Research on the Financing Income of Supply Chains based on an E-Commerce Platform

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ABSTRACT

Rapid economic development has brought about the expansion of the supply chain. In the context of the demand for finance and emerging financial technology tools, supply chain finance on e-commerce platforms is developing rapidly. It not only strengthens the ability to serve the real economy, but also brings market risks caused by excessive supply chains. In the Internet era, IoT technology promotes the exchange of information, while it also has certain risk characteristics. This research implements the peaks over threshold (POT) model to investigate the value at risk (VaR) and expected loss (ES) in the supply chain of e-commerce platforms under the risk of unexpected changes in the market. The study finds that the supply chain of e-commerce platforms based on Internet of Things (IoT) technology suffers less risk in losses. The application and expansion of this technology will effectively lower the market risk of supply chain finance and better serve economic development.

Keywords: E-commerce Platform; Supply Chain; Market Risk; POT Model

1. Introduction

As an important input element of production, capital is the fundamental resource for the operation of modern economic activities. Enterprises need external financing to expand the production. In traditional economic activities, companies obtain capital through bank loans. As the provider of capital, banks pay attention to investment income and risks. The bank only assesses the risk in the lending enterprise itself, without the consideration of the supply chain risk, i.e. risks in the enterprise's upstream and downstream stakeholders (Tang, 2005; Yan et al., 2017; Li et al., 2019; Kumar et al., 2021). Due to ignoring risks arising from the upstream and downstream in the supply chain, traditional investment and financing tools no longer meet the demand, which leads to the emergence of supply chain finance (Clarysse et al., 2014; Wang, 2016; Karam and Jamali, 2017; He et al., 2018; Wang et al., 2020a). Supply chain finance involves three parties, i.e., the investor, the financier, and the focal firm. Specifically, the financier's investment in the investor requires the credit guarantee of the focal firm in the financier's supply chain. In supply chain finance, banks are usually more than investors. This is due to the lowering of financial preparation thresholds. In addition, e-commerce platforms have become an important investor (Shi et al., 2015; Jinshi and Yongrui, 2016; Yueliang et al., 2017; Yue et al., 2020; Sambrekar and Rajpurohit, 2020).

The supply chain finance of e-commerce platforms expand the service scope and methods of investment and financing. E-commerce platforms have a large number of financing companies. The supply chain is also rapidly stretched, which increases market risks caused by the excessively long supply chain (Li et al., 2006; Dunke et al., 2016; Chen et al., 2019; Yu et al., 2018). The outbreak of COVID-19 has a huge impact on international trade and economic activities in various countries and regions. Due to the long supply chain, some commodities are in short supply. In addition, because of the rupture of the supply chain, the price of raw materials and final products has diverged. The pandemic not only introduces difficulties for business operations but also causes a serious negative impact on the financing environment.

The development of e-commerce platform supply chain finance suffers from this impact. How to reduce the market risk caused by the long supply chain has attracted attention from the financial industry and academia. The use of IoT technology strengthens the interconnection of supply chain information (Pande et al., 2016; Pena et al., 2017; Yu et al., 2017; Hamidi and Jahanshahifard, 2018; Yan et al., 2020; Al-Qerem et al., 2020) and reduces the market risk of e-commerce platforms for loans to SMEs. However, the introduction of new technologies also has new risks. This paper aims to develop methods to reduce the market risk of the e-commerce platform supply chain.

The remainder of the paper is presented as follows. In Section 2, the literature introduces risks in the practice of e-commerce supply chain finance and typical financing models. Section 3 presents the theoretical model in this paper, which relies on the POT theoretical model to explain the financing modes and changes in risk loss. Section 4 conducts an empirical analysis by verifying whether IoT technology effectively reduces the losses caused by market risks and the financial operational risks in the e-commerce supply chain. Section 5 concludes the findings.

