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Full length research paper

Finance, production, manufacturing and logistics: VaR models for dynamic Impawn rate of steel in inventory financing

He Juan[1]*, Jiang Xianglin[2], Zhu Daoli[3], WangJian[1] , Chen Lei[4]

[1]College of Traffic ,Transportation and Logistics, Southwest Jiaotong University, Chengdu 610031,China
[2]Institute for Financial Studies, Fudan University, Shanghai 200433,China
[3]School of Economics and Management, Tongji University, Shanghai 200092, China
[4]Department of Credit Risk Management in Chengdu, Huaxia Bank 61000,China

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This paper presents a framework of setting the impawn rate dynamically by dividing the impawn period into different risk windows. Besides, it proposes that compared with pledging loan of bonds and stocks, the essence of inventory financing is to forecast the long-term risk from short-term data, and trade off between the risk window and the term of financial product (impawn period). Based on the dataset of spot steel (φHRB335), usually traded in the over-the-counter markets, this paper establishes the model of VaR-GARCH(1,1)-GED, which can better depict the feature of the heteroskedasticity, leptokurtosis and fat-tails of the returns, forecasts VaR of steel during the different risk windows in the impawn period through methods of out-of-sample. To improve the coverage of the model, this paper introduces the coefficient K, and then gets the impawn rate consistent with the risk tolerance of banks. The main results show that the amended model may control the risk better while reducing the efficiency loss compared with existing methods. It puts forward a dynamic impawn rate mode for banks.

***Keywords*:** finance; logistics; dynamic impawn rate; long-term risk forecasting; inventory financing.

INTRODUCTION

With the trend that industry competition transforms enterprises competition to supply chain competition, supply chain finance appears. Recently, Euromoney magazine defines the supply chain finance as the most popular topic in banking transaction service over the past few years, and asserts that the needs of the business will continue to grow in next several years. Supply chain finance is pricing and market transaction of capital and relevant service to meet the capital demand of supply chain productive organization(Hu Y F, 2009), and is also an innovative service integrating logistics and finance provided by logistic enterprises(Chen X F, 2005). Put another way, supply chain finance provides a systematic financial solution to capital restriction problem. Compared with mixed operation in foreign developed countries, supply chain finance in China is pledged collateral business participated by commercial banks, core enterprises, SME (small & medium enterprises) and warehouse supervision enterprises and so on(Feng, 2007). Besides, different from foreign developed futures market, inventory financing is mainly based on inventory in form of spot transactions (such as material, products, half-finished products, etc.) rather than foreign popular rights pledge (receivable account, accounts payable and derivatives). In brief, the development of domestic supply chain finance is not only the business extension of traditional warehousing changing to modern logistics, and more important is that its adaption to the present market under which it is so hard to finance for many SME while offering loans for banks. That is to say, it may

*Corresponding author. E-mail: hejunlin93@163.com; 919164419@qq.com

commendably remit banking competition and financing dilemma of SME.

Although supply chain finance market has great potential in China, the worry about its risk has restricted the prosperity of inventory financing itself. According to “National Income Accounts and Statistical Yearbook” (People's Bank of China, 2006), the current inventory of all enterprises amounts to 5.1294 trillion Yuan in China, 3.0326 trillion Yuan of which are of small and medium enterprises, and 102.4 billion Yuan are of farmers. If the discount rate of loans is 50%, these financial assets can generate secured loans of about 2.6 trillion Yuan, which equals to new loans of financial institutions in one year. However, most banks did not make full use of abundant inventory resources. The pivotal point is lack of risk management techniques about inventory financing.

Inventory financing, as one of main models of supply chain finance in China, make inventory as the pledge to strongly mitigate credit risk of loans. During evaluation of the loans, pledge inventory must be evaluated to find whether it can maintain its capability of guarantee for loan which is reflected by impawn rate (usually called loan-to-value ratio in other literatures). In commercial banks practice, “management approach from supply chain financing activities” (The following simply defined as “management approach”) provides the pledge loan based on the rights of commodities or commodities. The impawn rate shall not exceed the highest level of 70%, and the impawn period shall not exceed one year. Current banking practice still rely on the experience to determine the impawn rate, which would be far from consistent with the risk tolerance level of banks. Therefore, as a core issue, it is important to set impawn rate not only for the risk control of supply chain finance but also for promotion of the development of the business.

