Proceedings of the 5th International Conference on Financial Technology and Business Analysis
DOI: 10.54254/2754-1169/2026.39077

Multi-Factor Monte Carlo Actuarial Simulation and Financial Early Warning Research on the Cash Flow Risk of Real Estate Enterprises by Ownership Type

Qingzheng Sun

College of Computer Science, Sichuan University, Chengdu, China
sunqingzheng@stu.scu.edu.cn

Abstract. China's property market has undergone profound industrial restructuring in recent years. Against the background of continuous industry downturn, real estate developers with different ownership types have demonstrated notable divergence in their capacity to withstand external liquidity shocks. Traditional static financial early warning approaches often fail to capture dynamic volatility and tail risks faced by property firms. This study selects a sample of 87 A share listed real estate firms spanning 2018 to 2023. It separately calibrates four stochastic factors, including sales growth, financing cost, construction cost growth and debt maturity ratio for state owned, private and mixed ownership enterprises. A multi factor Monte Carlo cash flow risk model with 100 000 simulation paths is constructed to estimate the three year default probability, expected cash flow gap and 95% conditional tail expectation (CTE). The empirical results reveal that private developers suffer prominent default risks and severe tail losses, whereas mixed ownership enterprises maintain the most stable cash flow performance. By identifying the heterogeneity of corporate cash flow risks via simulation techniques, this research provides quantitative references for financial institution credit decisions, industry oriented regulation and internal liquidity management of real estate firms.

Keywords: Real estate, Ownership, Monte Carlo simulation, Cash flow risk, Conditional tail expectation

1. Introduction

China's real estate sector has been in a prolonged downturn, with mounting cash flow strains and widening gaps in how firms of different ownership types absorb shocks. Backed by policy support and cheaper credit, state-owned developers have remained relatively stable; by contrast, many highly leveraged private developers have defaulted on debt or halted projects, while mixed-ownership firms fall somewhere in between [1]. Accurate measurement of cash flow risks of different types of real estate enterprises and improvement of dynamic financial early warning systems have become the common core needs of industry supervision, bank credit and enterprise operation.

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DOI: 10.54254/2754-1169/2026.39077

With respect to the effect of ownership nature on financial risks among real estate firms, it has been proved that the proportion of state-owned shareholding will significantly change the capital structure and financing ability of real-estate firms, whereas their state-owned peers hold inherent advantages in gaining access to bank credit facilities. Financing constraints are significantly lower than those of private real estate enterprises, and there are essential differences in the logic of debt behavior between the two [2]. Research on China's A share listed firms further indicates that ownership nature constitutes a core determinant of firms' free cash flow volatility and the extent of inefficient investment, and the cash flow risk characteristics of real estate enterprises of different ownership types cannot be described by a unified model [3].

In terms of the quantitative method of cash flow risk, Monte Carlo stochastic simulation is widely used in real estate stress testing scenarios. By applying random shocks to risk factors and simulating loss distribution under extreme scenarios, it provides a feasible framework for bank credit risk measurement [4]. Overseas studies further used the Monte Carlo method to conduct historical stress tests on bank credit asset portfolios, and verified the effectiveness of this method in risk quantification under extreme scenarios [5].

Most of the existing research on the financial early warning of real estate enterprises is based on static financial indicators. Although Deng Xudong et al. developed a Logistic regression early warning model using multi dimensional cash flow indicators with satisfactory predictive accuracy, the model is essentially a static point in time assessment. It fails to simulate long run cash flow fluctuations arising from the interaction of multiple risk factors [6]. In recent years, default prediction research based on machine learning has significantly improved the identification ability of enterprise default risk by integrating multi-dimensional features, but it still pays insufficient attention to ownership heterogeneity [7].

To sum up, the existing research either ignores the property rights heterogeneity of real estate enterprises, or the risk warning is static. Combined with the multi-factor Monte Carlo actuarial simulation method, this paper calibrates the random parameters of sales, financing, cost and debt maturity structure respectively according to the three types of state-owned, private and mixed-ownership real estate enterprises, measures the cash flow gap and CTE tail risk under different market scenarios, and then optimizes the original static financial early warning system, providing a reference for the fine risk control of the real estate industry.

