Risk Assessment of Fluorochemical Companies under Carbon Trading

-- A Case Study of Juhua Corporation's Refrigerant

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Abstract. Under the "Dual Carbon" strategy, promoting the development of the carbon trading market has become a key component of the national energy and environmental strategy, with the chemical industry serving as the "pioneer" in the country's efforts to achieve carbon peaking and carbon neutrality. This paper explores this emerging trend using Juhua Corporation's refrigerant business as a case study. First, it examines the carbon trading mechanism, highlighting the promising prospects following the European Union's inclusion of the chemical industry in the carbon market. Next, through an in-depth analysis of the company's refrigerant business and relevant policies, the paper conducts scenario-based stress testing from two perspectives: refrigerant technology evolution and the tightening of carbon trading policies. The analysis is primarily based on the KMV model to assess the investment risks for Juhua's refrigerant industry in the future. Finally, the paper proposes practical recommendations based on the findings, offering significant insights for the transformation and development of fluorochemical companies within the context of the carbon trading market.

Keywords: Carbon Market; Chemical Enterprises; Risk Assessment; Stress Testing.

1. Introduction

As societal development progresses, climate issues have become increasingly critical, attracting widespread attention from the international community. The concept of the "greenhouse effect" was first proposed at the end of the 19th century [1]. The IPCC has issued several assessment reports, highlighting that climate change will cause significant, widespread, and irreversible damage to both human societies and ecological systems [2].

In the 1990s, climate change evolved from a purely scientific issue into a major economic and political challenge. Since greenhouse gas emissions affect global public goods, climate change must be addressed through international cooperation. In 1992, the foundational document, the "United Nations Framework Convention on Climate Change," was officially adopted [3]. In 1997, the "Kyoto Protocol" was successfully ratified, marking the first time in human history that greenhouse gas emissions were legally constrained, thus establishing the international framework for addressing climate change [4].

In the context of escalating global climate change, China, as one of the largest carbon-emitting countries, has actively implemented measures to tackle the climate change challenge. In 2020, China clearly outlined the "Dual Carbon" goals: achieving carbon peaking by 2030 and carbon neutrality by 2060, thereby positioning carbon reduction as a central pillar of its future development. Carbon emissions trading serves as the cornerstone of China's greenhouse gas reduction efforts [5]. Although the system currently applies only to the power generation sector, it will soon cover eight major energy-intensive industries, and is expected to encompass 72% of China's carbon emissions by 2025.

In 2022, the chemical industry faced a downturn. The instability of the global economy placed pressure on the sector, fluctuations in raw material prices impacted the cost structures of chemical companies, and stricter environmental protection policies posed additional challenges [6]. These factors led to sales difficulties, overproduction, challenges in accurately forecasting and controlling costs, and issues related to upgrading equipment and improving production processes, all of which further exacerbated profit pressures.

Currently, research on the relationship between carbon market trading and traditional chemical enterprises is relatively limited. An in-depth theoretical analysis of how carbon market trading mechanisms impact traditional chemical companies, such as Juhua Co., Ltd., will help fill this research gap. It will also explore the role and impact of the carbon market across various industries and provide guidance for the government in formulating more precise and effective carbon market trading and industrial policies. This will not only promote emission reductions and green development within enterprises but also offer insights into how companies can adjust their strategies and operations in the carbon trading context.

From a practical standpoint, analyzing the real-world effects of carbon market trading mechanisms and policies on enterprises can offer guidance for companies aiming to achieve green transformation, enhance environmental performance, and facilitate industrial upgrading. Additionally, the findings can assist traditional chemical enterprises like Juhua Co., Ltd. in formulating adaptation strategies to maintain competitiveness within the carbon market trading environment. Enterprises can apply the research conclusions to identify suitable carbon reduction strategies and investment directions. The study results can also be used to assess the real-world impact of carbon market policies, providing a basis for governmental policy adjustments. This will contribute to achieving carbon reduction targets and optimizing industrial structures.

