Risk Measurement, Analysis, and Prediction Methods for Online Financial Services

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Abstract. The analysis and research on the risk of online financial business is divided into four main areas; the construction of metrics, analysis and modeling, risk prediction, and risk monitoring and control. It mainly uses high-frequency data to update the dynamic factor model, converts the results to low-frequency data to derive the systematic risk indicators; based on the Markov interval transformation model, the unpredictable and uncertain mechanisms are used as stochastic variables to identify the characteristics of the risk changes to cope with the Internet financial risks. The study concludes that the Internet financial risk has a certain trend and periodicity, and the presented market is relatively stable; due to the close connection between Internet finance and traditional financial industry, the resonance effect can bring certain risk to the whole financial market, and it is still necessary to pay attention to the changing risk factors and take corresponding risk management measures.

Keywords: Financial model, financial technology, data analysis, risk management, big data.

1. Introduction

At the present stage of social development, the rapid development of information technology has become the basis for the development of all walks of life, because of its convenience not only reduces the cost but also improves the efficiency of the transaction, and the financial market is also gradually transferred from the traditional offline to online. Internet finance is the product of upgrading and innovation of the Internet industry from traditional financial business. Internet finance model usually includes the following aspects: online financing and investment, third-party payment, financial technology innovation, mobile payment, online sales and marketing, online financial management and so on. The core value of the Internet is to make it easier and faster for people to connect from each other, and the large-scale and continuous network world has brought new opportunities and challenges for the development of the financial industry.

Taking China's Internet finance as an example, since 2013, China has relaxed its financial regulatory policies and introduced policies such as "inclusive finance" and "Internet Plus", which have promoted the deep integration of Internet finance and the real economy and enabled China's Internet finance to enter a new stage of development. However, due to the rapid development of Internet finance, the Internet finance industry has become more and more popular. However, due to the rapid development of Internet finance, the lack of financial regulatory system, platform risks, technical immaturity, information security and other issues, resulting in the need for more stringent supervision and control than traditional financial business to ensure the sustainable development of Internet finance.

Internet finance is the landing point of financial digital transformation and fintech innovation, which highly relies on information technology and uses Internet technology as a medium to realize the digitization, networking and inclusion of financial services and products, as well as to make financial services more convenient and efficient, and to provide more creative opportunities for the financial industry.

2. Related work

Traditional financial risk measurement mainly has model measurement method, index measurement method used to measure different financial risks; model measurement method, such as " value-at- risk, VaR ", need to go through the historical data and statistical models, in order to get the accurate risk measurement results, the index measurement method uses a specific index or market data to measure the level of risk of the financial market or investment portfolio [1]. Compared with the depth and breadth of traditional financial risk measurement research, the risk research of Internet finance mainly adopts the method of combining qualitative analysis and quantitative calculation. Based on this method, a preliminary index system is established for the evaluation of Internet financial risk, designed a mathematical model for calculating the weights of the index system, and gave the final evaluation index system consisting of the names and weights of the indexes in the form of a list [2]. The evaluation index system of Internet financial is constructed systemic risk through principal component analysis to measure the Internet financial systemic risk. It takes the difficulties of Internet financial regulation as an entry point to elaborate the functions of big data technology for the collection, management, analysis, and information integration of Internet financial analysis data to strengthen the performance of financial regulatory system [3]. The above research assesses and measures Internet financial risks by establishing an indicator system or model for Internet financial risk evaluation. These indicator systems or models can provide scientific basis and decision-making support for Internet financial risk management and supervision. However, problems such as data uncertainty, subjectivity and model limitations need to be overcome in practice to improve the accuracy and reliability of the assessment [4].

Internet finance is the embodiment of the perfect fusion of high technology and traditional finance [5], but the risk of its existence is not only the risk of traditional finance already exists, but also face the risk of information technology and a new type of financial risk and other issues, which also leads to its more complex. The risk and regulation of traditional financial industry is relatively more mature and stable, after a long period of development and more perfect regulatory system, and real-time supervision by regulatory agencies [6]. Compared with traditional finance, Internet finance due to its attributes and emerging nature makes the risk factors are different from traditional finance [7]. As Internet finance is still in the development stage, it is necessary to consider traditional financial risks while dealing with Internet financial risks [8]; apply the Internet scientifically to avoid technical risks caused by Internet information technology [9].

