Exchange Rate Risk Assessment of Cross-border E-commerce Based on BP Neural Network

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Objectives: At present, the domestic exchange rate system takes the market supply and demand as a benchmark, and then compares with other currencies to complete the exchange rate setting. This approach allows the RMB exchange rate to be more flexible and elastic. The RMB is controlled through the market mechanism. However, for many cross-border electricity suppliers in China, if the exchange rate of RMB fluctuates widely, they will face the operational risks brought by exchange rate fluctuations.Methods: In recent years, due to the continuous appreciation of the RMB, the cross-border e-commerce companies are under pressure.Results:BP neural network is an ideal processing tool to deal with the risk assessment of cross-border e-commerce caused by exchange rate changes, and it also has a very good future for practical application.Conclusion: In this paper, the exchange rate risk of cross-border e-commerce companies in China was evaluated by BP neural network.

Keywords:exchange rate; cross-border e-commerce; BP neural network
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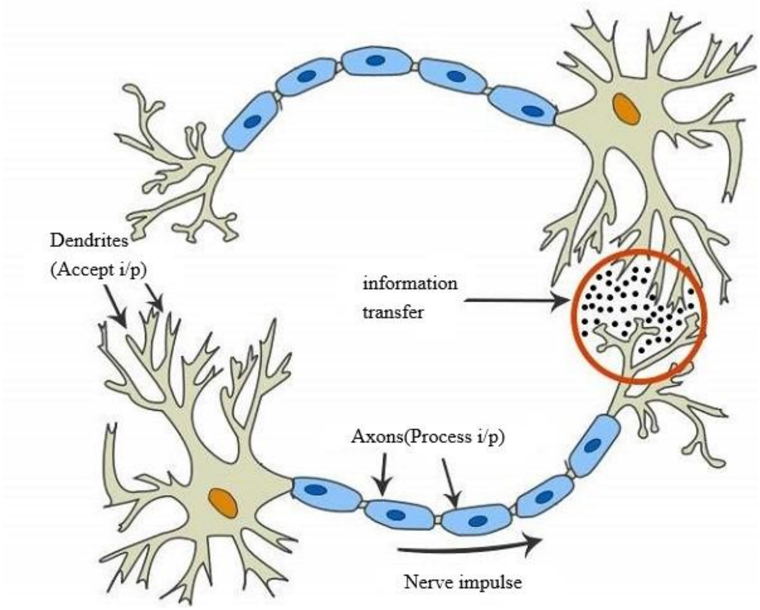
Different from domestic e-commerce, the operational issues that the cross-border e-commerce needs to deal with are more complicated, of which the exchange rate is a very crucial issue [1]. Fluctuations in exchange rates not only affect the electricity suppliers' profits, costs, etc., but also make the daily operations and activities of cross-border e-commerce face many new challenges. Fluctuations in the exchange rate may make a year of earnings of a company all vanish like soap bubbles, and moreover, they can even lead to losses when it's serious. With the expansion of the business scale of cross-border e-commerce, the risk of exchange rate fluctuation faced by the cross-border e-commerce is becoming bigger and bigger[2]. However, the entire cross-border e-commerce industry does not fully understand and prevent the exchange rate risk. Under the current RMB exchange rate management methods in China, there are also very few ways to better prevent the occurrence of the exchange rate crisis. Analyzed from the survey data, the trade financing is the most widely used circumvention method, and other methods include RMB forward market transactions, forward transactions, currency swap and other financial derivatives, so as to avoid the exchange rate risk [3]. Although there are various exchange rates risks of financial derivatives, taking into account the actual situation of the current market environment, interest rates and exchange rate control, these products have their own respective defects. Meanwhile, taking into account the expectation of appreciation of the RMB exchange rate, the fluctuations of the RMB exchange rate will become more and more intense. In view of this situation, the research on the early warning and prevention of cross-border e-commerce exchange rate risk is of great practical significance [4].