2. Literature Review

2.1 Development Status of the Carbon Trading Market

The development of China's carbon market can be divided into three stages: First Stage (2002-2012): China participated in international carbon trading through the Clean Development Mechanism (CDM) projects established by the Kyoto Protocol, generating Certified Emission Reductions (CERs). Second Stage (2013-2020): Carbon emission trading pilots were launched in various regions, and in addition to quota trading, the National Certified Voluntary Emission Reductions (CCERs) could be used to offset emissions, thus establishing a domestic carbon market [7]. However, due to low trading volumes, project irregularities, and imbalances in supply and demand, project registrations for CCERs were suspended in March 2017, although existing CCERs can still be traded. Third Stage (2021-Present): On July 16, 2021, China's national carbon trading market was established, initially covering only the power generation sector. With an annual coverage of approximately 4.5 billion tons of CO_2 emissions, it has become the largest carbon spot market in the world [8].

The current development of the carbon market can be understood from three perspectives: the national carbon market, pilot carbon markets, and the CCER program. Official trading began on July 16, 2021, with a trading volume exceeding 4.1 million tons on the opening day. By the end of January 2023, the cumulative trading volume of carbon emission allowances reached 230 million tons [9]. Trading primarily occurs at the end of compliance periods, with December and November accounting for 13% and 70% of the total volume, respectively. After the first compliance period, the market experienced a decline in trading activity.

Since October 2011, pilot carbon trading schemes have been launched in cities such as Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, Shenzhen, and Fujian. Due to regional differences in economic development, energy consumption, and carbon market design, there are significant variations in trading volume, transaction amounts, and prices. As a key supplementary component of the carbon market, the National Development and Reform Commission (NDRC) has approved a total of 2,871 CCER projects, with 861 registered and 287 reduction projects [5]. The majority of CCER projects focus on renewable energy, including wind, solar, and hydroelectric projects. Between 2014 and 2021, the top seven carbon trading pilots traded 442 million tons of CCERs, with the Shanghai Carbon Exchange accounting for 171 million tons [10].

2.2 Carbon Trading Products

Carbon trading refers to the exchange of carbon emission allowances, where the government sets a total carbon emissions cap and allocates carbon emission quotas (i.e., emission rights) to emission entities. As these entities adjust their operations, they may experience either a surplus or a deficit in carbon allowances, which can be freely bought and sold in the market [11].

The primary carbon trading products include CER, CCER, and CEA carbon allowances: CER (Certified Emission Reduction) refers to the emission reductions achieved through the Clean Development Mechanism (CDM) as outlined in the Kyoto Protocol [10]. It is a specific term used for emission reductions verified by the United Nations' CDM Executive Board, with validation by a Designated Operational Entity (DOE) [12]. Once the United Nations issues a CER certificate, these reductions can be traded internationally, primarily between developed and developing countries. CCER (Chinese Certified Emission Reduction) is similar to CER, but it pertains specifically to emissions reductions within China. CCERs are issued for reductions achieved through projects, mainly in renewable energy sectors such as wind power, solar energy, and biomass [13]. Although CCERs are primarily used in international markets, they are considered equivalent to CERs in China's carbon market. CEA (Chinese Emission Allowance) refers to the carbon quotas allocated by the Chinese government to key emission units for specific periods. Each unit of CEA represents the right to emit one ton of CO_2 equivalent [12]. The trading of CEA is primarily focused on the allowances allocated to these key emission units.

2.3 Domestic Trading Mechanism

Based on international experiences with carbon emissions trading, the basic method for the allocation of carbon emission allowances in China is as follows: the carbon emission allowances allocated to enterprises represent the annual upper limit of carbon dioxide emissions they can discharge for free, with one unit of allowance corresponding to one ton of CO_2 emissions [14]. Enterprises must surrender the allowances they hold by the end of the compliance period. If the surrendered allowances cover the emissions for that year, the enterprise will fulfill its compliance obligations; otherwise, the enterprise must purchase additional allowances to meet the required level. The allowances held by an enterprise come from two main sources: firstly, the initial allocation from the primary emissions allowance market, and secondly, allowances obtained through trading in the secondary market. The initial allocation is issued by the government, converting previously unrestricted emission rights into scarce assets [15]. These initial allowances can be either distributed for free or auctioned. In the case of free allocation, enterprises can acquire allowances from the government without charge, whereas in the case of auctioned allowances, enterprises must pay to acquire the necessary allowances [16].