2. Literature review

2.1. The supply chain of an e-commerce platform embedded in IoT technology

The advancement of technology and the soundness of infrastructure have effectively promoted the widespread application of IoT technology. IoT technology is mainly used to process, collect, store, and share information so that connections between people and things and things and things can be built (Yang et al., 2013; Jin et al., 2020; Gupta and Gugulothu, 2018). There are many companies in the supply chain of e-commerce platforms. The processing of corporate information is very complicated, which increases transaction costs. As there is false or incorrect content in the information, it results in information asymmetry between investment and financing parties, and an increase in the market risk of supply chain finance for e-commerce platforms (Mishra et al., 1998; Sufi, 2007; Brown et al., 2014; Liu et al., 2021a). In e-commerce platform supply chain finance, the inventory pledge financing model is a mature model and regarded as an effective way to reduce supply chain risks.

In the inventory pledge model of the e-commerce supply chain, the financier needs to obtain a certain guarantee before proceeding with the e-commerce platform. As it involves inventory pledges, it is necessary to manage the pledged inventory. It is rare for investors to directly manage inventories. They usually rely on third-party logistics companies as agents. First, logistics companies embed electronic tags on pledged goods to monitor the quantity and location of pledged goods in real time. Second, logistics companies aggregate the collected real-time information, establish a database, and use cloud computing to conduct relevant analysis. Finally, based on the results of the analysis, external instructions are issued. For example, when the market for pledged goods changes or the content of the lender’s contract is adjusted, instructions will change accordingly in response. Logistics companies are the primary participants in the use of IoT technology, while information sharing by other participants is still essential. Due to the sharing of real-time information, the transparency of financing businesses increases, while losses caused by information asymmetry and moral hazard decrease. In this case, market risks reduce for investors.

2.2. Typical application of the inventory pledge financing model

Due to the existence of transaction costs and information asymmetry, financial behavior could be fraudulent. In the meantime, investors, companies, banks, and e-commerce platforms need genuine market information and timely processing capabilities. The application of IoT technology is the result of this demand. In the inventory pledge financing model, the use of IoT technology can (1) effectively reduce the moral hazard caused by information asymmetry, (2) enable investment and financing entities to understand the dynamic changes in market information in a timely manner, and (3) gradually adapt to the high market competitive environment (Lv et al., 2021, Liu et al., 2021b).

The development of the inventory pledge financing model must rely on IoT technology, while the orderly operation of the model must grasp the following three important contents (Ran et al., 2020). First, it requires full access for the collection of data and information on investors, third-party logistics companies, core companies, financiers and the upstream and downstream parts of their supply chain, such as operating conditions, assets and liabilities, and market price fluctuations. In the context of the development in the big data industry and the gradual establishment of a sound credit system, information is complete and credible (Papadopoulos et al., 2016; Liu 2020). Second, it needs to store information in suitable equipment. The storage and transmission of information requires corresponding media. The common media in reality are electronic tags, video surveillance equipment, GPS positioning equipment, etc. This sound equipment is used to realize the monitoring, management, and communication of pledge information (Li et al., 2020; Cao, 2020). The media mainly require third-party logistics companies to deploy. For investment and financing parties regarding how to control investment risks, the key is to master the remote interface function, which can query and manage real-time information at any time (Song et al., 2020). Through the remote interface function, the e-commerce platform can grasp the status of the pledge, conduct the approval of the loan business, and send warehouse instructions. Financing companies can also manage through remote interfaces. Third, in the inventory pledge financing model, the management of pledged goods plays an important role to prevent the loss and damage of pledges (Sun et al., 2020). This mainly relies on the direct management of third-party logistics companies. When a logistics company collects pledged goods, relevant information such as the quantity, price and ownership of the pledged goods shall be entered into the IoT system as soon as possible (Wang et al., 2020b). Through the big data analysis of the same type of pledge by the existing IoT system, it is possible to quickly and effectively assess whether the investment and financing activities through the pledge are normal (Yang et al., 2020). If it is normal, the information will be fed back to both investment and financing parties. E-commerce platforms lend money, while financing companies can also effectively obtain capital loans. Of course, during the pledge period, because the third-party logistics company has real-time information on the value or price of the same type of goods, it can conduct preliminary research and judgment on the expected market price of the pledge. The results of the research and judgment will be used by e-commerce platforms to decide to invest or rearrange in investment behavior.

