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Operational Risk Assessment of Commercial Banks' Supply Chain Finance

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Abstract: Supply chain finance (SCF) operations require extensive activities and a high level of information transparency, making them vulnerable to operational issues that pose significant risks of financial loss for commercial banks. Accurately assessing operational risks is crucial for ensuring market stability. This research aims to provide a reliable operational risk assessment tool for commercial banks' SCF businesses and to deeply examine the features of operational risk events. To achieve these goals, the study explores the dependency structure of risk cells and proposes a quantitative measurement framework for operational risk in SCF. The loss distribution analysis (LDA) is improved to align with the marginal loss distribution of segmented operational risks at both high and low frequencies. A tailored copula function is developed to capture the dependency structure between various risk cells, and the Monte Carlo algorithm is utilized to compute operational risk values. An empirical investigation is conducted using SCF loss data from commercial banks, creating a comprehensive database documenting over 400 entries of SCF loss events from 2012 to 2022. This database is analyzed to identify behaviors, trends, frequencies, and the severity of loss events. The results indicate that fraud risk and compliance risk are the primary sources of operational risks in SCF. The proposed approach is validated through backtesting, revealing a value at risk of CNY 179.3 million and an expected shortfall of CNY 204.9 million at the 99.9% significance level. This study pioneers the measurement of SCF operational risk, offering a comprehensive view of operational risks in SCF and providing an effective risk management tool for financial institutions and policymakers.

Keywords: operational risk; supply chain finance; loss distribution analysis; copula; commercial banks

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1. Introduction

Supply chain finance (SCF) has become a critical financial tool for optimizing working capital management and liquidity flow across supply chain operations and transactions through innovative financing and risk mitigation strategies [1]. Over the past decade, SCF has attracted increasing attention from both commercial banks and corporate clients [2–4]. The global SCF market has witnessed remarkable growth, reaching an estimated value of USD 1.8 trillion in 2021, reflecting a 38% year-on-year increase (BCR Publishing Co., Ltd., London, British).

However, the rapid expansion of SCF has also amplified operational risks, posing substantial challenges to financial institutions. According to the Basel Committee on Banking Supervision [5], operational risk refers to potential financial losses resulting from inadequate or failed internal processes, personnel errors, system malfunctions, or external events. While it includes legal risks, it explicitly excludes strategic and reputational risks. In recent years, fraud and non-compliance have emerged as key operational risks in SCF, leading to substantial financial losses worldwide [6]. Notable cases have illustrated the devastating consequences of these risks. In 2020, Singapore's major oil trading firm, Hin Leong Trading, collapsed after it was revealed that the company had engaged in financial fraud, concealed massive losses, and mismanaged debt within its SCF operations. This failure resulted in approximately USD 3.5 billion in bad debt risks for multiple banks and financial institutions. Similarly, in 2021, the UK-based SCF firm Greensill Capital filed for bankruptcy following severe liquidity issues driven by over-reliance on short-term financing and inadequate risk controls. The fallout from Greensill's collapse amounted to an estimated USD 10 billion in losses for global investors. According to the International Chamber of Commerce (ICC), fraud-related annual losses could reach up to USD 5 billion due to business disruptions alone. These incidents collectively highlight the pressing need for robust operational risk management frameworks tailored to the unique complexities of SCF. Addressing these challenges requires proactive risk measurement and effective regulatory mechanisms to safeguard the stability and sustainability of SCF systems worldwide.

Despite the increasing prevalence of operational risks in SCF, existing research has predominantly focused on credit risk and market risk assessment [7–10]. This has resulted in a notable research gap in the quantitative measurement and assessment of operational risks within SCF. Operational risks in SCF are characterized by complex transactional relationships, asymmetric information flows, and intricate supply chain processes, which collectively heighten the exposure to fraud and operational failures [11,12]. Furthermore, the absence of effective regulatory mechanisms often exacerbates these vulnerabilities, leading to frequent violations of operational rules and substantial financial penalties for financial institutions [13,14].

The accurate measurement of operational risk in SCF is crucial for financial system stability. The Basel Committee on Banking Supervision [5] mandates banks to maintain sufficient capital reserves to offset operational risk losses, making precise risk assessment a critical element of regulatory compliance and financial stability. However, operational risk measurement is inherently challenging due to the presence of fat-tailed and skewed loss distributions, which complicate risk estimation processes [15,16].

The loss distribution approach (LDA) has emerged as a prominent method for operational risk quantification [17]. Initially developed in actuarial research, LDA has been widely adopted by financial institutions to estimate operational risk exposure. Researchers have also integrated advanced statistical techniques, such as Extreme Value Theory (EVT) and piecewise-defined severity distributions, into LDA models to enhance their accuracy and stability [18–20]. In addition, dependencies between operational risk events across different risk cells are rarely independent. Studies have shown that operational losses in different cells often share common underlying environmental factors, resulting in nonlinear and asymmetric correlations [21,22]. Copula theory, a statistical tool for modeling joint distributions, has become a key technique for capturing these dependencies in operational risk assessment [23–25].

Nevertheless, despite advancements in risk quantification methodologies, there remains a lack of comprehensive research focusing on SCF's unique operational risk characteristics. Current studies often address these risks from a macro perspective, overlooking

micro-level dependencies between risk cells and the intricate dynamics of SCF transactions [26].

This study aims to bridge this research gap by developing a multivariate operational risk assessment model tailored specifically for SCF. Using an enhanced loss distribution approach (LDA) integrated with copula theory and Monte Carlo simulation, this study seeks to accurately quantify operational risks while capturing the dependencies between distinct risk cells. Additionally, we aim to construct an operational risk loss database for SCF to support empirical analysis and model validation.

The key contributions of this study are as follows:

(1) We develop an enhanced LDA model, integrating copula functions to account for nonlinear dependencies between operational risk cells in SCF.
(2) A structured operational risk loss database for SCF is constructed, providing empirical data to improve model accuracy and reliability.
(3) Backtesting is conducted to ensure the robustness and applicability of the proposed model.

Through these contributions, this study seeks to establish a comprehensive and practical framework for operational risk assessment in SCF. The findings aim to provide valuable insights for financial institutions and regulatory agencies, facilitating better risk management, improved regulatory compliance, and enhanced financial system stability.

The structure of this study is as follows: Section 2 provides a theoretical foundation by introducing the core concepts of supply chain finance, identifying key risks, analyzing operational risk characteristics, and reviewing quantitative measurement models; Section 3 introduces the data collection process and operational risk measurement framework; Section 4 examines the attributes of operational risk loss occurrences, categorizes risk cells, quantitatively assesses operational risk values, and conducts comparative analysis; Section 5 provides an in-depth interpretation of the findings, including comparative insights with previous models; and Section 6 highlights the theoretical contributions, policy implications, research limitations, and future directions.

2. Literature Review

2.1. Overview of Supply Chain Finance

Since the 1980s, supply chain management (SCM) has gained significant prominence, driven by advancements in production division methods and rapid economic growth. Initially, SCM primarily concentrated on logistics and information flow, with limited consideration for financial flow within supply chains. However, by the late 20th century, it became evident that bottlenecks in financial flows could undermine the efficiency gains and cost savings achieved through specialized production. Small and medium-sized enterprises (SMEs), in particular, faced significant financing challenges due to their limited creditworthiness, which often prevented them from accessing low-cost financing from traditional banks. To address these challenges, supply chain finance (SCF) emerged as a vital mechanism bridging the gap between enterprises and financial institutions, aiming to alleviate SMEs' financing difficulties [27,28].

SCF represents an intersection of supply chain management and financial innovation [29] and can be understood from two primary perspectives: finance-oriented and supply chain-oriented [30–32]. From the finance-oriented perspective, SCF is primarily viewed as a financial solution provided by financial institutions. This approach focuses on enhancing cash flow, facilitating the exchange of materials and information, improving access to capital, and reducing financing costs [11,33]. In this framework, financial institutions play a pivotal role in ensuring the efficiency and security of financial flows through credit authorization and risk management mechanisms.

In contrast, the supply chain-oriented perspective emphasizes collaboration among supply chain members. From this viewpoint, SCF not only addresses financial challenges but also integrates inventory optimization, supply chain process management, and fixed asset financing solutions. It prioritizes resource integration and value co-creation across the supply chain, embedding financial planning, supervision, and control within a cross-organizational collaborative framework [34,35]. Thus, SCF has evolved into a comprehensive financial service concept that not only mitigates financing shortages and improves cash flow within the supply chain but also strengthens the supply chain system, enhancing its competitiveness in the broader industrial ecosystem.

As a result, various SCF models have emerged. Some are led by financial institutions, which provide comprehensive financing services to borrowing enterprises, typically leveraging the creditworthiness of core enterprises or supervising pledged assets through third-party logistics providers [36]. Common models include credit-guaranteed financing [37], purchase order financing [38], reverse factoring [39], warehouse financing [40], inventory financing [41], and warehouse receipt pledge financing [42]. However, these models face significant challenges due to the limited adoption of advanced information technology and insufficient risk analysis capabilities. Consequently, financing is often restricted to enterprises directly linked to core businesses, and lengthy financing periods fail to meet the urgent financing needs of SMEs. Additionally, financial institutions' lack of understanding of industry-specific characteristics and supply chain operational details hinders their ability to offer effective, risk-controllable financing services. This can also lead to agency problems, such as a moral hazard, where borrowers may collude with third-party logistics providers to misappropriate funds, exposing financial institutions to substantial risks.

Alternatively, some SCF models are led by core enterprises, distribution companies, or e-commerce platforms, such as trade credit [43], buyer financing [44], equity financing [45], and platform financing. These entities are deeply embedded in supply chain operations and possess comprehensive knowledge of supply chain processes and information. This allows them to enhance risk control, offer value-added services, and streamline operations through digital platforms, overcoming traditional geographical constraints and expanding the scope of supply chain finance. Nevertheless, operational risks remain a significant challenge in these models.

Overall, the cross-entity and cross-industry nature of SCF inherently generates high operational risk. The complexity of managing cash flows, logistics, and information across multiple participants and domains introduces significant uncertainty. Moreover, the diverse range of SCF models—each with its own risk profile, such as credit-guaranteed financing, purchase order financing, factoring, warehouse receipt pledge financing, and platform financing—further complicates risk identification and assessment for financial institutions.

2.2. Risks Associated with Supply Chain Finance

In the process of developing supply chain finance (SCF) operations, financing companies and financial institutions face various types of risks, including supply risk, disruption risk, credit risk, market risk, and operational risk. These risks have a profound impact on the stability and sustainable development of supply chain finance, with operational risk, in particular, emerging as a key factor hindering its steady growth. As a result, the effective control and management of these risks, especially operational risk, is essential for ensuring the sustainable development of supply chain finance [9,46–49].