The distribution of free allowances is based on various benchmarks and can be broadly classified into two methods: the historical method and the benchmark method. The historical method includes the total historical emissions method (grandfathering) or the historical emission intensity method. These methods determine the amount of free allowances an enterprise receives during the compliance year based on the total emissions or average emissions per unit of production in previous years, and an annual adjustment factor is applied to control total emissions [8]. The benchmark method, also known as the reference method, uses the emission intensity of advanced enterprises within certain technological parameters—such as the same production process or within a specified production scale range—as a benchmark [17]. Typically, this includes the top percentiles of enterprises in the industry. The free allowance allocation for a compliance enterprise is then determined by its actual production output and the benchmark value.

3. Data and Methods

3.1 Data

The corporate data used in this study are derived from the annual reports of Juhua Co., Ltd. Established in 1998, the company is one of the eight major chemical production bases formerly under the Ministry of Chemical Industry. With a development history spanning over 60 years, the company has undergone three distinct phases of business development: the first phase focused on establishing factories and developing fertilizers and organic chemicals; the second phase, beginning in the 1990s, involved the introduction of advanced foreign fluorochemical production technologies; and the third phase, starting in 2005, marked a new round of industrial restructuring, driven by high-tech industries. The company maintains a clear ownership structure, with Juhua Group as the controlling shareholder and the Zhejiang State-owned Assets Supervision and Administration Commission as the actual controller. As of 2023, Juhua Group holds 52.7% of the company's shares directly and an additional 2.21% through its wholly-owned subsidiary, Zhejiang Juhua Investment Co., Ltd., bringing its total shareholding to 54.91%. Juhua Co., Ltd. operates five business divisions, 24 wholly-owned or majority-owned subsidiaries, and four branch offices. Furthermore, the risk-free rate used is based on the one-year government bond rate, sourced from the China Bond Information Network. Policy data are sourced from the company's official website. The refrigerant market structure and outlook data are derived from the "Analysis of the Development Trends and Investment Prospects of the Chinese Refrigerant Industry (2024-2030)."

3.2 Methods

3.2.1 ARIMA Model

The ARIMA (AutoRegressive Integrated Moving Average) model is a fundamental statistical tool used for time series forecasting, particularly effective for univariate data exhibiting trends and patterns over time. The model integrates three key components: autoregression (AR), differencing (I for Integrated), and moving average (MA). The autoregressive part models the current value of the series as a linear combination of its previous values, expressed mathematically as

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t \quad (1)$$

The integrated component involves differencing the series to achieve stationarity, which is crucial for reliable modeling, and is denoted by

$$\Delta^d Y_t = Y_t - Y_{t-d} \quad (2)$$

Applying an ARIMA model begins with data preparation and exploration, including visualizing the time series to identify trends and seasonality, followed by assessing stationarity using tests such as the Augmented Dickey-Fuller (ADF) test. If the series is non-stationary, differencing is applied to stabilize the mean. The next step involves identifying the appropriate orders of the ARIMA model (p, d, q) by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots to determine the significance of lagged terms. Once the model parameters are estimated, typically using Maximum Likelihood Estimation (MLE), the model undergoes diagnostic checks to ensure that residuals resemble white noise, indicating a good fit. Information criteria like Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) may be used to compare and select the best model. Finally, the fitted ARIMA model is employed to forecast future values, and its performance is validated using out-of-sample testing and metrics such as Root Mean Squared Error (RMSE) to assess accuracy. The ARIMA model's flexibility and interpretability make it a versatile choice for various forecasting applications, although it relies on the assumption of linearity and requires the time series to be stationary, which may necessitate multiple transformations.

