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University of Warsaw, Poland

## \*CORRESPONDENCE

Wee-Yeap Lau,  
wylau@um.edu.my

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# Can the modified ESG-KMV logit model explain the default risk of internet finance companies?

Li Zeng<sup>1,2</sup>, Wee-Yeap Lau<sup>1,2\*</sup> and Elya Nabila Abdul Bahri<sup>1,2</sup>

<sup>1</sup>Department of Economics and Applied Statistics, University of Malaya, Kuala Lumpur, Malaysia,

<sup>2</sup>Faculty of Business and Economics, University of Malaya, Kuala Lumpur, Malaysia

With the rapid development of internet finance in China, the risk management of internet finance has become an urgent issue. This study analyzes the factors that affect the default risk of Chinese internet finance companies based on measuring the distance to default of companies. This study incorporates ESG rating into the evaluation model to comprehensively reflect the default risk factors. The traditional KMV model is modified with ESG rating, and results are used to construct the panel logit model. Based on internet finance firms listed on China A-Shares data from 2016 to 2020, our results show the following: first, the modified ESG-KMV logit model can effectively analyze the influencing factors of the internet finance default risk. Second, ROE, accounts receivable turnover ratio, asset-liability ratio and z-value are important factors that affect the default risk of internet finance companies. Third, it is also found that COVID-19 has significantly impacted the default risk of internet finance companies. As a policy implication, the regulator can incorporate ESG into the measurement of the default risk to create more awareness among internet finance companies on the importance of the environment and sustainability to human societies.

## KEYWORDS

default risk, ESG, KMV, internet finance, early warning system

## 1 Introduction

After 2013, China ushered in a great development in internet finance (Ping and Chuanwei, 2013). With the rise of new internet finance models such as Yu'eobao, P2P, and crowdfunding, 2013 was known as "the first year of the internet finance in China" (Guan and Gao, 2022). Internet finance is a brand new financial model that makes payment more convenient and cost-effective. The most important thing is that the division of labor and specialization in the financial industry has been greatly diluted under the internet finance model. Market participants are more popular, and the huge benefits of internet finance market exchanges are more inclusive to ordinary people. However, internet finance also faces more complex risks than traditional financial models as a new financial model (Xu et al., 2020). With the development of the internet financial market, credit risk is gradually showing more complex and diversified characteristics, which also seriously impacts the internet financial market (Xiao-li and Long, 2013; Ma and Ly, 2019; Wang and Yang, 2020).

Although internet finance makes it easier and faster for investors to obtain information related to financial products, it also gives fund-raisers more chances to hide their real situation, such as misreporting information or concealing information (Zhongkai and Hassan, 2019). Investors find it very difficult to discover a practical way to solve the real situation of the fundraiser like the participants in the traditional financial market, thus leading to the emergence of the misbalance phenomenon between investors and fund-raisers. The information risk caused by information asymmetry factors will not be lost due to the convenience of the internet financial market (Xie et al., 2016). Still, it will become more complex due to network trading for its trading participants. Subsequently, the internet financial market has branched into various sectors, from crowdfunding to payments, insurance, and other financial industries (Xie et al., 2015). In addition, due to the convenient and fast characteristics of internet financial facilities, once a large-scale default event occurs in the internet financial market, its credit risk will quickly spread to the entire financial industry by borrowing network channels. Therefore, compared with the credit risk of the traditional financial market, the credit risk of the internet financial market is higher (Ping and Chuanwei, 2013; Xie et al., 2016; Xu et al., 2020).

Credit risk has been studied for a long time, and many models have been applied to the evaluation process of the credit risk (Altman and Saunders, 1997; Caouette et al., 1998; Dong and Wang, 2014; Li and Wang, 2011). Traditional credit risk assessment methods focus on qualitative indicators and rely on experts' professional skills and subjective judgment. Among them, the more famous method is the 5C analysis method, which is based on the analysis of character, the evaluated enterprise's capacity and capital, collateral, and conditions (Wu et al., 2021). In addition, the traditional credit risk assessment methods also include similar characteristic analysis and financial ratio analysis. The credit scoring model is a statistical model that reflects the evaluated object's credit status with systematic data. The model can predict the likelihood that a borrower will default and become insolvent (Chen et al., 2016; Guo et al., 2016).