To address these challenges, a considerable body of research has been conducted in the field of SCF risk management. Existing studies primarily focus on two key areas: risk measurement and risk control. In terms of risk measurement, scholars have made

significant advancements in understanding credit risk and market risk, particularly in the measurement of credit risk. These studies typically rely on financial data, credit ratings, and historical default rates to assess and predict credit risk [50–52]. However, operational risk research remains relatively limited, with most studies concentrating on its measurement. Unlike credit and market risks, which are well researched, operational risk involves not only individual operational failures but also systemic risks across various stages of the supply chain, such as information errors, process defects, technological malfunctions, and management vulnerabilities. The complexity and uncertainty inherent in operational risk pose significant challenges for developing appropriate measurement models.

Although existing studies have introduced methods such as value at risk (VaR) [53], Analytic Hierarchy Process (AHP) [54], and Bayesian Networks [55] to assess operational risk, these approaches, while effective in certain contexts, still face limitations, particularly in terms of precision and applicability. The VaR model, for example, is commonly used to measure market and credit risks but performs poorly when applied to operational risk, especially in the context of non-routine events or extreme risks. The AHP method, which relies on expert judgment to construct hierarchical decision-making frameworks, tends to produce subjective results and struggles to account for the dynamic interrelationships among complex, multi-variable operational risks. Bayesian Networks, which model causal relationships to assess risks, require large volumes of high-quality data for accurate modeling—a challenge in real-world applications.

Therefore, there remains a pressing need for further improvement in operational risk measurement systems, particularly in developing models that are tailored to the specific characteristics of the SCF business model. Addressing these challenges will be a critical area for future research.

2.3. Operational Risks Measurement and Supply Chain Finance

In order to address financial risks and maintain the stability of the financial system, the Basel Committee on Banking Supervision (BCBS) requires banks to maintain sufficient capital reserves to fulfill obligations and minimize potential losses [5]. Therefore, the main approach to reducing operational risks is to thoroughly evaluate operational risk in order to determine the capital charge. It is important to highlight that SCF has a higher operational risk exposure compared to other financial products because of its complex data exchange and intricate supply chain processes. Ensuring the safety and reliability of fund flows and transactions is a top priority for SCF, which requires a thorough transaction background. Nevertheless, because of the unequal access to information between commercial banks and participants in the supply chain, banks face challenges in comprehensively grasping the details of transactions and recognizing potential risks. This vulnerability exposes them to the possibility of being misled or falling victim to fraud [11,12]. Furthermore, SCF encompasses various aspects of the supply chain, involving a multitude of entities and intricate processes. This complexity increases the likelihood of business operation rule violations during the operational process [14]. In addition, due to the lack of effective market regulation, the SCF business model often encounters issues with financial institutions, such as banks, facing frequent fines [13]. Thus, it is crucial to develop a quantitative measurement model for supply chain operational risk that incorporates the loss characteristics of operational risk in SCF.

The cornerstone for assessing operational risk is the collection of operational risk loss data associated with supply chain financing activities by commercial banks, as stressed by Wei et al. [56]. Several institutions and scholars have developed structured operational risk databases specifically for commercial banks. These databases aim to provide fundamental data for the purpose of operational risk assessment. Notable examples of operational

loss databases include the Italian Commercial Bank Association's Italian Operational Loss Database DIPO (Database Italiano Perdite Operative), the Swiss Zurich Operational Risk Exchange Association's ORX (Operational Riskdata eXchange), and Gao's external database documenting commercial bank operational risk events in China between 1987 and 2012. Nevertheless, as supply chain finance is a relatively new concept, there is currently no existing operational risk database specifically tailored to the commercial bank SCF business line. In the absence of historical operational risk data, certain researchers depend on the manual collection of public information to construct specialized databases [19,57–59]. The intent of this study is to develop a new operational risk database for SCF with the purpose of supplying essential data for measuring operational risk.

2.4. Operational Risks Measurement Models

The operational risk capital charge framework consists of four stages. The Basic Indicator Approach (BIA), the simplest method, calculates required capital by multiplying a financial indicator, such as gross income, by a fixed percentage (the "alpha" factor). The Standardized Approach (SA) refines this by dividing a bank's activities into standardized business units, with capital charges calculated for each unit based on indicators, such as gross income or asset size, multiplied by a fixed percentage (the "beta" factor). The total capital charge is the sum across all business lines, with alpha and beta factors potentially being calibrated using 20% of current regulatory capital.

The Internal Measurement Approach (IMA) allows banks to use internal loss data for capital calculation, guided by supervisory standards. Operational risk is categorized in a matrix of business lines and risk types, with required capital calculated for each combination by multiplying expected loss by a fixed percentage (the "gamma" factor). Expected loss is based on an exposure indicator (standardized by regulators) and two internal data terms: loss probability and loss severity. The gamma factor, derived from industry data, can be adjusted using a risk profile index to reflect a bank's specific risk compared to the industry. The total capital charge is the sum across all business line and risk type combinations.

The loss distribution approach (LDA), the most sophisticated method and the focus of this paper, estimates the probability distributions for both loss severity and event frequency over a one-year period for each business line/risk type combination, based on internal data. The bank then computes the probability distribution for total operational loss, with required capital determined by the sum of value at risk (VaR) for each combination.

Among these approaches, the Advanced Measurement Approach (AMA) is the most sophisticated and risk-sensitive. The Basel Committee on Banking Supervision (BCBS) encourages banks to adopt the AMA for operational risk management. Of the various methods developed, the LDA is the most widely applied.

Loss distribution analysis (LDA) is the predominant approach for quantifying operational risk, as indicated by its extensive utilization [15,16]. LDA, initially popular in actuarial research, was proposed by Frachot et al. [17] as a method for estimating operational risk in commercial banks. This approach necessitates modifying the parameter distribution to accurately reflect both the frequency and severity of the loss. LDA is increasingly being used in research to assess the operational risk of various business departments in commercial banks, including third-party payment platforms [58], electronic banking transaction risk [60], as well as other industries such as defect risk in residential construction [61], operational risk of telecommunications companies [62], and the metal machinery industry [63]. Yet, the untapped potential of the swiftest expanding SCF sector within commercial banks remains unexplored.

Furthermore, the distribution of operational risk losses exhibits fat tails and skewness, which might impact the precision of operational risk quantification models, presenting difficulties in measurement. To provide a more accurate description of this feature, some researchers integrate piecewise-defined distribution and Extreme Value Theory (EVT) into LDA models to enhance their performance. Li et al. [18] and Wang et al. [19] integrated EVT into LDA and introduced a piecewise-defined severity distribution model (PSD-LDA) to assess the operational risk of commercial banks. The empirical findings suggest that the model exhibits strong fitting capability and can provide more accurate estimates of operational losses. Zhou et al. [20] introduced a technique called the right truncation method with probability-weighted least squares. To accurately model heavy-tailed distributions, this method combines the properties of the right truncation distribution and the minimization of probability-weighted distance. The findings demonstrated that the model enhanced the stability of estimating operational risk.

Some studies argue that when quantifying operational risk, the dependencies between more finely divided risk cells must be characterized. The incidence rate of operational loss risk cell events is not independent, but rather follows a complex nonlinear connection, and risk cell characteristics might influence risk measurement accuracy [22]. Operational losses in different risk cells may be caused by the same claim production mechanisms or by shared underlying environmental variables [21]. Although scholars are increasingly arguing for including loss category dependencies into LDA to generate a more precise evaluation of operational risk [22,64,65]. However, most study viewpoints are at the macro level, without diving into the relationships between different risk components or investigating how to describe and measure them [26]. Thus, the objective of this study is to create a multivariate operational risk measuring model for SCF utilizing improved LDA and Monte Carlo approaches, with a focus on the integration of specific operational risk cells. The goal is to fully portray the nonlinear interaction between SCF operational risk components while enhancing evaluation accuracy.

When it comes to identifying and capturing nonlinear and asymmetric correlations between assets or risks, particularly at the tail of distributions, copula theory is the most fundamental and frequently applied method among many available strategies for creating correlations [66]. In operational risk assessment, the marginal distribution and copula approaches can be used to calculate the joint distribution of losses across multiple risk cells, allowing for the quantification of global operational risk. For example, Chapelle et al. [23] used copula to explicitly represent loss dependency, combining the marginal distributions of many business lines into a single joint loss distribution. Abdymomunov and Ergen [24] used the copula framework to investigate the relationship between operational risk losses inside and between commercial banks, finding a very substantial correlation between tail losses of various operational risk loss types within commercial banks. Chen and Liang [25] demonstrated that the use of copula functions in commercial banks can effectively manage the dependency structure between two operational risk cells—external fraud risk and internal fraud risk—and reduce estimation failure due to improper distribution selection. We are the first to employ the copula function to show the correlation between operational risk cells in SCF, as well as to incorporate SCF risk cell dependency into the operational risk assessment model.

Overall, the literature on operational risks in supply chain finance currently has three major flaws. Research on SCF operational risks primarily centers around the utilization of information technology tools for risk management. These tools include big data and blockchain, as highlighted in recent studies [67–71]. Evaluation is essential for effective management, yet the current body of literature does not provide a thorough understanding of the various factors and the extent to which they impact operational risks in supply

chain finance. There is a significant body of literature that pertains to operational risk assessment, with a particular emphasis on the banking sector as a whole. Researchers have focused on refining their perspectives to explore the operational risk assessment of specific business lines in banks. However, they have failed to consider the supply chain finance business, which is in high demand and significantly impacted by operational risks. There remains a need for a more thorough investigation of the operational risks associated with supply chain finance business conducted by commercial banks. Additionally, it is important to highlight that current research on modeling methods for operational risk assessment primarily concentrates on macro perspectives, with relatively less attention given to micro perspectives. By analyzing the characteristics of operational loss in supply chain finance business, this study examines the relationship between risk cells of operational risk and their impact on operational risk. In the context of China, there is a lack of research evaluating the operational risk of commercial bank supply chain finance business by dismantling its operational risk cells. According to iResearch Consulting, the estimated value of China's SCF market in 2021 was CNY 3.29 billion (approximately USD 516 million), accounting for around 30% of the global market share. Regulatory authorities in the Chinese SCF market require an objective tool to gain a comprehensive understanding of operational risk events and identify notable abnormal events.

By providing a framework for measuring operational risk in supply chain finance, and being the first study to look at operational risks in commercial bank SCFs quantitatively, this study aims to fill a gap in the existing literature. This research collected real data on operational risk incidents in supply chain finance and classified them into separate risk cells to provide a more accurate depiction of operational risk distribution in the supply chain finance sector of commercial banks. A risk quantification model was created to evaluate the Chinese market, including the interconnectedness of operational risk cells. Backtesting was conducted to ensure the study's reliability.

3. Materials and Methods

3.1. General Data Collection

The financial regulatory system in China faces ongoing challenges, such as incomplete information disclosure [72] and the lack of a unified data collection mechanism [73]. Operational risk data are difficult to obtain because some operational risk occurrences are considered business secrets or scandals, whereas China's supply chain finance (SCF) is making significant strides. Unfortunately, commercial banks' operational risk databases lack the most up-to-date information on supply chain finance operational risks.

This study gathers operational risk data on SCF in commercial banks and builds a database. The process of constructing a commercial bank SCF operational risk database involves five steps: determining the time interval, selecting keywords, conducting searches on data source websites, documenting event characteristics based on actual operational loss events, and cleaning up the collected data. Figure 1 illustrates the process of constructing the database.

