



Intellectual Property Risk Tracking Method based on Kalman Filtering

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Abstract. As the intellectual property pledge financing market continues to develop, this approach has increasingly become a crucial funding channel for technology-driven small and micro enterprises. At the same time, the risks and problems therein have also been exposed. Among them, the effective supervision of financing enterprises after loans has become one of the urgent problems to be solved in the current market. This paper, grounded in an analysis of market demand, first examines the challenge of monitoring the operational risks of enterprises post-intellectual property pledge financing. Subsequently, it devises a Kalman filtering-based risk tracking model. The proposed model comprehensively assesses enterprises' debt-servicing capabilities by integrating multiple financial metrics, including the current ratio and quick ratio. The Kalman filtering model is utilized to obtain the parameter set of specific enterprises. By comparing the parameter set of specific enterprises with the overall risk threshold of the detection samples, enterprises are classified into three different types: healthy enterprises, light-risk enterprises, and heavy-risk enterprises. The model offers enterprises, banks, and third-party regulatory agencies a novel real-time risk tracking approach grounded in dynamic financial analysis.

Keywords: Intellectual property pledge financing, Kalman filtering, Risk Tracking, Dynamic financial analysis

1 Introduction

In recent years, the scale of China's intellectual property pledge financing market has been continuously expanding, from 93.17 billion yuan in 2016 to 300 billion yuan by the end of 2023 [1], providing ample market space and development opportunities for high-tech small and micro enterprises. At present, the research on intellectual property pledge financing mostly focuses on the construction of the intellectual property pledge value assessment system [2], the multi-method research on the intellectual property pledge financing model [3][4], the application of financial technology innovation in intellectual property pledge financing [5][6], and the risk pricing of intellectual property itself [7][8]. And there are also some studies conducting overall research on the intellectual property pledge financing market [9][10]. Few scholars have put forward authoritative opinions on the issue of enterprise risk supervision and post-loan infor-

mation asymmetry. The existence of this problem will cause potential problems such as the raised threshold for commercial banks to issue loans and the reduced confidence of commercial banks in granting loans, ultimately leading to the gradual disorder of the market order of intellectual property pledge financing.

Based on this, to alleviate the issue of post-loan information asymmetry and address the market challenge of supervising enterprises' post-loan risk activities, this paper designs the "Intellectual Property Risk Tracking Method Based on Kalman Filtering". By applying the recursive principle of Kalman filtering in the dynamic financial analysis of enterprises, it is to promote banks and third-party institutions to effectively supervise the risk activities of enterprises after loans, further ensure the market order, and promote the forward development of the intellectual property pledge financing market.

2 Methodology

2.1 Establishment of State Space Model

Kalman filtering describes the state estimation problem of complex systems using finite-dimensional systems or linear state space models of physical processes that generate observations. In a complex system, a state variable refers to a minimum group of internal variables that can fully represent its behavior in the time domain, such as $x_1(t)$, $x_2(t)$... A column vector composed of $x_n(t)$, while in the process of enterprise risk measurement, this paper selects 18 financial indicators such as current ratio and quick ratio to construct the column vector of the enterprise, which is expressed as:

$$x(t) = [x_1(t) \dots x_n(t)] \quad (1)$$

The state space model of a time series can be represented by the state equation and the observation

equation of state:

$$x_t = A_t x_{t-1} + u_t \quad (2)$$

observation equation:

$$y_t = H_t x_t + v_t \quad (3)$$

Among them: and are the state variables at time points t and $t - 1$ respectively; It is the state change matrix of the system, that is, the parameter vector estimated from historical data; Represents the process noise of the system, which is a sequence of white noise, $\sim N(0, Q_t)$; Q_t is the symmetric non-negative definite variance matrix of the noise in the system state process. Represent the measured value; It is the observation matrix at time point t ; v_t represents the measurement noise, which is a sequence of white noise, $v_t \sim N(0, R_t)$; And it satisfies $E(v_t) = 0$, $E[(v_t), (v_t)^T] = R_t \delta_t$, where R_t is the symmetric positive definite variance matrix of the observed noise of the system; δ_t is the Kronecker δ function