Altman (1968) first proposed the famous Z-Score model and applied it to analyze enterprises' financial crisis and default risk. In addition, there are logistic and neural network models proposed by scholars (Angelini et al., 2008; Sanford and Moosa, 2012). With globalization, financial market openness has also increased over the years. However, it has also created more frequent incidents of financial crises, where measuring credit risk is increasingly valued by major banks and regulators (Sachs et al., 1996). Since the 1990s, more modern foreign companies and scholars have begun to pay attention to and successfully developed a series of credit risk measurement models. For example, in 1993, KMV Company launched the KMV model, which could estimate the default probability of borrowing enterprises (Rehm and Rudolf, 2000; Gou and Gui, 2009; Zhang et al., 2010). In 1997, Morgan (1997) and other

cooperative financial institutions put forward the CreditMetrics model based on value-at-risk. In 1997, Credit Suisse issued a Credit Risk + model similar to the default mode (Wilde, 2010).

In recent years, a large number of scholars in China have used the KMV model to study the credit risk in the financial field and prove the effectiveness of the KMV model (Valášková et al., 2014; Zhao et al., 2016; Liu and Chen, 2020; Yu, 2021). Internet finance is an emerging field, and some scholars have applied this model to this field. Xiao-li and Long (2013) used the traditional KMV model to calculate the volatility of the asset value ( $\sigma_A$ ), distance to default (DD), and expected default frequency (EDF) of 18 listed companies in China. Aware of the rise of internet finance in China, Xu (2022) chose internet finance companies as objects to study the feasibility of KMV to measure their credit risks. The research results prove the feasibility and effectiveness of KMV in the current credit risk calculation of internet finance in China.

However, in the process of studying the credit risk in the field of internet finance, there is a lack of research on the impact of ESG. ESG is the abbreviation of environmental, social, and governance factors, reflecting the enterprise's environmental, social responsibility, and corporate governance factors on the three dimensions. ESG is an important concept and standard for the international community to measure enterprises' ability to achieve sustainable development (Gillan et al., 2021).

Scholars have proved the relative influence of ESG on financial risk. Scholtens and van't Klooster (2019) analyzed the significant relationship between bank performance and sustainability from the perspective of the risk and proved that this sustainability may affect the entire financial system. Moreover, ESG is considered a key factor influencing investor decisions. The importance of ESG is reflected in financial performance in many studies. Friede et al. (2015) proposed that ESG positively impacts CFP based on more than 2000 empirical studies. Scholars in different countries have verified the positive relationship between ESG and financial performance based on local conditions, such as the United States, China, and Germany (Velte, 2017; Zhao et al., 2018; Dalal and Thaker, 2019; Okafor et al., 2021).

Some scholars have analyzed the relationship between ESG and firm value from different perspectives, such as the influence of company size or CEO power. Overall, ESG has positively impacted the enterprise value and its role in valuation (Aouadi and Marsat, 2018; Fatemi et al., 2018; Li et al., 2018; Wong et al., 2021). In recent years, COVID-19 has become an important factor affecting global development. During this period, the impact of ESG became even more pronounced. Umar and Gubareva (2021) used wavelet analyses to point out that ESG indices can maintain positive effects despite catastrophizing like COVID-19. Broadstock et al. (2021) have studied how ESG can perform better in times of crisis and mitigate financial risk to some extent. There are still many studies on the relationship between ESG and risk in the context of COVID-19. Most scholars

have proposed the importance of ESG in the face of disasters (Ferriani and Natoli, 2021; Umar et al., 2021; Lööf et al., 2022). Therefore, the special background of COVID-19 should also be taken into account in the research.

Scholars have proved the relative influence of ESG on the financial system risk. Scholtens and van't Klooster (2019) analyzed the significant relationship between bank performance and sustainability from the risk perspective and proved that this sustainability may affect the entire financial system. Regarding credit risk, scholars have studied the relationship between ESG and credit risk from different perspectives. Bannier et al. (2022) studied the relationship between companies' social responsibility and credit risk of US and European companies from 2003 to 2018. Höck et al. (2020) studied the relationship between the ESG level and credit risk premium from the perspective of a bond investment. Barth et al. (2022) analyzed the relationship between the credit risk of American and European companies and ESG from the perspective of credit spreads. Ahmed et al. (2018) analyzed the relationship between ESG and credit risk from banks' perspectives. No matter from which angle of analysis, most of the final conclusions given by scholars are that there is a significant relationship between them. In addition to the credit risk analysis, some scholars analyzed the impact of ESG from the credit rating perspective. They believed that ESG should be considered in the process of credit rating (Devalle et al., 2017; Kiesel and Lücke, 2019; Höck et al., 2020; Michalski and Low, 2021). Chodnicka-Jaworska (2021) used a group event model to verify the importance of ESG factors in credit ratings, especially in the context of COVID-19. Brogi et al. (2022) showed that higher ESG awareness is closely associated with a better reputation measured by the Altman Z-Score. The research results support the rationality of introducing ESG awareness parameters into the credit evaluation of borrowers. Therefore, ESG factors should be considered in analyzing the credit default risk.