The rise of the Internet has greatly increased the accessibility of information sources and opened up new avenues for sharing data. Researchers now have increased access to collect data from events reported by media and other open channels [57,74]. With the help of public data sources, this study seeks to compile a thorough database of operational risk losses in Chinese commercial banks' supply chain finance operations. The data sources encompass six distinct categories: reports issued by banks, disclosures from national regulatory agencies, notices from financial industry associations, information from commercial intelligence agencies, academic research findings, and news from media and other public channels. Some of the websites that can be accessed are the China Banking and Insurance

Regulatory Commission, the People's Bank of China, China Judgments Online, Wanlian, Hexun, and Sohu. A time interval was set from January 2012 to December 2022 to facilitate a website search. A comprehensive search was carried out, utilizing precise terms such as "supply chain finance", "trade finance", "inventory pledge", "warehouse receipt pledge", "accounts receivable financing", "factoring", "fraud", "attack", "loss", and "penalty" to delicately identify operational risk events.

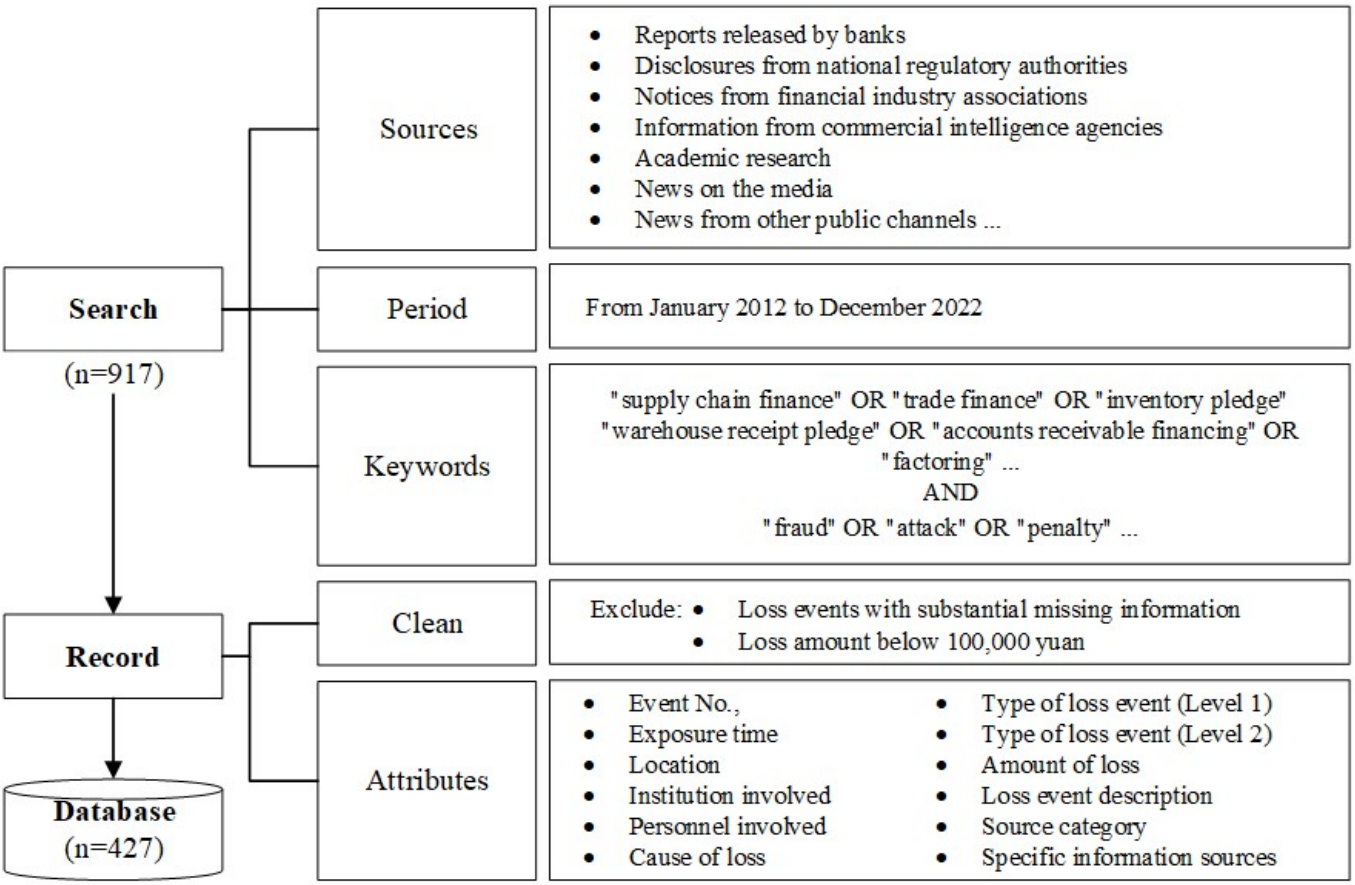


Figure 1. The process of commercial banks' SCF operational risk database construction.

Operational risk loss data are recorded according to specific guidelines: (1) Each loss event is assigned a distinct number for identification purposes. (2) Risk is classified according to internationally recognized criteria established by the Basel Commission, specifically referring to the classification standards for primary and secondary losses outlined in the Basel Accords. (3) The loss of cases is based on the amount of the case recorded. The amount from the beginning to the end is in or had been in a state of exposure to risk, rather than the actual amount of loss; that is, the total actual loss after the recovery of the amount through various means such as justice. (4) If the specific loss amount is not explicitly mentioned but the relevant information and amount are provided, the concerned amount will be appropriately converted into the loss amount. (5) Document various time points relevant to the case, including the time of occurrence, end time, and exposure time. (6) Utilize the reporting date as a point of reference when the date of the event is ambiguous. (7) Each data entry should be accompanied by a comprehensive case description, including a source news link, documentation information, and other relevant data sources.

Furthermore, it is important to clean up and organize the collected lost data correctly. During the data screening process, loss events with substantial missing information, such as unknown loss amounts and unidentified institutions, will be excluded. After verification, a total of 917 operational risk loss cases involving commercial banks were collected. The

largest loss recorded was CNY 2.073 billion, while the smallest loss amounted to CNY 3500. Given the tendency of commercial banks to store large amounts of data in their operational risk loss databases, it is important to note that smaller losses may not be accurately represented in public media reports [66]. In light of this, we decided to exclude loss cases that were below CNY 100,000. We were left with a total of 427 cases from 106 commercial banks for analysis, after applying the specified threshold.

The data from each event are recorded uniformly, encompassing 12 characteristics. These include event number, exposure time, location, institution involved, personnel involved, cause of loss, loss type (Level 1), loss type (Level 2), amount of loss, loss event description, source category (news, legal case files, journals, administrative penalty information, bank announcements, and other sources), and specific information sources. We conducted a thorough analysis of the exposure date, loss amount, loss cause, and loss event type, as presented in Sections 3.1 and 3.2. We utilized the operational risk assessment model proposed by combining the initial two sets of data to measure, as demonstrated in Sections 4.3–4.5.

Note that the method of gathering data has inherent potential biases and limits that might introduce noise into risk assessment. The data collection process heavily relies on public sources, potentially limiting the capture of undisclosed risk events. Certain internal operational risk loss events in banks may involve the handling of sensitive information, including internal operations, customer data, and confidential financial transactions. In addition, there is a lot of misleading and fraudulent material on the Internet that is difficult to spot. There is potential for the collection of information that may be inaccurate, incomplete, or misleading. Plus, if the data samples chosen during the data collection process are not representative, bias can result.

3.2. Methods

In this paper, we propose a novel operational risk assessment framework for commercial bank supply chain finance businesses. The traditional loss distribution analysis (LDA) model is enhanced by incorporating the copula model. An LDA model is constructed to take into account the dependencies between risk cells. The six main steps of the framework are as follows: the analysis of loss data; loss data division by risk cells; the estimation of risk cells loss distribution; the characterization of dependency among risk cells; the computation of value at risk (VAR) and expected shortfall (ES) values for total loss distribution; and the assessment of operational risk values' efficacy. Figure 2 depicts the overall framework.

Step 1: Loss data analysis. An examination of the distribution time and amount patterns of losses in the supply chain finance business market of commercial banks is required. This analysis will involve studying the exposure time, reasons for losses, types of losses (level 1 and level 2), and amounts of losses using partial statistics. Additionally, market policies and dynamics will be taken into consideration. By examining the various types and causes of operational risk events, we can pinpoint the high-frequency loss type events and delve into the common loss characteristics resulting from their causes. From this, one can identify the types of operational risk loss events that occur more frequently and analyze their causes and characteristics.

Step 2: Loss data by risk cells. Given the findings from step 1, it is crucial to analyze the similarities among standard operational risk loss types. This will enable the incorporation of a wide range of operational risk categories and the depiction of typical operational risk cells in the commercial bank supply chain finance business. Retrieve a dataset associated with standard operational risk cells from the database in advance. The dataset provided will serve as fundamental data for future operational risk assessment models.

