network information propagation-related attributes to construct the contagion chains features. In this way, each contagion chain was represented by a five-dimensional vector. In detail, the attributes included: (1) the number of nodes and edges of the contagion chain, noted as $N(c_i)$ and $E(c_i)$, respectively. (2) The density of the contagion chain, noted as $D(c_i)$. This was defined as the ratio of the number of edges to the number of possible edges in a network with nodes. It measures the proportion of possible ties that are actualized among the members of a network. (3) The average clustering coefficient of the contagion chain, noted $C_i$. This is computed as the average of the clustering coefficients $C_i$ of all of the nodes in the chain. It is closely related to the transitivity of a graph and serves as an indicator of a small world. (4) Average shortest path length, noted as $l_G$. This is calculated by finding the shortest paths between all pairs of nodes and taking the average over all paths of the length thereof. It gives the number of steps it takes to get from one member of the network to another and measures the efficiency of information or mass transport on a network.

We chose to use spectral clustering for mining the contagion chain structure patterns. The approach frequently outperforms traditional methods such as k-means or single linkage, especially in graph-based clustering tasks [44]. Moreover, it can be solved efficiently by standard linear algebra. There are three major steps:

1. Create the similarity graph between the contagion chains. We chose to fully connect the graph with the Gaussian similarity function to transform a given set $x_1, \ldots, x_n$ of datapoints with pairwise similarities $s_{i,j}$ or pairwise distances $d_{i,j}$ into a graph $G = (V, E)$.

2. Compute the first $k$ eigenvectors of the Laplacian matrix to define a feature vector for each contagion chain. The graphed Laplacian matrix is defined as $L = D - W$, where adjacency matrix $W$ is the weight between the vertices of the graph and $D$ is the diagonal degree matrix. It has been proven that the matrix $L$ has as many eigenvalues of zero as there are connected components (or clusters), and the corresponding eigenvectors are the indicator vectors of the connected components.

3. Run k-means on these features to separate objects into $k$ classes. Projecting the points into a non-linear embedding enhances the cluster properties in the data so that they can be easily detected. In particular, the simple k-means clustering algorithm has no difficulty detecting the clusters in this new representation with the estimation of $k$ when the eigenvalues are zero.

Figure 7 lists the eight basic contagion chain patterns discovered by the above approach. The outbreak (or default crisis) starts from the node in red and spreads through the guarantee network in eight patterns. In detail, they are:

P.1 Direct contagion pattern. The basic contagion pattern is where the default can only be spread to its (one) adjacent node and then the contagion is stopped.

P.2 Single chain contagion pattern. This usually extends from the direct contagion pattern, with more nodes involved in the contagion chain. The default crisis can only spread across the single chain in the same direction. The length of the entire single strand is arbitrary and all chains in the structure are categorized according to this pattern.

P.3 Mutual contagion pattern. This describes a situation in which two corporations simultaneously guarantee one another (mutual guarantees) and obtain funds from a bank. Both nodes are fragile because no matter which one encounters the default crisis, the other will be affected.

P.4 Mutual-ext contagion pattern. This is usually an extension of the mutual contagion pattern, where the contagion chain involves other nodes.

P.5 Loop-mutual contagion pattern. This is of a loop structure, when three or more nodes simultaneously guarantee one another. Such a structure is quite vulnerable as any default crisis may spread to all of the nodes in the loop.

P.6 Loop-mutual-ext contagion pattern. This is usually extended from the loop-mutual contagion pattern, when the contagion chain involves other nodes.

P.7 Star contagion pattern. The default crisis of one node will affect many other nodes and then the contagion will stop. This can occur when corporations provide guarantees for the same (weak) corporation; the default may spread to all of the companies that provide support.