Through an in-depth analysis of the functions, mechanism and development dimensions of the essential characteristics of Internet finance, it can be found that it interacts with traditional finance, and Internet finance differs from traditional finance in its mode of operation, service model and innovation [10], which make Internet finance more flexible and innovative in many aspects, but it still has the pro-cyclical characteristics of financial risks and mutual transmission characteristics. The Internet finance industry has been a major player in the financial industry for many years. From the level of the financial industry, macroeconomic fluctuations and the risks of the financial industry are closely related. Economic downturns and financial instability are mutually reinforcing, and an increase or decrease in the size of the economy may lead to instability in financial institutions. It may affect investor confidence in financial institutions and affect the overall level of financial risks [11].

Based on the interaction relationship between Internet finance and traditional finance, as well as their differences in function, mechanism and development level, this paper will launch a predictive study on the attributes and characteristics of Internet finance, such as its digital nature, high dependence on technology, crossing the limitation of time and space, innovativeness, convergence, and user participation.

3. Design of Financial Risk Measurement and Analysis Methods

3.1. Content of the study

The main content of this study includes four parts: first, to improve the accuracy of risk measurement as well as the timeliness and continuity of the effect produced by the study in time. Internet financial risks will be measured from multiple dimensions, such as Internet finance, traditional finance, and macroeconomics, through a mixed-frequency dataset; second, a set of factor scores will be calculated to identify the various factors that lead to Internet financial risks and to determine how much impact they have on the risks generated. Thus, more targeted measures are taken to reduce the risk; third, the Markov interval transition model is used to help us understand how the Internet financial risk transfers from one state to another, such as the probability of low, medium and high risk, and how long it stays at different levels of risk, to help better understand the trend of the change of the Internet financial risk; and lastly, the Internet Finance Risk Index to measure the risk level of Internet finance. Two methods, namely the "Fixed Coefficient Method" and the "Rolling Forecast Method", are used to forecast future risks. Through these studies, the results of the research can provide effective guidance for relevant decision-making, so that we can more accurately grasp the risk situation of the Internet finance industry and make more informed decisions.

3.2. Modeling Design

A dynamic factor model is used to extract a potential factor from the mixture of variables that represents Internet financial risk. This factor changes over time and can explain the co-movement between multiple variables. Dynamic factor modeling can help us identify key factors from complex data and better understand the trends and characteristics of Internet financial risks.

An "autoregressive model (AR(p))" is used to help describe the change in a variable over time. The value at the current moment (moment t) is a linear combination of the previous p moments (moments t-1, t-2, all the way up to moment t-p), plus a random error term (white noise). Such a model allows the current value to be correlated with values from the past few moments, and as p increases, the model can be able to capture longer-term time dependence.

For example, if the AR(1) model is expressed as:

$$xt = \alpha 1 * xt\text{-}1 + \varepsilon t \tag{1}$$

Where xt denotes the value at the current moment, xt-1 denotes the value at the previous moment, α1 denotes the coefficient, and εt denotes the random error term.

If the AR(2) model is expressed as:

$$xt = \alpha 1 * xt\text{-}1 + \alpha 2 * xt\text{-}2 + \varepsilon t \tag{2}$$

Where, in addition to the value xt-1 at the last moment, the value xt-2 before the last moment is considered and the corresponding coefficient α2 is added.

AR(p) models are commonly used in time series forecasting and analysis, and by fitting a model to historical data, they can be used to predict future values and help us understand the dynamic relationships between time series data. In dynamic factor modeling, the AR(p) process is used to represent changes in dynamic risk factors, which can better explain the co-movements and trends among risk indicators.

