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Exploring the Pricing Strategy of Insurance in China Based on the TOPSIS Method

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Abstract

This paper is based on the panel data of extreme weather in China from 2000 to 2023. Firstly, the TOPSIS method is adopted to determine the weights of various indicators affecting the underwriting of insurance companies and establish a risk assessment system. Secondly, the break-even method is used to formulate the premium pricing strategy, and sensitivity analysis is conducted to test the sensitivity of each indicator. Further analysis is carried out to determine when and where the insurance company's underwriting risk is the lowest and the return is the highest. Finally, from the perspective of developers, the model is optimized. Based on the exploration of the influencing factors of building disaster resistance, the disaster resistance coefficient of disaster-resistant buildings is considered to establish a community disaster resistance capacity system model. Developers can determine whether to develop based on the local disaster resistance capacity indicators and the disaster resistance coefficient of disaster-resistant buildings.

Keywords: property insurance, TOPSIS, Break-even analysis, sensitivity analysis

1. Introduction

Against the backdrop of global climate change, the frequency of extreme weather in recent years has had a severe impact on property owners and the insurance industry. The climate continues to deteriorate, and economic losses due to extreme weather are scientifically predicted to continue to increase, driving property insurance premiums up sharply. The interplay between rising insurance costs and the widening global insurance coverage gap has put the insurance industry in a dilemma.

At present, the core issues that need to be explored and resolved in depth cover the following key aspects: first, how insurance companies can build a long-term and stable development model to achieve their own sustainable development while meeting the requirements of profitability; second, analyzing the affordability and willingness of homeowners to pay for high insurance costs from the perspectives of consumer behavioral economics and risk-tolerance capacity; third, how real estate and community developers can scientifically and reasonably determine the time, location and conditions of construction based on GIS, climate risk assessment models and urban planning theories in the process of project planning and implementation [1].

In-depth research on the above topics will theoretically improve the academic system of risk management, insurance and other interdisciplinary fields and provide a basis for subsequent research; in practice, it will help the real estate and insurance industries to cope with extreme weather risks, promote innovative changes and optimal allocation of resources in the industry, and safeguard economic and social stability [2].

2. Research Design

2.1 Data Processing

In this paper, the number of extreme weather from 2000 to 2023 is selected for Poisson distribution test. According to the results of the Poisson test, based on the variable Years, significance = 7.045, P = 0.933, P-value is greater than 0.05, which shows non-significance at the level, and the data obeys the Poisson distribution. It indicates that the probability of occurrence of extreme weather events is small and the probability of occurrence is stable. Therefore, in this paper, the weighted average of the frequency of past extreme weather occurrences is used as the frequency of future extreme weather occurrences.

The data sources are from EM-DAT and Our world in data, this paper collects five extreme weather indicators in China from 2000 to 2023, which are the average number of extreme weather events per year, the total economic losses directly caused by extreme weather, the total number of deaths in extreme weather, the total number of casualties caused by extreme weather, and the number of people made homeless by extreme weather, with a total of 161,373 raw data. After filling in missing values and removing outliers, the five extreme weather indicators were standardized, resulting in five groups of 159 usable data.

2.2 Disaster Risk Assessment Models

In this paper, by establishing a disaster risk assessment system, the TOPSIS method is used to determine the weights of the indicators of the risk level of extreme weather regions in China[3].

Table 1. Indicator weights for risk level of extreme weather regions in China

Norm	Information entropy	Information utility value	Weights
Total economic losses due to the disaster	0.877	0.123	7.724
Average number of extreme weather events per year	0.942	0.058	3.666
Total deaths in extreme weather	0.279	0.721	45.322
Total casualties in extreme weather	0.546	0.454	28.541
Homelessness due to extreme weather	0.765	0.235	14.747

Under the risk assessment system, the weight of the total economic losses caused by regional disasters in China is 7.724%, the weight of the average number of extreme weather events per year is 3.666%, the weight of the total number of deaths in extreme weather is 45.322%, the weight of the total number of injuries and deaths in extreme weather is 28.541%, and the weight of the number of homeless people caused by extreme weather is 14.747%. The maximum value of the weight of the indicator is 45.322% for the total number of deaths in extreme weather and the minimum value is 3.666% for the average number of extreme weather events per year.

It shows that the total number of deaths in extreme weather, the total number of casualties in extreme weather, and the number of homelessness caused by extreme weather have a greater impact on the risk assessment system and should be emphasized, as shown in Table 2.