In recent years, the domestic and foreign scholars have made some beneficial explorations on volatility and risk management of collateral pledged. Cossin and Huang (2003) derive a general framework for collateral risk control determination in repurchase transactions(Cossin D, 2003). In the domestic research, given that the price of the pledged stock is fluctuant randomly, Li Yi-xue, Feng Geng-zhong et al implement risk estimation strategies of “main body + debt” and analyze loan-to-value ratio decision of banks with downside risk constraint when price distribution of the stock at the end of the loan follows general distribution and several special distributions(Li Y X, 2007). These results have played positive and practical role in deeply understanding and capturing the actual volatility and risk level of pledged inventory market. However, it is important to note that the quantitative models above are mostly based on the mathematical optimization method and take the bank expected revenue as the objective function. To put it simply, there are many theoretical modeling and cases based on individual samples while the empirical researches based on large number of samples are scarce.

With the rapid development of modern financial risk management technology, the domestic and overseas researchers have proposed risk management tools to manage inventory financing, and made considerable progress. As a main risk analysis and measurement method, VaR (Value at Risk) raised by J. P. Morgan in the 90th of last century, has been widely used in the academics and practice(Jorion, 2001). Although VaR could simply refer to the amount of money that assets are likely to lose over predefined period and at a given confidence level, it is difficult to measure the risk precisely. The main reason is that the most common parametric method of calculating VaR not only depends on the distribution of return of assets but also the volatility. Abundant empirical researches show that the returns of asset usually do not follow the independent normal distribution in the efficient financial market, but features leptokurtosis, fat-tails and volatility clustering. Unfortunately, the existing researches strongly rely on the normal assumption of returns of assets, while taking little account of the characteristics of fat tails and heteroscedasticity. For instance, whether using the VaR method to measure market risk of stocks(Wang, 2003), or studying impawn rate of the standard warehouse receipt(Li, 2010), both are based on the assumption of the efficient financial market where returns obey independent normal distribution.

The most popular model taking account of this phenomenon is the Autoregressive Conditional Heteroscedasticity (ARCH) process, introduced by Engle (1982) and GARCH model extended by Bollerslev(1986) (Bollerslev, 1986; Engle, 1982). Therefore, GARCH model is introduced in the financial management field and then widely used in financial practice as one of main approaches to predicting volatility. Ricardo(2006) applies the GARCH theory to prediction of the volatility of financial series accompanied with other heavy tails distributions to estimate the maximum possible loss may be occurred. Gong Rui, Chen Zhong-chang (2005), Liu Qing-fu et al (2006)respectively describe the characteristics(fat-tails, volatility clustering) of the financial time series and constructs the GARCH models for calculating time-varying value at risk based on the volatility and distributions of returns of index of stock and copper futures in China.(Gong R, 2005; Liu Q F, 2006)

The literatures above mostly estimate market risk of stock index, bonds and futures of commodities based on the GARCH models, which have relatively robust risk control measures, such as price limits, daily settlement and margins rules etc. Besides, the liquidity is good, and the settlement time is short. Hence, most of current research based on the GARCH models focuses on short-term risk within two weeks especially daily risk. Compared with bonds, stocks and futures, spot commodities traded in the OTC (over the counter market) have rare risk measures. Moreover, the liquidity is disproportional to risk rate. The low liquidity and inevitably relatively long settlement time of spot pledged collateral causes high risks in inventory financing. The key point of inventory financing is to forecast long-term risk, in other words, to predict value at risk of N months later based on past samples. Put another way, the essential of setting impawn rate dynamically is to resolve two problems: one is how to trade off between risk holding horizon and the term of financial products; the other is to trade off between data frequency and forecast frequency, that is to say how to predict the long-term (multi-periods) risk based on historical samples.

As the biggest producer and consumer of steel in the world, steel is always important raw materials of pillar industries of China such as real estate, automobile, equipment manufacturing, et al. Besides, with the characteristics of better liquidity, easy storage and non-perishable, steel has been as an ideal pledge. In the latter half of 2008, with the impact of the international financial crisis, the price of steel had a sharp diving, which had caused price risk of inventory financing to increase dramatically. So setting appropriate impawn rate dynamically based on VaR method can control the price risk of inventory and improve the efficiency of financing quantificationally.