P.8 Star-ext contagion pattern. This is extended from the star contagion pattern, but with more complex structures involved. The default of one node may be spread to several other order nodes.
The patterns gradually grow more complicated with the more nodes involved and more complex the guarantee relationships. In practice, the contagion chains are combinations of these patterns, and a network may have several instances of the same pattern. Figure 8 gives the example of the P.8 pattern detected in two guarantee networks. The default spreads across the chain (in red) and then stops.

5 Visualisation Design and Interaction
In this section, we describe the interface of the iConVis system that supports financial experts interactively and iteratively exploring and explaining the contagion risk for networked-guarantee loans. We designed the four coordinated views (see Figure 1) to facilitate the closed-loop analysis process and iterative level of detailed exploration, following Shneidermans mantra.

5.1 The Guarantee Network Explorer
The Guarantee Network Explorer (GNE) view facilities an overview of and zooming in on a level of detail of a guarantee network, using a network tessellation layout. It provides intuitive and metaphorical symbols of contagion risk (through the Contagious Effect Badge (CEB) described in Section 5.2) to support selection by financial interest. The view usually works as a starting point. A set of interactive tools are provided to enhance the in-depth analysis of each network.

Guarantee network tessellation. As the statistics show, many of the networks are composed of tens or hundreds of nodes, with rare networks composed of thousands of nodes [30]. The naive force-directed graph layout visualizes the whole dataset as a hairball and introduces serious visual clutter. We designed a grid layout to tessellate the guarantee networks, as Figure 9 shows. In detail, the networks are laid in order of their complexity (i.e., the number of nodes) for the common prejudice that complex networks are more prone to induce large-scale corporate defaults (see Concern 2 in Section 3.1).

Interactions. Rich interactions, including brushing, zooming in/out, view panning, and dragging are all supported. The zooming operation enables navigation of the networks at different levels of detail. The dragging operation facilitates exploration of the networks in the canvas. Some more enhanced interaction tools have been developed to support in-depth analysis of the networks. At the bottom of the GNE view in Figure 1, from left to right, these are: 1) expanded view and 2) risk badge trigger. The risk badges are visual symbols of the contagion risk of the overall network. When the risk badge trigger button is on, all risk badges are overlayed on the networks to help experts locate networks of interest. More details are provided in the following section. 3) Box selection. Users can select the network of interest and highlight the nodes and edges, making the CEM, CIE, and NIE views display the corresponding content. 4) Edge width trigger. The edge width trigger is proportional to the guarantee amount. It is useful when analyzing specific networks. We also defined two buttons. The first is to obtain better performance when loading all networks. The second is for use when the width of the edge is not apparent in the network tessellation view. 5) Color palette. Nodes can be colored by a default rate (a graph neural network-based prediction that will be discussed in subsequent research), type, and size of businesses.

5.2 Visual Signaling of Contagion Effect
Addressing the T.2 and T.4 requirements and based on the behavior of contagion, we created the Contagion Effect, a novel financial metric for quantifying the severity of the risk of contagion. Based on this core metric, we designed a Contagion Effect Matrix view to encode the risks of each network in a matrix manner. It also works as a filter for chain-level analysis. It is further abstracted as the Contagion Effect Badge, a visual chart indicating the risk levels appearing in the GNE view.

In economics and finance, the contagion effect explains the impact of a spreading crisis in a situation where one shock in a particular economy or region spreads out and affects others [1, 45, 6, 29, 12]. However, as far as we know, there has to date been no measurements quantifying the contagion effect for the guarantee network problem. In this research, we identify the contagion risk associated with networked loans as an important yet unexplored interdisciplinary research problem. We explicitly define the contagion effect of pattern $P_i$ as:

$$E_i = f_i * v_i$$

where $f_i$ is the frequency and $v_i$ is the length of the contagion chain pattern. In practice, networks may have various compositions of contagion chain patterns, which means the default may spread in drastically different ways. The frequency $f_i$ describes how much risk is induced by pattern $P_i$, and $v_i$ describes how many other nodes it may infect at most. Quantifying the contagion effect arranges the patterns in the contagion effect matrix (CEM).