3. Methodology

In the process of e-commerce platform supply chain finance, the use of IoT technology increases the transparency of transaction activities, strengthens the ability to manage market information, and effectively reduces the market risk of traditional supply chain finance, while the use of new technologies also brings other risks. Based on this, this paper builds a theoretical model to explore the risk changes of the inventory pledge financing model under the application of IoT technology.

3.1. Risk category

The use of new technology improves production conditions and provides transaction efficiency. While reducing investment and financing risks, the risks brought by its own technical characteristics cannot be avoided. The development of technology strengthens the attributes of materials and reduces the dependence on manpower. However, the IoT system may receive signal interference and interruption, which results in differences in information transmission and wrong decisions. As far as the IoT itself is concerned, the inventory pledge financing model of the e-commerce supply chain has three major operational risks: perception layer risk, network transmission layer risk and application layer risk. The business activity that relies on the inventory pledge of the IoT is also inseparable from human management. It also has this conventional risk, which includes internal fraud, external fraud, risks caused by loss and damage to the pledge, and operational errors by practitioners.

3.2. Theoretical model

Most distributions of financial asset returns present a thick-tailed characteristic. This characteristic must be addressed in the measurement of financial branch lines. Extreme value theory can effectively solve this challenge. Therefore, based on the

POT model, this paper constructs a loss distribution model of operational risks in e-commerce supply chain finance in the inventory pledge financing model by estimating relevant parameters, calculating the VaR and ES values of the risk shock under a certain confidence level, and obtaining the loss caused by the risk shock.

3.2.1. Extreme value theory

Extreme value theory (EVT) uses the data distribution characteristics of existing data to infer the probability of an event that has not occurred. It is mainly used in the case of extreme deviations from the data mean. Extreme value theory mainly includes two models: the block maximum method (BMM) and peaks over threshold (POT). The BMM divides the data into continuous parts to simulate extreme data, but the requirement is that the sample data obey the same distribution (Ferreira and De Haan, 2013). The POT model establishes a reasonable threshold based on risk loss samples, then models the sample data that exceed the threshold (Bezak et al., 2014), estimates related parameters, and measures the VaR and ES.

3.2.2. The formula of VaR and ES

With technological progress and the rapid development of cross-border trade in goods and services, financial markets play an important role in global economic and trade activities, which has also exacerbated financial risks. Therefore, risk management has become increasingly important and has become a vital part of the core competitiveness of countries, regions, and enterprises. Methods or tools for measuring risk have also been born one after another, and VaR is one of them. VaR is the maximum possible loss of the portfolio value of an investment in a certain period of time under a certain degree of confidence. The formula is as follows:

$$P\left(X < -VaR\right) = \alpha \tag{1}$$

X represents the loss or gain of the investment portfolio. When $X>0$, it indicates gain; otherwise, it indicates loss. *VaR* represents the maximum loss suffered by the portfolio. α stands for confidence. However, the accuracy of VaR's risk loss measurement also has certain conditions, that is, in the case of large samples; otherwise, the accuracy of the measurement will be biased. At the same time, the result of the VaR measurement can only reflect the probability of loss and cannot give a specific loss value. If there may be a huge investment loss, the drawbacks of VaR will be highlighted. Since VaR is not subadditive in mathematical problems, the ES (expected shortfall) model can measure the conditional expectation that exceeds VaR, and it can also solve the problem of sample thick-tailed distribution. Its formula is as follows:

$$ES_{\alpha}\left(X\right)=E\left[-X \mid -X > VaR_{\alpha}\left(X\right)\right] \quad (2)$$

3.3. Setting of the theoretical model

3.3.1. POT model of risk tail distribution

Though it is feasible to use historical data to calculate VaR, the analysis of special sample data has greater limitations. In particular, there is a lack of the sample data of operational risk in e-commerce supply chain financial business. The sample distribution usually does not have the characteristics of normal distribution and has the characteristics of peak and thick tail distribution, which justifies the use of extreme value theory.