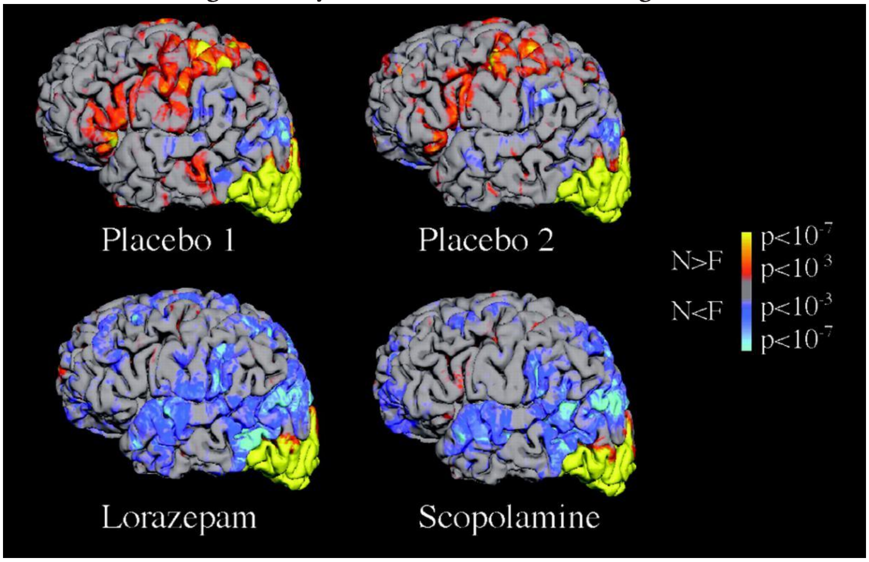
Research on neurons has been around for a long time. As early as 1904, biologists knew the structure of neurons [5]. The neuron usually has multiple dendrites for receiving information; however, it has only one axon, and there are many axons at the end of the axon, which can send information to other neurons. The end of the axon transmits signals by connecting to dendrites of other neurons [6]. The location of this connection is biologically known as "synapse" [7].

Figure 1
Structure of Nerve Cells



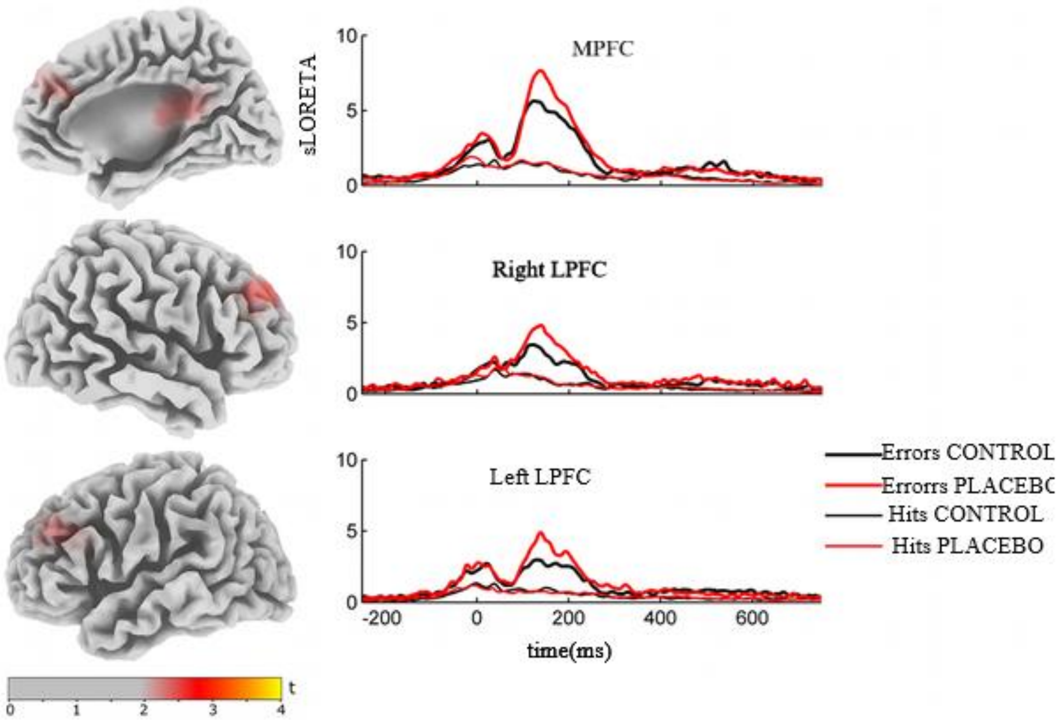
Neuroscientists have also done some research on the human brain. Now, people are more aware of how perception, such as vision, hearing, touch and other perceptions are processed by the nervous system step by step, at the same time, people also find the main function partition in the brain (the partition is sometimes subdivided), such as the visual cortex, somatosensory cortex, premoter cortex and so on. However, for the consciousness, thinking such abstract concept, there is no way to find a region to technically manage the consciousness [8]. It can be understood that the consciousness and thinking are basically scattered throughout the brain and connected by some information channels in various cortices. These complicated connections make the human brain have unparalleled information association ability [9].

Figure 2
The Processing Pathway of Information Processing in the Brain



The study on the operation mechanism of human brain neural network and the use of the computer aided method to simulate the neural network to solve the problem has become an important research topic[10]. Because the trade activities of the cross-border e-commerce stride across multinational markets, which mean that the economic system of the related trading activities is a highly complex nonlinear system, moreover, the market environment change can't be accurately predicted. Therefore, the decision-makers hope to be able to establish a nonlinear model that can be changed in accordance with different economic activities and can predict environmental changes. The previous judgment techniques can't accurately analyze the results [11]. BP neural network can carry out the analysis of large amounts of data to the nonlinear system. Especially at the aspect of many adjustment parameters and nonlinear simulation calculation, it has good operation and analysis ability, which can better handle problems. The method is to unify various conditions of the outside world, and finally take the exchange rate risk as a "black box" to analyze. BP neural network's self-learning function can predict the risk that the cross-border e-commerce's exchange rate risk may face, so that decision-makers can take effective measures in time [12].