Contagion Effect Matrix. This matrix was designed to visualize the contagion effect of the patterns in a network. As Figure 10 shows, the column is the length $v$ of the contagion chain pattern. The rows are...
the frequency $f_i$ of the contagion chain pattern, where we directly used the count of instances of the pattern. In this view, all of the patterns are spatially arranged into four quadrants according to the behavior of the contagion. Each quadrant is encoded with a color designating the risk level (consistent with the color specifications in the financial sector). These colors form the basis of the risk badge. Each cell also displays the count of the instances of this pattern for a selected network in the top-left corner.

Fig. 10. Contagion effect matrix, where the patterns are arranged by the contagion behaviour.

We categorized these into four kinds of contagion behavior by the range of influence and vulnerability level. Q.I: For chain-like patterns (P1 and P2), the default can only spread across a single chain. Usually, such nodes and defaults will not lead to massive defaults. It is relatively easy to break the contagion path by removing the key node on the chain. Q.II: For mutual patterns (P3 and P4), the defaults can infect one another (P3 and P4). Such patterns are vulnerable because of mutual guarantees. Q.III: For loop-mutual patterns (P5 and P6), the default may spread more easily than in chain-like and mutual patterns, due to the existence of loop-mutual guarantees. Q.IV: For star-like patterns (P7 and P8), the default in the center chain position may affect all supporting corporations. Such kinds of contagion may distress large numbers of companies.

The layout of the CEM is meaningful. First, the patterns on the left half are more vulnerable to crisis due to the existence of the loop-mutual pattern and broader range of influence, as more nodes are involved in a network than in the right-half patterns. Experts may, in practice, wish to have more guarantee patterns in the right half of the CEM to provide stabler situations. Second, the patterns in the different quadrants can be converted into one another in real situations, providing clues to useful decomposition strategies when splitting a complex network into pieces to avoid potential systemic risks. For example, mutual patterns are more basic than loop-mutual patterns, and when splitting a network during a risk outbreak, we can remove the nodes with a Q.III pattern and generate patterns in Q.II or even in Q.I.

Contagious Effect Badge Contagion chain patterns pervade each of the guarantee networks. Quantifying the proportional composition can help to identify the type of contagion risk. The patterns can be integrated effectively with financial indicators such as those in the Capital Accord for better risk-level assessments of guarantee networks. We explicitly define the contagion score as a four-dimensional vector $[EDA, pq_1, pq_2, pq_3, pq_4]$, where $EDA$ is the total amount of exposure of the nodes in the network and $pq_j$ is the percentage share of instances of this kind of contagion behavior.

The CEB is designed as a four-slice pie chart to symbolize the risk levels, based on the contagion score. The size of the CEB is proportional to the relative exposure risk ratio (compared to the maximum exposure of all guarantee networks). The portion of each share of the CEB is encoded as $pq_j$ to chart the contagion behaviors. The badge can be overlayed onto the networks in the CNE view (see Figure. 11), allowing users to quickly locate networks of interest.

Fig. 11. Overlaying the CEB on the networks in the CNE view allows the user to quickly locate networks of interest. The size and color of the CEB encodes the relative exposure ratios and contagion types. Note that the risk levels are not consistent with the complexity of the networks, and users need only choose the network of interest via the CEB. This was emphasized in the training session during the case studies.