Consequently, 49 listed internet finance companies in China are selected as samples to establish a revised KMV model using ESG ratings. Based on this, it uses a panel logit regression to further find the influence factors of the internet finance credit risk in China. This study's contribution to the credit risk field incorporates ESG rating into the evaluation model to comprehensively reflect the default risk factors in internet finance. It also considers the relationship between COVID-19 and internet finance credit risk. As a policy implication, the regulator can incorporate ESG into the measurement of default risk to create more awareness among internet finance companies on the importance of the environment and sustainability to human societies.

## 2 Modified KMV-logistic with the ESG rating model

This study adopts a mixed model to verify the importance of ESG in credit risk management in internet finance. Based on the aforementioned analysis, we believe ESG should be considered in credit risk research. First, the logic of the traditional KMV model is stated. Then, ESG rating data are used to correct the default point of the KMV model. After obtaining the default to distance corrected by ESG, it uses the idea of quantile to determine the internet finance industry's critical point of DD. The results of DD are used as the explained variable to establish the panel regression model. Finally, the mixed ESG model is used to find the factors affecting the default risk of internet finance. The factor found is the default risk analysis after considering ESG, which is more comprehensive than the original simple default risk analysis.

### 2.1 KMV model

In the 1990s, KMV Company proposed the KMV model to measure the probability of default, predicting the possibility of default of financial institutions such as companies or banks publicly listed in the security market. The calculation steps are as follows:

Step 1: Calculate the asset value and asset volatility.

$$E = V_A N(d_1) - D e^{-rT} N(d_2), \quad (1)$$

$$d_1 = \frac{\ln\left(\frac{V_A}{D}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}, \quad (2)$$

$$d_2 = d_1 - \sigma_A \sqrt{T}, \quad (3)$$

$$\sigma_E = \frac{V_E}{E} N(d_1) \sigma_A, \quad (4)$$

where  $\sigma_A$  is the volatility of  $V_A$ ,  $T$  is the debt maturity,  $E$  is the equity value of the company,  $D$  is the debt of the company,  $r$  is the risk-free rate, and  $\sigma_E$  is the volatility of the equity value.

Step 2: Calculate the default point and default to distance.

$$DPT = STL + 0.5LTL, \quad (5)$$

$$DD = \frac{E(V_A) - DP}{E(V_A)\sigma_A}, \quad (6)$$

where  $DP$  is the default point,  $DD$  is the default to distance,  $STL$  means short total liability, and  $LTL$  means long total liability.

Step 3: Estimate the expected default rate.

$$EDF = N(-DD), \quad (7)$$

where  $N()$  is the standard normal distribution function.

## 2.2 Modification of the KMV model with ESG rating

This study incorporates ESG ratings into the KMV model and modifies the traditional KMV model. The ESG rating adopted is Sino-Securities Index ESG Evaluation (also known as the Huazheng ESG rating in China). According to the ESG rating description of Sino-Securities, a rating above BBB indicates that the company has a relatively good ESG situation. Therefore, this study divides the rating into two parts to modify the KMV model. If the rating is above BBB, it will reduce default point weights. If the rating is below the BBB rating, it will be increased by a down-weighted default point. The weight determination is standardized according to the rating level. Table 1 shows the results of ESG rating correction.

The new distance to default and expected default probability of sample companies can be calculated using the modified KMV model. In this study, the distance to default is taken as the representative of the default of sample companies. According to the calculation results of distance to default, an early-warning line for default of internet finance companies can be set, and the sample companies can be further divided into default and non-default groups.

## 2.3 Panel logit model

The panel logit model is chosen according to the research object of whether the company defaults or not. The expression for the model is shown as follows :

$$L_{it} = \ln\left(\frac{P(Y=1)}{P(Y=0)}\right) = \alpha + \sum_{i=1}^n \beta_i \chi_{it} + \varepsilon_{it}, \quad (8)$$

where  $\chi_{it}$  are explanatory variables,  $\alpha$  is a constant term, and  $\beta_i$  is the parameter to be estimated.

If the company defaults,  $Y = 1$ . Suppose the company does not default,  $Y = 0$ . The default situation of internet finance companies is estimated according to the distance to default result calculated by the modified KMV model with ESG rating. The default data set is sorted according to the theoretical default rate based on the modified KMV model and takes 10% quantile as the critical default value. The smaller the distance to default, the higher is the default risk. The 10% quantile is set as the default criterion because 90% of the companies have a higher distance to default than the quantile. If the company's distance to default is lower than the distance to default at the quantile, the distance to default will be too low, and the default risk will be high. The sample companies with distance

to default ranking in the top 10% were set as 1, and the rest were set as 0.