Figure 3
Working Mechanism of Human Brain Neural Network

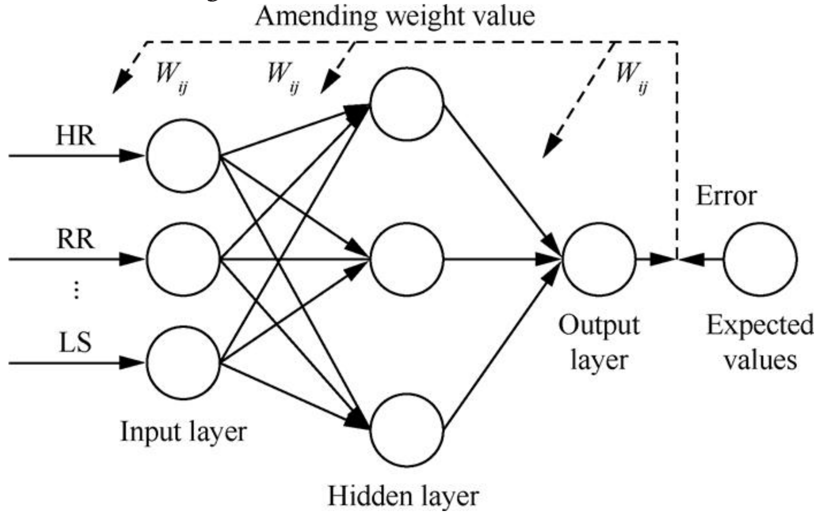


METHODS

BP Algorithm

A neural network composed of multiple interconnected neural units can simulate the reflections of things in real life through the biological nervous system. And people can conduct the targeted reflection training through the external parameter sample. The neural network can remember training without relying on other fixed algorithms, summarize the best solution to deal with such events from the training results, summarize the algorithm to deal with the calculation, and understand the laws of the data[13]. It is because of this nature of the neural network algorithm, the algorithm is very suitable for dealing with things that are complex in causation and have many unpredictable factor effects. By using very rich event data to train the BP neural network, the neural network can statistically analyze such events and derive the final results[14]. BP neural network model diagram is shown in Figure 4.

Figure 4
Diagram of BP Neural Network Model



BP neural network algorithm's learning is composed of two steps, namely, the signal forward propagation and the reverse error propagation. The former processes the events initially at the input level, and then enters the reverse error propagation phase [15]. According to the specific processing way, the error is returned to the input layer again, and the signal is divided equally to a unit; then, the error condition of the unit is obtained, and the error correction program is gained according to the error condition; next, repeating the process over and over again and modifying the weight, and this is the neural network learning process. This correction process or learning process will continue, until the calculated result has reached an acceptable level or reached the number of learning set previously [16]. BP network is a kind of network structure formed by the tightly connected interleaving of the input layer and the output layer, this enables the input layer and the output layer to establish a non-linear relationship, which greatly expands the field of application, and makes the output result is no longer between -1 to 1 [17]. BP algorithm needs to carry out a lot of learning and constantly revises the processing rules. The core of the algorithm is to input a large amount of learning samples into the algorithm, and finally makes the processing results be consistent with the expectations through the continuous reverse error propagation and the challenge processing way [18]. The concrete steps are shown as follows: 1. initialization. Each connection weight $[w]$, $[v]$ and the threshold θ_i, r_t is randomly given; 2. The output is carried out to each unit of the computational hidden layer, the output layer through the input and output mode given; 3. The new connection weights and thresholds are calculated; 4. Selecting the next input mode to return to step 2 for repeated training, until the errors meet the requirements [19].

The first is to carry out the initialization operation to the BP neural network model. A random number within the interval (-1, 1) is assigned to each connection weight. Then, setting the error function e, the calculation precision value and the maximum learning times M are given [20]. And the k input sample and the expected output are selected randomly.

$$d_o(k) = \left(d_1(k), d_2(k), \cdots, d_q(k)\right) \quad (1)$$

$$x(k) = \left(x_1(k), x_2(k), \cdots, x_n(k)\right) \quad (2)$$

The input and output of neurons in the hidden layer are calculated, and the partial derivative $\delta_o(k)a$ of the error function to each neuron in the output layer is calculated by using the expected output and actual output of the network. Then, the connection weights from the hidden layer to the output layer, the output layer $\delta_o(k)$ and the hidden layer's output are used to calculate the partial derivative $\delta_h(k)$ of the error function to each neuron in the hidden layer. $\delta_o(k)$ of each neuron of the output layer and the output of each neuron in the hidden layer are used to correct the connection weight $w_{ho}(k)$. The hidden layer neurons' $\delta_h(k)$ and the input of neurons in the input layer are used to correct the connection weight. Next is to calculate the global error.