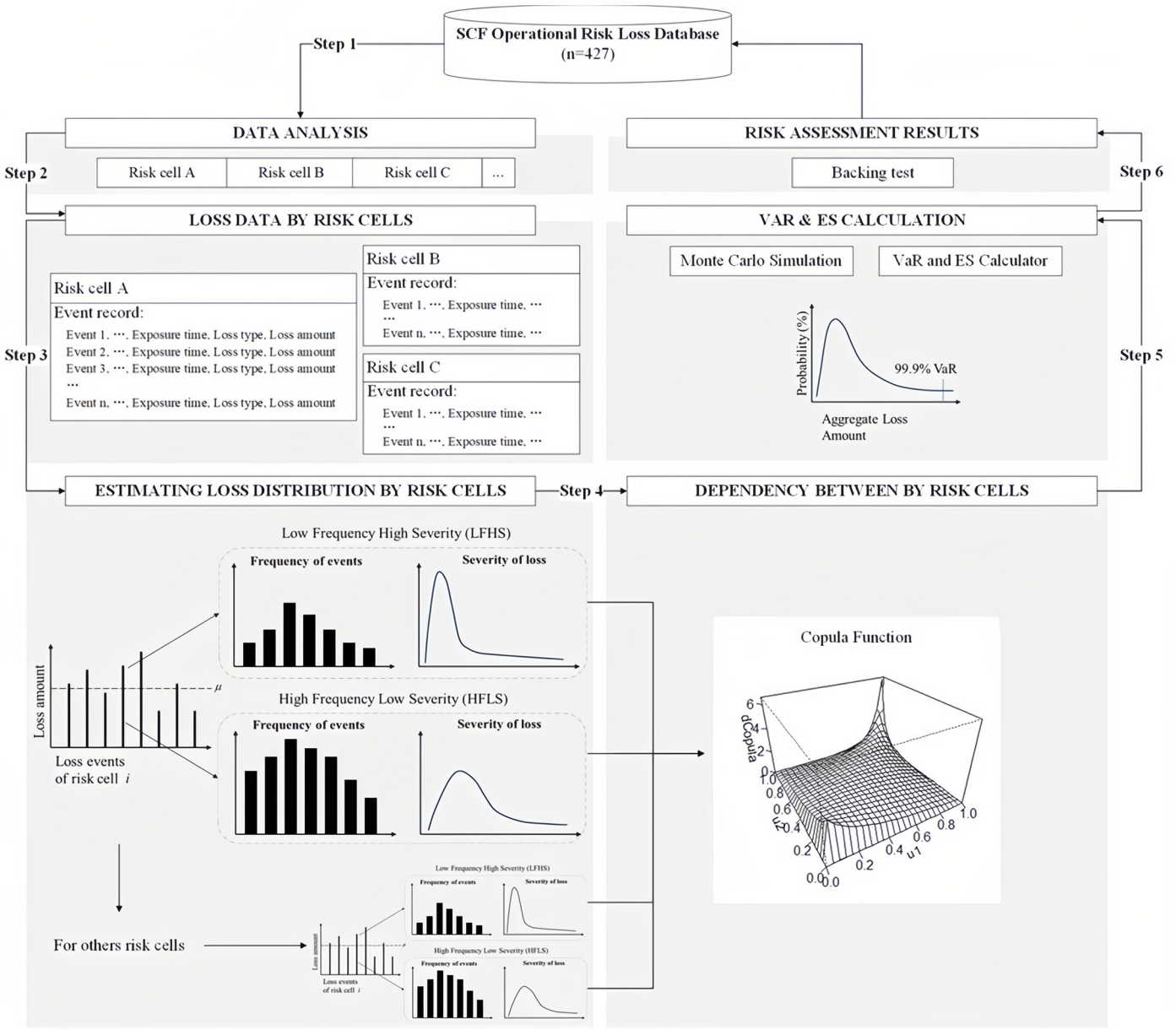


Figure 2. Risk cell-based operational risk assessment framework for commercial bank SCF.

Step 3: Estimation of risk cells loss distribution. This step involved creating an LDA model that took into account the relationship between risk cells in order to estimate the operational risk value. The model divides each risk cell's data into ordinary losses (high frequency, low severity; HFLS) and extreme losses (low frequency, high severity; LFHS), then applies classical distribution functions to fit their loss frequency and loss severity distributions, respectively.

Under the framework of LDA, assuming that the bank's supply chain finance business is divided into d categories of operational risk loss events, there are a total of d risk cells. For the i risk cell ($i = 1, \ldots, d$), N_i represents the number of loss events that occurred during the year and $X_{i,t}$ represents the amount of loss incurred by the i risk cell during the t loss. In order to calculate the probability distribution of total operational losses, it is necessary to model the possible losses of each risk cell to obtain the probability distribution of loss event frequency and severity distribution under these risk cells. The loss distribution of operational risk is obtained by convolving the loss intensity distribution and loss frequency distribution, and the risk level is evaluated.

To improve the assessment level of extreme risks, the peaks over threshold (POT) model is applied in combination with the LDA model. For the risk cell i, a threshold μ_i is determined based on the statistical characteristics of loss severity, and the operational loss data are divided into HFLS and LFHS. Observations below μ_i correspond to ordinary losses, and observations above μ_i correspond to extreme losses. Assuming that the operational risk loss frequency distributions of ordinary losses and extreme losses for risk cell i are $N_i^O(n)$ and $N_i^U(n)$, respectively, and the loss intensity distributions are X_i^O and X_i^U, respectively, then the total loss distribution $G(i)$ for risk cell i can be expressed as

$$G(i) = P(X_i \leq x_i) = \sum_{n=0}^{\infty} N_i^U(n) X_i^U(x_i) + \sum_{n=0}^{\infty} N_i^O(n) X_i^O(x_i) \quad (1)$$

On this basis, we fit the probability distribution and estimate the parameters of the frequency and severity of operational losses. For the frequency of operational losses, the $N_i^U(n)$ of LFHS and the $N_i^O(n)$ of HFLS are usually modeled using the Poisson distribution (PD) or negative binomial distribution (NBD) [75], where $N_i^U \sim F_i^{f,U}$ and $N_i^O \sim F_i^{f,O}$. For the severity of operational losses, the POT model usually uses the generalized Pareto distribution (GPD) to describe the distribution characteristics of extreme events above μ_i, denoted as $X_i^U \sim F_i^{s,U}(x; \xi_i, \beta_i, \mu_i)$. In this context, ξ_i represents the shape parameter in the GPD and β_i represents the scale parameter. For ordinary losses, this paper will choose multiple distributions to fit this part, such as the Lognormal distribution, Weibull distribution, and Gamma distribution, denoted as $X_i^O \sim F_i^{s,O}$. To construct the most suitable distribution function, we use the Kolmogorov–Smirnov (K-S) test for goodness-of-fit testing. Specifically, the key steps are as follows:

Step 3.1: Using a combination of Hill charts and excess mean function charts, determine a reasonable threshold μ for the risk cell i, which divides losses into two parts: HFLS and LFHS.

Step 3.2: Fit the marginal frequency distributions of HFLS and LFHS losses for risk cell i, denoted as $F_1, F_2, \ldots, F_d$ and $F_1', F_2', \ldots, F_d'$.

Step 3.3: Fit the marginal loss distribution of the risk cell i, HFLS, and LFHS losses, denoted as $S_1, S_2, \ldots, S_d$ and $S_1', S_2', \ldots, S_d'$.

Step 4: Characterization of dependency relationships among risk cells. In order to delve deeper into the relationship between individual risk cells, this particular step involves the creation of a suitable copula function, which is based on step 3. The purpose of this function is to accurately describe the dependencies between each risk cell. This function is then integrated into the LDA model, and the Monte Carlo simulation is utilized to observe the distribution of total operational risk losses for risk cells [23] as well as the overall operational risk losses.

Most studies assume that risk cells are completely positively correlated and completely independent, which is idealistic. In reality, these two assumptions are often not met. Simply summing up the operational risks of risk cells or simply combining risk data is inevitably arbitrary, often resulting in the overestimation or underestimation of the operational risks of multiple risk cells in a bank. Therefore, this study uses the copula function to connect the marginal distributions of the operational risks of each risk cell, obtaining the joint distribution of the operational risks of multiple risk cells in a bank's SCF business, which can further calculate the overall operational risk within the bank. The d-dimensional copula function $C(u_1, u_2, \ldots, u_d)$ is a multivariate joint distribution function that defines a uniform marginal distribution of random variables. By connecting the marginal distributions through the copula function, the overall operational risk loss

distribution within the bank, that is, the joint distribution of the operational risk losses of each risk cell, can be expressed as

$$G(x_1, x_2, \ldots, x_m) = C(G_1(x_1), G_2(x_2), \ldots, G_m(x_m)) \tag{2}$$

The following steps are outlined:

Step 4.1: Fit the dependence structure of the risk cell using a commonly used copula function, estimate the parameters of the copula function, and determine the optimal copula function to describe the frequency dependence structure based on the test results.

Step 4.2: Generate joint samples of random variables following a uniform distribution on (0,1) from the selected copula function $(u_1, u_2, \ldots, u_d, u'_1, u'_2, \ldots, u'_d)$.

Step 4.3: Given the marginal information of the frequency of loss events, convert the samples of copula $(u_1, u_2, \ldots, u_d)$ and $(u'_1, u'_2, \ldots, u'_d)$ into frequency samples through the inverse function.

$$(n_1, n_2, \ldots, n_d) = (F_1^{-1}(u_1), F_2^{-1}(u_2), \ldots, F_d^{-1}(u_d))$$
$$(n'_1, n'_2, \ldots, n'_d) = (F_1'^{-1}(u_1), F_2'^{-1}(u_2), \ldots, F_d'^{-1}(u_d))$$

Step 4.4: Generate a loss for $n_1, n_2, \ldots, n_d$ randomly from $S_1, S_2, \ldots, S_d$; generate a loss for $n'_1, n'_2, \ldots, n'_d$ randomly from $S'_1, S'_2, \ldots, S'_d$.

Step 4.5: Add up all the losses incurred in step 4.4 to obtain a possible scenario of overall operational risk losses.

Step 5: Computation of VaR and ES values for total loss distribution. The VaR and ES are calculated for commercial banks' operational risk. These calculations are carried out under a certain confidence level, using the estimated operational risk loss obtained in step 4.

According to Basel II, obtain a 99.9% VaR as the risk capital requirement. Finally, use the Kupiec's return test method to test the validity of the model used in this study to determine whether the model results are credible under the influence of assumptions and parameter estimation errors. Specifically, the model algorithm flow is as follows:

Step 5.1: Repeat steps 4.2–4.5 for N times to obtain N possible scenarios of internal overall operational risk in supply chain finance businesses considering the risk cell dependence structure, $\{L_1, L_2, \ldots, L_N\}$, and thereby obtain the total loss distribution of internal overall operational risk $G(\cdot)$.

Step 5.2: Sort the N possible losses of overall operational risk in descending order, and calculate the confidence level as VaR_α under α, as well as the sample mean exceeding VaR_α as the estimated value of ES_α.

$$\mathrm{VaR}_\alpha = \inf\left\{ L_{(p)} : p/N \geq \alpha \right\} \tag{3}$$

Step 6: Assessment of operational risk values' efficacy. During this step, a backtesting is performed to utilize Kupiec's Likelihood Ratio Test (LR Test) in order to assess the precision of VaR and ES. The objective is to determine if the unusual occurrence of the two risk values aligns with the anticipated abnormal occurrence at the chosen confidence level (Kupiec, 1995). Thus, the null hypothesis test is $H_0 : p = \alpha$. The test employs a binomial distribution to determine the likelihood of N true losses surpassing VaR (ES) at a given confidence level $1 - \alpha$ and sample size T. The likelihood ratio (LR) statistical test for Kupiec's null hypothesis is

$$\mathrm{LR} = -2\ln[(1-\alpha)^{T-N}\alpha^N] + 2\ln\left\{ [1-(N/T)]^{T-N}(N/T)^N \right\} \sim \chi^2(1) \tag{4}$$

4. Results

4.1. Data Analysis

The analysis is based on 427 loss events from 106 commercial banks. Figure 3 depicts the annual loss data, which show that the frequency of losses experienced a peak in 2016. In addition, there was a steady rise in the amount of losses from 2019 to 2020, which followed an abnormal surge in 2014. From the perspective of the entire market, we are of the opinion that the loss peak is associated with an increase in the number of market participants, which implies a greater likelihood of loss. Country policies may potentially influence the quantity of participants.