Providing that substantial literature above, combined with existing research of impawn rate of inventory financing, this paper does some work as follows: (1) Different from the existing research statically setting impawn rate in the term of product (i.e. impawn period), this paper, taking account comprehensively of macroeconomic environment, the credit level of counterparty, the liquidity of pledged inventory and the risk preference of banks, first proposes a dynamic model setting dynamic impawn rate by dividing the impawn period into different risk windows to trade off the dilemma of risk holding period and the product term at the operational level. (2) In order to better depict the features of heteroscedasticity, leptokurtosis and fat-tails, it introduces Generalized Error Distribution, then builds VaR-GARCH (1,1)-GED model rather than the Risk Metrics based on normal assumption, and then proposes the formula of long-term VaR to deal with the problem between data frequency and forecast frequency. (3) as far as the predication of volatility concerned, the prediction out of sample is more practical (White, 2000), so , this paper predicates volatilities of different impawn period out of samples. (4) Since it's impossible for any model to precisely forecast risk, this paper sets the parameter K to improve risk coverage. (5) The Hit sequences will be established based on failure rate in back testing to ensure reliability of the research.

The rest of the paper is organized as follows. Section2 set up models, including VaR-GARCH model for longer-term risk forecasting and dynamic impawn rate model. Section 3 is the empirical analysis, including the sample selection, the data characteristic description and the detailed result analysis. Section 4 is model evaluation. And the final section concludes.

Model assumption

Given that the price of pledged inventory, like financial assets, fluctuates, this paper adopts the international common practice under which banks have to have tools and methods to timely evaluate value of pledged inventory before practicing inventory financing. Therefore, the models are set up based on the following assumptions.

- Logistics enterprises and banks closely cooperate with each other;
- The impawn rate varies during impawn period with the varying macroeconomic environment, credit level of counterparty, liquidity of pledged inventory and the risk preference of banks;
- Considering the term of inventory financing is less than one year, so the interest rate is assumed as constant.

Model set-up

Allowing for the characteristics of heteroscedasticity, leptokurtosis and fat-tail, VaR-GARCH(1,1)-GED model is used to estimate the volatility of return rate of pledged inventory; furthermore the long-term price risk, which indicates the maximum possible loss over a predefined time horizon at certain level of confidence established previously, will be calculated based on VaR(value at risk). The risk-free value of pledged inventory, which can be obtained by subtracting the VaR, is also the amount of loan. The steps of this model are organized as follows:

Yield rate of pledged inventory:

$$R_t = \ln P_t - \ln P_{t-1} \qquad (1)$$

Where R_t is defined as the logarithmic return, P_t is the price at time t.

Volatility of yield rate of pledged inventory

In financial literature, the volatility of financial assets is the standard deviation of return rate. Similarly, the volatility of pledged inventory is the standard deviation of its return in this paper. Recent substantial empirical studies indicate that financial assets are characterized of volatility clustering, which contribute to the heteroscedasticity of returns. Accordingly, GARCH model is introduced to depict this trait above. Besides, current research shows that GARCH (1,1) model might describe most of the time-varying variance of financial series. Therefore, we use the GARCH (1,1) to forecast the volatility of inventory, and establish the conditional mean equation and conditional variance equation as follows:

$$R_t = \mu_t + \sigma_t z_t,\ z_t \sim i.i.d.,\ E(z_t) = 0,\ Var(z_t)=1 \quad (2)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (3)$$

Where μ_t is the conditional mean, allowing for that the most of log-returns of financial assets are independent or low-order serial correlations, which is basic idea in current research of volatility of financial assets(see(Tsay, 2005)). Thus, to assume previously $\mu_t = 0$. $\varepsilon_t \equiv \sigma_t z_t$ is stochastic disturbing term, also called residuals. In this formula, z_t is the Innovations; σ_t^2 is the condition variance att, α_0 is constant; α_1 is the ARCH parameter, β_1 is the GARCH parameter, and $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta_1 > 0$.

In the current practice, the Innovation z_t is usually assumed to follow normal distribution. However, it usually features fatter tails in practice. The student distribution was firstly introduced by (Bollerslev, 1987), while (Nelson, 1991) suggested the so-called Generalized Error Distribution (GED) for better approximating the fat-tails of the innovations. Consequently, this paper assume z_t follows GED. The density function of GED is,

$$f(x,v) = \frac{v}{\gamma 2^{(1+1/v)} \Gamma(1/v)} \exp\left(-\tfrac{1}{2}\left|x/\gamma\right|^v\right) \quad (4)$$

Where $\gamma = [2^{(-2/v)} \Gamma(1/v) / \Gamma(3/v)]^{1/2}$;

when $v = 2$, z_t follows normal distribution; for $v < 2$, the distribution of z_t has fatter tails than normal distribution.

VaR and impawn rate

Taking into account of both the volatility of pledged inventory price and the time horizon from risk identification to risk treatment, the calculation of VaR in inventory financing is a process of long-term risk forecasting, rather than daily ones, which not only meet the demand of emerging business (supply chain finance et al) but also the regulations of Basel Accord Ⅱ or even the latest version Basel Accord Ⅲ that banks must report longer term VaR to supervision institutions.