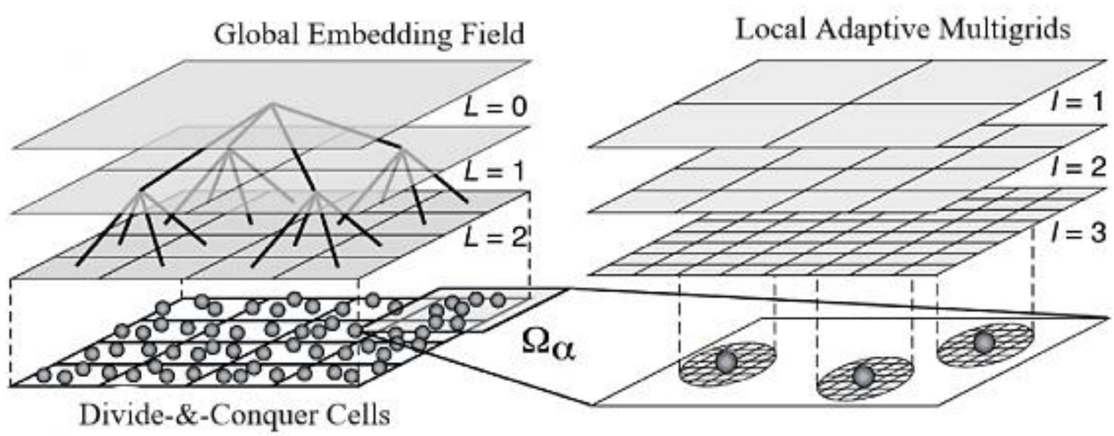
$$E = \frac{1}{2m}\sum_{k=1}^{m}\sum_{o=1}^{q}(d_o(k) - y_o(k))^2 \quad (3)$$

The verification judgment is carried out to the error, and whether it reaches the planning requirements. When the error has been narrowed down to the scope of the plan, or the training times have reached the established number, then the algorithm can be stopped. Otherwise, it is necessary to restart the next algorithm training program.

RBF Algorithm

RBF neural network is a radial basis function neural network, its main feature is that it can speed up the network connection speed in a particular area, so as to speed up the learning speed of the neural network in a particular direction. Its network structure is a single hidden layer, a forward network, which is totally divided into three layers. The specific is shown in Figure 5. The beginning layer is responsible for the input signal, which is also known as the input layer; the middle is the hidden layer, each hidden layer contains a lot of small units, the specific number is determined by the specific issues to be resolved; the final layer is the output result, this layer is generally a relatively simple linear function.

Figure 5
RBF Neural Network Structure Figure



RBF neural network forms a hidden layer by selecting the appropriate input location at the input layer and through the middle hidden unit. However, the data does not enter the hidden layer directly through the connection way, it is mapped through the vector. After determining the correlation with hidden units in the hidden layer, the mapping relationship is fixed. Hidden layer and the final output layer are also connected throug h the mapping, this connection is unidirectional, and the output result is a sum of a hidden layer unit.

$$y_n = \sum_{i=1}^{h} w_i \varphi_i\left(\left\| x - c_i \right\|\right) \quad (4)$$

According to the data selection rules, the RBF network can be divided into the following two categories: (1)the data center selects a sample from the sample input. This method chooses the data center of the sample from the input, such as OLS algorithm, evolutionary optimization algorithm and so on. The characteristic of this algorithm is that once the data center is determined, it will not change again. However, a hidden node data is fixed at the outset, but it can also change constantly in the learning process. (2) Data center dynamic adjustment method. The data center location for this learning process is constantly changing, such as the most commonly used dynamic clustering method, resource allocation networks, gradient training methods, etc.

K-means clustering algorithm is a common algorithm in the RBF network learning algorithm. At first, the unsupervised learning method is used to determine the data center of the RBF neural network in the h hidden node, and find out the expansion constant of the hidden node based on the distance between each data center. Then, the supervised learning training is adopted to get the output weight of the hidden node.