We assume that $X_1, X_2, \cdots, X_n$ represent sample data of various types of loss events of operational risk, and random variables are independent and identically distributed. The distribution function is defined as $F(x)$. We choose a reasonable variable X from the sample data as the threshold μ. The conditional distribution function exceeding the threshold μ is defined as $F_{\mu}\left(y\right)$.

$$F\left(x\right)=P\left(X-\mu \le x \mid X > \mu\right), x \ge 0 \quad (3)$$

Derived from the conditional probability formula, we can obtain the following formula:

$$F_{\mu}\left(y\right)=\frac{F\left(y+\mu\right)}{1-F\left(\mu\right)}=\frac{F\left(x\right)-F\left(\mu\right)}{1-F\left(\mu\right)}$$

then,

$$F\left(x\right)=F_{\mu}\left(y\right)\left[1-F\left(\mu\right)\right]+F\left(\mu\right) \quad x > \mu \quad (4)$$

According to the theorem of Balkema et al., the sample data that exceed the threshold in the sample data are set to $y(y_1,y_2\cdots,y_t)$, $y=x-\mu$. When the threshold μ is large, the tail extremum of y will obey the generalized Pareto distribution (GPD), and the formula is as follows:

$$F_{\mu}(y)\approx G_{\delta,\theta,\mu}(y)=\begin{cases}1+\left[1+\delta\dfrac{x-\mu}{\theta}\right]^{\frac{1}{\delta}} & \delta\neq 0\\ 1-\exp\left(-\dfrac{x-\mu}{\theta}\right) & \delta=0\end{cases} \quad (5)$$

Since $y=x-\mu$, we have:

$$G_{\delta,\theta}(y)=\begin{cases}1+\left[1+\delta\dfrac{y}{\theta}\right]^{\frac{1}{\delta}} & \delta\neq 0\\ 1-\exp\left(-\dfrac{y}{\theta}\right) & \delta=0\end{cases} \quad (6)$$

$G_{\delta,\theta}(y)$ is the generalized Pareto distribution (GPD), δ is the shape parameter, and θ is the scale parameter. When $\delta>0$, GPD presents a thick-tailed distribution. The estimated values of θ and δ need to be obtained through the application of the maximum likelihood estimation method to further judge the distribution of GPD.

After selecting the threshold μ, the first derivative of formula (5) is obtained. Then, the probability density function is:

$$g_{\delta,\theta}(x)=\begin{cases}\dfrac{1}{\theta}+\left(1+\dfrac{\delta}{\theta}x\right)^{-\left(1+\frac{1}{\delta}\right)} & \delta\neq 0\\ \dfrac{1}{\theta}e^{\frac{x}{\theta}} & \delta=0\end{cases} \quad (7)$$

Substituting $y(y_1,y_2\cdots,y_t)$ into formula (7), the log likelihood function formula is:

$$L(\delta,\theta\mid y)=\begin{cases}-n\ln\theta-\left(1+\dfrac{1}{\delta}\right)\sum_{i=1}^{n}\ln\left(1+\dfrac{\delta}{\theta}\right)y_i & \delta\neq 0\\ -n\ln\theta-\dfrac{1}{\theta}\sum_{i=1}^{n}y_i & \delta=0\end{cases} \quad (8)$$

Then, formula (8) is maximized to obtain the estimated values of the parameters θ and δ.

Assuming that N_{μ} represents the number of samples greater than the threshold μ,

n represents the total number of samples, and the estimate of $F(\mu)$ can be expressed as $(n-N_\mu)/n$, then by substituting $F_\mu(y)$ and $F(\mu)$ into formula (4), $F(x)$ is obtained:

$$F(x)=\begin{cases}1-\dfrac{N_\mu}{n}\left(1+\dfrac{\delta}{\theta}(x-\mu)\right)^{\frac{1}{\delta}} & \delta\neq 0\\ 1-\dfrac{N_\mu}{n}e^{-\frac{(x-\mu)}{\theta}} & \delta=0\end{cases} \tag{9}$$

$F(x)$ is the tail estimation of some samples exceeding the threshold. From the definition of VaR above:

$$VaR_\alpha=F^{-1}(\alpha) \tag{10}$$

When the confidence level α is given, the inverse function of formula (9) is the estimated value of VaR_α:

$$VaR_\alpha=\begin{cases}\mu+\dfrac{\theta}{\delta}\left\{\left[\dfrac{n}{N_\mu}(1-\alpha)\right]^{-\delta}-1\right\} & \delta\neq 0\\ \mu-\theta\ln\left[\dfrac{n}{N_\mu}(1-\alpha)\right] & \delta=0\end{cases} \tag{11}$$