2. Study design and data

2.1. Sample selection and data sources

This paper takes the China Real Estate Industry (K70) in the Industry Classification Results of Listed Companies issued by the China Securities Regulatory Commission in 2021 [8] as the sample database, cross-confirms with the constituent stocks of the real estate development sector of East Money, and selects A-share listed companies whose main business is real estate development and operation from 2018 to 2023 as the research objects. Excluding ST and *ST companies, listed companies after 2018, companies that have transformed into non-real estate main business (property, intermediary services and transformation enterprises), B shares and companies with missing core financial data; Individual companies whose actual controllers are complex and difficult to be classified (such as New Huangpu and Calxon) are also excluded. There are 96 enterprises in the initial list, and 87 valid sample enterprises are obtained after the above processing, including 53 state-owned enterprises, 30 private enterprises and 4 mixed ownership enterprises. It is worth noting that the sample includes Yango Group, Tahoe Group, Languang Development, Zhongnan

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Construction, Shimao, Zhongtian Financial Group, Myhome Real Estate and other representative private real estate enterprises that will be delisted from 2023 to 2024, which helps to more fully describe the tail risk characteristics of private real estate enterprises.

Corporate financial data come from annual reports of listed companies over the years (obtained from the East Money F10 financial database [9]), mainly including operating income, operating cost, interest expense, interest-bearing debt and its maturity structure, cash and other items in the balance sheet and income statement. The industry-level macro data such as the average sales price of commercial housing and the construction and installation cost index come from the public database of the National Bureau of Statistics. In order to avoid extreme values interfering with parameter calibration, all continuous variables are winsorized at the 1% and 99% quantiles.

2.2. Selection of variables

Referring to the existing research and combined with the cash flow formation mechanism of real estate enterprises, this paper selects four core random variables as the input factors of Monte Carlo simulation: (1) The growth rate of commercial housing sales (g) reflects the payment collection ability of real-estate firms' sales side, which directly affects the operating cash inflow and is measured by the year-on-year growth rate of operating income. (2) Comprehensive financing cost (i), which reflects the pressure of debt interest expense and affects financial cash outflow, is measured by the proportion of interest expense in the average balance of interest-bearing debt, among which interest expense is taken from the interest expense item in the income statement. (3) The growth rate of construction and installation cost (h) reflects the rigid expenditure at the development end and affects the cash outflow at the investment end. Because the construction and installation expenditure is not separately listed in the statement, it is approximately measured by the year-on-year growth rate of operating cost. (4) Debt to maturity ratio (λ), reflecting the rigid pressure of short-term debt repayment, is measured by the proportion of interest-bearing debt due within one year to the total amount of interest-bearing debt. Interest-bearing debt is defined as the aggregate of short-term borrowings, non-current liabilities due within one year, long-term borrowings, bonds payable and lease liabilities.

3. Monte Carlo simulation model

3.1. Factor dynamic process

Assuming that each risk factor follows geometric Brownian motion (GBM), its stochastic differential equation is as follows:

$$dX_t=\mu X_t dt+\sigma X_t dW_t \tag{1}$$

Where μ is the drift term (reflecting the long-term trend of factors), σ is the volatility, and dWt is the increment of standard Brownian motion. By discretizing Equation (1), the evolution path of the factor at Δt time step is obtained:

$$X_{t+1}=X_t\cdot\exp[(\mu-\frac{\sigma^2}{2})\Delta+\sigma\sqrt{\Delta t}\cdot\varepsilon_t],\ \varepsilon_t\sim N(0,1) \tag{2}$$

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Where εt is a random disturbance that follows a standard normal distribution and is used to drive Monte Carlo sampling. In this paper, the simulation period is T=3 years, the step size Δt=1 year, and the number of samples is N=100000.