## 3 Data and variable selection

### 3.1 Data selection

This work aims to study the factors influencing the credit risk of listed internet finance companies based on considering ESG rating. This study takes 49 listed internet finance companies in China as the research sample, and the period is from 2016 to 2020. Data were obtained from the Wind database.

### 3.2 Variable selection

In selecting variables, this study selects independent 12 variables based on the summary of the previous literature. The COVID-19 outbreak occurred in December 2019, so the year 2020 affected by the outbreak was used as the annual dummy variable in this study. Then, the stepwise regression method is performed to select appropriate independent variables. The 12 alternative variables are shown in Table 2. The observation frequency of this study is the year. Correlation analysis was used before the model estimation to check whether the key explanatory variables are highly correlated. The results are shown in Table 3, and there is no high correlation between alternative independent variables.

After establishing the regression equation, all variables are considered by the stepwise regression method. According to the value of McFadden R-Squared of the logit regression model, the statistical significance of variables and whether they conform to the actual economic significance are evaluated. According to the regression results of the model, five indicators are screened out: ROE, RT, ALR, z, and Year 2020.

At the same time, according to literature research and economic common sense, this study puts forward the following hypotheses:

- H1: The possibility of internet finance companies defaulting decreases as the return on equity increases.
- H2: The possibility of internet finance companies defaulting decreases as the accounts receivable turnover rate rises.
- H3: The possibility of internet finance companies defaulting increases as the asset liability ratio rises.
- H4: The probability of internet finance companies defaulting increases as the z-value increases.
- H5: The probability of internet finance companies defaulting increases with COVID-19.

TABLE 1 Results of ESG rating correction.

Sino-Securities ESG rating	Code	Weight	Revised plan	Revised default point result
AAA	4	0.4	Decrease	$DPT \times (1 - 0.40)$
AA	3	0.3		$DPT \times (1 - 0.30)$
A	2	0.2		$DPT \times (1 - 0.20)$
BBB	1	0.1		$DPT \times (1 - 0.10)$
BB	1	0.07	Increase	$DPT \times (1 + 0.07)$
B	2	0.13		$DPT \times (1 + 0.13)$
CCC	3	0.2		$DPT \times (1 + 0.20)$
CC	4	0.27		$DPT \times (1 + 0.27)$
C	5	0.33		$DPT \times (1 + 0.33)$

TABLE 2 List of independent variables to be selected.

Variable name	Variable symbol	Variable definition
Return on equity	ROE	Net income/Shareholder's equity
Net profit margin on sales	NPM	Net profit/Sales revenue
Receivable turnover	RT	Net credit sales/Average accounts receivable turnover
Inventory turnover	IT	Net sales/Average inventory at selling price
Total assets turnover	TAT	Net sales/Average total assets
Liquidity ratio	LR	Current assets/Current liabilities
Total profit growth rate	TPG	Annual profit growth/Total profit of last year
Total asset growth rate	TAG	Total asset growth/Total assets of last year
Asset liability ratio	ALR	Total liabilities/Total assets
Equity multiplier	EM	Total assets/Total shareholders' equity
Z-value	z	Z-score calculated according to Altman's Z-score model
Year of 2020	Year 2020	Year of COVID-19

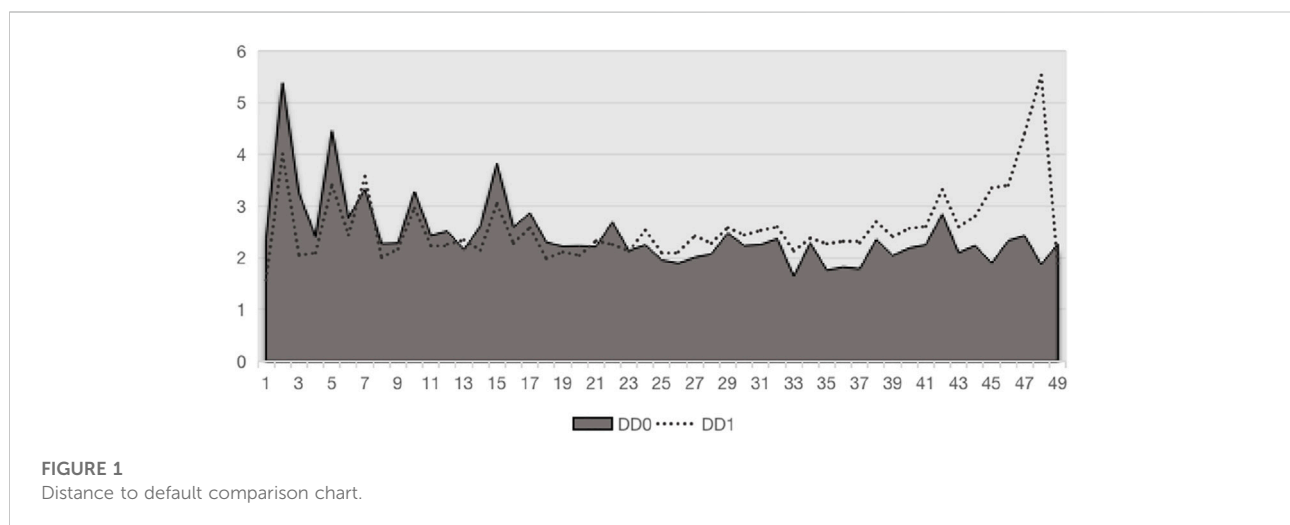
TABLE 3 Correlation matrix.