Table 2. TOPSIS evaluation method calculations

Year	Positive ideal solution distance (D+)	Negative ideal solution distance (D-)	Composite score index	Rank
2008	0.306	0.915	0.749	1
2003	0.778	0.459	0.371	2
2001	0.853	0.257	0.232	3
2014	0.917	0.219	0.193	4
2013	0.929	0.214	0.187	5
2006	0.914	0.208	0.185	6
2004	0.917	0.172	0.158	7
2016	0.944	0.173	0.155	8
2015	0.962	0.157	0.140	9
2010	0.898	0.141	0.136	10
2000	0.950	0.139	0.127	11
2005	0.942	0.137	0.127	12
2012	0.937	0.125	0.118	13
2002	0.944	0.123	0.115	14
2017	0.966	0.121	0.111	15
2023	0.969	0.107	0.100	16
2009	0.967	0.098	0.092	17
2011	0.957	0.089	0.085	18
2021	0.977	0.078	0.074	19
2018	0.980	0.075	0.071	20
2007	0.973	0.059	0.057	21
2019	0.981	0.056	0.054	22
2022	0.985	0.056	0.054	23
2020	0.984	0.055	0.053	24

In China's extreme weather regions, insurance companies are not recommended to underwrite in 2008, 2003, 2001, 2014, 2013, 2006, 2004, and 2016, as the risk of underwriting in these years is large; in 2023, 2009, 2011, 2021, 2018, 2007, 2019, and 2022, the risk of underwriting in 2020 decreases sequentially, The risk of contracting in 2020 decreases in turn, and the risk of contracting in 2020 is the smallest, and the insurance company can maximize the profit of contracting in this year; the risk of contracting in the intermediate years is moderate, and it is recommended that the insurance company underwrites in this year according to its own profitability.

2.3 Premium Pricing Model

In this paper, we quantify the total production cost(C), total claims(C_c), claims ratio(R_c) and sales revenue(B) in the premium pricing strategy by measuring various cash flow position indicators of the insurance company, as shown in Equations 1-4:

$$C = fixed\_\cos t + unit\_\text{var}\,ible\_\cos t * number\_of\_policies \tag{1}$$

$$C_C = R_c \times number\_of\_policies \times average\_individual\_claim\_amount \times \frac{1}{(1+i)^t} \tag{2}$$

$$\text{where} \quad i = \text{discounted rate}, t = \text{year}$$

$$R_c = disaster\_occurrence\_coefficient * disaster\_coefficient \tag{3}$$

$$B = sales\_revenue * sale\_unit\_price \tag{4}$$

Meanwhile, based on the risk assessment system, a suitable premium pricing strategy was established, and the benchmarking factors for the insurance strategy were determined based on the insurer's own profitability and the time value of money, as shown in Table 3.

Table 3. Benchmark values for insurance strategies

Benchmark indicators	Reference value
Expected claim rate	0.03
Average cost per policy	7000
Average amount per claim	200000
Time value of money discount rate	8%
Fixed costs	3000

According to Figure 1, the higher the breakeven point, the higher the number of policies at breakeven, the lower the possibility of generating profits from the policies, and the weaker the ability to adapt to changes in the owner's requirements. The lower the break-even point, the lower the number of policies at break-even, the higher the profitability of the policies, and the stronger the ability to adapt to changes in the owner's requirements.

The break-even point increases as the expected claim rate increases, and the growth trend is logarithmic and slow, when the expected claim rate is less than 0.2, the number of policies is less than 20, and the break-even point is low. The break-even point decreases as the average cost per policy increases, and the growth trend is logarithmic and slowly decreases. When the average cost per policy is greater than $15,000, the number of policies is less than 20, and the break-even point is lower. The break-even point increases as the average amount per claim increases. When the amount of claims is less than $70,000, the number of policies is less than 20, and the break-even point is lower. The break-even point decreases in a stepwise fashion with the increase in the discount rate for the time value of money, but the discount rate for the time value of money has a smaller overall effect on the break-even point. The break-even point increases in a stepwise fashion with the increase in fixed costs, and the fixed cost range of $2,000-$50,000 has a lesser impact on the break-even point[4]. Therefore, insurance companies should choose to underwrite in a way that makes the break-even point as small as possible as a way to maximize profits.

Because of the different range intervals of the above benchmark indicators, this paper carries out a sensitivity analysis of the benchmark indicators to observe the degree of sensitivity of the changes in the benchmark indicators to the changes in the break-even point after normalization. The greater the degree of sensitivity, the greater the impact of the sensitive factor on the break-even point, and thus is a key parameter of the premium pricing strategy system, this paper through the sensitivity analysis of the five benchmark indicators, the results are shown in Figure 2.