Supposing k is the number of iterations, the cluster center at the time of k superposition is $c_1(k), c_2(k)\cdots, c_h(k)$, and the corresponding clustering domain is $w_1(k), w_2(k), \cdots, w_h(k)$. Then, the steps of using the $k-means$ clustering algorithm to determine the RBF network expansion constant σ_i and the data center c_i are shown below: (1)algorithm initialization: different values of h centers are selected, and let $k=1$. There are different methods for selecting the value of the cluster center, so it is necessary to ensure that the h values are different. (2) Calculating the distance of all cluster centers and the input $\left\|x_j\text{-}c_i(k)\right\|, i=1,2,\cdots,h, j=1,2,\cdots,N$ of the sample. (3) For the sample input x_j, the classification can be conducted in accordance with the minimum distance principle, that is, when $i(x_j)=\min_i\left\|x_j\text{-}c_i(k)\right\|, i=1,2,\cdots,h$, x_j is classified as the i class. (4) The new cluster centers are recalculated: $c_i(k+1)=\frac{1}{N_i}\sum_{x\in w_i(k)} x, i=1,2,\cdots,h$. Among them, N_i is the number of samples in the i clustering domain $w_i(k)$. (5) If $c_i(k+1)\neq c_i(k)$, then is to turn to the step 2; otherwise, the clustering ends, and turns to step 6 right now. (6) The width of each hidden node is determined by the distance between the cluster centers: $\sigma_i = kd_i$, among them, d_i is the distance between the i-th data centers in the other adjacent data centers and the hidden layers. Assuming $\varepsilon=\left\|y\text{-}\hat{y}\right\|$ is the approximate error, if the timing signal $y=\left[y_1, y_2, \cdots, y_N\right]^T$ is given, and $\hat{\mathrm{H}}$ is determined, then, the following formula can be adopted to calculate theRBF network output weight, which is w.

$$\varepsilon=\left\|\mathrm{y}-\hat{\mathrm{y}}\right\|=\left\|\mathrm{y}-\hat{\mathrm{H}}\mathrm{w}\right\| \quad (5)$$

Usually, w can be obtained by the least square method:

$$w=\hat{H}^{+}y \quad (6)$$

Among them, $\hat{H}^{+}$ is the pseudo inverse of $\hat{\mathrm{H}}$:

$$\hat{H}^{+}=\left(\hat{H}^T\hat{H}\right)^{-1}\hat{H}^T \quad (7)$$

3.3 GARCH model

The GARCH model is developed by the ARCH model. GARCH model is originally a method for establishing a time series with heteroscedasticity in the ARCH class model. The general model $\mathrm{GARCH}(\mathrm{p}, \mathrm{q})$ can be expressed as:

$$y_t = x_t'\beta+\varepsilon_t, \varepsilon_t=\sqrt{\mathrm{h}_\mathrm{t}}\cdot v_t, \mathrm{h}_\mathrm{t}=\alpha_0+\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2+\sum_{j=1}^{p}\theta_j h_{t-j} \quad (8)$$

Among them, $\mathrm{h}_\mathrm{t}=\mathrm{var}(\varepsilon_t|\varphi_{t-1}), \varphi_{t-1}$ is all the information at the $\mathrm{t}-1$ moment and before, this information is not only a conditional variance, but also an independent and identically distributed random variable. They are independent of each other and satisfy their own needs.

$$E(v_t)=0, D(v_t)=1, E(v_t v_s)=0(t\neq s);$$
$$\alpha_0>0, \alpha_i\geq 0, \theta_j\geq 0, \sum_{i=1}^{q}\alpha_i+\sum_{j=1}^{p}\theta_j<1 \quad (9)$$

Assuming that there are different distribution forms, they are usually considered as a standard normal distribution. However, the empirical studies show that the yield distribution of the coarse tail distribution and Nelson use the standardized distribution to adjust the deviation of the tail. The probability density of the standardized distribution t is:

$$f(x,d)=\frac{\Gamma\left(\left(d+1/2\right)\right)}{\left[(d-2)\pi\right]^{1/2}\Gamma(d/2)}\left(1+\frac{x^2}{d-2}\right)^{-(d+1)/2} \quad (10)$$

GARCH(p，q) model can be considered as the extension of the ARCH model, so GARCH(p，q) also has the processing procedure that is similar to the ARCH(q) model. GARCH model is fit for the situation of a small amount of calculation, and the high order ARCH process is described simply, this means that it can get a higher rate of utilization. GARCH(p，q) model assumes that the conditional variance is a lagging residual square function, this means that the remaining symbols have a small effect result, that is, the price change of the positive conditional variance and the negative reaction of the price change are symmetrical. GARCH(p，q) model can't completely deal with the negative correlation problem between the volatility of the return on assets, so TARCH and EGARCH and other asymmetric models are introduced and applied to the actual modeling.

TARCH model was first proposed by Zakoian. It has the following forms of conditional variances:

$$h_t=\alpha_0+\sum_{i=1}^{q}\alpha_i\varepsilon_{t-i}^2+\varphi\varepsilon_{t-i}^2 d_{t-1}+\sum_{j=1}^{p}\theta_j h_{t-j},\, d_t=\begin{cases}1,\varepsilon_t>0\\0,\varepsilon_t\le 0\end{cases} \quad (11)$$

Among them, d is a nominal variable. Because of the introduction of d_t, the effect of the asset price rise information ($\varepsilon_t>0$) and fall information ($\varepsilon_t\le 0$) to the conditional variance is different. At the time of rising, $\varphi\varepsilon_{t-i}^2 d_{t-1}=0$, and the influencecan be expressed by the coefficient $\sum_{i=1}^{q}\alpha_i$; at the time of fall, $\sum_{i=1}^{q}\alpha_i+\varphi$. If $\varphi\ne 0$, it shows that the function of the information is asymmetrical; while when $\varphi>0$, the leverage effect exists.