2.2 Recursive Calculation Process

Suppose the initial state x_0 of the observed target is not correlated with u_1 , Specifically, the mean is $E(x_0) = u_0$, and the covariance matrix is $E[(x_0 - \mu_0)(x_0 - \mu_0)^T] = P_0$; And if x_0 , u_t and v_t are statistically independent of each other, then there exists:

$$E[x_0, uTt]=0$$

$$E[x_0, vTt]=0$$

$$E[u_0, vTt]=0$$

If the estimated state and the conditions satisfying the above formula, the system state noise and the system observation noise satisfy the above hypothetical conditions, Q_t is the non-negative definite variance matrix of the system state noise, and R_t is the positive definite variance matrix of the observation noise. At point t , the observed value is, the prior estimate of the state quantity is \hat{x}_t^- , and the posterior estimate of the state quantity is \hat{x}_t . Then, the prior error and the posterior error can be defined as:

$$e_t^- = x_t - \hat{x}_t^- \tag{4}$$

$$e_t = x_t - \hat{x}_t \tag{5}$$

The covariances of the prior error and the posterior error are respectively expressed as:

$$p_t^- = E[e_t^- e_t^{-T}] \tag{6}$$

$$p_t = E[e_t e_t^T] \tag{7}$$

The posterior estimates are expressed by the prior estimates to obtain the calculation equation of the Kalman filter:

$$\hat{x}_t = \hat{x}_t^- + K(y_t - H_t \hat{x}_t^-) \tag{8}$$

Among them, K is called the Kalman gain or Kalman coefficient, which is the adjustment factor used to minimize the mean square error estimation:

$$K_t = \frac{P_t^- H_t^T}{H_t P_t^- H_t^T + R_t} \tag{9}$$

As indicated by Formula above. When the measurement noise is very small and the credibility of the measurement value is very high, the value of K is closer to 1; Conversely, if the credibility of the prior estimate is high, then the value of K is closer to 0. It can be seen that the Kalman gain plays a role in adjusting the weights between the actual measured values and the predicted measured values, so as to make the posterior estimated values closer to the true values. Based on the above theoretical derivation, the state update equation and the measurement update equation are derived as follows. State update equation: The estimated state value at the current point in time is obtained from the previous state

$$\hat{x}_t = A_t \hat{x}_{t-1} + u_t \quad (10)$$

Calculate the estimated value of the covariance of the state at the current point in time

$$P_t^- = A_t P_{t-1} A_t^T + Q_t \quad (11)$$

Measure the update equation: Calculate the Kalman gain

$$K_t = \frac{P_t^- H_t^T}{H_t P_t^- H_t^T + R_t} \quad (12)$$

Update the status estimate value through measurement

$$\hat{x}_t = \hat{x}_{t-1} + K(y_t - H_t \hat{x}_{t-1}) \quad (13)$$

Update error covariance

$$P_t = (I - K_t H_t) P_t^- \quad (14)$$

From the above formulas and it can be known that in the state update equation, the state quantity at the current time point can be estimated by using the estimated value obtained at the previous time point and the covariance of the error, and a prior estimated value can be obtained. In the measurement update equation, the obtained prior estimated values are combined with the measured values to obtain an improved posterior estimated value, which is used as the input of the state update equation to continue the estimation at the next time point. Thus, a recursive process of "prediction - correction" is formed in a continuous loop

2.3 Establishment of the Spatial State Model for Risk Early Warning of Pledge financing

Establish the Observation Equation and the state Equation. It is a random variable composed of, representing the financial status of a financing company in period t; It is composed of N dimensions the random vector represents the financial ratio of a financing company in period t. Since the original data of the company first needs to undergo global principal component processing, what is actually presented in this part is the principal component obtained from global principal component processing rather than the original data. Suppose it cannot be observed, but can be obtained through estimation. The relationship between the two

observation equation:

$$y_t = H_t x_t + v \quad (15)$$

equation of state:

$$x_t = A_t x_{t-1} + B_t u \quad (16)$$

Among them: and are the parameter vectors that can be estimated based on the data; v follows and is a covariance matrix. And can be vectors independent of time. The sum is a vector with a dimension of N dimensions (the number of global principal components) and one column at time t. u obedience is the variance.