3.2. Cash flow structure

The accounting identity of annual net operating cash flow CFt of an enterprise (with reference to the Monte Carlo stress test framework [4]) is constructed as the carrier of risk measurement:

$$CF_t=S_t-C_t-D_t\cdot i_t-D_t\cdot\lambda_t \tag{3}$$

Where St is the sales revenue (initial value S_0=100, accumulated according to the sales growth path of Equation (2)), Ct is the construction and installation cost expenditure (initial value C0=60, accumulated according to the growth path of construction and installation cost), Dt is the balance of interest-bearing debt (initial value D0=80), it is the financing cost, λt is the debt-to-maturity ratio. The cash balance Casht is accumulated according to Casht=Cash0+ΣCF, where Cash0=80. There is usually a correlation between sales growth and financing costs, and between financing costs and the debt-to-maturity ratio. Therefore, the correlation coefficient matrix Σ is applied to the random disturbances of each factor and Cholesky decomposition is used to generate correlated random numbers to describe the linkage effect between factors.

3.3. Risk determination and risk index

Drawing on practical criteria for credit-risk identification among real-estate firms, this paper specified the following default trigger conditions: net operating cash flow is negative in two consecutive years, and the cash-to-short-term debt ratio (CSDR), defined as cash divided by short-term interest-bearing debt, is below 0.5. Default probability is computed as the proportion of simulated paths that satisfy these trigger conditions:

$$P_{def}=P(CF_t<0\cap CF_{t+1}<0\cap CSDR_{t+1}<0.5) \tag{4}$$

$$CSDR_t=\frac{Cash_t}{(D_t\cdot\lambda_t)} \tag{5}$$

In addition to the probability of default, this paper further measures the three-level risk indicators. First, the Expected Cash Flow Gap, which measures the average level of potential capital gap at the end of the simulation period:

$$E[Gap]=\frac{1}{N}\cdot\sum_{k=1}^{N}\max(-CF_T^{(k)},0) \tag{6}$$

Second and third, VaR and conditional tail expectation (CTE) based on the CFT distribution of terminal cash flows. Where VaR is the quantile loss at a certain confidence level, and CTE is the

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conditional average loss when the loss exceeds VaR. The two jointly describe extreme tail risk:

$$\mathrm{VaR}_{\alpha}=\mathrm{Q}_{\alpha}\left(\mathrm{CF}_{\mathrm{T}}\right);\mathrm{CTE}_{\alpha}=\mathrm{E}\left[\mathrm{CF}_{\mathrm{T}} \mid \mathrm{CF}_{\mathrm{T}} \leq \mathrm{VaR}_{\alpha}\right] \tag{7}$$

In this paper, α=95% is taken. As a consistent risk measure, CTE can better reflect the degree of extreme losses in the tail than VaR [10, 11].

3.4. Parameter calibration and correlation processing

According to the type of ownership, the parameters of the three types of real estate enterprises are calibrated respectively. The drift term and volatility are estimated from the factor series of the sample companies from 2018 to 2023:

$$\widehat{\mu}=\frac{1}{\mathrm{n}} \cdot \sum_{\mathrm{k}=1}^{\mathrm{n}} \ln \frac{\mathrm{X}_{\mathrm{k}}}{\mathrm{X}_{\mathrm{k}-1}} \tag{8}$$

$$\widehat{\sigma}=\sqrt{\left[\frac{1}{(\mathrm{n}-1)} \cdot \sum_{\mathrm{k}=1}^{\mathrm{n}}\left(\left(\ln \frac{\mathrm{X}_{\mathrm{k}}}{\mathrm{X}_{\mathrm{k}-1}}\right)-\widehat{\mu}\right)^{2}\right]} \tag{9}$$

To suppress abnormal jumps in historical data, log returns are winsorized at ±50%. The initial values of each factor i0 and λ0 are the mean values of various real estate enterprises in the current period. The correlation coefficient matrix between factors is estimated from the sample panel data: the annual growth rate series is adopted for the growth rate of sales and construction and installation costs, and the within-company logarithmic rate of return series is adopted for the financing cost and debt-to-maturity ratio. Among them, the growth rate of sales and the growth rate of construction and installation costs are highly positively correlated (0.93), mainly because the two are measured by the year-on-year operating revenue and operating cost, respectively, and there is a mechanical linkage of proxy measures; The financing cost is weakly positively correlated with the debt-to-maturity ratio (0.14), and the sales growth rate is approximately uncorrelated with the financing cost (−0.04). The correlation coefficient matrix is applied to the random number generation process by Cholesky decomposition:

$$\Sigma=\mathrm{LL}^{\mathrm{T}}, \mathrm{Z}=\mathrm{L} \cdot \varepsilon \tag{10}$$