5.3 Chain Instance Explorer The Chain Instance Explorer (CIE) is a tailored financial coordinate system for middle-level (contagion chain) risk analysis. A flower petal zooming interaction has been designed to distinguish the chain instances of the same pattern by their financial metrics. Figure. 12 (a) shows the financial coordinate system designed for this research, where the $y$-axis is the exposure and $x$-axis is the total guarantee amount of the chain. Each flower in the financial coordinate system represents a chain instance. In practice, multiple nodes may have the same exposure and guarantee amount (refer to Section 3.1) and enclose one another. Thus, we propose a flower petal zooming visualization design for the coincident object selection problem. Each chain instance is designed as a petal-shaped node in the financial coordinate system. When multiple petals come together on the coordinate system, they form a flower. The number in the center shows the count of coincident chains. Each petal is clickable for the user to select the chain instances in other views. The design intention is to avoid possible visual clutter by iterative brush and zooming interactions supported for selection in extremely dense cases (see Figure. 12 (c)). The CIE is coordinated with the CEM and GNE, enabling financial experts to explore contagion chains case-by-case.

5.4 Node Instance Explorer In order to facilitate low-level (i.e., node-level) detail on demand for the finest grain analysis of guaranteed loans, we provide the node instance explorer. It is composed of the following five tabs (see Figure. 13).

In detail, they are: 1) Node projection tab. This provides an overview of the companies by similarities in their guarantee network structures. The nodes are first represented as vectors by node2vec [19] and then projected by t-SNE visualization [43]. Box brush interaction is supported for a coordinated analysis. 2) Financial distributions tab. Four important financial statistics (i.e., exposure, registered capital, business size, and business type) are provided. The histograms are visualized by cross-filters to enable a further fine-tuning that includes or excludes records. More sophisticated indicators may be included in the full system when deployed. 3) Overall picture tab. Repulsed bubbles (corporations) are laid along their exposure axis (i.e., their amount of debt) to prevent visual clutter. The bubble sizes are proportional to the corporations registered capital. When a user clicks a bubble, the contagion chain is displayed in the GNE. 4) Detailed view by business
6 Case Study

We conducted case studies to evaluate the effectiveness and usability of the proposed system and approach. Before the case studies, we conducted a training session to walk the experts through our system, including the visual encodings and user interactions. Then, the experts explored the contagion patterns using the system and investigated their subjects of interest. Through these case studies, the experts obtained valuable insights into this contagion problem. We then interviewed the experts to collect their comments and feedback.

6.1 Case 1: Network Level Contagion Risk Assessment

It is likely that thousands of guarantee networks composed of tens of thousands of nodes/links exist. Usually, financial experts are forced to adopt an ad hoc approach (i.e., begin with one node and follow the vine to analyze the neighbors). This is a bottom-up methodology and does not provide experts with the bigger picture. Thus, it is difficult for the domain experts to dive into the massive body of data and analyze their topics of interest. The iConVis system grants them the ability to avoid this analysis strategy. Below is the analysis procedure followed and conclusions offered by expert $E_4$.

Initially, the expert was attracted by the contagion risk matrix as it was in a central position and featured bright colors (see Figure 14, view C1.a). He familiarized himself with the red-green credit risk color setting. By default, the numbers along the rows were the instance counts of the patterns, arranged by length (CEB columns). He reviewed the numbers in the contagion risk matrix for a short while, and gave overview-level comments on contagion risk (from a top-down perspective). The main insights provided by the expert were as follows. (a) The main contagion risk comes from the star-like and loop-mutual patterns (there was a large number of instances in P5 to P8). This means the revolving and joint liability guarantees (see the definitions provided in Figure 7 [30]) are common in practice, while other patterns such as the star-shaped guarantee are relatively stable from the contagion risk perspective. In practice, the star-shaped guarantee is usually shaped by a professional guarantee company; the joint liability guarantee may be formed by subsidiaries and parent companies, and the revolving guarantee often emerges from business peers of similar size. Different resolution strategies should be adopted for different kinds of guarantee and contagion patterns. (b) There are more instances of the P7 and P8 patterns than of the P5 and P6 patterns. This is caused by the fact that in practice, there are more joint liability guarantees than revolving guarantees. In the case of preventing large-scale corporate default, it is more urgent for experts to cut contagion chains to prevent more businesses being affected. (c) The risk of contagion is not proportional to the complexity of the guarantee network (see the GNE view in Figure 14, view C1.a). The expert emphasized that this was an important discovery, correcting a misunderstanding in the financial sector that more complex networks are more dangerous. The GNE view demonstrates that the CEB can effectively represent risk composition and provides a clue for selecting analytical priorities.