	Y	ROE	NPM	RT	IT	TAT	LR	TPG	TAG	ALR	EM
Y	1										
ROE	-0.19 (0.00)	1									
NPM	-0.21 (0.00)	0.29 (0.00)	1								
RT	-0.08 (0.23)	0.03 (0.61)	0.05 (0.44)	1							
IT	0.05 (0.41)	-0.07 (0.29)	-0.03 (0.69)	-0.02 (0.77)	1						
TAT	-0.08 (0.22)	0.03 (0.69)	0.06 (0.37)	-0.01 (0.85)	-0.02 (0.80)	1					
LR	0.09 (0.18)	0.16 (0.02)	0.15 (0.02)	0.16 (0.01)	0.05 (0.40)	-0.11 (0.08)	1				
TPG	-0.13 (0.04)	0.48 (0.00)	0.40 (0.00)	0.03 (0.65)	0.03 (0.69)	0.05 (0.47)	0.09 (0.15)	1			
TAG	-0.06 (0.34)	0.30 (0.00)	0.23 (0.00)	-0.02 (0.81)	-0.06 (0.32)	0.13 (0.04)	0.27 (0.00)	0.24 (0.00)	1		
ALR	0.09 (0.15)	-0.21 (0.00)	-0.31 (0.00)	-0.06 (0.34)	-0.06 (0.31)	0.09 (0.17)	-0.37 (0.00)	-0.14 (0.03)	-0.21 (0.00)	1	
EM	0.14 (0.03)	-0.40 (0.00)	-0.14 (0.03)	-0.02 (0.78)	-0.03 (0.67)	-0.00 (1.00)	-0.10 (0.12)	-0.06 (0.38)	-0.10 (0.11)	0.12 (0.07)	1

Note: sample period: January 2016 to December 2020. Values in parenthesis are *p*-value.

TABLE 4 Descriptive statistics of independence variables.

Items	N	Minimum	Maximum	Mean	Std. deviation
ROE	245	-428.53	56.29	-4.75	42.97
RT	245	0.09	8,819.73	71.29	598.75
ALR	245	4.24	472.36	56.63	58.09
z	245	-16.32	95.38	6.25	10.94
Year 2020	245	0.00	1.00	0.20	0.40



The credit default risk of internet finance companies results from a combination of factors. It mainly includes repayment ability and repayment willingness. For a company, the factors that affect the repayment ability and willingness include the company's profitability, operating capacity, capital structure, bankruptcy probability, and macro-environment. If its profitability is strong, it has more revenue to pay off its debts. High operating capacity means that the company's assets are used efficiently, and the company will have a lower probability of default. A company with a low debt ratio means that the lower the company's debt load, the less likely the company will default. The Z-value is an indicator that comprehensively reflects the probability of a company going bankrupt. The lower the probability of bankruptcy, the less likely the company will default. China's economic environment is affected by various factors, such as COVID-19. Hence, the closer we reach 2020, the higher the likelihood companies will default. Based on this, this study proposes the aforementioned hypotheses.

## 4 Results and discussion

### 4.1 Descriptive statistics of independence variables

Descriptive statistics of influencing factor variables of sample companies are shown in Table 4 as follows.

### 4.2 Descriptive statistics of the dependence variable

Distance to default and expected default probability are two corresponding values. This study chooses distance to default as an index to measure the company's credit default status. The distance to the default of sample companies is the dependent variable of this study.