Table 1. Correlation coefficient matrix between factors (sample estimation)

Variables of interest	Sales growth rate (g)	Financing cost (i)	Construction and installation cost growth (h)	Debt to maturity ratio (λ)
Sales growth rate (g)	1.00	-0.04	0.93	0.01
Financing cost (i)	-0.04	1.00	-0.04	0.14

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Table 1. (continued)

Construction and installation cost growth (h)	0.93	-0.04	1.00	0.02
Debt to maturity ratio (λ)	0.01	0.14	0.02	1.00

4. Empirical results

Calibration results of stratification parameters

Table 2 reports the parameter calibration results of the four factors of the three ownership types. It can be seen that the financing cost level of private real estate enterprises is the highest (i0=4.21%), and shows a significant upward trend (μi=8.96%), while the financing cost level of state-owned holding and mixed ownership real estate enterprises is lower and relatively stable; The maturity debt ratio of private real estate enterprises (λ₀=0.326) was significantly higher than that of state-owned holding (0.216) and mixed ownership (0.268), and the rigid pressure of short-term debt repayment was the highest. From the perspective of volatility, the overall volatility of all factors of private real estate enterprises is higher, and the volatility of factors of mixed ownership real estate enterprises is the lowest. These disparities give rise to substantial cash-flow-risk divergence among the three ownership groups of real-estate firms at the fundamental level.

Table 2. Calibration results of stratification parameters of the three types of real estate enterprises

Type of ownership	μ_g (%)	σ_g (%)	μ_h (%)	σ_h (%)	i0(%)	μ_i (%)	σ_i (%)	λ0	μ_λ (%)	σ_λ (%)
State-owned	13.7	46.37	17.77	56.0	2.95	0.23	28.68	0.216	3.07	38.25
Private	8.53	45.37	12.45	54.29	4.21	8.96	28.69	0.326	8.26	37.93
Mixed ownership	9.42	18.46	11.48	20.65	3.18	6.79	18.74	0.268	1.24	23.77

Note: μg and σg are the mean and volatility of sales growth respectively; μh and σh are the mean value and volatility of the growth rate of construction and installation cost; i0 is the initial value of financing cost, μi and σi are the drift and fluctuation of the log return of financing cost; λ0 is the initial value of the debt to maturity ratio, and μλ and σλ are the drift and fluctuation of its log return.

4.1. Default probability and cash flow distribution

Table 3 reports the core results of the Monte Carlo simulations. Under 100,000 samples, the default probability of private real estate enterprises within 3 years is 24.26%, about 52.7 times that of mixed ownership real estate enterprises (0.46%), and significantly higher than that of state-owned holding real estate enterprises (6.70%); The expected cash flow gap (21.46) and CTE tail loss (-64.28) of private real estate enterprises are the largest among the three categories. Although the default probability of state-owned holding real estate enterprises is lower than that of private enterprises, it is still significantly higher than that of mixed ownership. The main reason is that the scale and volatility of state-owned real estate enterprises in the sample are quite different, and some local state-owned enterprises in business difficulties are included, and their cash flow resilience is weaker than that of mixed-ownership real estate enterprises represented by Vanke and Gemdale.

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Table 3. Core results of monte carlo simulation (N=100000)

Type of ownership	Probability of default (%)	Expected cash flow gap	VaR5%(cash flow)	CTE95%(cash flow)
State-owned	6.70	8.87	-48.25	-31.22
Private	24.26	21.46	-85.18	-64.28
Mixed ownership	0.46	1.56	-11.94	-7.53

Figure 1 shows the distribution of net cash flow of the three types of real estate enterprises at the end of the third year. The distribution of private real estate enterprises shifts significantly to the left, and the tail is elongated, indicating that their cash flow is more likely to fall into a large gap under adverse scenarios. State-owned real-estate firms show an intermediate distribution profile, whereas mixed-ownership firms are concentrated in the positive range with the most stable cash-flow outcomes. Figure 2 visually illustrates default-probability differences among the three ownership groups. Figure 5 plots sample simulated cash-flow paths for these groups, where paths for private firms exhibit markedly larger downward magnitude and higher volatility.