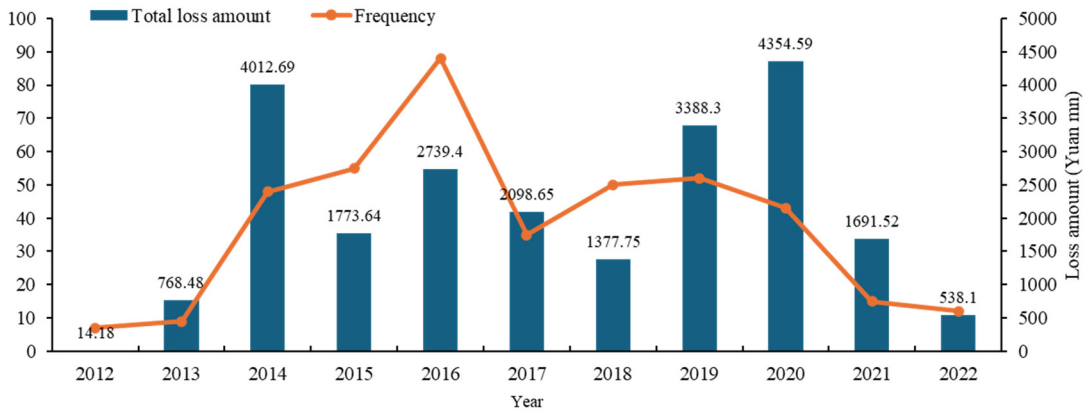


Figure 3. Annual distribution of operational risk loss frequency and amount in bank supply chain finance from 2012 to 2022.

In 2016, the Chinese government introduced policies aimed at promoting the growth of supply chain finance. These policies emphasized the need to actively develop accounts receivable financing and encouraged large enterprises and government procurement entities to confirm accounts receivable to facilitate financing for small and medium-sized enterprise suppliers. In 2019, a number of policies were extensively implemented to facilitate the accelerated growth of the supply chain finance sector. The document issued by the General Office of the State Council of the People's Republic of China has explicitly stated the need to decrease reliance on mortgage guarantees and increase the proportion of credit loans and accounts receivable financing. The Chinese government actively promotes supply chain finance with the aim of utilizing supply chain finance tools to facilitate industrial restructuring and drive economic development and transformation in China.

In addition, Figure 3 illustrates a significant decline in loss frequency in 2017, followed by a gradual decrease to a lower level after 2020. This trend can be attributed to the implementation of market regulations. In 2017, the government emphasized the importance of effectively preventing risks associated with supply chain finance and standardizing the management of accounts receivable asset-backed securities (ABS), including their issuance and duration. In 2020, several national departments collaborated to release official documents that outlined 23 policy requirements and measures aimed at mitigating risks in supply chain finance and enforcing stricter regulations. These measures included the implementation of guarantees for movable assets and rights, such as accounts receivable pledges and factoring.

Interestingly, before 2017, there was a roughly positive correlation between the frequency of losses and the amount they incurred. This was due to the early market disorder in Chinese commercial banks' development of the supply chain finance business. For example, in 2014, a private metals trading firm, Decheng Mining, was accused of duplicating

warehouse certificates stored at Qingdao to use metal cargo as collateral for multiple bank loans. This supply chain finance fraud event led to a loss of 3.6 billion yuan for 13 banks.

Conversely, since 2019, the decreasing loss frequency has brought higher loss amounts, which means that there are more extreme and vicious loss events. Despite the reduction in the frequency of typical operational risk loss events during this period, a multitude of high-risk vulnerabilities remain undetected. For instance, in 2019, Minxing Pharmaceutical Co., Ltd. (Fuzhou, China) was suspected of forging the official seal of Fujian Medical University Affiliated Union Hospital (Fuzhou, China), fabricating materials and accounts receivable, and defrauding financial institutions, such as Industrial Bank Co., Ltd. (Fuzhou, China), of CNY 2.2 billion. In 2020, Kingold Jewelry (Wuhan, China) used 83 tons of fake gold bars as collateral to secure the equivalent of USD 2.8 billion in loans from more than a dozen Chinese financial institutions.

Based on the analysis, it is visible that the recorded operational risk loss events accurately depict the evolving supply chain finance market in response to policy changes. This suggests that the constructed database provides an objective reflection of the development of supply chain finance in China's commercial banks. It is worth noting that the data collection is relatively comprehensive, although it may not encompass a few undisclosed corporate events.

Next, we conduct descriptive statistics on the loss of 427 events in the database, as displayed in Table 1. Based on the data in Table 1, it is clear that there is a wide range of losses, with a minimum of CNY 100,000 and a maximum of CNY 2.072 billion. This suggests that the loss data are quite varied. With a skewness coefficient of $8.32 > 0$, the median loss of these 427 high-risk cases is lower than the average age, indicating a skewed distribution of loss rates to the right. The kurtosis coefficient is $80.99 > 3$, which suggests that the loss distribution of operational risk exhibits a peak and fat-tailed pattern. The presence of right skewness and fat-tailed characteristics in the distribution of losses is indicated, as evidenced by Figure 4.

Table 1. Statistical characteristics of operational loss amount (yuan mn).

Statistics	Mini	Max	Median	Mean	Std	Skewness	Kurtosis
427	0.1	2172.5	9	42.76	166.58	8.32	80.99

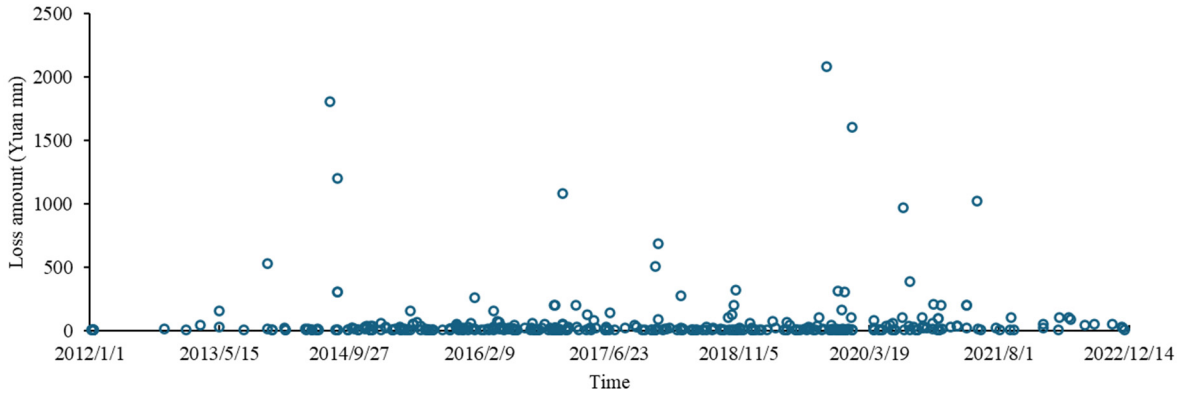


Figure 4. Loss amount distribution of the operational in supply chain finance.

Figure 4 organizes the operational risk events in the order of their occurrence. The majority of operational risk loss cases are grouped at the bottom, where the loss amounts are lower. These risk events meet the characteristics of "high frequency, low severity" (HFLS) loss events, while the number of operational risk loss events with large loss amounts is relatively small, which is consistent with the characteristics of "low frequency, high

severity" (LFHS) loss events. Therefore, the statistical characteristics of the SCF operational loss distribution are in accordance with the characteristics of operational risk in commercial banking.

4.2. Data Division by Risk Cells

In order to more accurately evaluate the operational risk of the commercial bank supply chain finance business, we divide these events into risk units based on the analysis of loss data. This allows us to study more representative operational risk loss events, analyze their characteristics, and measure their impact.

According to the definition of operational risk loss types as outlined in the Basel Accord, operational risk losses in supply chain finance are categorized into seven types: internal fraud (IF), external fraud (EF), employment practices and workplace safety (EPWS), clients, products, and business practices (CPBP), damage to physical assets (DPA), business disruption and system failures (BDSF), and execution, delivery, and process management (EDPM). The frequency distribution of the seven loss types is illustrated in Figure 5, based on a statistical analysis of 427 operational risk loss events.

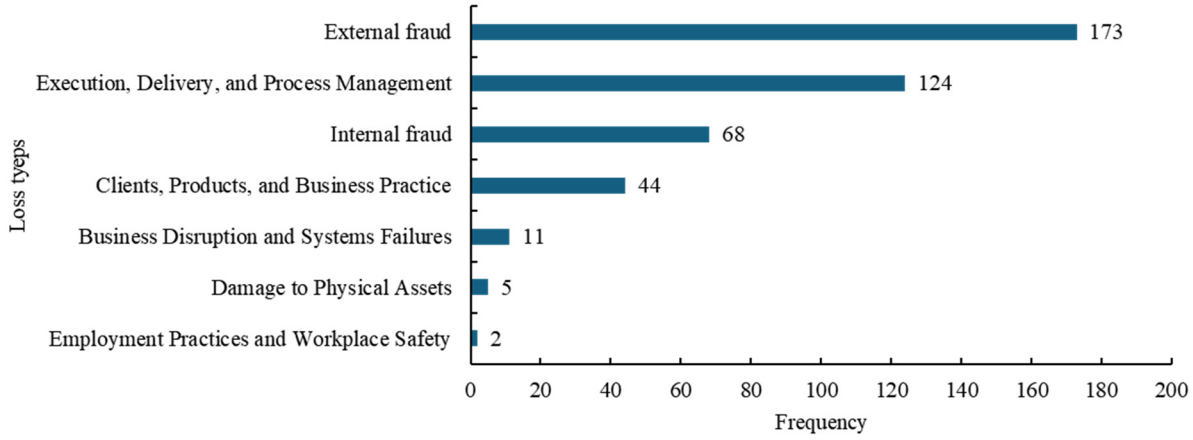


Figure 5. Summary frequency of different risk cells for SCF business line.

Internal and external fraud in supply chain finance accounted for 57% of the total number of cases, totaling 241 cases. Emphasizing pledges, trade contract signings, guarantees, transactions, and other interactions are the main areas of concern when it comes to fraud risk-loss events. Some common examples include "false transactions", "repeated financing", and "self-insurance and self-financing". Individuals, whether from within the organization or outside, exploit weaknesses in internal controls to create fake transactions, false trade histories, and counterfeit documents in order to deceive commercial banks into granting substantial loans, resulting in significant financial losses for the banks.

CPBP and EDPM loss events account for 39% of the total number of cases, totaling 168. Among them, there are 124 risk events related to execution, delivery, and process management. The supply chain financial service targets encompass all aspects of the supply chain, involving a wide range of subjects and complex processes. Consequently, commercial banks often violate business operation rules, leading to frequent EDPM loss events such as "collateral management failures", "missing deadlines", and "disputes with partners". At the same time, compared to mature financing products, commercial banks operating supply chain financial businesses are still in the growth stage, and China's regulatory authorities are constantly improving and standardizing the management system of supply chain financial businesses. Commercial banks intentionally or unintentionally fail to act in accordance with industry laws and regulations or best practices stipulated by regulatory authorities, resulting in fines. Common CPBP loss events include "inadequate

post-loan management", "lax background review of business transactions", and "illegal loan issuance". We classify CPBP and EDPM events as compliance risk loss events, which refer to economic losses incurred by commercial banks due to their own operations violating business operation rules, laws, and regulations.