3.2.2 GM(1,1) Model

The GM(1,1) model, a cornerstone of Grey System Theory, is an effective predictive tool designed for time series analysis, particularly when dealing with limited or incomplete data. The

model begins by applying an Accumulated Generating Operation (AGO) to the original data, which helps to emphasize underlying trends and reduce random fluctuations. This transformed data is then used to construct a first-order differential equation that captures the deterministic pattern of the series. By estimating the model parameters through methods such as least squares, the GM(1,1) model generates forecasts based on the established relationship. To enhance its predictive capability, the Grey-Markov model integrates the GM(1,1) approach with Markov chain properties, allowing it to account for both deterministic trends and probabilistic transitions between different states. The application process involves data collection and preprocessing, transformation through AGO, parameter estimation, model construction and solving, and finally, generating and validating forecasts against actual observations. This hybrid model is particularly valuable in fields like economics, engineering, and environmental science, where data scarcity and uncertainty are common challenges. Its ability to produce reliable predictions with minimal data inputs makes it a vital tool for decision-making and strategic planning, although its assumptions of linearity and consistent system behavior may limit its effectiveness in more complex or highly volatile environments.

3.2.3 KMV Model

The KMV Model is a sophisticated credit risk assessment tool widely utilized in the financial industry to estimate the probability of a firm's default. Developed by KMV Corporation, which is now part of Moody's Analytics, the model leverages insights from option pricing theory to provide a nuanced analysis of a company's financial health and creditworthiness.

At its core, the KMV Model treats a company's equity as a call option on its assets. This perspective is rooted in the Merton Model of corporate liability, where equity holders have the right, but not the obligation, to "buy" the company's assets by paying off its debts at a predetermined strike price (the face value of debt). If the value of the company's assets exceeds this strike price at debt maturity, equity holders exercise the option, effectively preventing default. Conversely, if asset values fall short, default occurs.

The detailed procedure is as follows. First, the Black-Scholes option pricing model (Eq. 3) is employed to estimate the market value of the company's assets and the volatility of those assets, based on the market value of the company’s equity, its volatility, time to maturity, the risk-free lending rate, and the book value of liabilities.

$$\frac{\partial \mathrm{V}}{\partial \mathrm{t}} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 V}{\partial S^2} = \mathrm{rV} - \mathrm{rS}\frac{\partial \mathrm{V}}{\partial \mathrm{S}} \tag{3}$$

Second, the company’s default threshold is calculated based on its liabilities (the default threshold is the sum of the company’s short-term debt with a maturity of less than one year and half of the book value of its outstanding long-term debt). The distance to default for the borrower is then computed.

Finally, by analyzing the relationship between the company’s distance to default and the expected default frequency (EDF), the company’s expected default probability is derived.

4. Results

4.1 ARIMA Model

After conducting a thorough analysis of the refrigeration industry, we recognize that the sector is currently at a pivotal crossroads, primarily influenced by two key factors: the technological transition from third-generation to fourth-generation refrigerants, and the increasingly stringent national carbon trading policies.

The updates brought by technological iteration not only promise substantial profits for enterprises but also entail higher research and development (R&D) costs. This is particularly evident in Juhua Co.'s refrigerant business, where the fourth-generation refrigerants yield higher profit multiples than the third-generation ones, but come with higher material and R&D expenses. On the other hand, as carbon trading policies tighten, companies are likely to face significant financial pressures in the short term. This will affect cash flow and may also increase the risk of default. Especially against the

backdrop of China's chemical industry transitioning to the full carbon trading system, this risk becomes particularly pronounced.

Therefore, given these two major factors, it is of paramount importance to develop a risk assessment model specifically tailored to Juhua Co.'s refrigerant business. Such a model will not only enable us to more precisely quantify future market and financial risks but also provide the company's management with a more robust, scientifically grounded foundation for decision-making. In an era filled with uncertainty and challenges, an effective risk assessment model offers not only profound insights into the present situation but also provides early warning signals for managing future risks, thereby enabling the enterprise to better navigate a variety of challenges.