Since the study requires the use of mixed frequency risk variables, and the AR(p) model is mainly applicable to the analysis of same frequency data. Therefore, before the beginning of the study needs to be analyzed by converting the mixed frequencies to high frequency risk factors without losing important information using the Litterman frequency conversion method, which is mainly used to convert the frequencies by introducing the coefficient matrix of the a priori combined conversion matrix. The conversion matrix is mainly used to map low-frequency data to high-frequency data or to aggregate high-frequency data into low-frequency data, thus ensuring that the converted data retains the important features and dynamic trends of the original data, while safeguarding the effectiveness of the risk measure. Assuming a low-frequency time series data Xt, which is collected on a monthly basis, and utilizing Litterman's frequency conversion method to convert these data into high-frequency data Xt length, such as the data collected daily. t length the data represented by t length is the daily point in time; the following equation can be established:

$$X_t\ length = \beta \chi_t + \mu_t \tag{3}$$

Where Xt length is the high frequency data, Xt is the low frequency data, and β is the transformation matrix; this matrix is used to convert the low frequency data to high frequency data. In this example, since we want to convert from monthly to daily data, β is a 2x1 matrix, where the first element denotes the daily rate of change and the second element denotes the monthly rate of change; and μt = μt-1 + εt denotes the time series of the high-frequency data Xt, where μt is the value of the high-frequency data, and εt is the random error term yan, which conforms to a normal distribution N(0,V). ε t=ρ εt-1+δt is the autoregressive model of the random error term εt, ρ is the autoregressive coefficient, δt is the random perturbation term, and the initial condition μt=0 indicates that the starting value of the HF data is 0.

$$y_k = \sum_{t=b_k}^{d_k} f x_t \tag{4}$$

The parameter setting in the above equation determines the method and constraints for high-frequency conversion based on different data types, i.e., flow variables, stock variables, and index variables. Such a conversion method allows quarterly data to be converted to higher frequency monthly data, ensuring the accuracy and validity of the high-frequency data, and thus better analyzing and predicting the dynamics of the data.

(1) Indicator selection and data sources

For the construction of the systematic risk indicator system of Internet finance, it is necessary to comprehensively consider the risk of the Internet financial market, the traditional financial industry, the macro-economy and risk influencing factors and other aspects for consideration:

(2) Internet financial market risks

Four main indicators were selected as the basis for risk assessment. These indicators include the growth rate of e-commerce market transactions, the ratio of Internet payments to online banking transactions, the capital adequacy ratio of P2P platforms, and the online non-performing loan ratio.

In addition, the risks of the Internet finance industry are mainly composed of three aspects: Internet finance platform operation risks, industry development risks and market risks. Online lending is the main source of Internet financial risks in China, and P2P problem platforms reflect Internet financial platform operation risks. The volatility of financial asset prices can reflect the level of market risk, while Internet financial market risk can be measured by the volatility of share prices of listed companies in the secondary market. Therefore, the cumulative number of P2P problematic platforms and the volatility of the Internet financial index are used as proxy variables for the risk indicators of the Internet financial industry in the study for risk assessment and analysis. Among them, the volatility of the Internet finance index is estimated using the GJRGARCH (1, 1)-ST model, which uses the skewed t-distribution to capture the non-normal characteristics of the financial time series, while the GJRGARCH model is used to capture the asymmetric effects of the financial time series.

(3) Traditional Financial Sector

The study focuses on the risks faced by the traditional financial sector in China's financial markets, with a particular emphasis on credit risk and liquidity risk. As the operation mechanism of the financial market is not yet perfected, traditional financial institutions still face a "strong regulatory environment", which makes credit risk and liquidity risk the main challenges. The study selects bank NPL ratio and TED spread as the proxy variables for the risk of traditional financial industry to reflect the situation of credit and liquidity pressure. By gaining a deeper understanding of the risk profile of the traditional financial industry, the study aims to provide effective risk management strategies and reveal how these risks are transmitted to the Internet financial industry.