The distance to the default of sample companies was calculated using the modified KMV with the ESG model. Then, the average value of distance to default from 2016 to

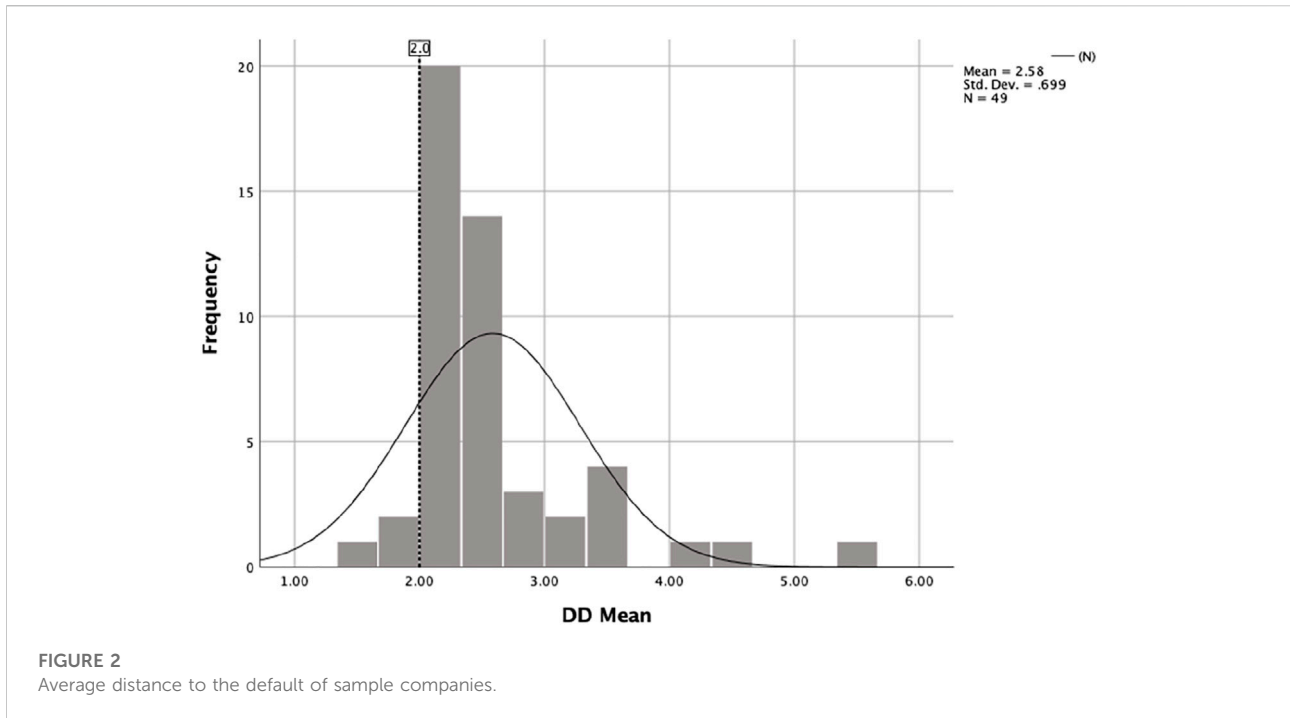


TABLE 5 Descriptive statistics of the dependent variable.

		Frequency	Percentage	Valid percentage	Cumulative percentage
Valid	0	158	64.5	64.5	64.5
	1	87	35.5	35.5	100.0
	Total	245	100.0	100.0	

Note: dependent variable is the distance to the default.

TABLE 6 Hausman test results.

Item	Result
Chi2 (5)	0.26
Prob > chi2	0.9983

TABLE 7 Wald test results.

Item	Result
Wald chi2 (5)	27.16
Prob > chi2	0.0001

2020 was calculated. Figure 1 shows the original distance to default means and corrected distance to default mean with the ESG rating of 49 sample companies.  $DD_0$  refers to the original distance to the default mean result, and  $DD_1$  refers to the modified results with an ESG rating.

The distance to default means is arranged in an ascending order. Then, the distance to default means of 10% quantile is taken as the critical default value. The frequency histogram of the average distance to default is shown in Figure 2. Distance to default = 2 is the default threshold.

According to the critical value of distance to default, all data can be divided into default and non-default groups. If the

distance to default is lower than the critical value 2, the dependent variable is set as 1. If the distance to default is higher than 2, the dependent variable is 0. Descriptive statistics for the dependent variable data is shown in Table 5.

## 4.2 Panel logit regression results

The distance to the default of sample companies is classified as the independent variable. The five selected variables, ROE, RT, ALR, z, and Year 2020, are independent variables to establish a

TABLE 8 Logit regression results.

Item	Coefficient	Std. error	z	P>  z	[95% Confidence interval]	
Constant	-1.97***	0.43	-4.56	0.00	-2.82	-1.12
ROE	-0.01**	0.05	-2.43	0.02	-0.2	-0.00
RT	-0.02**	0.01	-2.05	0.04	-0.04	-0.00
ALR	0.01**	0.04	2.47	0.01	0.00	0.02
z	0.12***	0.04	3.39	0.00	0.05	0.19
Year 2020	1.30***	0.39	3.35	0.00	0.54	2.07

Notes: the asterisk\*\*\* and \*\*denote statistical significance at 1% and 5%, respectively. Sample period: January 2016 to December 2020.

TABLE 9 Odds ratio results.