The expert continued his analysis via the GNE view. Figure 14, views C1.b and C1.c give the two networks selected. The expert first clicked the CEB button to overlay all of the risk badges on all of the networks. From the C1.a view, he quickly located two networks. Although the 11 guarantee networks all had complicated network structures, from the size and composition of the badge colors, the expert was able to obtain an overview of how serious the risk was and what types of risk existed in the network. The other networks in view C1.a had badges either with a greater proportion in green (composed of simple structures) or a smaller radius (less exposure to risk). Therefore, the first network was prioritized as a network of interest. Both networks were composed of a similar number of nodes but radically different network structures. Contrary to earlier assumptions, the network in C1.b was more highly prioritized for analysis than was the one in C1.c, though it looked simpler in terms of network structure. The number in CEM (see the arrow in blue in Figure 14) confirms that the network in C1.b had many more star-like and loop-mutual patterns. This indicates significant risk of contagion during economic downturns. Moreover, the CEB of C1.b is larger than that of C1.c,
meaning that there is more exposure in the former guarantee network and thus it should attract more attention from banks. This case study validates the usefulness of the contagion effect matrix and extended visual symbology of CEB in a top-down analysis.

6.2 Case 2: Chain Level Contagion Risk Analysis

The expert then moved his analysis to chain-level contagion risk. He highlighted the network of interest (C.1.b in Fig 14) and showed faint attention in the others. The network was composed of contagion patterns in the CEB. Specially, it was composed of 19 instances of the P.8 pattern, eight instances of the P.6 pattern, and four instances of the P.7 pattern. This means that the network would be vulnerable during a crisis and might influence many nodes. The numbers provide the risk behavior and guide the choice in preventative measures for possible large-scale corporate default. The expert needed to analyze the contagion chains case-by-case because all of their financial information was different and thus they demonstrated different levels of risk.

Therefore, he chose to analyze the instances in pattern P.8, as Figure. 15 shows. In the CIE view, the expert observed that though there were multiple similar chains, some resided on the x-axis, meaning there was no risk exposure (i.e., all the funds were repaid to the bank). There were some nodes in the upper part of the coordinate system that required analysis. Thus, the expert zoomed in on the upper part (C.2.b) and clicked on the nodes to view the chains. The contagion chains in C.2.c and C.2.d were in red.

The two contagion chains attracted the attention of the expert. He explained that both were of a complex structure composed of star-ext (see Figure. 7). Such shapes are multifaceted and difficult to extract via traditional ad hoc examination. Since both chains are vulnerable and have a high range of influence in case the default spreads, they need to be addressed, especially during an economic down period. For example, from the contagion risk perspective, the experts suggested that we could retain financial stability by providing individual financial aid or cutting the network at the blue triangle node, as they are in a pivotal position. In practice, preventive measures should be considered in a more sophisticated fashion. The tool provided them with an in-depth analysis of the risk patterns. Moreover, different from the common perception, networks with more nodes were not found to be inherently more risky, as the network structure and financial information are also critical in such assessments. The symbolism of the contagion effect provided intuitive and effective representation. Such visual encoding will help to save experts much in terms of analytical energy.

6.3 Expert Interviews

After the case studies, we conducted informal interviews with the experts and gathered their comments and feedback regarding system usability, visualization design, and system interactions.

**System Usability:** The system received high endorsement by both experts. They agreed with and approved of the contagion chain risk metric, visual design, and analysis loop. 

**Ea** said that the analytical approach and system enhanced his analytical capabilities. Since it was extended on the widely accepted Capital Accord risk management system, though there are some novel concepts such as the Risk Badges, Contagion Risk Matrix, and others, the system was easily understood and accepted by the financial experts. 