(4) Internet Business

The study of Internet finance chooses average mobile Internet household traffic and the number of new cybersecurity handling incidents as proxy variables for the risk indicators of the Internet industry. The analysis of these indicators can reveal the healthy development of the Internet industry and the risk factors that may affect the Internet finance industry.

(5) Macro-Economic

Economic growth and economic uncertainty are two key aspects; when the economy is good, Internet finance is conducive to smooth development, while when economic uncertainty increases, Internet finance risks increase. To measure macroeconomic risk, industrial value added, and economic policy uncertainty are selected as proxy variables, while four indicators, namely, volatility of GDP growth, inflation rate, growth rate of fiscal deficit and ratio of short-term foreign debt to foreign exchange reserves, are chosen.

4. Empirical results and analysis

4.1. Internet Finance Risk Measurements

4.1.1 Risk index

In the estimation of the dynamic factor model, a second-order equation of state lag order was used, which helps to capture the dynamics of the risk factors more accurately. In addition, normalization was performed during data processing and no constant terms were introduced in the quantile equations. With the exception of the TED spread and the number of new cybersecurity processing events, we can see from the coefficient estimates in Table 1 that the coefficients on most of the risk variables are statistically significant. This suggests that the mixed-frequency dynamic factor model used is effective in explaining most of the risk information in the system of risk indicators. First, the coefficient of industrial value added is negative due to macroeconomic factors, while the coefficient of economic policy uncertainty is positive. This means that when the macroeconomic growth rate decreases, the risk of Internet finance increases, while the increase in economic policy uncertainty also leads to a rise in the risk of Internet finance. This further confirms the influence of macroeconomic factors on Internet finance. Secondly, analyzing in terms of the characteristics of the Internet industry, the coefficient of the average mobile Internet household traffic is positive, indicating that the increase of this factor will further trigger the Internet financial risk. This indicates that the development of the Internet industry and the progress of Internet technology will increase the risk of Internet finance to a certain extent, especially when the market order and regulatory system are not yet mature.

Table 1. Estimation Results: Coefficients of Mixing Frequency Dynamic Factor Measurement Equations

Category	I	E	D	M
C	-0.533	0.012	0.001	0.001
T-statistic	-4.346	2.987	9.083	6.645

Over time, the Internet finance industry has undergone a series of developments and changes, removing some of the industry's irregularities and chaos and making it more in line with the nature of finance. In this process, the risk factors of Internet finance have gradually merged with those of macroeconomics and the traditional financial sector. With the maturity of the Internet finance industry and the improvement of regulation, the risks are gradually reduced, while the risk resonance and business complementary effects between the Internet finance and the traditional financial sector become more obvious. The risk index established by this study better reflects the development history and risk change characteristics of the Internet finance industry.

4.1.2 Index validity testing

Internet search data were used to objectively quantify the market's perceived level of Internet financial risks. Through the daily search data of Internet financial risks, 110 risk perception variables are initially screened and identified, and these variables are downgraded using principal component analysis to obtain the Internet financial risk perception index, which reflects the overall level of market perception of risks. At the same time, this risk perception index is correlated with the actual Internet financial risk index, and it is found that there is an obvious correlation between them. This indicates that there is a certain synchronization between the market's risk perception and the actual risk level, i.e., the market can accurately perceive and reflect the risk of Internet finance to a certain extent. This approach can also play an active role in risk management and decision-making, providing more comprehensive information and insights for regulatory and business decisions.

4.2. Identification of risk factors

Calculating factor scores through regression analysis is a common method that can help us understand the extent to which different risk metrics influence risk factors. The following equation can be used:

$$Y = b + a_1X_1 + a_2X_2 + \cdots + a_pX_p + \varepsilon \tag{5}$$

Y is the extracted risk factor; b is the intercept term; a_1, a_2, ... a_p are the regression coefficients, which represent the degree of influence of each risk indicator on the factor; X_1, X_2 ... X_P are the values of the risk indicators; and ε is the error term, which represents the random errors that the model cannot explain.