Establish the K-order Expectation Model. Afterwards, a K-order prediction P() is established, where ξ is the filter, is the principal component of the original data of the sample company after global principal component processing, and has. And. Among them, follows a normal distribution, and the mean and variance are respectively

$$\text{Mean} = \hat{x}_{t+k|t} = \prod_{i=1}^k A_{t+1+k-i} \hat{x}_t \tag{17}$$

$$\begin{aligned} \text{Variance} = P_{t+k|t} = & \prod_{i=1}^k A_{t+1+k-i} P_t \prod_{i=1}^k A_{t+1+k-i}^T + B_{t+k} R_{t+k} B_{t+k}^T + \\ & \sum_{i=2}^k \prod_{j=1}^{i-1} A_{t+1+k-j} B_{t+1+k-i} R_{t+1+k-i} B_{t+1+k-i}^T \prod_{j=1}^{i-1} A_{t+1+k-j}^T \end{aligned} \tag{18}$$

Among them, in formula 18, the superscript T represents the transformation rank; P is the variance of |. Suppose that and are independent of time, then there are and. The above mean and variance can be transformed into:

$$\text{Mean} = \hat{x}_t + k|t = Ak\hat{x}_t \tag{19}$$

$$\text{Variance} = P_{t+1}|t = Ak\hat{x}_t P_t (A_k)^T + \Sigma_i^k = 2A_i - 1BRB(A_{i-1})^T \tag{20}$$

Calculate the Kalman gain to Obtain the Latest Dynamic Value. When there are observed values, updates are required. It also conforms to the normal distribution:

$$\text{Mean} = \hat{x}_{t+1} = A_{t+1} \hat{x}_t + P_{t+1}|t H_{t+1}^T F_{t+1}^- (y_{t+1} - H_{t+1} A_{t+1} \hat{x}_0) \tag{21}$$

$$\text{variance} = P_{t+1} = P_{t+1}|t - P_{t+1}|t H_{t+1}^T F_{t+1}^- H_{t+1} P_{t+1}^T |t \tag{22}$$

in the formula: $P_{t+1}|t = A_{t+1} P_t A_{t+1}^T + B_{t+1} R_{t+1} B_{t+1}^T$, $F_{t+1} = H_{t+1} P_{t+1}|t H_{t+1}^T + Q_{t+1}$

Suppose both the state update equation and the measurement update equation are independent of time, and it can be confirmed that the sum is the best estimate of the mean and variance of |ξ= at t=0, then we can recursively obtain the sum. At the point when t=1, it exists

$$\hat{x}_1 = A \hat{x}_0 + (AP_0A + BQB)H^T (H(AP_0A + BRB)H^T + Q)^{-1} * (y_1 - HA \hat{x}_0) \tag{23}$$

$$P_1 = AP_0A + BRB - (AP_0A + BRB)H^T * (H(AP_0A + BRB)H^T + Q)^{-1} H (AP_0A + BRB) \tag{24}$$

By analogy, we can obtain and from \hat{x}_1 and P_1 to get \hat{x}_2 and P_2 , \hat{x}_3 and P_3 , until \hat{x}_n and P_n .

2.4 Early Warning Space Model Parameters: Maximum Likelihood Estimation

After the state space model is established, it is necessary to estimate the parameters in the model using historical data. The most commonly used parameter estimation method is the maximum likelihood estimation method, this thesis also adopts this method to analyze the system performance of the state space. Maximum likelihood estimation is a parameter estimation method based on large samples, which has the characteristics of consistency, convergence effectiveness and convergence integrity.