Item	Odds ratio	Std. error	z	P>  z	[95% Confidence interval]	
Constant	0.14***	0.06	-4.56	0.00	0.06	0.32
ROE	0.99**	0.00	-2.43	0.02	0.98	1.00
RT	0.98**	0.01	-2.05	0.04	0.96	1.00
ALR	1.01**	0.00	2.47	0.01	1.00	1.02
z	1.13***	0.04	3.39	0.00	1.05	1.21
Year 2020	3.69***	1.43	3.35	0.00	1.72	7.90

Notes: the asterisk\*\*\* and \*\*denote statistical significance at 1% and 5%, respectively. Sample period: January 2016 to December 2020.

panel logit model. Before panel data analysis, the Hausman test is performed on the data to determine whether the fixed-effect logit model or random-effect logit model is used in this study. According to Table 6, the  $p$ -value is greater than 0.05. The test statistic does not reject the hypothesis. This result shows that the random-effect model is better than the fixed-effect model. Therefore, this study adopts the random-effect logit model for regression.

Table 7 shows the model fitting effect. The  $p$ -value is 0.0001, which means that the model's overall fit is significant at 1%.

The panel logit results of the model and odds ratio results are shown in Table 8 and Table 9. The influence of the index variable on the credit default risk of listed internet finance companies is judged according to the regression coefficient of the variable. Suppose the regression coefficient of the index variable is positive, in that case, it indicates that the index positively correlates with the default risk of listed internet finance companies. The variation of indicator variables will lead to an increase in the default risk of networked financial companies. Suppose the regression coefficient of the index variable is negative, in that case, it indicates that the index is negatively correlated with the default risk of internet finance companies. The variation of index variables will reduce the default risk for internet finance companies.

According to the regression results in Table 8, the regression coefficients of return on equity are negative, and it is significant at

5%. This shows that the higher the profitability of the Internet financial company, the lower is the default risk. The profitability of an enterprise represents its ability to resist risks. The more profit an enterprise has, the more funds it will invest in ESG, thus reducing its default intention. Therefore, assumption H1 is supported. The inventory turnover coefficient was negative and significant at 5%. With accounts receivable turnover speed and high management efficiency, enterprise ESG performance will improve. Companies are less likely to default. The fast turnover of enterprise assets will bring high liquidity, and the speed of profit will be faster. Enterprises will invest their excess capital in ESG, thus reducing their default risk. This result supports hypothesis H2. The regression coefficient of the asset liability ratio is positive, indicating that it is positively correlated with the credit risk of internet finance companies. A high debt-to-asset ratio means that a higher percentage of a company's total assets are financed by borrowing. Hence the company will default more. This conclusion supports hypothesis H3.

The regression coefficient of the Z-value is positive and significant under 1%, indicating that it is positively correlated with the credit risk of Internet finance companies. The Z-value itself is a measure of the risk of failure. Companies with a higher risk of bankruptcy are more likely to default. Therefore, H4 has been proved. The regression coefficients for Year 2020 are positive and significant at 1%. The significance of the time



TABLE 10 Further logit regression results.

Variable	Model (9)	Model (10)
Constant	-2.83*** (0.00)	-1.74*** (0.00)
$L_{it-1}$		0.79** (0.03)
ROE	0.00 (0.74)	0.01*** (0.01)
RT	-0.20 (0.13)	-0.20 (0.06)
ALR	0.01*** (0.01)	0.01 (0.07)
z	0.17*** (0.00)	0.07* (0.05)
Year 2020	1.81*** (0.00)	1.03*** (0.01)
Wald test	22.86*** (0.00)	29.01*** (0.00)
Obs	196	196

Notes: The asterisk\*\*\*, \*\*, and \*denote statistical significance at 1%, 5%, and 10%, respectively.

dummy variable Year 2020 indicates that COVID-19 impacts the default of internet finance companies. COVID-19 is a catastrophic global health event that has affected the economic growth of the internet finance industry and increased the risk of default. The conclusion supports hypothesis H5. Therefore, all hypotheses are supported.

According to Table 9, when the ROE of an internet finance company increases by 1 unit, the probability of the default risk of the internet finance company decreases by 0.01 (1-odds ratio) units. Similarly, when the accounts receivable turnover of an internet finance company increases by 1 unit, the probability of default risk of the internet finance company decreases by 0.02 units. Likewise, when the asset liability ratio, Z-value, and Year 2020 increase by 1 unit, the probability of the default risk of internet finance companies will increase by 1.01, 1.13, and 3.69 units, respectively. Consequently, COVID-19 has a greater impact on the credit risk of internet finance among all the influencing factors.