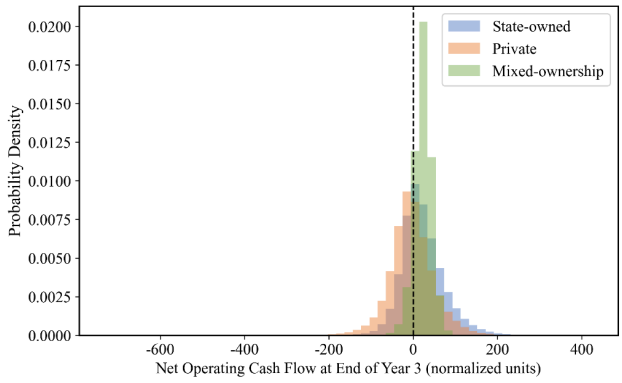


Figure 1. Cash flow distribution of the three types of real estate enterprises at the end of the third year

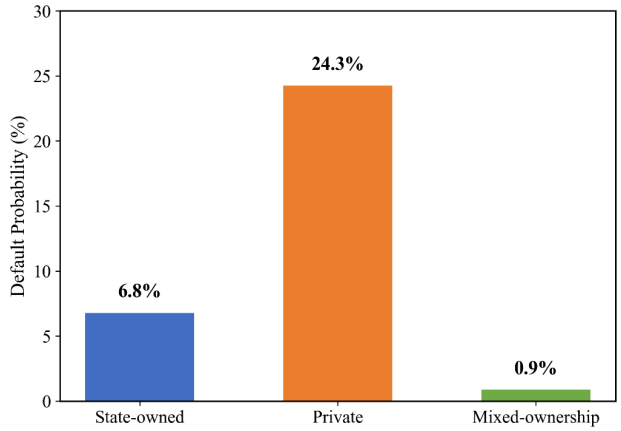


Figure 2. Comparison of default probability of three types of real estate enterprises within 3 years

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4.2. Cash flow gap and tail risk

Figure 3 compares the expected cash flow gap and CTE95% tail loss of the three types of real estate enterprises. The expected gap (21.46) and CTE loss (64.28) of private real estate enterprises are the largest in the three categories, which means that once the default occurs, the severity of their capital gap is the highest; State-owned holding real estate enterprises followed; Mixed ownership real estate enterprises are significantly lower than the former two. The simulations indicate that private real-estate firms not only carry a high default probability, but also suffer the greatest loss depth and display the most pronounced tail-risk features under default-event scenarios.

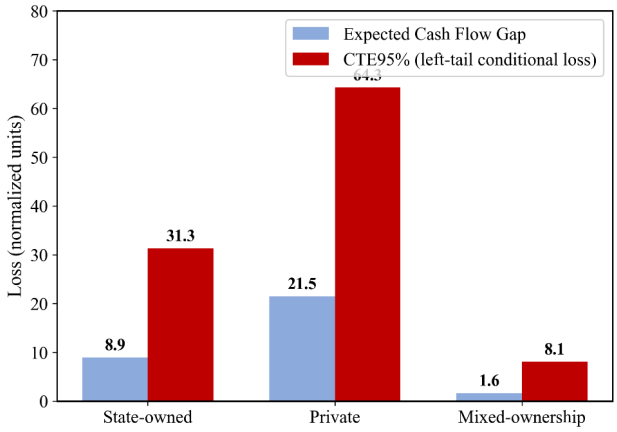


Figure 3. Comparison of expected cash flow gap and CTE95% tail loss of three types of real estate enterprises