As shown in Figure 5, the proportion of IF, EF, CPBP, and EDPM reached 96%. As a result, this study mainly explores four types of loss events: internal fraud, external fraud, clients, products, and business practices, and execution, delivery, and process management, with a total of 409 cases. Notably, information asymmetry and complex process operations provide significant opportunities for fraudulent activities, often involving collusion between internal and external parties. Therefore, internal and external fraud events are uniformly classified as fraud risk cells. In parallel, the rapid development of supply chain finance has led to legal regulations lagging behind actual operations. This discrepancy causes banks to frequently fail to comply with relevant laws, regulations, or internal policies and procedures, resulting in substantial fines and significant losses due to legal disputes arising from unregulated behaviors. Consequently, compliance risk is identified as the second major source of operational risk in supply chain finance. These primary risk cells, fraud and compliance risk, are not unique to China, but are also prevalent in the global supply chain finance market [76]. Jadwani et al. [77] highlighted the importance of studying compliance risk and developing effective strategies to minimize it, which holds significant value for bankers, regulators, and academics.

We classify IF and EF events as fraud risk loss events and CPBP and EDPM events as compliance risk loss events. Fraud and non-compliance are the two primary categories of SCF operational risk losses. In this scenario, the operational risk of the commercial bank's SCF business is measured using the risk cell m = 2. Table 2 displays the statistical characteristics of operational losses in each risk cell. Table 2's findings reveal that the loss distribution of the two risk cells has a significant right skew when compared to the normal distribution. Hence, it is imperative to address the issue of right skew during the subsequent measurement procedure.

Table 2. Statistical characteristics of risk cells' operational loss amount (yuan mn).

Risk Cell	Mini	Max	Median	Mean	Std	Skewness	Kurtosis
Fraud	241	0.26	2173	9.98	60.23	209.4	6.88
Compliance	168	0.17	2000	8	30.42	127.28	10.02

4.3. Segmented Marginal Distribution Goodness-of-Fit Test

A two-stage measurement method is utilized to fit the loss severity distributions of HFLS and LFHS for fraud and compliance risk cells, respectively. First, determine an appropriate threshold for dividing losses into HFLS and LFHS. Figures 6 and 7 depict the average excess plot and hill plot of fraud risk and compliance risk, respectively, using the supply chain finance operational risk database. Figure 6 shows a structural change in fraud risk when it reaches 36.21 million. At this time, there are 33 losses that exceed the compliance risk event threshold; thus, the fraud risk threshold is set at 36.21 million. Similarly, Figure 7 shows that the threshold for compliance risk cells is 90 million, with 19 losses above the compliance risk event level.

The subsequent step involves the selection of the optimal loss severity and loss frequency distribution, and the parameter estimation is conducted using the maximum likelihood estimation method. The KS-test is a commonly employed method for evaluating the degree of fit between empirical data and the distribution function. Consequently, the KS test is implemented in this investigation, with a confidence level of 5%. A p value of

more than 5% suggests that the data are consistent with the distribution model, and a larger p value suggests a more effective distribution fitting effect.

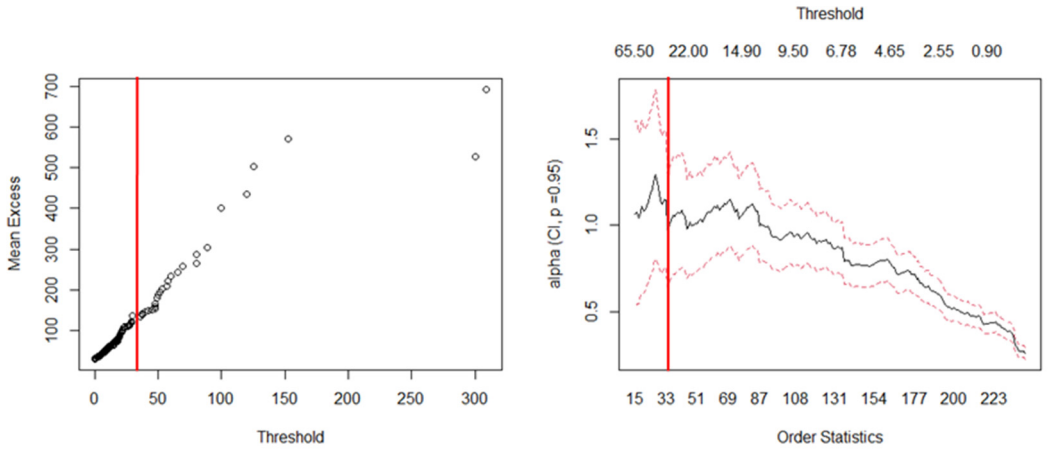


Figure 6. Mean excess plot (**left**) and hill plot (**right**) of fraud risk cell.

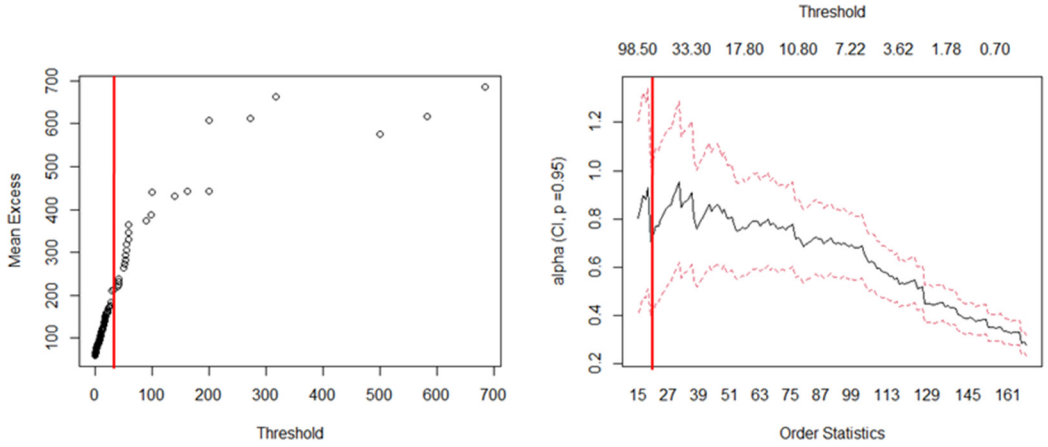


Figure 7. Mean excess plot (**Left**) and hill plot (**Right**) of compliance risk cell.

The HFLS loss severity distribution of fraud risk and compliance risk is fitted using the Lognormal distribution, Weibull distribution, and Gamma distribution under constant double-truncated distribution conditions, respectively. Table 3 displays the fitting results. It is evident from Table 3 that the three double-truncated distributions exhibit satisfactory fitting for both risk cells under constant double-truncated conditions, and all three passed the significance test. The Weibull distribution has the best fitting effect for compliance risk, while the Gamma distribution has the best fitting effect for fraud risk. In comparison to compliance risk, the three double-truncated distributions exhibit superior fitting effects for fraud risk.

Subsequently, the loss severity distribution of LFHS was modeled using the Extreme Value Theory (EVT)-based generalized Pareto distribution (GPD). The estimation results of the parameters and the test results of the fitting are presented in Table 3. The GPD is well suited to the tail risk of both risk cells, as evidenced by the KS test value and significance level p value in Table 3. Also, both risk cells exhibit a high goodness of fit. The excess distribution plots, as depicted in Figure 8, demonstrate the close distribution of actual extreme loss data on both sides of the theoretical distribution curve. This indicates that the GPD is capable of effectively fitting the extreme loss data associated with fraud risk and compliance risk in the supply chain finance business. Figure 9 depicts Q-Q plots, which show that the scatter plot frequently has a positive slope at each diagonal line, indicating

that the theoretical data roughly follow a standardized exponential distribution and that the GPD distribution fits well. The results obtained further confirm that the thresholds we selected were reasonable.

Table 3. Parameters estimation and KS test results of loss severity distributions.

Loss Part	Risk Cell	Distribution	Parameter Value		KS Test	*p* Value
HFLS losses	Fraud	Gamma	$\alpha = 1.044$	$\beta = 8.843$	0.055	0.527
		Weibull	$\alpha = 1.039$	$\beta = 8.367$	0.056	0.514
		Lognormal	$\mu = 1.661$	$\sigma = 1.171$	0.103	0.479
	Compliance	Gamma	$\alpha = 0.750$	$\beta = 18.375$	0.072	0.363
		Weibull	$\alpha = 0.825$	$\beta = 12.426$	0.069	0.426
		Lognormal	$\mu = 1.661$	$\sigma = 1.397$	0.093	0.357
LFHS losses	Fraud	GPD	$\sigma = 42.5$	$\xi = 0.752$	0.130	0.637
	Compliance	GPD	$\sigma = 222$	$\xi = 0.431$	0.150	0.784

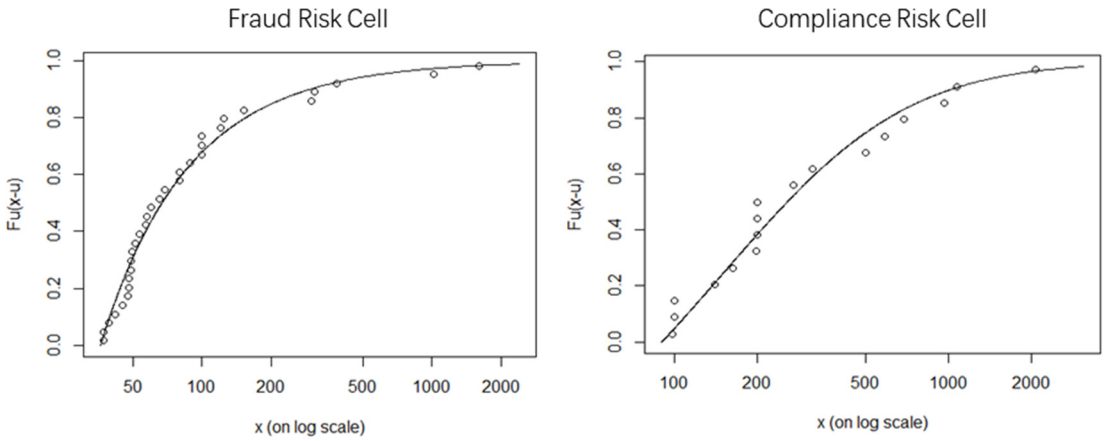


Figure 8. Excess distribution plots of risk cells LFHS part.

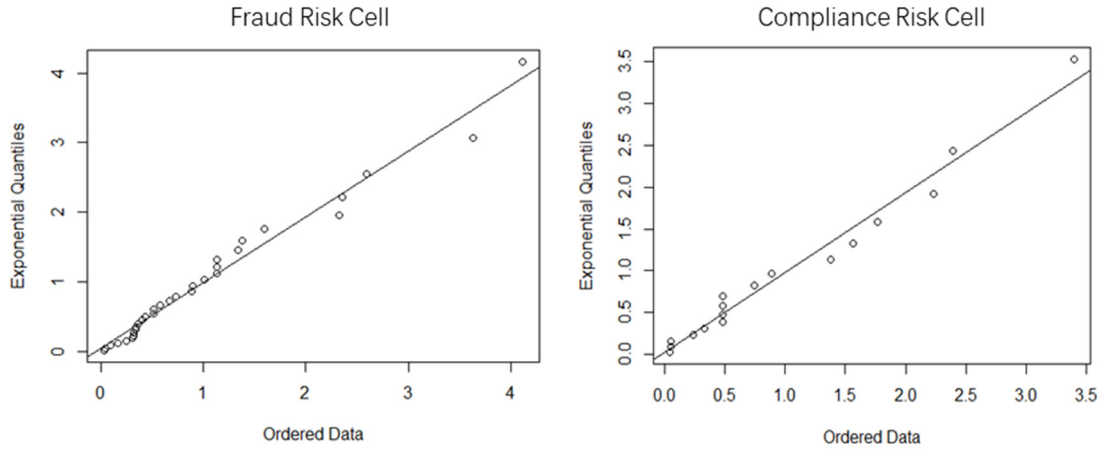


Figure 9. Q-Q plot plots of risk cells LFHS part.