EGARCH model is also the exponential GARCH model, which is created by the very famous algorithmic researcher Nelson in the United States. Its priority work is to study the asymmetry of the conditional variance h_t and the reaction of positive and negative interference in the market. At this time, h_t is the ε_{t-1} anti-symmetric function.

$$\ln(h_t)=\alpha_0+\sum_{j=1}^{p}\theta_j\ln(h_{t-j})+\sum_{i=1}^{q}\left(\alpha_i\left|\frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}}\right|+\varphi_i\frac{\varepsilon_{t-i}}{\sqrt{h_{t-i}}}\right) \quad (11)$$

The conditional variance in the model uses the natural logarithm form, which means that the leverage effect belongs to an exponential type. If $\varphi\ne 0$, then it means that the information is asymmetric; if $\varphi<0$, then it means that the lever effect is very big. Therefore, EGARCH model can better reflect the asymmetric situation in the financial market. In addition, because h_t is expressed as the exponential form, this means that parameters can't be controlled within a reasonable range, and this is also the most prominent character of the EGARCH model.

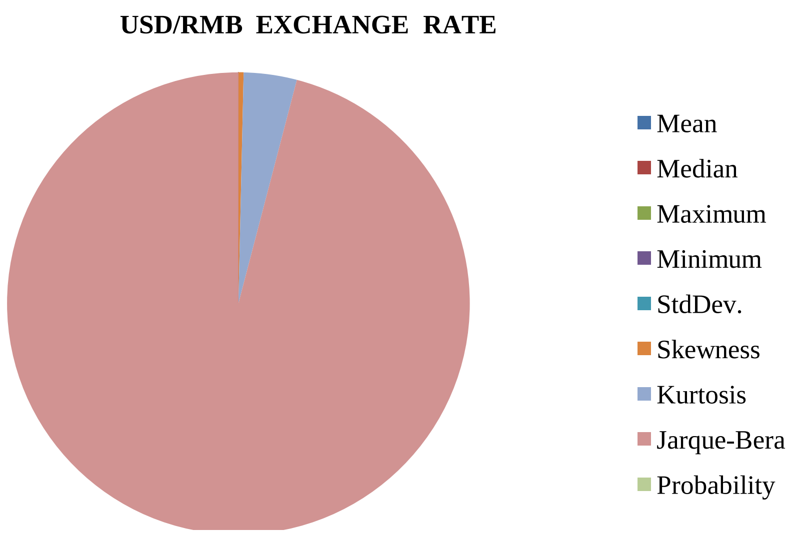
RESULTS

In this paper, on the basis of the neural network working mechanism of the human brain, the computer algorithm was adopted to design and implement a risk evaluation model: GARCH model, at the same time, the cross-border e-commerce exchange rate risk was selected as the main research object, furthermore, the exchange rate risk between USD and RMB was selected for evaluation.

From March 4, 2015 to October 27, 2017, the exchange rate data information in this time period was obtained through the CCER database. There were a total of 751 data samples, and a detailed data analysis was conducted. The original data was processed. Firstly, the logarithm r of the time series yt variable of the USD / RMB exchange rate was taken, namely, the daily return of rate of USD / RMB exchange rate.

The detailed data features are shown in Figure 6. The highest value is 4.777270, which means that the exchange rate fluctuation does not show a normal distribution law; the skewness is -0.410429, which means that the daily return of rate of the USD/ RMB exchange rate has a left thick tail characteristic. The detailed statistical data of Jarque-Bera is 119.7655, and this means that the return of rate of the exchange rate does not show a normal distribution law. The typical peaks and thick tails of the financial data are obvious.

Figure 6
The Daily Return of Rate of Usd/Rmb Exchange Rate



In this paper, the ADF statistical quantity was used to test the smoothness of the rate of return rt. And the test results are shown in Table 2.