4.3. Sensitivity analysis

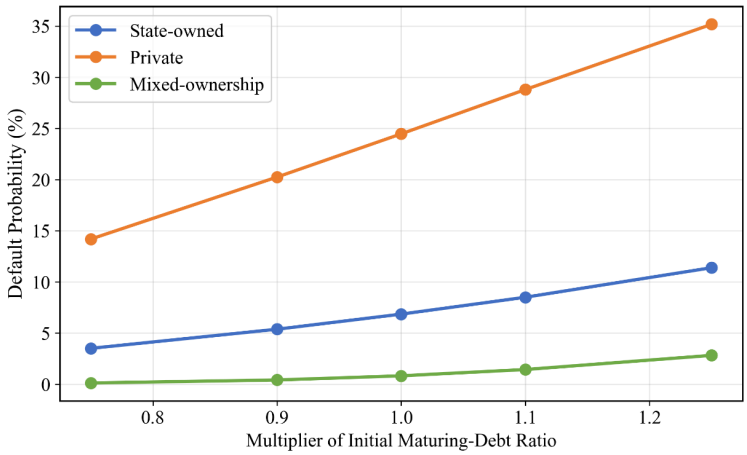


Figure 4. Sensitivity analysis of the initial maturing-debt ratio

In order to examine the robustness of the model conclusions, Figure 4 shows the response of the default probability when the initial value of the debt-to-maturity ratio λ0 is changed within the range of 0.75 to 1.25 times the benchmark value. The results show that the default probability of the three types of real estate enterprises increases monotonically with the increase of the debt-to-maturity ratio. Among them, private real estate enterprises are the most sensitive to changes in short-term

DOI: 10.54254/2754-1169/2026.39077

debt repayment pressure, with default probability rising from 13.7% to 34.8%, followed by state-owned holding (from 3.4% to 10.9%), and mixed ownership real estate enterprises are the least sensitive (from 0.0% to 2.1%), as shown in Figure 4. This shows that the difference in maturing debt structure is one of the important factors leading to the default risk differentiation of the three types of real estate enterprises.

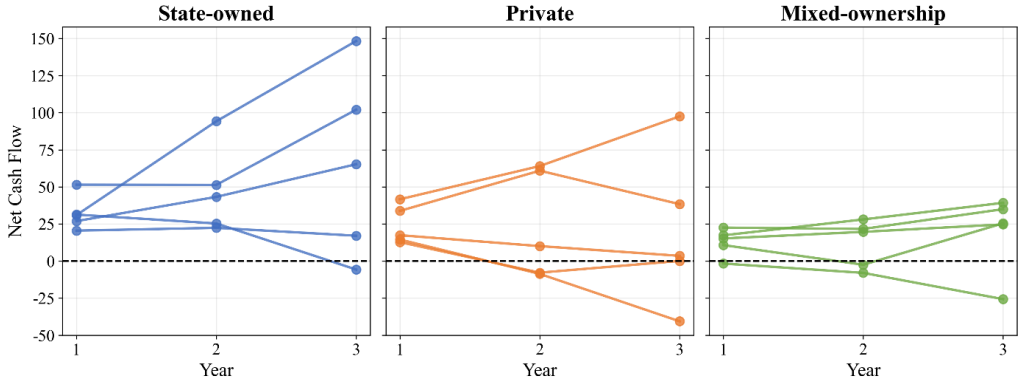


Figure 5. Simulation samples of cash flow path of representative companies of three types of real estate enterprises (5 paths)

5. Discussion

5.1. Economic interpretation of the results

The simulation results confirm that ownership nature exerts a substantial influence on real-estate firms' cash-flow risks. To begin with, firms diverge in terms of financing constraints. Private real-estate firms incur higher financing costs, which trend upward — a pattern that mirrors their refinancing frictions and widening credit spreads amid the industry-wide downturn. However, state-owned real-estate firms benefit from implicit state credit backing to sustain low-cost financing, which is consistent with the existing research conclusions on the differences between capital structure and financing constraints [2, 3]. Second, the difference in debt structure. The maturing-debt ratio of private real estate enterprises is significantly higher, and the combined decline in sales receipts is easy to trigger a short-term debt repayment crisis [12]. Third, the fluctuation difference in sales. The sales growth rate of private real estate enterprises fluctuates greatly, tail risks are prominent, and the high-leverage expansion mode lacks buffer under demand contraction. Mixed-ownership real estate enterprises have both state-owned credit resources and market-oriented governance mechanisms. In the sample, the sales and financing ends of Vanke, Gemdale and other leading real estate enterprises are relatively stable, so the cash flow risk is the lowest.

