Credit Risk Assessment of Carbon Assets: Evidence from Chinese Listed Firms

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Abstract. This study presents a model to assess credit risk in Chinese listed companies, with a particular focus on incorporating carbon-related factors. By integrating macroeconomic indicators, ESG (Environmental, Social, and Governance) scores, and industry variables, the study examines the impact of carbon risk on default probabilities. Notably, it highlights a negative correlation between high ESG scores and default risks, emphasizing the importance of environmental factors in credit risk analysis within the carbon finance market. These findings provide valuable insights for credit risk management, particularly in relation to environmental sustainability and the pricing of carbon assets.

Keywords: Carbon Assets; Credit Risk Assessment; ESG

1 Introduction

It is widely acknowledged that climate risk poses an existential threat to human survival [1–3]. To achieve national sustainable development and high-quality growth and advance the construction of a harmonious human community, the Central Party Committee has decided to pursue “carbon peak and carbon neutrality.” Under the policy guidance of the Central Party Committee, the carbon emission trading market was officially launched in 2021, giving rise to various innovative financial services such as carbon emission rights pledges, carbon trusts, and carbon funds [4]. However, the intricate nature of climate change dynamics and the unique characteristics of carbon financial assets have hindered traditional financial markets from comprehensively exploring the pricing mechanisms and risk management frameworks associated with these assets. Promoting innovation in carbon financial products and services and leveraging the financial market’s role in carbon finance asset allocation have remained under-researched areas. Furthermore, the practical integration of carbon-related factors within corporate credit risk assessment is notably scarce.

Climate risk profoundly impacts supply chain finance, particularly regarding the carbon emissions associated with traditional high-carbon-emitting enterprises located upstream in the supply chain [1]. These enterprises may encounter increased costs, reduced profits, or even financial losses due to their transition towards low-carbon practices and technological advancements. Such challenges can impair their performance capacity and creditworthiness, triggering a detrimental “domino effect” throughout the supply chain. Consequently, it

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becomes imperative to promptly address the risk issues associated with carbon financial products within the context of supply chain management, aligning with the "dual carbon" objectives. Fortunately, advancements in big data analytics, blockchain technology, artificial intelligence, and the Internet of Things (IoT) offer new possibilities for accurately analyzing supplier qualifications and quantifying corporate carbon emissions. These technological developments enable enhanced transparency and understanding of environmental sustainability performance within the supply chain.

This study proposes a corporate carbon credit risk assessment model, whose primary function is identifying the credit risks of carbon financial services for enterprises. Specifically, the model can solve the following three problems: First, the model constructs an assessment system from the perspectives of macro-economy and micro-enterprise subjects, as well as economic and carbon-related risk indicators, covering four dimensions of credit risk indicators. It can reasonably analyze the impact of the air economy and carbon-related factors on the credit risk of underlying carbon assets, fully incorporating climate and environmental factors into the carbon credit risk assessment model. Second, the model uses digital technology to measure and analyze carbon-related credit risks, achieving quantitative risk calculations. Finally, the model helps the State Grid Corporation to study carbon financial service risk management mechanisms based on the results of risk credit risk assessments.

2 Carbon risk valuation model of carbon assets

This model is based on the forward density model established by Duan et al. (2012) [5], and it is a risk assessment model that considers the risk of listed companies exiting the market due to mergers and acquisitions or default bankruptcy.

The model acknowledges that default or bankruptcy are not the only reasons for a company to exit the public market. Risk analysis of listed companies needs to consider other possibilities of market exit. Therefore, exits from the public market for reasons other than default or bankruptcy are modelled as relatively independent "double random" processes. However, default or bankruptcy and other reasons are mutually exclusive events.

The objective of this model is to calculate the probability of a business defaulting in a future period after it has already survived for a certain amount of time. As illustrated in Figure 1, $p_{i,t}(3)$ represents the probability of a business in the t^{th} period (Today), having already survived for three periods and defaulting between the end of the third period and the end of the fourth period.