When the confidence level α is given, ES is as follows:

$$ES_\alpha(X)=E\left[X\mid X\geq VaR_\alpha(x)\right]=VaR_\alpha+E\left[X-VaR_\alpha\mid X>VaR_\alpha\right] \tag{12}$$

$$e(\mu)=E\left[X-\mu\mid X>\mu\right]=\frac{\theta+\mu\delta}{1-\delta}\qquad \delta+\mu\delta>0 \tag{13}$$

Combining the above formula, the estimated value expression of ES is as follows:

$$ES_\alpha=\frac{VaR_\alpha}{1-\delta}+\frac{\theta-\mu\delta}{1-\delta} \tag{14}$$

3.3.2. Threshold selection and parameter estimation

Based on the POT model of extreme value theory, the key to measuring operational risk is the correct selection of μ, because μ directly affects the accuracy of parameter estimates in GPD. Therefore, the size of the threshold μ needs to be reasonable; otherwise, the sample data that exceed the threshold will be too large or too small, which directly affects the fitting of the GPD distribution and causes a significant deviation.

To ensure rigor and accuracy, the thresholds are compared and screened by the mean excess function plot (Mefp), kurtosis, and Hill plot (Hp). Specifically, three methods are used to determine three thresholds. Then, the parameters δ and θ are obtained by using the maximum likelihood estimation method. Finally, the χ^2 goodness-of-fit test method is used to determine the optimal threshold.

In the mean excess function plot, the mean value of the sample has an upper limit. The mean value function of X is expressed as:

$$e(\mu)=\frac{\beta+\alpha\mu}{1-\alpha} \quad \beta+\alpha\mu>0 \tag{15}$$

Sample $X_1,X_2,\cdots X_n$'s mean function to estimate the excess mean function $e(\mu)$ is as follows:

$$e(\mu)=\sum_{i=1}^{n}\frac{(x_i-\mu)^+}{N_\mu} \tag{16}$$

When the scatter chart shows a significant linear change after exceeding a certain critical value, this critical value can be regarded as the threshold.

The Hill chart method arranges the samples $X_1>X_2>\cdots>X_k>\cdots>X_n$, which are independent random variables. The overall distribution obeys a thick-tailed distribution. Then, the Hill estimate can be expressed as:

$$\gamma_{k,n}=\frac{1}{k}\sum_{i=1}^{k}\ln\frac{X_i}{X_k} \tag{17}$$

If the scatter plot starts to show a stable linear state, the sample corresponding to this value is the threshold to be selected.

Different from the above two methods, the kurtosis method needs to calculate the kurtosis of the sample. The calculation expression of kurtosis is as follows:

$$K_n=\frac{\frac{1}{n}\sum_{i=1}^{n}(X_i-\mu_n)^4}{(S_n^2)^2} \tag{18}$$

In formula (18), $S_n^2=\frac{1}{n-1}\sum_{i=1}^{n}(X_i-\mu_n)^2,\mu_n=\frac{1}{n}\sum_{i=1}^{n}X_i$ 。

The kurtosis method calculates the kurtosis K_n of the sample data and compares it with the value of 3. If K_n is not less than 3, we remove X_i when $(X_i-\mu_n)^2$ reaches the maximum value and repeat the above steps until K_n is less than 3. After screening, maximum value X_i is the threshold.

After the threshold value is determined, the data that exceed the threshold value are rearranged into a new sample, and the statistics $\chi^2 = \sum_{i=1}^{M} \frac{(N_i - np_i)^2}{np_i}$ corresponding to each threshold value are lower. The smaller the χ^2 value is, the higher the degree of fit. Therefore, we select the threshold value corresponding to the smallest χ^2. This is the optimal threshold.