Using the ARIMA model, we forecasted equity volatility and the risk-free rate from 2018 to 2023 to extend through to 2040. The forecasted results are presented in Table 1.

Table 1. ARIMA model forecast result

Year	Equity volatility	Risk-free rate
2024	0.030439	2.408962
2025	0.034838	2.357012
2026	0.026006	2.38023
2027	0.023994	2.372225
2028	0.033282	2.56911
2029	0.03312	2.524874
2030	0.024193	2.407372
2031	0.026676	2.307821
2032	0.034957	2.678565
2033	0.030635	2.424891
2034	0.023713	2.461262
2035	0.029783	2.301785
2036	0.035221	2.624233
2037	0.028078	2.568132
2038	0.024634	2.456021
2039	0.032617	2.732897
2040	0.034178	2.713291

The values of parameters (p, d, q) in the ARIMA(p, d, q) model are presented in Table 2.

Table 2. The values of parameters (p, d, q)

Parameters	p	d	q
Stock volatility	2	2	1
Risk-free rate	1	2	1

To assess the predictive accuracy of the ARIMA model applied to our data, relevant statistical tests were conducted, including the residuals' normality test, relative RMSE test, and the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). All these tests passed, confirming that the results predicted by the model are valid.

4.2 GM(1,1) Model

Next, based on the Grey Model (GM(1,1)), we use equity market value, long-term debt, and current liabilities from 2018 to 2023 to forecast values up to 2040. The forecasted results are presented in Table 3.

By calculating the relative residuals to evaluate the forecasting accuracy of the GM(1,1) model, we found that the model demonstrates satisfactory predictive performance. Therefore, the forecasted results from the model are valid.

Table 3. GM (1,1) model forecast result

Year	Equity market value	Long-term debt	Current liabilities
2024	45,052,422,111.016	756,879,421.85	4,323,847,631.12
2025	45,857,896,976.69	856,879,421.85	4,323,847,631.12
2026	46,676,752,660.66	877,879,350.67	4,555,036,377.53
2027	47,509,368,437.00	998,879,279.49	4,786,225,123.95
2028	48,356,137,295.82	1,009,879,208.31	5,017,413,870.36
2029	49,217,462,830.22	1,140,879,137.13	5,248,602,616.77
2030	50,093,764,047.27	1,461,879,065.96	5,479,791,363.18
2031	50,985,473,409.08	1,482,878,994.78	5,710,980,109.59
2032	51,893,037,408.73	1,503,878,923.60	5,942,168,856.01
2033	52,816,918,440.33	1,524,878,852.42	6,173,357,602.42
2034	53,757,592,816.97	1,645,878,781.24	6,404,546,348.83
2035	54,715,550,692.73	1,866,878,710.07	6,635,735,095.24
2036	55,691,296,671.72	1,887,878,638.89	6,866,923,841.65
2037	56,685,350,985.03	1,908,878,567.71	7,098,112,588.07
2038	57,698,251,265.75	2,029,878,496.53	7,329,301,334.48
2039	58,730,552,895.99	2,050,878,425.35	7,560,490,080.89
2040	59,782,829,566.82	2,071,878,354.18	7,791,678,827.30

4.3 KMV Model

4.3.1 Changes in Default Probability in Carbon Trading

Under the influence of standalone carbon trading policies, we have observed a year-on-year increase in the default risk of enterprises, with a specific rise of 6%. This increase has occurred alongside a continuous rise in enterprise market capitalization. However, if the financial performance of these enterprises declines, carbon trading policies may have a more pronounced impact on their risk profile. These observations have been incorporated into the KMV model for detailed analysis (see Fig. 1).