Unfortunately, as mentioned in the introduction, current researches are mainly concerned with short-term risk, while ignoring long-term risk measurement. The best-known method in practice is square-root rule with formula as $VaR(T) = VaR(1) * \sqrt{T}$. Although such scaling is widely used, it is valid only when the return follows the independent normal distribution with a zero trend. However, the return typically features leptokurtic and fat tails, so the scaling is no longer valid when applied to evaluation of long-term risk in inventory financing. Considering all above, in order to obtain more precise VaR, (Dowd, 2004) proposed the revision of square-root rule.

$$VaR(T) = P_t[1 - \exp(\mu_t T + F_\alpha^{-1} \sigma_t \sqrt{T})] \quad (5)$$

Where P_t is defined as the initial value of unit pledged inventory (for simplicity, this paper denotes the unit price as the initial value). F_α^{-1} denotes the left quantile at certain the level of confidence.

Compares to the square root rule, this modified model has made much improvement and is able to avoid the predication of day-to-day volatility. However, it still relies on the square root rule more or less. In order to improve the deficiency of two approach above, Philippe Jorion (2001), Ruey S. Tsay(2005), (Andersen, 2006) and Ricardo.A(2006) argue that the conditional variance of the long time horizon equals to the sum of daily conditional variances under the efficient market hypothesis that the return is independent.

$$\mu\left[t : t+T \left| t\right.\right] = \sum_{i=1}^{T} R_{t+i} \quad (6)$$

$$\begin{aligned} \sigma^2\left[t : t+T \left| t\right.\right] &= \sigma_{t+1|t}^2 + \sigma_{t+2|t}^2 + \cdots + \sigma_{t+T|t}^2 \\ &= TV_L + \frac{1-(\alpha_1+\beta_1)^T}{1-(\alpha_1+\beta_1)}(\sigma_{t+1|t}^2 - V_L) \end{aligned} \quad (7)$$

Where $\sigma_{t+i|t}^2 = V_L + (\alpha_1 + \beta_1)^{i-1}(\sigma_{t+1|t}^2 - V_L)$.

Hence, the formula (5) can be modified in the following way,

$$VaR(T) = P_t\left[1 - \exp\left(\mu[t : t+T|t] + F_\alpha^{-1}\sigma[t : t+T|t]\right)\right] \quad (8)$$

In banking practice, it is necessary to set the appropriate risk window (risk holding horizon) to measure risk. Furthermore, it facilitates to control market risk (i.e. price risk) of inventory financing to set impawn rate dynamically. As is well known, risk window and confidence level are the two key parameters when VaR is applied to forecast the possible maximum loss. As regards the risk window T, it is always defined as settlement time, which is consistent with the maximum T ideally since in banking practice, most of assets are monetary assets of good liquidity and therefore these

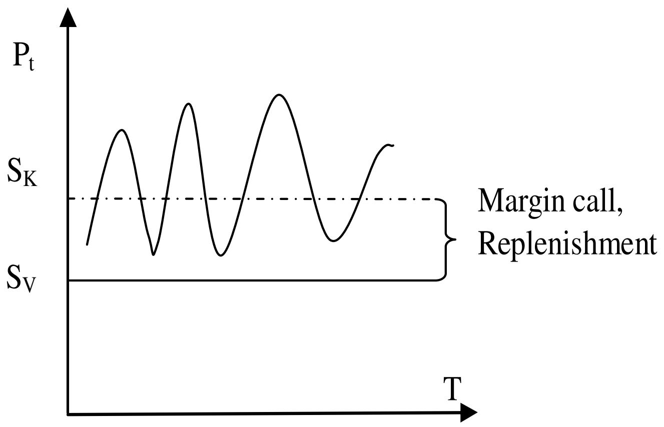

Figure 1. The design of mechanism of impawn rate

areas are mainly concerned with daily VaR. However, as for the pledged inventory, theoretically, we should consider comprehensively the liquidity of supply chain financial market, the sample size and pledged asset position adjustment to adjust it. In Practice, according to their personal risk preferences, banks are concerned with not only the liquidity of pledged inventory, but also credit level of counterparty and some financial indicators such as level of solvency, profitability. In addition, according to the recommendation of internal model of market risk measurement of commercial bank which was issued by China Banking Regulatory Commission, the level of confidence is set as 99%.