4. Results and discussion

4.1. Sample selection and descriptive statistics

As e-commerce platforms are still developing, there is no complete database available. The data in this research is collected from the publsihed sources of the Internet and media. Although the sample cannot fully cover the overall risk of supply chain financial operations, it has certain random characteristics. The data or case samples are typical, which brings the characteristics of thick-tailed distribution to the selected samples. It is also in line with the POT model used in this article. In addition, e-commerce platforms are often accompanied by banks and other financial institutions in the investment process. Although the published data or case samples only describe banks as investors, they contain investment components of e-commerce platforms. The collated sample includes data from e-commerce platforms, banks and other financial institutions. In addition, to analyze whether IoT technology reduces the risk loss suffered in the e-commerce supply chain, one of the criteria for the sample is that there is significant market risk in the period of the sample collected, e.g., when the stock market turns from a bull market to a bear market, market risks change drastically. Therefore, this study selects the sample data of the Chinese market in the interperiod of 2014-2017. Table 1 shows the preliminary results of the analysis of the samples. The risk loss unit is CNY, and the unit is ten thousand.

Table 1

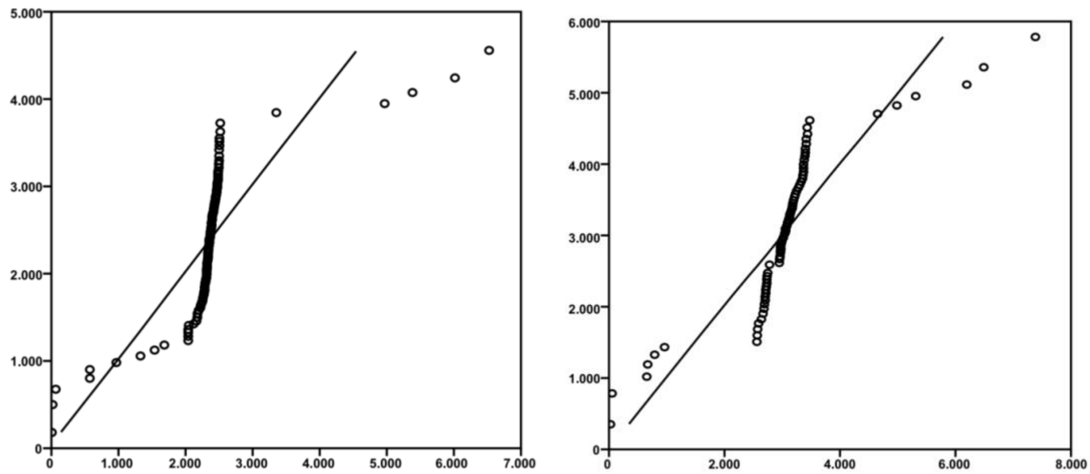
Basic statistics by operational risk category

	N	Mean	Median	Max	Min	Skewness	Kurtosis
Internal fraud	68	1621.71	1618.23	6219	22	1.87	11.46
External fraud	41	2643.28	2517.34	6863	31	1.36	4.03
Loss or damage of pledge	12	853.19	774.58	3535	23	2.07	3.72
Practitioner operating errors	9	352.02	276.83	2201	10	2.16	7.38
IoT system risk	25	1492.84	1343.52	2179	13	1.62	8.33

Table 1 shows that the skewness of the sample data is greater than 0, which indicates that the distribution of the sample data is skewed to the right. At the same time, the kurtosis of the sample data is greater than 3, which shows that the data samples may have thick tail characteristics. In addition, the average value of the sample data is also greater than the median value. In summary, preliminarily, the sample data present thick tail characteristics and highlight the characteristics of high loss and low frequency.

4.2. Further verification of the thick tail characteristics

A preliminary analysis of the sample data shows that the sample data may have characteristics of a thick-tailed distribution. To further ensure the accuracy of the results, this paper uses SPSS software and selects the Q-Q diagram to further verify and analyze whether the sample data show the distribution characteristics of thick tails and obtain the sample data Q-Q diagrams of various loss events, as shown in Fig. 1.