As shown in Table 4, when it comes to the estimation of loss frequency distributions, which is frequently fitted using negative binomial distribution (NBD) and Poisson distribution (PD). The loss frequency distribution of the HFLS part of both risk cells is characterized by the NBD, while the LFHS part of both risk cells is characterized by the PD. Similarly to the results of loss severity fitting, it is evident that the fitting effect of fraud risk loss frequency is superior to that of compliance risk loss frequency.

Table 4. Parameters estimation and KS test results of loss frequency distributions.

Loss Part	Risk Cell	Distribution	Parameter Value		KS Test	
					D-Value	*p*-Value
HFLS losses	Fraud	N. binomial	$r = 5$	$P = 0.625$	0.151	0.963
		Poisson	$\lambda = 18.909$		0.363	0.110
	Compliance	N. binomial	$r = 2$	$P = 0.537$	0.177	0.881
		Poisson	$\lambda = 13.545$		0.328	0.189
LFHS losses	Fraud	Poisson	$\lambda = 3$		0.229	0.828
	Compliance	Poisson	$\lambda = 1.727$		0.266	0.416

4.4. Risk Measurement of Risk Cells

This section further examines the dependence between HFLS and LFHS, as well as the dependence between fraud risk cell and compliance risk cell, after obtaining the fitted distribution functions of loss frequency and loss severity for the two risk cells' HFLS and LFHS parts. It then selects the optimal copula model to describe the dependence structure between them. The Monte Carlo simulation is employed to quantify the operational risk of the two risk cells and compute risk values, VaR, and ES, under varying confidence levels.

In order to determine whether the loss dependence structures of HFLS and LFHS differ, we computed the correlation coefficients between them. The linear and global correlation coefficients between the annual frequencies of the two risk cells for HFLS, LFHS, and overall loss are presented in Table 5. So, to account for linear and potential nonlinear correlations, the global correlation coefficient is computed through the application of mutual information in communication theory.

Table 5. Linear and global correlation coefficients between risk cells.

Loss Type	Fraud/Lhiability Risk Cell	
	Linear	Global
HFLS	0.7491	0.7606
LFHS	0.5013	0.5639
Holistic	0.6550	0.6944

The findings in Table 5 reveal that, initially, all global correlation coefficients are greater than the corresponding linear correlation coefficients. This is due to the fact that global correlation coefficients can include additional nonlinear correlations. Secondly, the correlation coefficients between HFLS and LFHS are, in fact, distinct. In particular, the correlation coefficients of HFLS are all greater than those of LFHS. This suggests that HFLS events exhibit stronger frequency correlations, necessitating the consideration of the correlation of all losses in a variety of methods. This is in accordance with the conclusion of Zhu et al. [75]. Moreover, the correlation coefficients of overall losses are comparatively similar to those of HFLS, whereas the coefficients of LFHS are lower than those of the overall losses. This further suggests that the operational risk modeling results may be overestimated by merely considering the overall losses.

Following that, we established a multivariate distribution copula model using rank estimation [78] and selected the copula model that accurately captures the overall dependence structure between two risk cells. Table 6 illustrates the findings. It is evident from the table that the p value of the t-copula is 0.769, which is greater than the Gaussian copula's 0.441. Thus, the t-copula is selected as the appropriate choice for characterizing the frequency dependence between the risk cells. Within the set, a notable correlation exists between the two risk cells. In addition, there is a detectable correlation between the HFLS component of

the compliance risk events and the LFHS component of the fraud risk events. This implies the potential for a transmission effect between low-frequency loss events of fraud risk and high-frequency loss events of compliance risk.

Table 6. Parameter estimation and goodness-of-fit test results for copulas.

Copula	LossType	HFLS_F	HFLS_L	LFHS_F	LFHS_L	*p* Value
t-copula (v = 2, ρ = 0.673)	HFLS_F	1	0.807 **	0.506	0.123	0.769
	HFLS_L	0.807 **	1	0.771 *	0.503	
	LFHS_F	0.506	0.771 *	1	0.682 *	
	LFHS_L	0.123	0.503	0.682 *	1	
Gaussian-copula (ρ = 0.373)	HFLS_F	1	0.720	0.429	−0.056	0.341
	HFLS_L	0.720	1	0.797	0.406	
	LFHS_F	0.429	0.797	1	0.523	
	LFHS_L	−0.056	0.406	0.523	1	

Note: *, and ** denote statistical significance at the 10%, and 5% levels, respectively.

Afterwards, we implemented the Monte Carlo algorithm to execute 100,000 simulations and compute the operational risk metrics, VaR, and ES. Table 7 displays the operational risk metrics of fraud and compliance risk cells without considering the dependence structure used to compare the operational risk losses. Table 8 exhibits the operational risk metrics of China's commercial banking supply chain finance business, one considering the dependence structure and the other without.

Table 7. Estimated operational risk value of SCF by risk cells.

Value at Risk (VaR)	Fraud	Compliance	Expected Shortfall (ES)	Fraud	Compliance
$VaR_{90\%}$	127.065	73.309	$ES_{90\%}$	276.575	189.215
$VaR_{95\%}$	211.628	137.763	$ES_{95\%}$	389.875	277.584
$VaR_{99\%}$	476.052	343.448	$ES_{99\%}$	744.158	559.588
$VaR_{99.9\%}$	1101.866	847.201	$ES_{99.9\%}$	1582.643	1250.26
$VaR_{99.99\%}$	2224.098	1786.601	$ES_{99.99\%}$	3086.244	2538.225

Table 8. Estimated operational risk value of SCF with and without dependence structure.

Value at Risk (VaR)	With Dependence	Without Dependence	Expected Shortfall (ES)	With Dependence	Without Dependence
$VaR_{90\%}$	178.334	200.375	$ES_{90\%}$	409.894	465.789
$VaR_{95\%}$	303.970	349.391	$ES_{95\%}$	574.015	667.459
$VaR_{99\%}$	737.549	819.499	$ES_{99\%}$	1047.296	1303.746
$VaR_{99.9\%}$	1793.142	1949.067	$ES_{99.9\%}$	2049.613	2832.903
$VaR_{99.99\%}$	3449.736	4010.699	$ES_{99.99\%}$	4218.777	5624.469

The findings suggest that as the confidence level rises, so does the associated risk value. According to Table 7, the operational risk metrics for the fraud risk cell are higher than those for the compliance risk cell. This is consistent with the statistical characteristics of the two types of risk cells previously obtained. By analyzing Table 8, it was found that the risk values of considering the dependency structures of two risk cells are lower when compared to the risk values of not considering them. This implies that the t-copula function effectively depicts the dependency structure between risk cells, which, to varying degrees, reduces the overall operational risk of commercial bank SCF businesses, resulting in an

average reduction of approximately 10% in capital costs. This result further supports the perspective of Fantazzini et al. [79], emphasizing the importance of taking into account the dependence structure of risk cells in order to accurately assess the overall operational risk of commercial banks. The copula function's introduction takes into account the dependence structure between risk cells during the measurement process, resulting in more realistic and accurate measurement results. This, in turn, significantly reduces the regulatory capital required for commercial bank operational risks.

It is recommended by BCBS to use a confidence level of 99.9% when determining the economic capital requirements for preventing losses over one year [5]. Thus, the operational risk capital should be calculated as the VaR at a 99.9% confidence level. According to Table 8, the operational risk of China's commercial banking supply chain finance business is estimated to be CNY 1793.142 million. BCBS [5] highlights ES as an important metric due to its cautious approach to risk measurement. Based on the ES criterion, the capital needed for operational risk in China's commercial banking supply chain finance business is CNY 2049.613 million.

4.5. Backtesting

The sample size is $T = 409$. Based on the LR value and significance level, we can determine whether to accept or reject the null hypothesis. Table 9 displays the backtesting results, showcasing the failure rates of 5, 2, 1, and 1 for VaR and ES at the 95% and 99.9% levels, respectively. At the significance level of $\alpha = 1\%$, the critical value of LR is 6.6349. Meanwhile, the four risk values are less than the critical value, and all pass the LR test. It has been proven that the calculated VaR and ES values are near to actual losses, enabling an accurate assessment of operational risk.

Table 9. The results of backtesting.

Risk Value	$\mathbf{VaR_{99\%}}$	$\mathbf{ES_{99\%}}$	$\mathbf{VaR_{99.9\%}}$	$\mathbf{ES_{99.9\%}}$
Failure number	5	2	1	1
LR	1.100	1.944	1.355	1.355

5. Discussion

To evaluate the operational risk value of SCF, seven methodologies were compared: the Basic Indicator Approach (BIA), the loss distribution approach (LDA), the LDA considering frequency dependence (LDA-FD), the LDA based on a piecewise-defined distribution without dependence (LDA-PD), the LDA based on a piecewise-defined distribution with dependence (PSD-LDA), the LDA with piecewise-defined frequency dependence (LDA-PFD), and the proposed method in this paper. The results in Figure 10 demonstrate significant differences in the value at risk (VaR) estimates across these methods, particularly at the 99.9% confidence level.

The BIA method yielded the highest VaR estimate, reaching CNY 7863.46 million, a value significantly exceeding those of all other methods. As a straightforward approach relying on aggregate financial indicators, BIA is inherently limited by its lack of granularity and its inability to account for the nuanced risk profile of the data. Consequently, this results in an overestimation of operational risk capital, making BIA less suitable for precise risk modeling.

In contrast, the standard LDA method provided a much lower VaR estimate of CNY 1973.97 million. By incorporating both frequency and severity distributions of losses, LDA achieves greater refinement compared to BIA. However, its inability to model dependency structures within the data limits its overall precision, particularly when addressing complex interrelationships among loss events.

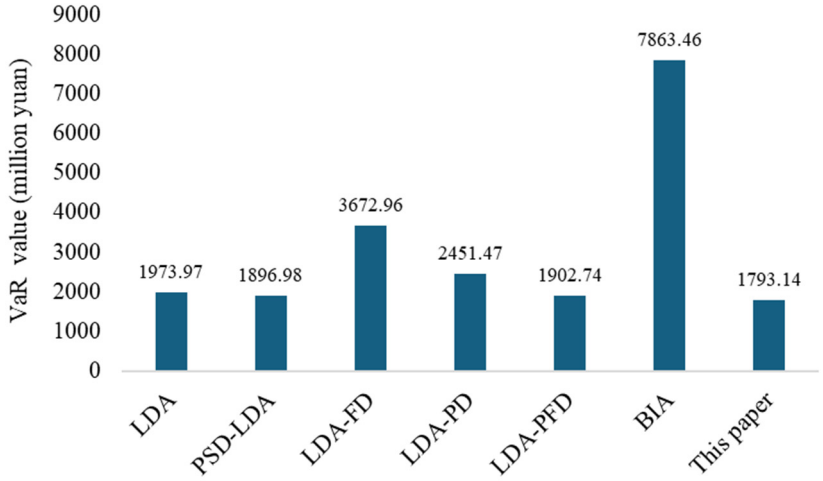


Figure 10. Operational risk value of SCF by different methods.