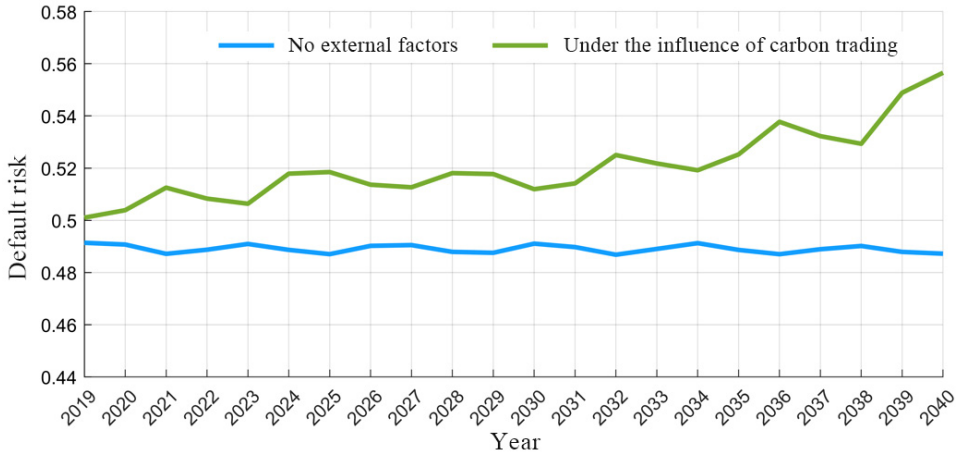


Fig 1. The trajectory of default probability under the impact of standalone carbon trading

In the KMV model, the key parameters for assessing the default probability of enterprises include market capitalization, debt levels, and stock price volatility. As the government increases carbon quotas and carbon prices continue to rise, operational costs for enterprises increase, which directly affects the stability of their market capitalization and stock price volatility. Even when market value is steadily increasing, rising operational costs may lead to higher debt levels, thus increasing the probability of default.

4.3.2 Changes in Default Probability with Technological Iteration

In the context of evolving technologies, corporate default risk is closely linked to technological iterations. Specifically, when fourth-generation technology entered mass production in 2024, the default rate experienced a significant shift (see Fig. 2). From 2024 to 2030, as enterprises transitioned from second-generation to third-generation production capabilities, default risk remained at a low level. This period is characterized by relatively stable financial conditions and low risk. However, between 2030 and 2040, as enterprises moved from third-generation to fourth-generation technologies, profits grew significantly, and the default probability decreased by as much as 3%. This reduction in default risk was not only a result of high profits but also signaled a continued downward trend.

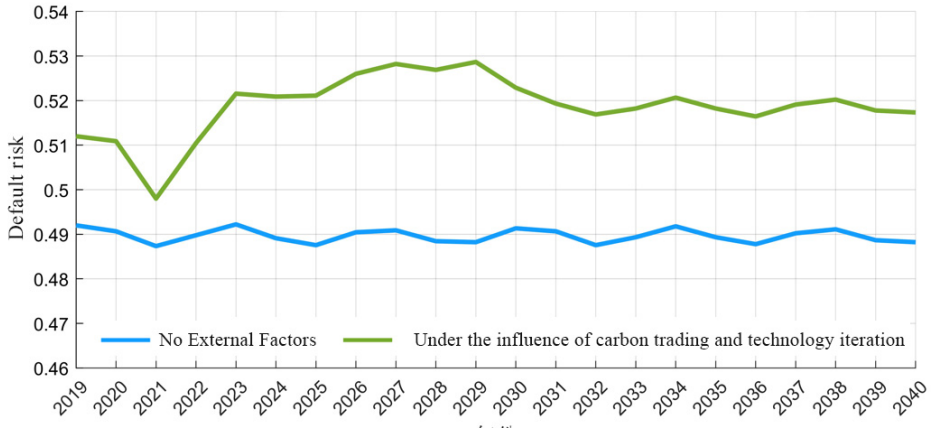


Fig 2. The trajectory of default probability under the impact of technological iteration

In the KMV model analysis, these technological iterations had a notable impact on the enterprise's market value, debt levels, and stock price volatility. The growth in market value, stock price stability, and prudent debt management all contributed to the reduction in default probability. Overall, technological upgrades in core business operations played a crucial role in significantly improving the financial health of enterprises and mitigating default risk. These findings further validate the effectiveness of the KMV model in forecasting and evaluating corporate default risks.