Table1
USD/RMB Exchange Rate Daily Rate of Return Sequence Unit Root Test

Yield			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-27.10633	0.0000	0.0000	0.0000
Test critical values	1% level	0.0000	-3.438865	0.0000
Test critical values	5% level	0.0000	-2.865188	0.0000
Test critical values	10% level	0.0000	-2.568768	0.0000

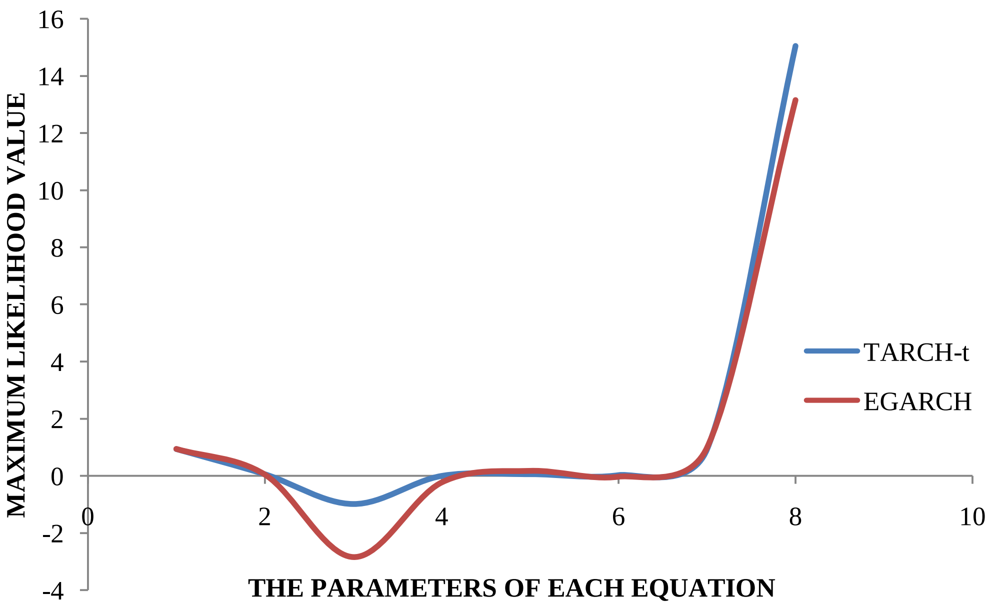
According to the final results, it can be understood that because ADF value is less than the critical values under different meanings, the previous hypothesis is denied, and there is no unit root in the sequence,furthermore, rt sequence can be considered that it's stable. Then, the relevant tests are generated on the yield sequence rt. The corresponding results show that rt sequence has no definite evidence to confirm their correlation in lower order, but it shows a weaker correlation in higher order. In addition, there are differences in variance in the test, and there is a possibility of heteroscedasticity. Because rt sequence has the lower correlation in higher order, the $ARMA$ model can be established, and the following mean model is obtained after testing, comparing and removing the non-significant variables repeatedly.

$$r_t = 0.938952 r_{t-1} + 0.057935 r_{t-6} - 0.0971226 \varepsilon_{t-1} + \varepsilon_t \quad (12)$$

The correlation of residual sequence and residual squared sequences after the r_t mean equation fitting was checked. The results show that the residual sequence is independent, and there is no significant correlation, while there is a significant correlation in the square of the residual difference.

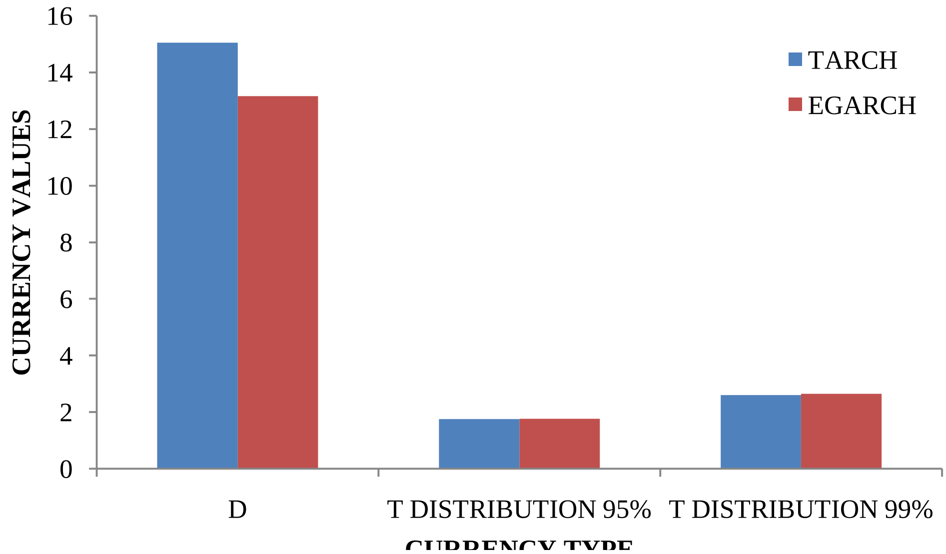
According to the check analysis above, it can be seen that the daily rate of return on USD / RMB exchange rate is a stationary number, and there is no autocorrelation, but there is a heteroscedasticity, which conforms to the condition of establishing the $GARCH$ model. According to the results of the existing empirical analysis, selecting the lag order (p, q) in which it is (1, 1) is more suitable. The conditional mean equation is set to t student distribution. The variation trend of the parameters of each equation estimated by using the maximum likelihood is shown in Figure 7.