After determining the risk window and confidence level based on theory analysis as well as banking practice, we can calculate the VaR during the risk window, and obtain the risk-free value which is the amount of loan as mentioned above. The ratio between the risk-free value and current price of pledged inventory is the impawn rate.

$$\begin{aligned}\omega &= \frac{P_t - VaR}{P_t} \times 100\% \\ &= \frac{S_k}{P_t} \times 100\%\end{aligned} \qquad (9)$$

Where ω is defined as impawn rate. Obviously, S_k denotes the risk-free value.

Although the VaR-GARCH (1,1)-GED model can portray the leptokurtic and fat tailed and volatility clustering of return to a certain extent, it is possible that the risk would be underestimated. Accordingly, the liquidity, the credit level of counterparty and the cost of replenishment and closed position are considered comprehensively, and then the warning level is brought to control the risk of bank in this paper.

As can be seen from Figure.1, during the risk window T, when the price of steel falls below the warning level, margin call or replenishment will be done till the value of steel regresses above the warning line. Closed position will be done if companies refuse to do them in time. Based on this, we set the correction factor K = 1.1 ~ 1.2(which references the guidelines of stock collateral issued by China Securities Regulatory Commission, 2004). In banking practice, banks should take into account comprehensively that macroeconomic environment, the credit level of counterparty, the liquidity of pledged inventory and the risk preference of themselves to set K reasonably, which also helps to remit the adverse selection and moral hazard to some extent. In the empirical analysis followed, this paper assumes K = 1.1, and the modified model will be:

$$\begin{aligned}\omega &= \frac{P_t - VaR}{P_t} \times \frac{1}{K} \times 100\% \\ &= \frac{S_K \times 1/K}{P_t} \times 100\% \\ &= \frac{S_V}{P_t} \times 100\%\end{aligned} \qquad (10)$$

Where S_V is defined as the amount of pledged loan.

Numerical experiments

Sample selecting

In this section, in order to evaluate the models, we take the steel rebar (φHRB335) as sample, which is widely used in the industries of real estate and infrastructure industries. The data set is obtained from XiBen new line stock and ShangHai futures exchange for the period of September 5th, 2005 to December 31th, 2009. The data from September 5th, 2005 to December 31th, 2009 tend to be as the sample used to estimate the parameters; the rest will be as test sample. Then we carry on a series of simulated pledge with the starting date of impawn contract as January 1th, 2009. The impawn period is set to be the maximum 12 months. Obviously, it is important to trade off the impawn period and risk holding period. Generally speaking, the longer risk holding period is, the more radical banks tend to be; the shorter holding period is, the more conservative banks tend to be. In banking practice, risk holding period can be attempt to set respectively as:1 week, 2 weeks, 1 month, 2 months, 3 months, 4 months, 5 months, 6 months, 7 months, 8 months, 9 months, 10 months, 11 months, 12 months.

Descriptive statistics of log-return of steel rebar price

As shown in Figure 2, the log-returns series show

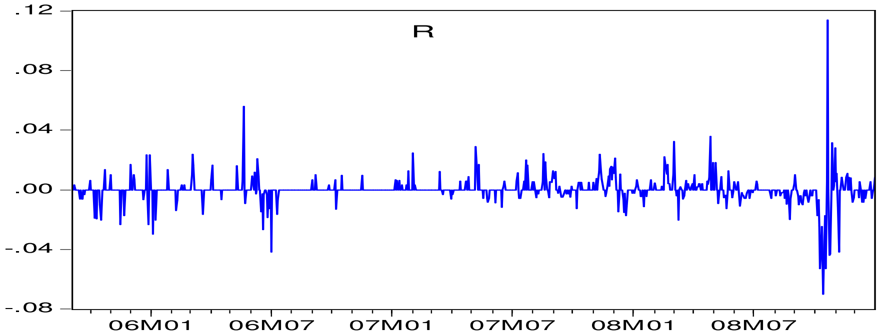

Figure 2. The linear graph of log-return of steel rebar in Shanghai

Table 1. Description of basic features of log-returns

Mean	S.D	Skewness	Kurtosis	J-B	D-W
0.000129	0.009	1.038	42.976	57887.78(0.0000)	1.955

Table 2. The results of ADF test of log-returns

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.82975	0.0000
Test critical values:	1% level	-3.437695	
	5% level	-2.864672	
	10% level	-2.568491	

Table 3. The results of ARCH effect test

Heteroskedasticity Test: ARCH			
F-statistic	31.55798	Prob. F(5,855)	0.0000
Obs*R-squared	134.1414	Prob. Chi-Square(5)	0.0000

significant volatility clustering which indicates that ARCH effect possibly exists in log-returns. Table 1 provides summary statistics as well as the Jarque–Bera statistic for testing normality. In almost all cases, the null hypothesis of normality is rejected at any level of significance, as there is evidence of significant excess kurtosis and positive skewness. D-W value is close to 2, so the log-returns may be as independent.