4.3.3 Changes in Default Probability under the Combined Impact of Factors

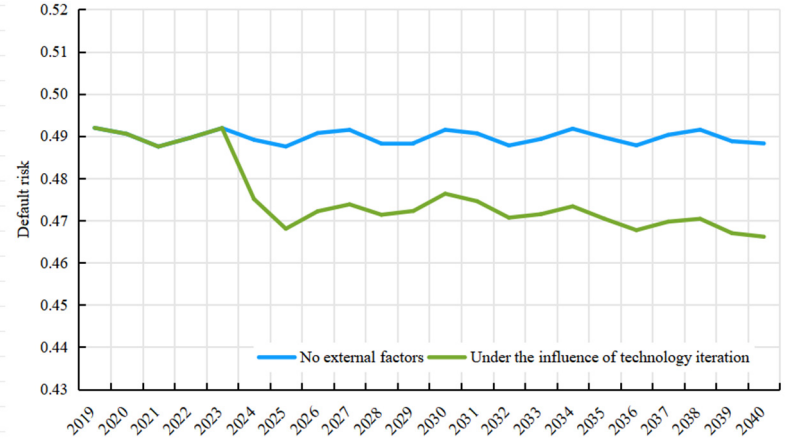


Fig 3. Default probability under the impact of carbon trading and technological iteration

In our risk assessment study, particularly within the analytical framework of the KMV model, we observed that two key factors influence the financial condition and default risk of enterprises in different directions. As shown in the results from Fig. 3, in the early stages, the carbon trading policy

placed pressure on the financial conditions of enterprises. Due to the gradual increase in carbon quotas and the continuous rise in carbon prices, both operational costs and default risk increased. This directly affected the evaluation of market value and debt levels in the KMV model, thus raising the default probability.

However, regarding technological iteration, especially the shift from third-generation to fourth-generation production capabilities, we observed that this transition not only significantly enhanced the profitability of the core business but also boosted the enterprise's market value. In the KMV model, the growth in market value and the relative stability of debt levels helped reduce default probability, thereby partially offsetting the negative pressures from carbon trading.

Nonetheless, the hedging effect brought by technological progress is not all-encompassing. In other words, while technological upgrades can mitigate the negative impacts of carbon trading, they cannot eliminate them. Therefore, for the chemical and other related industries, it is crucial to proactively prepare for and address the financial risks posed by carbon trading policies.

Overall, enterprises and industry decision-makers need to consider both key factors within the KMV model's analysis to assess potential financial risks more comprehensively and accurately. This will help them formulate appropriate strategies and countermeasures, ensuring the financial health and stability of enterprises in a complex and volatile business environment.

5. Conclusion

After conducting a series of in-depth analyses and simulations, we have drawn two core conclusions that provide critical guidance for the future strategy of Juhua Co., Ltd.

First, the full implementation of carbon emissions trading in the future is expected to increase Juhua Co., Ltd.'s financial strain and default risk to some extent. Based on the financial stress tests using the KMV model, it is predicted that this policy will result in a 2-5% increase in the default probability. Such an increase should not be underestimated in strategic planning and risk management. Particularly under the increasingly stringent global carbon reduction and carbon trading policies, this risk is likely to become a key factor affecting the long-term, stable development of the company.

Second, although the technological upgrade from the third to the fourth generation introduces new market opportunities and potential profits for Juhua Co., Ltd., these positive effects are relatively limited and insufficient to fully offset the negative impact of carbon trading. Even considering the potential economies of scale and market competitiveness generated by the technology upgrade, the profits from these factors are not enough to completely counterbalance the additional financial burden imposed by the carbon trading policy.