For a given dataset, given the transition density, assuming the process has Markov property and density depends on the parameter θ , if the transition density of is, then the joint density is:

$$p(r_{t1}, L, r_{tN} | \theta) = p(r_{t1} | \theta) \prod_{i=1}^{N-1} p(t_i + 1, r_{i+1}; r_{t_i} | \theta) \quad (25)$$

Among them, p_0 is the prior density of r_{t1} . Then the likelihood function is:

$$L(\theta) = \prod_{i=1}^{N-1} p(t_{i+1}, r_{t_{i+1}}; t_i, r_{t_i} | \theta) \quad (26)$$

Maximum likelihood estimation of parameter θ :

$$\hat{\theta} = \operatorname{argmax}_{\theta} L(\theta) \quad (27)$$

The maximum likelihood estimation of parameters can be obtained by taking the partial derivative of the maximum likelihood function or by taking the logarithm of the maximum likelihood function and then taking the partial derivative.

Combined with this study, it is assumed that the first-order condition matrix and the second-order condition matrix of the known process are given for the known function and the existence:

$$E[r(s)|r(t)] = f_1(r(t), r(s), s - t) \quad (28)$$

$$\operatorname{var}[r(s)|r(t)] = f_2(r(t), r(s), s - t) \quad (29)$$

Suppose $r_{t+\Delta t}$ follows a normal distribution with a mean of $f_1(r(t), r(s), s-t)$ and a variance of $f_2(r(t), r(s), s-t)$. Parameter estimation can be obtained by maximizing the quasi-likelihood function:

$$\begin{aligned} RT = & -\frac{N-1}{2} \ln 2\pi - \frac{1}{2} \sum_{i=1}^{N-1} \ln f_2(r_{t_{i+1}}, r_{t_i}, \Delta t) \\ & - \frac{1}{2} \sum_{i=1}^{N-1} \ln \frac{(r_{t_{i+1}} - f_1(r_{t_{i+1}}, r_{t_i}, \Delta t))^2}{f_2(r_{t_{i+1}}, r_{t_i}, \Delta t)} \end{aligned} \quad (30)$$

The normal approximation method is superior to quasi-likelihood because it uses a true moment function. This method assumes to be small enough, thus.

Let G be the last period of the observed value y , where and are equal, the latter follows a normal distribution, with a mean of 0 and a variance of.

Among them, it was established. Since in the financing risk research sample, we know the degree of financing risk of the company in each period, we can partially observe x . Placing it in the likelihood equation can improve the accuracy of the equation. Based on the degree of financing risk that the company has experienced in each period of data, the probability of its financing risk crisis is:

$$P(X_t > b_s) = \int_b^\infty p(x_t|\xi_t)dx_t \quad (31)$$

Among them, is the critical value, and is obtained from the aforementioned equation. The revised likelihood equation is:

$$1 = -\frac{NG}{2} \log(2\pi) - \frac{1}{2} \sum_{t=1}^G \log|F_t| - \frac{1}{2} \sum_{t=1}^G e_t^T F e_t + \sum_{t=1}^G (\log(P(X_t > B_s)\delta_t + \log(P(X_t < B_s))) \quad (32)$$

From the parameter set obtained from the above data and equations, the most suitable parameter set for the financing enterprise can be obtained.

3 Analysis

3.1 Enterprise Risk Threshold Measurement

his study uses statistical analysis methods to determine the risk - judgment thresholds for companies, based on the data of predicted samples. Under the premise that the confidence probability α is 95%, if the confidence coefficient is set as α , and the mean of the calculated states of the sample companies is set as mean, and the standard deviation is set as std, then the lower limit of confidence down for the risk sample companies to have a crisis is: $\text{down} = \text{mean} - \alpha \times \text{std}$

Similarly, under the premise that the confidence probability α is 95% and the confidence coefficient is α , let the mean and standard deviation std of the calculated state of the sample be set. Then, the upper limit of confidence up for the crisis of the healthy sample company is: $\text{up} = \text{mean} + \alpha \times \text{std}$

Based on the above results, it can be known that the lower confidence limit is down and the upper confidence limit is up. From this, we draw the judgment boundary of the early warning: When the predicted value of financing risk is greater than the lower confidence limit down, the financing enterprise is highly likely to have severe financing risk. When the predicted value of financing risk is less than the upper limit of confidence up, the financing enterprise is in a healthy state of financing risk. When the predicted value of financing risk is between down and up, the financing enterprise is highly likely to be in a state of mild financing risk.