5.2. Comparison with existing research and policy implications

Compared with the Logistic early warning model based on static financial indicators [6], the Monte Carlo framework in this paper can describe the superposition evolution and tail scenario of multiple risk factors in the time dimension, making up for the deficiency of static time point judgment; Compared with the general default prediction model based on machine learning [7], this paper calibrates parameters according to ownership stratification to better adapt to the risk characteristics of subdivided groups. At the practical level, the results of this paper have direct reference value for bank credit management, industry supervision and real estate enterprise operation. First, banks can

DOI: 10.54254/2754-1169/2026.39077

set risk pricing and credit line according to the different ownership types of real estate enterprises, and prudently grant credit to private real estate enterprises with high default probability and high tail loss; Second, based on simulated capital-gap magnitudes, regulators can optimize pre-sale fund supervision for commercial housing and hierarchical debt governance for real-estate firms, to facilitate policy implementation for ensuring housing project deliveries. Third, guided by simulation results, real-estate firms may moderate their land-acquisition pace, refine debt-maturity structures, and build up adequate liquidity buffers.

5.3. Limitations of research

This study is subject to several limitations. First, financing cost is proxied by the ratio of interest expense to interest-bearing debt. Since this metric excludes capitalized interest expense, it may underestimate real-estate firms' actual financing costs. Nevertheless, because this measurement approach is consistent across firms with different ownership structures, it does not bias our relative comparison-based conclusions. Second, this paper approximated the growth rate of construction-and-installation costs with the growth rate of operating costs, creating deviations from genuine construction-and-installation investment inputs. Third, the sample size for mixed-ownership firms is small (only four firms), which limits its statistical representativeness. Fourth, although the factor correlation matrix is estimated from sample panel data, estimation precision is constrained by the limited sample size (especially there are only 4 companies with mixed ownership), and the high correlation between sales and cost growth may be affected by the quality of the proxy variable. The above limitations need to be improved in subsequent studies by expanding samples, obtaining detailed data and estimating correlation structures.

6. Conclusion

Using panel-data of 87 A-share listed real-estate firms spanning the period 2018-2023, this paper calibrates four random factors of sales growth rate, financing cost, construction and installation cost growth rate and debt-to-maturity ratio respectively, according to the three types of state-owned, private and mixed-ownership real estate enterprises, and constructs a multi-factor Monte Carlo cash flow simulation model (sampling 100,000 times). This paper calculates the default probability, expected cash flow gap and CTE tail risk of three types of real estate enterprises. The main conclusions are as follows:

First, there is marked divergence in cash-flow risks among the three ownership groups of real-estate firms. Private real-estate firms exhibit a default probability of 24.26%, which is roughly 52.7 times the figure for mixed-ownership firms (0.46%), and significantly higher than that of state-owned holding real estate enterprises (6.70%). Their financing cost level, upward speed and maturing debt pressure all rank first among the three types. Second, private real estate enterprises not only have a high probability of default, but also have the deepest tail loss under the default scenario, with CTE95% of −64.28, far exceeding that of state-owned holding (−31.22) and mixed ownership (−7.53). Third, the cash flow risk of mixed-ownership real estate enterprises is the lowest, indicating that the combination of state-owned credit resources and market-oriented governance is helpful in improving the anti-risk ability of real estate enterprises. Fourth, the sensitivity analysis shows that the debt-to-maturity ratio is an important factor affecting the difference in the default probability of the three types of real estate enterprises.

The above findings indicate that the multi-factor Monte Carlo simulation model with ownership-based stratified parameter calibration can effectively capture the heterogeneous and tail

DOI: 10.54254/2754-1169/2026.39077

characteristics of cash-flow risks in the real-estate industry. This approach serves as a beneficial complement to traditional static financial early-warning systems. Accordingly, regulators, financial institutions, and real-estate firms can adopt differentiated risk-management strategies to support the stable and sustainable development of the real-estate sector.

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