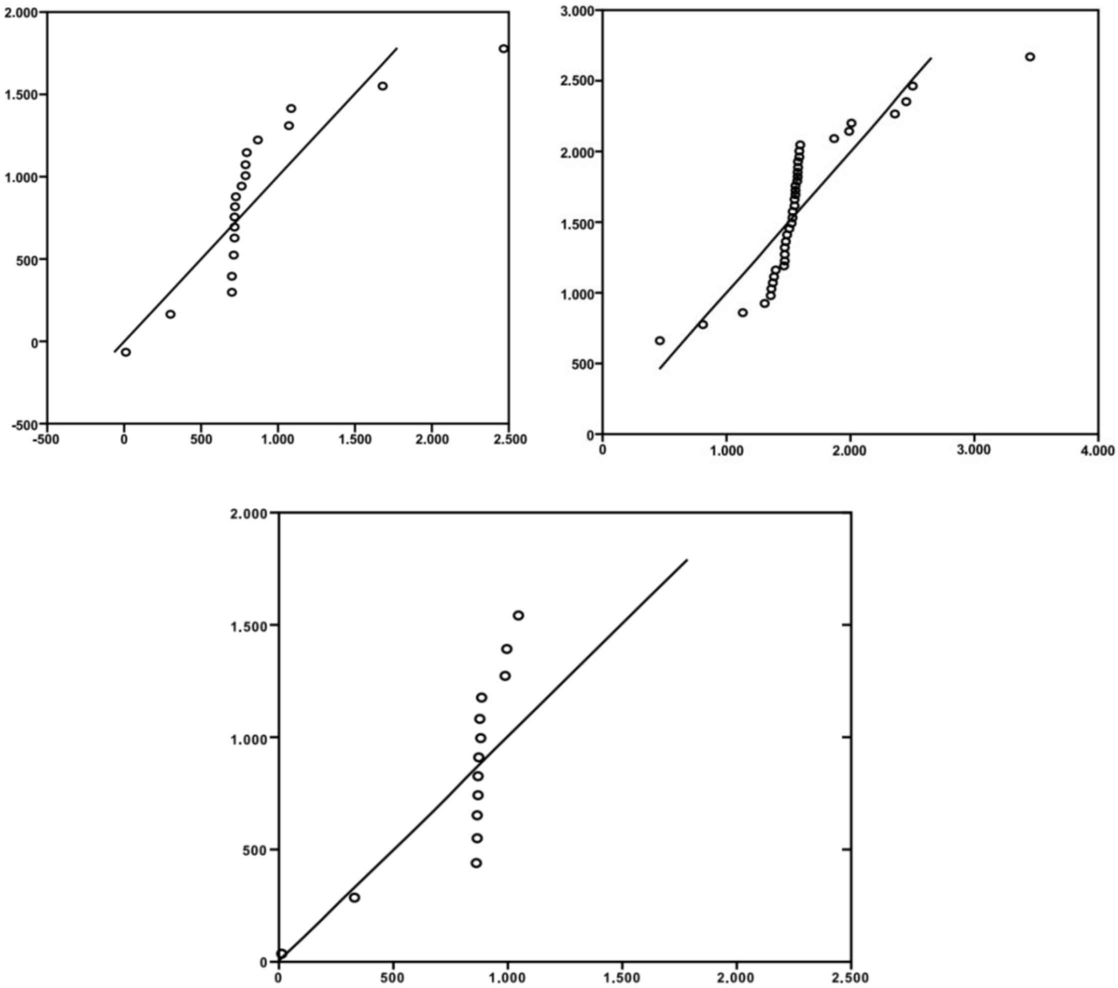


Fig. 1. Sample data Q-Q diagram by operational risk category

Fig. 1 shows that the data points in the Q-Q graph do not show a straight-line shape but a curved shape upwards. It can be concluded that the collected operational risk loss sample data obey a thick-tailed distribution.

4.3. The optimal threshold and POT model parameter estimation

Using the mean function graph method, the Hill graph method and the kurtosis method, we calculate the threshold μ_i (i=1,2,3) in formula (8) and further measure the estimated values of δ and θ corresponding to various thresholds. The optimal threshold is selected by using the goodness-of-fit method to test and judge, and the minimum corresponding threshold is used as the optimal threshold for the loss-type event. The above calculation results are shown in Table 2.