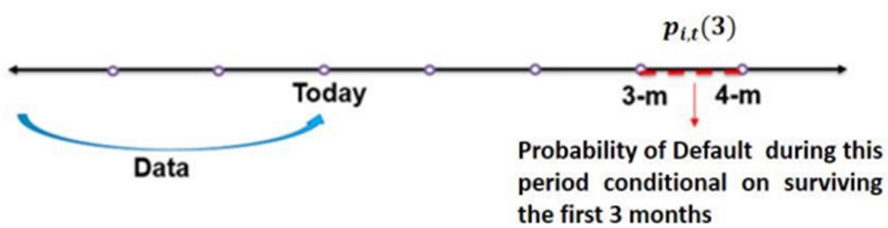

Fig. 1. Forward probability in the CRI model.

2.1 Probability of a business exiting the market

A business denoted as *i*, the process of default and other market exits are modeled as two independent random Poisson processes, with parameters λ_{it} and ϕ_{it}, respectively. Therefore, the survival probability of the business during the interval $[t, t+\tau]$ is:

$$\mathbb{E}_t\left[e^{-\int_t^{t+\tau}(\lambda_{it}+\phi_{it})ds}\right] \tag{1}$$

Therefore, the probability of the business surviving until the end of period t and default occurring in the interval $[t, t+\tau]$ is:

$$\mathbb{E}_t\left[\int_t^{t+\tau} e^{-\int_t^{s}(\lambda_{it}+\phi_{it})ds}\lambda_{is}du\right] \tag{2}$$

At this point, let the cumulative probability of business i exiting the market for any reason during the interval $[t, t+\tau]$ be:

$$F_{it}(\tau) = 1 - \mathbb{E}_t\left[e^{-\int_t^{t+\tau}(\lambda_{it}+\phi_{it})ds}\right] \tag{3}$$

Let:

$$\psi_{it}(\tau) = -\frac{\ln[1 - F_{it}(\tau)]}{\tau} \tag{4}$$

Then, $e - \psi_{it}(\tau)\tau = 1 - F_{it}(\tau)$ represents the survival probability for the interval $[t, t+\tau]$. The forward exit probability density is:

$$g_{it}(\tau) = \frac{F'_{it}(\tau)}{1 - F_{it}(\tau)} = \psi_{it}(\tau) + \psi'_{it}(\tau)\tau = \frac{\partial}{\partial\tau}[\psi_{it}(\tau)\tau] \tag{5}$$

So,

$$\psi_{it}(\tau)\tau = \int_0^{\tau} g_{it}(s)ds \tag{6}$$

Let the time at which business *i* exits the market for any reason be denoted as τ_{Ci}, and the probability that the business exits due to default be τ_{Di}. It is easy to deduce that $\tau_{Ci} \leq \tau_{Di}$. Thus, the forward default probability density for the business is:

$$\begin{aligned} f_{it}(\tau) &= e^{\psi_{it}(\tau)\tau} \lim_{\Delta\tau\to 0} \frac{\mathbb{E}_t[P(t+\tau < \tau_{Ci} = \tau_{Di} < t+\tau+\Delta\tau)]}{\Delta\tau} \\ &= e^{\psi_{it}(\tau)\tau}\frac{\partial}{\partial\tau}\mathbb{E}_t\left[\int_t^{t+\tau} e^{-\int_t^{s}(\lambda_{it}+\phi_{it})ds}\lambda_{is}du\right] \end{aligned} \tag{7}$$

This equates to the default probability during the interval $[t, t+\tau]$ being:

$$\int_0^{\tau} e^{-\psi_{it}(\tau)s} f_{it}(s)ds \tag{8}$$

2.2 Estimation of the forward exit probability density for businesses

This model uses a linear model to estimate businesses' forward default probability density and forward exit probability density. The explanatory variables include macro variables M_t, carbon risk factors C_{it}, and individual micro variables X_{it}, which are respectively:

$$\begin{cases} \ln f_{it}(s) = \alpha_0 + \boldsymbol{M}_t \boldsymbol{\alpha_M}(s) + \boldsymbol{C}_{it} \boldsymbol{\alpha_C}(s) + \boldsymbol{X}_{it} \boldsymbol{\alpha_X}(s) \\ \ln \tilde{g}_{it}(s) = \ln[g_{it}(s) - f_{it}(s)] = \beta_0 + \boldsymbol{M}_t \boldsymbol{\beta_M}(s) + \boldsymbol{C}_{it} \boldsymbol{\beta_C}(s) + \boldsymbol{X}_{it} \boldsymbol{\beta_X}(s) \end{cases} \tag{9}$$

This model definition ensures that $g_{it}(s) \geq f_{it}(s)$ because the total exit probability density must not be less than the default probability density since default is only one of the reasons for a business to exit the market. The variable selection is shown in the Table 1:

Table 1. Variable definition.