Table 2. Risk Indicator Factor Result

Category	I	E	D	M
C	-0.163	0.012	0.511	0.383
T-statistic	-5.263	3.186	23.367	12.729

There are significant differences between different risk indicators in influencing the Internet financial risk factors. Among them, the non-performing loan ratio of commercial banks, the number of P2P problematic platforms, the fluctuation of the Internet finance index and the scale of the Internet finance industry explain the Internet finance risk to a higher degree. This means that both the stability of traditional financial institutions and the scale of Internet financial platforms significantly affect the overall risk level of Internet finance (Table 2).

Therefore, in assessing the risks of Internet finance, we must comprehensively consider a wide range of factors, including policy adjustments, market size and the performance of traditional financial institutions. At the same time, we also need to recognize the differences between Internet finance and traditional finance, which pose new challenges to risk management and regulation.

4.3. Characteristics of the risk interval

A methodology for analyzing Internet financial indices using Markovian interval transformed autoregressive (MS-AR) model helps to better characterize Internet financial risks. The model is used to identify different states of Internet financial risks and consider the transfer probabilities between states. In the construction of the model, the number of states, the dependencies between states and the lag order of Internet financial risks are first determined, and the most appropriate model is selected through a series of information criteria.

The mathematical expression of the MS-AR model is as follows:

$$\mathrm{y_t = \alpha(S_t) + \beta_1(S_t)_{y_{t-1}} + \cdots + \beta_p(S_t)_{y_{t-p}} + \mu(S_t)} \tag{6}$$

In this equation, y_t represents the observed value of the time series, which is affected by different autoregressive coefficients β, intercept term α, and random perturbation term μ in different states. And St represents the state that the time series is in, which is a discrete variable that is usually used to represent risk or other states of interest.

By using the state transfer probability matrix, the transfer probabilities between different states can be determined, which in turn identifies the changes in the state of Internet financial risk. For example, a high risk state may correspond to a period of turbulence in the Internet financial market, while a low risk state may correspond to a period of stability in the market.

The estimation results of the model show that the average duration of the low-risk state is long and Internet finance is in a low-risk state most of the time. This implies that the Internet finance market is relatively stable in most cases. However, high-risk states can occur, for example, during 2018-2019, which may correspond to certain market turbulence events that lead to shifts in risk states.

4.4. Risk Forecasting

To forecast China's Internet financial risk, we used the MS-AR model and set the forecasting time span as one year, from April 2022 to March 2023. To improve the prediction accuracy, we first averaged the daily risk indices for each month to obtain the average risk level for each month. Next, we used two different forecasting methods:

The first is the fixed coefficient forecasting method, in which we make only one estimate to obtain a collection of coefficients, which we then use to forecast the risk level for the next 12 months without further adjustments to the coefficients.

The second is the rolling forecast method, which is more complex. First, we performed an in-sample estimation to obtain a set of estimated coefficients. Next, we used these coefficients to forecast the first month's risk level out-of-sample. We then expanded the estimation window to include the previously predicted values and used the new estimated coefficients to predict the risk level for the next month. This process was repeated until we had predicted monthly risk values for the next 12 months.

5. Concluding

With the gradual transition of the Internet finance industry from "low threshold, loose rules and weak regulation" to "high threshold, strict rules and strong regulation", the risk level of the whole industry has shown a downward trend. The increase in the standardization and supervision of the financial market on the Internet financial industry also highlights the risk resonance and business complementary effect between the Internet financial and traditional financial sectors. The Internet financial risk factors of involves multi-dimensional identification, including macroeconomics, the Internet industry, the traditional financial industry and the Internet financial industry and other dimensions to analyze risk factors. Factors such as traditional financial institutions' business risk, Internet financial platform business risk, Internet financial market risk and the scale of the Internet financial industry have high explanatory power for changes in Internet financial risks. Internet finance provides a new perspective on the understanding of financial innovation risk, synthesizes, and analyzes multi-source data and complex structural models, and describes the nature and evolution of financial innovation risk more comprehensively.

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