Table 2

Threshold selection and parameter estimation by operational risk category

	μ_1(Mefp)	μ_2(Hp)	μ_3(Kurtosis)	χ^2	N (>μ_i)	δ	θ
Internal fraud	1553	1506	2947	1.32	11	0.35	1341
External fraud	2664	2544	1957	0.02	4	0.32	1428
Loss or damage of pledge	801	1339	1483	0.03	3	0.18	1663
Practitioner operating errors	329	617	802	0.41	8	0.13	809
IoT system risk	1288	1692	1254	1.21	4	0.25	1121

4.4. Estimation of the VaR and ES values

Through the POT model, we calculate the estimated values of θ and δ, which are tested by the chi-square goodness-of-fit method. The optimal threshold is also obtained. We substitute the θ and δ parameters into formulas (11) and (14) and calculate the VaR and ES values. According to theoretical analysis, the measurement of credit risk, market risk and operational risk should be at the same confidence level. The calculated VAR and ES estimates depict various types of loss events with a confidence level of 99.9% for operational risk, as shown in Table 3.

Table 3

VaR and ES values by operational risk category

	Internal fraud	External fraud	Loss or damage of pledge	Practitioner operating errors	IoT system risk
VaR	4243.21	3846.19	1049.83	4038.13	914.51
ES	6802.56	5421.28	1644.22	1956.72	1802.69

Further, to compare and analyze the changes in losses caused by market risks, this article divides the period into two subperiods, 2014-2015 and 2016-2017. According to the above method, we obtain e-commerce supply chain inventory pledge financing based on IoT technology. The VaR and ES of each type of loss event of operational risk in the model are shown in Table 4.

Table 4

VaR and ES values by operational risk category in different risks

Period: 2014-2015					
	Internal fraud	External	Loss or	Practitioner	IoT system

		fraud	damage of pledge	operating errors	risk
VaR	3649.82	2811.28	907.03	2863.06	739.35
ES	6030.11	3945.94	1123.44	1259.82	1543.17
Period: 2016-2017					
	Internal fraud	External fraud	Loss or damage of pledge	Practitioner operating errors	IoT system risk
VaR	3631.98	2719.44	998.76	3060.82	701.46
ES	5871.37	3829.25	1233.68	1289.15	1525.66

Table 4 shows that when the market risk increases, the VaR value changes as follows: the value of internal fraud decreases by 178,600, the value of external fraud decreases by 918,400, and the value of lost and damaged pledges increases by 917,300. The number of operational errors rose by 1977.6 thousand, while the risk of the IoT system dropped by 378,900. The ES value changes as follows: the value of internal fraud decreased by 1,587,400, the value of external fraud decreased by 1,166,900, the value of lost and damaged pledges increased by 1,102,400, the value of operational errors by practitioners increased by 293,300, and the risk dropped by 175,100. This shows that before and after market risk, the risk impact of e-commerce supply chain finance is relatively small. The e-commerce supply chain inventory pledge financing model based on IoT technology effectively reduces the market risk of the supply chain.

5. Conclusion

Based on the sample data of losses caused by operational risks in the inventory pledge financing business carried out by e-commerce platforms from 2014 to 2017, this paper uses the POT model to calculate the VaR and ES values for different types of operational risk losses and compares the changes in market risks. The changes in operational risk losses of categories find that the risk impact of e-commerce supply chain finance is relatively small. The e-commerce supply chain inventory pledge financing model based on IoT technology has effectively reduced the market risk of the supply chain.

With the vigorous development of e-commerce, the e-commerce supply chain is bound to be stretched at a high speed, which also brings credit risks and market risks. In particular, the COVID-19 pandemic quickly swept the world and greatly impacted international trade, the economic development of various countries and regions, and traditional e-commerce supply chain finance. By implementing IoT technology to strengthen the interconnection of supply chain information, the application and expansion of this technology effectively lower the market risk of supply chain finance and better serve economic development. Therefore, it is necessary to continuously strengthen the application of IoT technology in e-commerce supply chain finance, reduce the credit risk and market risk of e-commerce platform loans to SMEs, and improve the ability to resist risks. Future research can focus on optimizing the supply chain financing operation mode under an e-commerce platform.

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