The LDA-FD model, which incorporates frequency dependence, produced the second highest estimate of CNY 3672.96 million. While this approach improves accuracy by accounting for the relationship between loss frequencies, the results suggest that neglecting severity dependencies or other interconnected factors can still lead to the overestimation of risk under extreme scenarios.

LDA-PD, employing a piecewise-defined distribution to address data heterogeneity, generated a VaR estimate of CNY 2451.47 million. Its ability to segment data into distinct intervals enhances its adaptability, allowing for more granular risk assessment. However, the absence of dependency modeling diminishes its effectiveness, leading to higher estimates compared to models that incorporate such structures, such as PSD-LDA. The PSD-LDA model builds upon LDA-PD by introducing dependency modeling, thereby refining the segmentation process. This integration results in a lower VaR estimate of CNY 1896.98 million, illustrating the value of combining data segmentation with dependency modeling to achieve greater accuracy.

Building on the piecewise-defined distribution framework, the LDA-PFD model incorporates frequency dependence, representing a more advanced approach to risk estimation. With a VaR estimate of CNY 1902.74 million, it outperforms both LDA-FD and LDA-PD while remaining slightly higher than PSD-LDA. This suggests that although piecewise-defined frequency dependence enhances the model's adaptability to data characteristics, its exclusion of severity dependency limits its overall precision, particularly when compared to PSD-LDA and the proposed method.

The comparison of LDA, LDA-FD, LDA-PD, PSD-LDA, and LDA-PFD underscores the critical importance of comprehensive dependency modeling in operational risk assessment. Methods that fail to fully account for dependencies—such as traditional LDA, LDA-PD, and LDA-PFD—tend to overestimate risk, particularly at higher confidence levels. In contrast, PSD-LDA and the proposed method demonstrate the clear advantages of integrating both frequency and severity dependencies alongside data segmentation.

The proposed method developed in this paper achieved the lowest VaR estimate of all approaches, at CNY 1793.14 million. This result highlights its ability to balance granularity, dependency modeling, and computational efficiency, providing a more realistic and precise evaluation of operational risk. By integrating data segmentation with the comprehensive modeling of frequency and severity dependencies, the proposed method effectively minimizes overestimation while maintaining computational feasibility. This balance between precision and practicality positions it as the most robust approach for operational risk capital estimation under the given data conditions.

6. Conclusions

The fast growth of supply chain finance has led to operational issues that pose a threat to the stability of commercial bank operations. Hence, there is a need for a framework to assess operational risks in the supply chain finance operations of commercial banks. Our research introduces a novel assessment approach that enhances the existing body of knowledge on managing risks in supply chain finance. This method is also of great practical importance to various stakeholders, including market regulators, banks, and industry groups.

6.1. Theoretical Implications

This study presents a novel framework to assess the operational risk of commercial bank supply chain finance businesses. The method utilizes the LDA model and considers the correlation between risk cells. The novelty of this resides in three distinct features. At first, we employ risk cells to depict the typical risk categories of loss events and categorize them into specific risk cells by concentrating on a particular type of loss event that initiates operational risk. Furthermore, we determine the frequency and severity of losses for each risk cell in segments by distinguishing between "HFLS" and "LFHS" loss occurrences. We then apply the most suitable distribution or approach to accommodate the two separate types of losses. Moreover, it takes into account the interdependence between risk cells in order to calculate operational risk losses. This model accurately simulates the entire distribution of operational risk losses by defining the nonlinear relationship between risk cells. Consequently, it could lead to the generation of fairer costs for operational risk capital. This study employs empirical research to estimate the operational risk capital cost of the entire supply chain finance market of Chinese commercial banks. The estimation relies on operating loss data from 2012 to 2022 for the supply chain finance businesses of Chinese commercial banks.

Empirical findings from the Chinese market indicate that operational risks in supply chain finance primarily stem from fraud risk and compliance risk. It is worth noting that the relationship between HFLI and LFHI losses is distinct, suggesting the need for separate modeling for each type of loss. Examining the complete dependencies, as opposed to only partial dependencies, can lead to either an overestimation or an underestimation of the outcomes. In addition, upon analyzing the segmented structure, it becomes apparent that there could be a transmission effect between high-frequency compliance risk loss events and low-frequency fraud risk loss events. Using the segmented dependency theory to look at how risk cells depend on each other for measurement can also help achieve a better picture of how each risk cell's marginal loss distribution works. In addition, the measurement model based on the copula function takes into account the dependency structure between risk cells, resulting in more realistic measurement results. With a significance level of 99.9%, the annual risk value and expected gap in supply chain finance for Chinese commercial banks amount to CNY 179.3 million and CNY 204.9 million, respectively. The study's results have successfully passed backtesting, confirming the reliability of the research findings and their efficacy as market alert indicators.

6.2. Policy Implications

This study has important real-world effects for creating good policies and managing the risks that come with operations in supply chain finance. Here are some suggestions:

1. The collaboration between the government, banks, and enterprises involved in supply chain finance should aim to establish a data-driven regulatory framework for managing operational risks. This study proposes a method for assessing risk that relies on a comprehensive database of risk events and the organization of risk cells. It is

advisable for all parties involved to utilize advanced technologies such as blockchain and big data to gather data from multiple sources, establish a database of supply chain finance operational risk events, and effectively monitor and report on various risk occurrences. In addition, it is advisable to employ supply chain finance operational risk assessment methodologies to accurately identify both typical risk categories and atypical occurrences within the business. This will aid organizations in reducing the financial impact of risks, enhancing their ability to adhere to compliance requirements and regulatory standards, and enhancing the proactivity and predictive capabilities of their risk management. Similarly, this data-centric approach enables regulatory authorities to formulate rules grounded in scientific evidence and practical reasoning, ensuring their effectiveness and enforceability. This enhances the efficiency and clarity of the regulatory system.

2. According to this study, the most common operational risks in the commercial bank supply chain financing industry are fraud and non-compliance. Legislation, industry associations, and governments should work together to develop a comprehensive system for controlling supply chain financial risks. Enhance and refine supply chain financing legislation and regulations. Use LegalTech to improve legal supervision and reduce risk. One example is the use of blockchain technology to improve the transparency and immutability of contracts, hence reducing the vulnerability to contract fraud. Industry associations should provide benchmarks and operating recommendations for supply chain finance. This would streamline all organizational processes while reducing operational risks and non-compliant behaviors. The government advocates for supply chain financing legislation and ensures that rules and regulations are continually updated and improved to meet the needs of growing businesses. Laws provide fundamental safeguards and assure their enforcement. Industry associations set norms and encourage self-regulation, while the government enforces them through legislation and regulations. Working together as a trio to generate unique solutions can effectively mitigate and resolve fraudulent activities and non-compliant operating risks in supply chain finance. This will encourage the financial market's robust and sustainable growth.
3. The operational risk value estimated in the SCF market of Chinese commercial banks in this study can serve as an indicator of market warning, as it helps meet the risk control criteria of regulatory bodies and ensures efficient capital usage. We require enhanced information disclosure and sharing mechanisms to facilitate the sharing of operational risk information, along with improved methods for gathering operational loss data, to drive further progress. The comprehensive and constantly improving internet information system, along with the increasingly effective information disclosure method, aids in collecting data for this study. This research framework utilizes strategies for promoting information transparency and gathering feedback. A new way of judging operational risks in the supply chain can help businesses, financial institutions, and government agencies share information and use knowledge from many fields to better understand the different types and traits of operational risks.

6.3. Limitations

This study is subject to several key limitations. Firstly, the data used were sourced from media reports and publicly available information within China's commercial banking industry. This reliance on secondary data introduces the potential for inaccuracies and omissions, which could impact the robustness of the findings. While the implementation of Basel III is expected to improve the quality and comprehensiveness of operational risk

disclosures by Chinese commercial banks, this limitation is likely to persist until more systematic and standardized data collection practices are in place.

Additionally, the scope of the study is limited by its narrow focus on fraud and non-compliance as the sole operational risks. This exclusion of other critical risk types, such as technology failures, personnel errors, and liquidity risk, reduces the comprehensiveness of the analysis. Given the increasing relevance of these risks in the modern banking environment, future research should broaden its focus to include these areas for a more holistic understanding of operational risk.

The study's applicability beyond China also remains uncertain. The model was primarily developed within the context of the Chinese financial market, which has unique regulatory, market, and economic conditions. These factors may affect the model's effectiveness in other regions, such as India, the US, Kazakhstan, or Poland, where market structures and regulatory frameworks differ. Further research is needed to assess the generalizability of the model across different financial systems. Moreover, the reliance on manual data collection raises concerns about the accuracy and completeness of the operational loss data. Although the study acknowledges this limitation, the absence of clear safeguards against potential data errors or omissions diminishes the confidence in the results. These gaps in the data could compromise the reliability of the conclusions drawn from the study.

6.4. Future Research

Future research could expand on several key aspects to enhance the robustness and applicability of the current study. First, while this paper relies on data from the Chinese market, there is significant potential to incorporate operational loss data from other regions. By doing so, researchers can assess the model's applicability in diverse markets and evaluate its broader suitability. This would also enable the identification of both common operational risks and region-specific risks in the global commercial banking supply chain finance market, further strengthening the scientific validity of the proposed model and providing valuable policy recommendations for global operational risk management.

In addition, expanding the scope of operational risks considered would offer a more comprehensive risk assessment. The current focus on fraud and non-compliance could be broadened to include technology risks, personnel-related risks, and liquidity risks, particularly in the context of treasury management. Incorporating these factors would deepen our understanding of the diverse challenges in supply chain financing and improve the model's generalizability across various financial environments.

Another important area for future research is the automation of operational loss data collection. Automating this process would help minimize human errors, improve the accuracy of the dataset, and ensure its completeness. This would, in turn, enhance the reliability of the model and mitigate concerns related to data omissions, making the model more robust. A detailed sensitivity analysis is also crucial for future studies. This analysis would assess how changes in key assumptions affect the model's results, providing insights into the model's stability and identifying potential risks associated with varying input parameters. Such an analysis would contribute to the credibility and robustness of the research findings.

Lastly, future research could explore the integration of treasury management analysis, with a particular focus on liquidity management. Liquidity is a critical aspect of operational risk in the supply chain finance context, especially in an environment characterized by fluctuating cash flows. Investigating how different liquidity management policies influence operational risks, and conducting sensitivity analyses of cash flow scenarios, would offer a deeper understanding of the impact of liquidity on operational risks. This would broaden

the scope of risk assessments and increase the practical relevance of the model in the field of supply chain financing.

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