Only when the time series is stationary, can we establish the GARCH model. Therefore, it is necessary to carry on Augmented Dickey-Fuller test (i.e. ADF unit root test). As shown in Table 2, in all cases, the null hypothesis is rejected at any level of significance (1%, 5%, 10%), so the time series of daily log-return is stationary. As shown in Table 3, the value is significant, which indicates that the ARCH effect exists in the residuals of daily log-returns.

Empirical results

As mentioned in Table 4, all the parameters of GARCH(1,1)-GED are significant. In additional, the value of AIC and SC is reasonable. Consequently, it is acceptable to assume z_t follows GED to depict the leptokurtosis and fat-tail of log-returns. The conditional mean and conditional variance can be rewritten as follows:

$$R_t = \varepsilon_t \qquad (11)$$

$$\sigma_t^2 = 3.40E-06 + 0.1115\varepsilon_{t-1}^2 + 0.7452\sigma_{t-1}^2 \qquad (12)$$

From equation (12), it can be obtained that:

Table 4. The parameter estimation of GARCH(1,1) –GED

	α_0	α_1	β_1	v	*AIC/ SC*
GARCH(1, 1)-GED	3.40E-06 (0.0000)	0.1115 (0.0000)	0.7452 (0.0000)	0.853 (0.0000)	-8.4295 -8.3965

$\alpha_1+\beta_1=0.86<1$, which denotes that the time series of daily log-return is stationary. The long-term variance can be calculated through the following the formula: $V_L=\frac{\alpha_0}{1-\alpha_1-\beta_1}=2.3724E-05$. Additionally, the parameter v is 0.853 obtained by Eviews. The corresponding quantile on left is -2.87when the confidence level is 99%. Combining with the equations (7), (8) and (10), the empirical results can be shown in table 5.

Model evaluation

Back testing of long-term risk

In order to test the accuracy of the VaR-GARCH (1,1)-GED model considering volatility clustering and heavy tails, we still have to test the risk coverage level (See Table 6) of VaR. Since the price risk is an inherently unobservable variable, We have to monitor VaR forecasts by checking not only whether our forecasts are realized, but whether they are consistent with subsequently realized returns given the confidence level. In the existing back testing methods of VaR, the most widely applied are failure rate method (see (Kupiec, 1995)) and internal back-testing model of Basel accord. Both the two methods are applied to examine the exceptions that the actual loss is beyond the daily VaR. For instance, when the time horizon is 1 year, the confidence level is 99%, the exceptions of less than 7 are accepted in the failure rate method, while only less 4 times may be accepted by Basel II internal green light area. But both of these methods are not suitable for back testing of long-term risk in inventory financing business.

Based on research above, the Hit function is established to test the accuracy of long term price risk predicting. Put another way, we have to observe the exceptions that the expected price of inventory (risk-free value) is higher than the actual price.

$$Hit_1=\begin{cases}1, & P_{t+i}<P_t-VaR\\ 0, & orelse\end{cases} \qquad (13)$$

Where $S_k=P_t-VaR$, which denotes the expected price (risk-free value, the warning level is called in this paper), f_1 is the observed number of exceptions in the sample. f_1/N is close to $1-\alpha$ statistically, if the bias is too large, the model could not predict the price risk correctly.
If the frequency of price of pledged inventory punctures the warning level S_K, and the cost of replenishment is too high, the risk might be underestimated, so it is necessary to test whether the price series P_t puncture the loan value S_V which is corrected by the parameter K. The function can be seen as follows:

$$Hit_2=\begin{cases}1, & p_{t+i}<S_V\\ 0, & orelse\end{cases} \qquad (14)$$

The main results show that the model of VaR-GARCH(1,1)-GED may predict the risk perfectly in most risk windows. Unfortunately, the failure rates are 12.3% and 3.5% in the risk windows of 3months and 4 months respectively, which are far beyond 1% corresponding to 99% confidence level. However, the risk coverage level (See Table 6) has been improved remarkably via K, which plays an important role as capital cushion.

Testing between the impawn rate and lowest value of the steel rebar

As mentioned in previous research, the impawn rate reflects the risk expectation of banks about pledged collateral. Thus, the impawn rate obtained by an effective model should be in positive correlation with the lowest value in the term of statistics, although it is unable to reflect for the specific one due to various random factors. Put simply, the closer the coefficient of correlation is to 1, the better the model performs.
Table7 and Table 8 present the lowest price of steel rebar under different risk windows and corresponding impawn rate during 12 months time horizon, the coefficient of correlation are respectively 0.999999, which is close to 1. This shows that the corrected model is efficient.