Variable		Variable Name	Description
Carbon Risk Factors	Macro Carbon Risk	National carbon market price return rate	Annualized carbon market price return rate
		National carbon market price volatility	Standard deviation of annualized return rate
		Carbon Policy Index	
	Individual Carbon Risk	Inclusion in national or local carbon market	0-1 dummy variable
		Company's dual-carbon strategy planning	0-1 dummy variable, based on company annual report and ESG report
		ESG Score	Central University of Finance and Economics International Institute of Green Finance ESG score
Macroeconomic and Market Variables		Market Return Rate	CSI 300 Index annualized return rate
		Risk-Free Rate	5-year government bond rate
Individual Financial Variables		Company Size	Total assets
		Cash to Total Assets Ratio	= Cash + Trading financial assets / Total assets
		ROA	= Net profit / Total assets at the beginning of the year
		Debt-to-Asset Ratio	= Total liabilities / Total assets

2.3 Model estimation

Based on the above definitions, this model utilizes Maximum Likelihood Estimation (MLE) to estimate the required parameters. Therefore, the corresponding separable pseudo-likelihood function for the model is:

$$\begin{cases} \mathcal{L}(\alpha_s) = \prod_{i=0}^{N} \prod_{t=1}^{T-s-1} \mathcal{L}_{it}(\alpha_s) \\ \mathcal{L}(\beta_s) = \prod_{i=0}^{N} \prod_{t=1}^{T-s-1} \mathcal{L}_{it}(\beta_s) \end{cases} \tag{10}$$

and

$$
\begin{aligned}
\mathcal{L}_{it}(\alpha_s) = {} & 1_{\{t_{0i} \le t, \tau_{Ci} > t+s+1\}} e^{-f_{it}(s)\Delta t} + 1_{\{t_{0i} \le, \tau_{Di} = \tau_{Ci} = t+s+1\}} \left(1 - e^{-f_{it}(s)\Delta t}\right) \\
& + 1_{\{t_{0i} \le, \tau_{Di} \ne \tau_{Ci}, \tau_{Ci} = t+s+1\}} e^{-f_{it}(s)\Delta t} + 1_{\{t_{0i} > t\}} + 1_{\{\tau_{Ci} < t+s+1\}} \\
\mathcal{L}_{it}(\beta_s) = {} & 1_{\{t_{0i} \le t, \tau_{Ci} > t+s+1\}} e^{-\tilde{g}_{it}(s)\Delta t} + 1_{\{t_{0i} \le, \tau_{Di} = \tau_{Ci} = t+s+1\}} \\
& + 1_{\{t_{0i} \le, \tau_{Di} \ne \tau_{Ci}, \tau_{Ci} = t+s+1\}} \left(1 - e^{-\tilde{g}_{it}(s)\Delta t}\right) + 1_{\{t_{0i} > t\}} + 1_{\{\tau_{Ci} < t+s+1\}}
\end{aligned} \tag{11}
$$

where $\Delta t = 1/12$, N is the number of businesses in the entire sample, and T is the time interval of the entire sample.

3 Analysis of default / delisting probability of Chinese-listed companies

This model obtains financial data on Chinese listed companies from the Wind database and the annual reports of the listed companies.

First, the model compares its estimated default probabilities with explicit benchmarks (such as credit ratings) to assess the model's fitting capability. In this context, as shown in Figure 2, the red horizontal line represents the median, the box represents the 25th and 75th percentiles, and the small circles represent the average values.

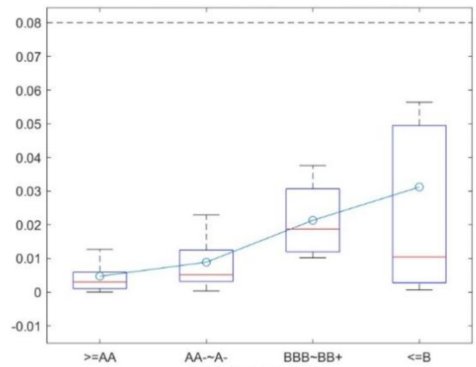

Fig. 2. Cumulative expected default probability for 2022 (credit rating).