In summary, Juhua Co., Ltd. must prioritize these two core risk factors in the future and implement appropriate countermeasures at both the strategic and operational levels. These measures may include strengthening the budget management of carbon trading costs, optimizing R&D investments to improve the cost-effectiveness of fourth-generation refrigerants, and continuously performing risk assessments to ensure that corporate decisions remain aligned with changes in the market environment and policies. Only through comprehensive and scientific risk management can Juhua Co., Ltd. achieve sustainable and steady development in an ever-changing market and policy environment.

Based on the findings of this study, companies can improve in the following areas: Risk Management Strategies. To effectively manage risks associated with carbon trading, companies should implement an early warning system for price fluctuations by utilizing a real-time data monitoring system to track changes in carbon prices. This approach is crucial in the highly uncertain carbon market, where price volatility can significantly increase short-term costs. By monitoring data in real time, companies can swiftly adjust their strategies, such as purchasing carbon allowances in advance or investing further when prices are low, thereby mitigating the adverse effects of price swings. Additionally, allocating a certain percentage of net profits each quarter to a dedicated risk reduction fund provides a financial buffer to cope with potential price increases, acting as a safety net

to alleviate financial pressure during periods of rising carbon prices. Ensuring compliance with carbon trading regulations is equally important, and establishing a robust internal auditing process that includes regular audits of carbon emissions and trading records can minimize legal risks and fines associated with non-compliance.

Furthermore, managing risks related to technology iteration is essential for sustainable development. Continuous investment in research and development, along with strengthening collaborations with universities and research institutions, can drive technological advancements that reduce carbon emissions and lower carbon trading costs, while also mitigating potential regulatory risks. In the long term, these investments may lead to higher production efficiency and reduced operational costs. Equally important is employee education and technical training; organizing regular internal training sessions and inviting external experts ensures that employees are proficient in and can effectively apply new technologies. This human resource investment facilitates a smooth transition to new technologies, preventing disruptions in production and avoiding additional costs due to technological unfamiliarity. Comprehensive market research before launching new technologies or products is also vital, as understanding market demand and potential reactions helps companies avoid high-risk investments and product developments. Through thorough market research, companies can more accurately position their products, reduce uncertainty regarding market acceptance, and potentially identify market risks in advance. These comprehensive strategies aim to mitigate the risks associated with both carbon trading and technology iteration. By implementing these measures, companies can not only address potential short-term challenges but also prepare for long-term, sustainable development.

Finally, this paper proposes the following policy recommendations: the government should consider introducing a more flexible carbon trading system by setting price caps and floors to mitigate the risk of price fluctuations that businesses face. Additionally, to encourage enterprises to invest in the development of low-carbon technologies, the government ought to offer corresponding research grants or tax incentives. Increasing transparency in carbon trading and corporate carbon emissions data is also essential; therefore, the government should promote policies related to information disclosure to ensure that all stakeholders can make more informed decisions. Furthermore, when formulating policies related to carbon trading and environmental protection, adopting a long-term strategic perspective and establishing a coherent regulatory framework is crucial to avoid introducing unnecessary uncertainty and risks for businesses. These proposed policy recommendations will not only assist companies in better managing the risks associated with carbon trading and technological iteration but will also provide valuable guidance for the government to more efficiently regulate market conduct and foster sustainable development.

In future research, the following directions can be considered: Given the limitations of individual models, it is essential to investigate how integrating various risk assessment and forecasting models, such as the KMV model and machine learning algorithms, can enhance accuracy and reliability. Additionally, beyond the direct financial effects, carbon trading can have significant implications for a company’s supply chain. Therefore, future studies should examine how optimizing supply chain strategies may mitigate the adverse effects of carbon trading. Furthermore, the relationship between corporate social responsibility (CSR) and risk management remains relatively under-researched. Exploring how enhancing CSR practices could reduce a company's risk exposure may provide valuable insights. By addressing these areas, future research can contribute to a more comprehensive understanding of risk management in the context of carbon trading and broader corporate strategies.

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