Table 5. The empirical results of different risk windows of 12 months impawn period

Risk window	1 week	2 weeks	1 month	2 months	3 months	4 months	5 months	6 months	7 months	8 months	9 months	10 months	11 months	12 months
Size N	5	12	23	43	65	87	108	130	153	174	196	218	239	261
P_t	3580	3580	3580	3580	3580	3580	3580	3580	3580	3580	3580	3580	3580	3580
P_{t+T}	3700	3700	3800	3330	3240	3350	3490	3800	4250	3630	3480	3480	3590	3740
VaR	106	165	228	309	377	433	480	523	564	599	632	664	692	721
S_K	3474	3415	3352	3271	3203	3147	3100	3057	3016	2981	2948	2916	2888	2859
S_V	3158	3104	3047	2973	2911	2860	2818	2779	2742	2710	2680	2651	2626	2599
ω	0.88	0.87	0.85	0.83	0.81	0.80	0.79	0.78	0.77	0.76	0.75	0.74	0.73	0.73

Table 6. The results of testing risk coverage level of model

Risk window	1 week	2 weeks	1 month	2 months	3 months	4 months	5 months	6 months	7 months	8 months	9 months	10 months	11 months	12 months
Size N	5	12	23	43	65	87	108	130	153	174	196	218	239	261
S_K	3474	3415	3352	3271	3203	3147	3100	3057	3016	2981	2948	2916	2888	2859
f_1	0	0	0	0	8	3	0	0	0	0	0	0	0	0
f_1/N	0	0	0	0	12.3%	3.5%	0	0	0	0	0	0	0	0
S_V	3158	3104	3047	2973	2911	2860	2818	2779	2742	2710	2680	2651	2626	2599
f_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
f_2/N	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 7. The impawn rate and lowest value under different risk windows during 12 months impawn period

Risk window	1 week	2 weeks	1 month	2 months	3 months	4 months	5 months	6 months	7 months	8 months	9 months	10 months	11 months	12 months
$P_{L,T}$	3580	3580	3580	3330	3140	3140	3140	3140	3140	3140	3140	3140	3140	3140
ω	0.88	0.87	0.85	0.83	0.81	0.80	0.79	0.78	0.77	0.76	0.75	0.74	0.73	0.73

Table 8. The correlation metrics of ω and $P_{L,T}$

	ω	$P_{L,T}$
ω	1.000000	0.999999
$P_{L,T}$	0.999999	1.000000

The analysis of efficiency of model

As mentioned in the introduction, the value of impawn rate is almost lower than 70% based on experience method in banking practice. This method may control risk while causing higher efficiency loss.

In the following text, we will compare the model of the impawn rate with the method of experience, and then introduce two indicators: efficiency loss θ_1, risk rate θ_2. To facilitate the processing, we select the upper limit (70%) of impawn rate in the method based on banks' experience.

$$\theta_1 = \frac{P_{t+T} - S_V}{P_t} \times 100\% \quad (15)$$

$$\theta_2 = \frac{S_V}{P_{t+T}} \times 100\% \quad (16)$$

Where $P_{t+\nabla T}$ is defined as the price at period-end of risk window; $\theta_2 < 1$ shows that the risk is under control.

As can be seen from Table 9, Table 10 and Figure3, the two indicators are in negative correlation, which is consistent with the facts in practice. Additionally, the risk rate of the two methods is less than 1. Thus, the risk is under control. But the efficiency loss is great in the experience-based method, even if we take the upper limit (70%) of impawn rate. Although the model in this paper has a certain degree efficiency loss, it has been greatly improved compared with the method based on experience in comparable short risk windows.