3.2 Enterprise Type Definition

With the risk - judgment thresholds established, the classification of enterprise types can be defined as follows.

Healthy enterprises: If the net profit and net cash flow from operations of an enterprise are both positive during the investigation period and show an increasing trend, it is recognized as a healthy enterprise. Light-risk enterprises: If the net cash flow from operating activities of an enterprise is negative at the end of the assessment period and positive in periods T-1 and T-2, and the net profit is negative in any period during the assessment period, it is recognized as a mild risk enterprise. Severe - risk enterprises are defined as follows: In this study, an enterprise is classified as a severe - risk enterprise if its net cash flow from operating activities remains negative for three consecutive periods and its net profit is negative in any two of these three periods.

The parameter values obtained from the maximum likelihood estimation using Kalman filtering mentioned above are compared with the warning values calculated by the statistical analysis method here to determine what type of enterprise a specific enterprise among the sample enterprises belongs to.

3.3 Innovative Significance

This paper proposes an innovative real-time risk tracking method based on the Kalman filtering theory. It not only considers the immediate financial data of the enterprise, but also takes into account the historical performance and development potential of the enterprise. It locates and supervises the funds and business risks after the enterprise's pledge financing from multiple dimensions, thereby providing more comprehensive and accurate information support for the enterprise's financing decisions. At the same time, it has effectively alleviated the problem of information asymmetry in the intellectual property pledge financing market. For pledge enterprises, this model can monitor their financing activities and financial data in real time. On the one hand, it can identify their long-term and short-term risks, achieve effective risk management, formulate appropriate asset operation policies, and enhance the information disclosure capabilities of enterprises.

For loan providers such as banks, this model offers a novel enterprise rating approach for investors, making enterprise business decisions and capital operations more transparent, thus deepening lenders' understanding of enterprises' pre - and post - loan capabilities and reducing information - asymmetry risks.

For third-party institutions in the intellectual property pledge financing link, the Kalman filtering model proposed in this paper provides a new regulatory means for third-party platforms, tracking and supervising the risks of enterprises after pledge from multiple dimensions such as the real-time financial situation of enterprises and the future development of enterprises, and improving the regulatory efficiency of third-party institutions

4 Conclusion

The Kalman filtering model proposed in this paper provides a new regulatory means for third-party platforms, tracking and supervising the risks of enterprises after pledge from multiple dimensions such as the real-time financial situation of enterprises and the

future development of enterprises. It provides an effective and practical regulatory tool for third-party institutions and banks to supervise the risk activities of enterprises, and improves the regulatory efficiency of third-party institutions.

Although this study selected 18 core financial indicators of enterprises through scientific methodology and constructed a determination system for the degree of enterprise risk, there are still certain limitations. On the one hand, the selection and processing of data may be affected by factors such as the sample range and data quality, resulting in limited universality of the model. On the other hand, there may be certain differences between the model assumptions and the actual operating conditions of enterprises, and the impact of some sudden factors or non-financial factors on enterprise risks has not been fully considered. Future research can further expand the sample range to incorporate data from more industries and enterprises of different scales, thereby enhancing the universality of the model. Meanwhile, explore the inclusion of non-financial indicators, such as corporate governance structure and market reputation, into the risk assessment system, improve the enterprise risk determination model, and provide more comprehensive and accurate decision-making basis for enterprise risk management.

Therefore, in the practical application of this method, banks and third-party financial institutions should flexibly adjust credit policies or product designs based on post-loan data feedback to better adapt to market changes. This means not only regularly reviewing the existing credit standards and processes, but also making timely adjustments in accordance with the latest economic environment, industry trends and the actual needs of customers.

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