Figure 7
Parameter Estimation of Each Model of Tarch (1, 1) and Egarch (1, 1)



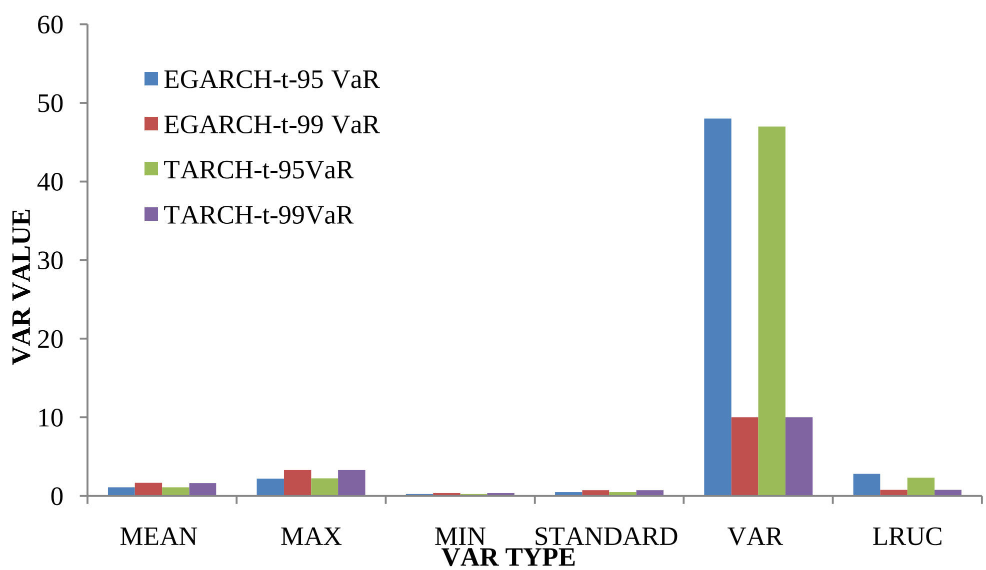
It can be analyzed from the data in above figure that the lever term φ is significantly different from 0, the lever item of TARCH is $\varphi > 0$, EGARCH lever item is $\varphi < 0$, that is to say, the effect of information is asymmetric. When the bad news is released, the fluctuation of the daily rate of return will become bigger and bigger; after the good news is released, the fluctuation of the daily rate of return will gradually become smaller.

Figure 8
The USD/RMB Exchange Rate is 95 % and 99%



By comparing the above models, it can be seen that the t student distribution describes the effect of thick tail to the VaR well at 95% and 99% confidence level. TARCH and EGARCH models accurately calculate the daily VaR value in t distribution. By comparing the LRuc value of each model with 3.841, it can be known that under the 95% confidence level, model TARCH − t − 95 , TARCH − t − 99 , EGARCH − t − 95 , EGARCH − t − 99 , EGARCH − g − 99 can pass the Kupiec check.

Figure 9
The Statistical Results of USD/RMB Daily VaR Value Calculated by the Model



As can be seen from the figure above, the daily rate of return of the cross-border e-commerce is a smooth, clustered sequence, and its distribution is characterized by peak and thick tail. TARCH-t and EGARCH-t can better simulate the exchange rate of return, and the model fitting shows that the bad impact is far greater than the good effect.

DISCUSSION

Due to the progress of algorithms and the increasingly powerful computing power of computers, the computer algorithms are becoming more and more mature, and more and more practical, which can reduce people's workload in many aspects, and make the computer algorithms get a lot of application in the real life. Different from domestic e-commerce, the operational issues that the cross-border e-commerce needs to deal with are more complicated, of which the exchange rate is a very crucial issue. Fluctuations in exchange rates not only affect the electricity suppliers' profits, costs, etc., but also make the daily operations and activities of cross-border e-commerce face many new challenges. Fluctuations in the exchange rate may make a year of earnings of a company all vanish like soap bubbles, and moreover, they can even lead to losses when it's serious. With the expansion of the business scale of cross-border e-commerce, the risk of exchange rate fluctuation faced by the cross-border e-commerce is becoming bigger and bigger. Especially in recent years, the cross-border e-commerce companies are under pressure due to the continuous appreciation of RMB. In dealing with the issue of cross-border e-commerce risk assessment resulting from changes in exchange rates, BP neural network is an ideal processing tool, and it also has a very good future for practical application. In this paper, on the basis of the neural network working mechanism of the human brain, the computer algorithm BP algorithm was adopted to design and implement a risk evaluation model: GARCH model; at the same time, the cross-border e-commerce exchange rate risk was selected as the main research object; furthermore, the exchange rate risk between USD and RMB was selected for evaluation.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

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