This model presents estimates of the default probabilities for 2022 based on data from 2021, and the charts for further years (2023 to 2016) are very similar to those for 2022. It is evident that, on average, the mean default probability increases as the credit rating decreases. Excluding extreme values, the default probabilities for ratings of AA and above mainly range from 0.1% to 0.7%, for A- to AA- between 0.2% and 1.2%, for BB+ to BBB between 1.2% and 3%, and for B and below between 0.5% and 5%.

This indicates that constructing this model and selecting explanatory variables in the example data can estimate the default probability of companies relatively well. However, the dispersion of probability estimates for companies with credit ratings of B and below is significantly larger, suggesting that this model has better estimation capability for companies with credit ratings higher than B.

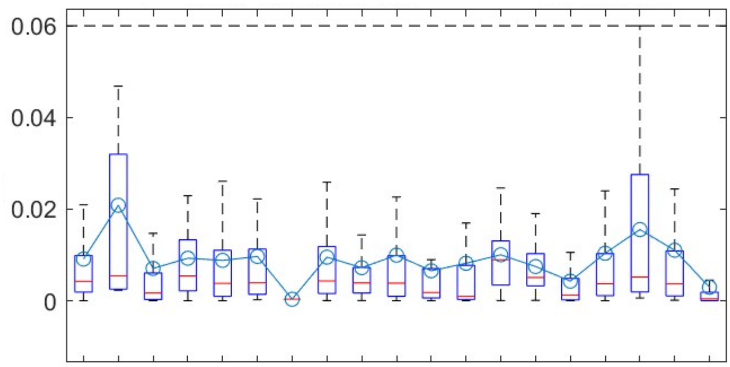

Fig. 3. Cumulative expected default probability for 2022 (industry heterogeneity).

This model categorizes and analyses the distribution of default probabilities based on the thirteen major industry categories defined by the China Securities Regulatory Commission. Figure 3 presents the results of our analysis, with the x-axis representing industries including Transportation, Warehousing, and Postal Services; Accommodation and Food Services; Information Transmission, Software, etc.; from left to right. The analysis reveals that industries such as accommodation and catering, mining, agriculture, forestry, and water conservation show higher default risks, while industries like finance, scientific research, culture and sports, and information technology exhibit lower default risks. The distributions of default and overall delisting probabilities for other years generally follow a similar trend.

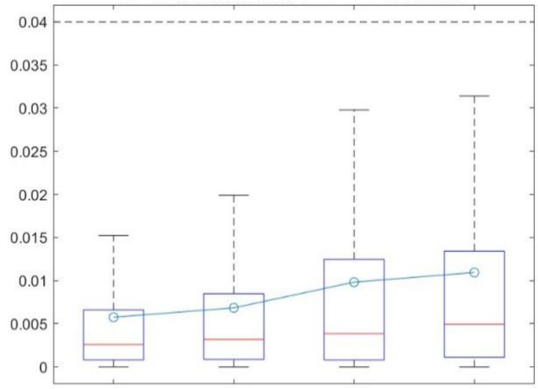

Fig. 4. Cumulative expected default probability for 2022 (ESG heterogeneity).

This model divides companies into four groups based on their ESG scores at the 25%, 50%, and 75% percentiles, categorized as low, medium-low, medium-high, and high, and calculates the default probability distribution for each group. Figure 4 presents the estimation results. Specifically, companies with higher ESG scores have relatively lower default probabilities. Specifically, the default probability for the high ESG group is generally between 0.05% and 0.7%, for the medium-high ESG group between 0.05% and 0.9%, for the medium-low ESG group between 0.05% and 1.2%, and for the low ESG group between 0.1% and 1.3%. This indicates that ESG grouping is a good reference variable for assessing a company's credit risk.

4 Conclusion

The study demonstrates the efficacy of the proposed model in estimating the default probabilities of Chinese listed companies, considering various factors like credit ratings, industry heterogeneity, and ESG scores. The results indicate that higher ESG scores correlate with lower default probabilities, and the model shows better estimation capabilities for companies with credit ratings above B. This study highlights the importance of including ESG factors in credit risk assessment and the potential of this model in predicting default risks in the context of carbon finance.

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