CONCLUSIONS

In response to the longer-term risk holding periods due to the insufficient liquidity of pledged inventory, this paper initially establishes the model of VaR-GARCH(1,1)-GED to forecast the long-term price risk, which better depict the characteristics of volatility clustering, leptokurtosis and fat-tails, subsequently obtain the analytical formula of VaR which is used to measure the risk of different risk holding periods, and finally set dynamic impawn rate by dividing the impawn period into different risk windows, taking account of macroeconomic environment, the credit level of counterparty, the liquidity of pledged inventory and the risk preference of banks. The conclusions are arrived as follows:

- The time series of return of rebar price in Shanghai, have significant characteristics of, fat-tails, volatility clustering. It is important to note that, the model may be able to predict the long-term risk in most cases; however, the failure rate of risk window both in 3 months and 4 months are far beyond the confidence level, which shows that the model is not able to predict the long-term risk perfectly, although allowing for the characteristics of fat-tails and volatility clustering. Consequently, the revision has to be done considering comprehensively macroeconomic environment and the volatility of pledged inventory, when banks and supervision institutions use the mature and sound VaR models to forecast risk. Based on this, the corrected parameter K was introduced into this paper. The results show that, the risk coverage level has been improved remarkably via K, which plays an important role as capital cushion. In addition, banks could get the upper bound of K via stress tests, for instance, in response to the extreme case, stress test might be carried on regarding to the price plunge of steel in 2008.
- There is a significant positive correlation between the impawn rates obtained from model and the lowest price in the future risk window. This model could reflect reasonably the risk expectation of banks about pledged steel. Moreover, compared with the empirical method widely used in banking, the model could control risk, while having the higher financing efficiency. Therefore, it may better improve the attraction of inventory financing by reducing the adverse selection and moral hazard to some extent.
- It is important to keep in mind that to simplify the operation in practice, this paper mainly discusses the prediction of time-varying volatility of returns based on VaR-GARCH(1,1)-GED model while unfortunately ignoring the autocorrelation of log-returns due to the insufficient liquidity of pledged inventory, which may be the critical factor resulting in the failure rate of far beyond 1% in the 3 months risk window. Thus, it remains for future research to improve the accuracy of longer-term price risk prediction of pledged inventory accompanied with the autocorrelation of log-returns. All these research could provide quantitative basis for decision making which may facilitate to release the risk and improve the returns for banks.

Table 9. Analysis of efficiency and risk based on experience of 12months impawn period

Risk window	1 week	2 weeks	1 month	2 months	3 months	4 months	5 months	6 months	7 months	8 months	9 months	10 months	11 months	12 months
θ_1	33%	33%	36%	23%	21%	24%	27%	36%	49%	31%	27%	27%	30%	34%
θ_2	68%	68%	66%	75%	77%	75%	72%	66%	59%	69%	72%	72%	70%	67%

Table 10. Analysis of efficiency and risk of VaR-GARCH(1,1)-GED model

Risk window	1 week	2 weeks	1 month	2 months	3 months	4 months	5 months	6 months	7 months	8 months	9 months	10 months	11 months	12 months
θ_1	15%	17%	21%	10%	9%	14%	19%	29%	42%	26%	22%	23%	27%	32%
θ_2	85%	84%	80%	89%	90%	85%	81%	73%	65%	75%	77%	76%	73%	69%

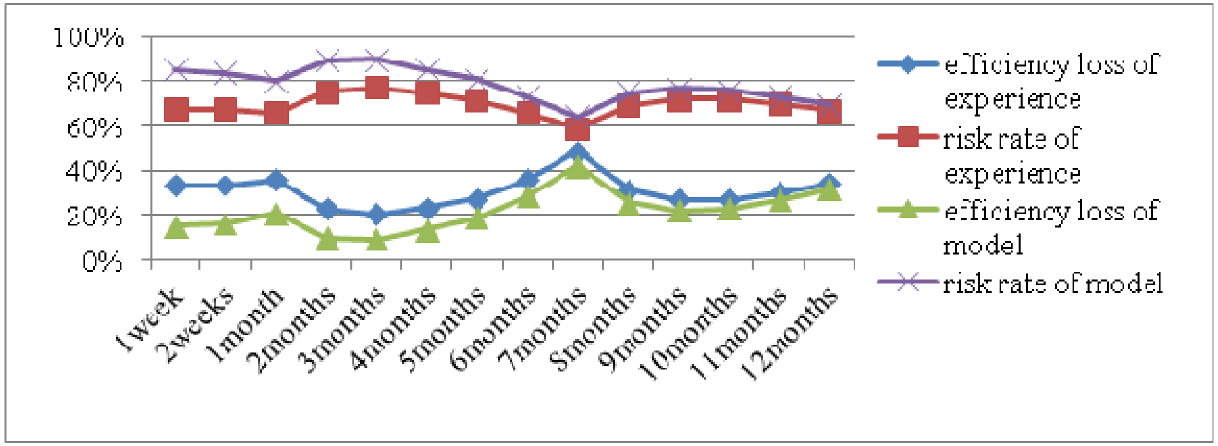

Figure 3. Comparison between VaR-GARCH(1,1)-GED mode and experience method during 12months impawn period

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