**Eb** expressed the same idea. They had no difficulty with grasping the key ideas and utilizing the concepts for analysis.

**Visualisation Design:** Both experts expressed a preference for the overall design. The light-yellow background design inspired a sense of spirituality and encouraged creativity. What they most appreciated was the risk badge idea. They felt it to be a powerful abstraction of what they wanted to understand. With such intuitive symbols, they did not need to use the mouse wheel to flip through Excel, page by page, and get lost (in their words). Moreover, they liked the compact and informative design of the views. They approved of the design of the grid layout for tessellating the guarantee networks, describing it as clear, concise, and providing all of the necessary information.

The petal and flower design in the CIE (see Figure. 12) attracted their interest, though during their first attempts, some of them ignored this. They praised its combined beauty and functionality. However, they also suggested that it would be more intuitive to give an overview of all the networks on one screen, such as in Figure. 9. At that time they needed to use the mouse to drag the canvas to see all of the networks,
System Interactions: The experts believed that the interactions in the views presented by our system were useful and could help them explore and analyze issues important to their work. The interactions among multiple coordinated views facilitated the closed-loop analysis process and iterative level of detailed exploration. Moreover, there were several functional buttons and selection/zooming interactions supported in each view. One expert said they were powerful but made the system a bit complex. However, he agreed that it was difficult to make a proper trade-off between complex functions and powerful analytical abilities. Due to the sophisticated interactions and massive amount of data being visualized, the systems operation was not always smooth, and this was its main imperfection.

7 Discussion
In this section, we discuss the significance, limitations, and future work of the visual analysis system iConVis.

Significance Decoding the risk associated with complex network structures and providing evidence of measures to prevent large-scale corporate defaults has significant social and theoretical value. We developed a contagion chain analysis from a data-driven perspective that serves as a feasible way to understand the contagion-related properties of networked-guarantee loans. We propose a systematic analytical approach, including a contagion risk metric and definition of contagion behavior as it relates to networked guarantee loans, and situate these within a rich theoretical framework. From the data mining aspect, we discovered and reported eight interpretable contagion patterns by analyzing real-world bank loan records. The patterns will help with analyzing the behavior of contagion and provide a basis for risk assessment in guarantee networks. From the visual analysis aspect, we propose iConVis, a powerful interactive and intuitive metaphorical visualization tool. Empirical case studies based on real-world financial guarantee loan data confirm the usefulness and significance in the real world. The results provided by our system will deepen our understanding of guarantee networks and offer a basis for preventing large-scale corporate defaults.

Limitations Despite the above advantages of iConVis, there are still some technical limitations. One major limitation is the performance. We had to make a trade-off between highly interactive software and the amount of information that could be rendered on a single page. We chose to visualize massive networks on SVG instead of CANVAS or WebGL because it has the best interactive support. In practice, the performance is acceptable for a prototype system but further performance optimization is required before the system is deployed.

Future work Future work will further extend our investigation of contagion behavior and facilitate systematic risk management and large-scale corporate default intervention in a visually analytical way. The dynamics of the guarantee network will be considered for more accurate risk assessments.

8 Conclusion
In this research, we report our progress on risk management in the networked-guarantee loan problem. We believe that this is the first study to identify and formalize the contagion chain risk management problem for networked loans. This new research avenue provides refreshing opportunities for both the computing and financial communities. In our work, a novel financial metric – the contagion effect – is formulated to quantify the infectious consequences of guarantee chains in a network. Based on this metric, we designed and implemented a series of novel and coordinated views to facilitate analysis of this financial problem. Experts evaluated the system using real-world financial data. The results deepen our understanding and ability to assess the potential risk of contagion in complex network structures, hopefully preventing potential large-scale corporate defaults.

Acknowledgments
This work was supported by NSFC (61802278) and the MOE Key Laboratory Foundation for AI (A12019004).

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