For further discussion, two extended models were established for comparison. In real economic life, many economic variables are affected not only by the same period factor but also by the early-stage factor of the variable. Therefore, the first-order lag variable of the dependent variable was added for analysis in this study. First, the dependent variable is regressed with first-order lag, and a new regression model (9) is established to analyze the explanatory power of the impact indicators. Second, the first-order lag variable of the dependent variable was added to model (8) as an independent variable, and model (10) was established to analyze the influence of its early value.

$$L_{it-1} = \ln\left(\frac{p(Y=1)}{p(Y=0)}\right) = \alpha + \sum_{i=1}^n \beta_i \chi_{it} + \varepsilon_{it}, \quad (9)$$

$$L_{it} = \ln\left(\frac{p(Y=1)}{p(Y=0)}\right) = \alpha + L_{it-1} + \sum_{i=1}^n \beta_i \chi_{it} + \varepsilon_{it}. \quad (10)$$

Table 10 shows the model regression results after adding lag variables, and the results of the Wald test show that the two models are still valid. In the regression results of model (9), the three variables ALR, Z and Year 2020 are still significant, indicating that these three variables are more robust than the other two variables. The regression result of the model (10) shows a significant relationship between the explained variables lagging one period and the original explained variables, which proves that the credit risk of Internet finance integrated with ESG is indeed affected by its early stage.

## 5 Conclusion

Based on the classic credit risk assessment model, this study constructs a KMV-logit mixed model to study the credit risk of Chinese listed internet finance companies. The traditional KMV model only considers financial factors but ignores non-financial factors. In this study, the ESG index is introduced into the KMV model. The revised KMV-logit mixed model effectively analyzes the influence factors of the default risk for internet finance companies.

Second, return on equity, receivable turnover, asset liability ratio, Z-value, and Year 2020 all affect the default risk of internet finance companies to a certain extent. Among the independent variables, Z-value and the year 2020 have the strongest relationship with default risk. The significant results of the year 2020 indicate that China's internet finance environment has increased risks because of COVID-19. The Z-value is calculated according to Altman's Z-value model and represents its bankruptcy probability. This finding further indicates that the default result obtained by the model is valid.

Moreover, this study introduced the hysteresis variable of the explained variable to conduct an extended analysis. The results proved that the credit risk of internet finance after incorporating ESG correction would be affected by its preliminary results. Meanwhile, among all explanatory variables, asset-liability ratio, Z-value and Year 2020 are more robust. The conclusion is calculated based on the data on internet finance companies in China, so it applies to the reality of China's internet finance industry. However, the research essence of this study is based on the impact of ESG on credit risk, which is similar to the global financial system. Therefore, this study has reason to believe that the conclusion can also be applied to other countries and industries. However, the specific situation needs further analysis using data from different countries.

The policy implications of this study are as follows:

From the enterprise level, internet finance firms should value ESG in the process of credit risk management and reshape the cognitive concept of sustainable development of the enterprise. ESG is not only in the single dimension of the sustainable idea of corporate social responsibility. It covers enterprise for a sustainable social environment and the internal governance of multi-dimensional concepts, especially during the current economic downturn with the impact of COVID-19. Enterprises are facing long-term transformation and upgrading and performance decline pressure. In this context, enterprises are prone to credit risks and may go bankrupt once they are poorly managed. Therefore, enterprises should strengthen ESG management and integrate it into the credit risk management process by improving their ESG performance to predict and manage credit risks. Based on the conclusion of influence factors, internet finance companies should pay attention to managing their own profitability, operating capacity, and debt capacity to enhance their ability to resist risks.

From an investor's perspective, ESG performance should be incorporated into investment choices. Under the background of sustainable development, investors are important external supervisors and administrators to promote listed companies to fulfill their social responsibilities and improve corporate governance. When choosing investment objects, corporate investors should pay attention to their financial performance and non-financial performance, such as environmental performance, social performance, and corporate governance performance. This can help enterprises better manage risks, achieve sustainable long-term returns, and enhance the sustainable competitiveness of enterprises.

From the perspective of the government, the company's ESG performance evaluation system and information disclosure system should be improved. Meanwhile, the government should combine the ESG performance of internet financial companies in credit risk supervision. For those companies with better ESG performance, the government can give appropriate policy support. The government can impose appropriate penalties for companies with poor ESG performance. The government should gradually guide companies to improve their ESG performance and consciously disclose ESG information to provide effective information for credit risk supervision.

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## Data availability statement

Publicly available datasets were analyzed in this study. These data can be found at: <https://www.wind.com.cn/en/edb.html>.

## Author contributions

The first author has sourced and analyzed the data, and drafted some parts of the manuscript. The second author has been involved in the modeling and discussion of research ideas and drafted some parts of the manuscript. The third author has involved in the discussion of ideas and drafted some parts of the manuscript.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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