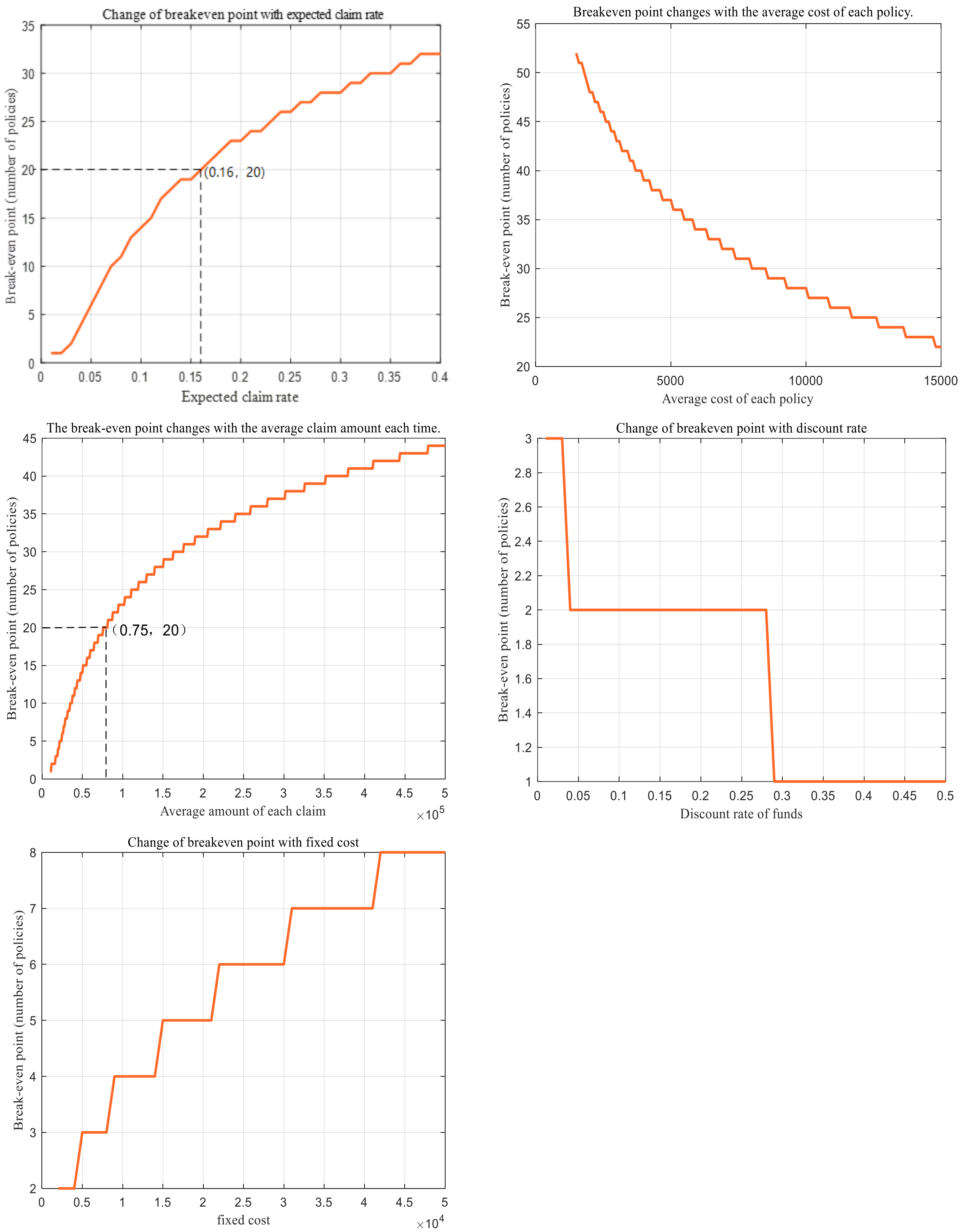

Figure 1. Change in break-even point

Based on Figure 2, it can be concluded that the average amount per claim has the greatest impact on the number of policies at the break-even point, and insurers should focus on monitoring this benchmark indicator, choosing to invest in the range where the average amount per claim is relatively small.

In order to identify the other sensitivities more precisely, the paper re-examines the other four (expected claim rate; average cost per policy; amount per claim; discount rate for time value of money; and fixed costs) with sensitivity, and the results are shown in Figure 3.

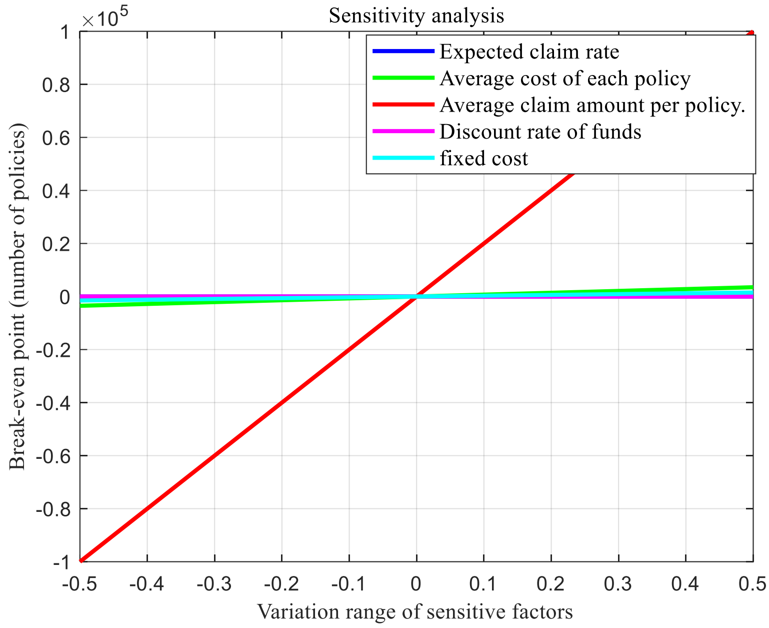

Figure 2. Sensitivity analysis results

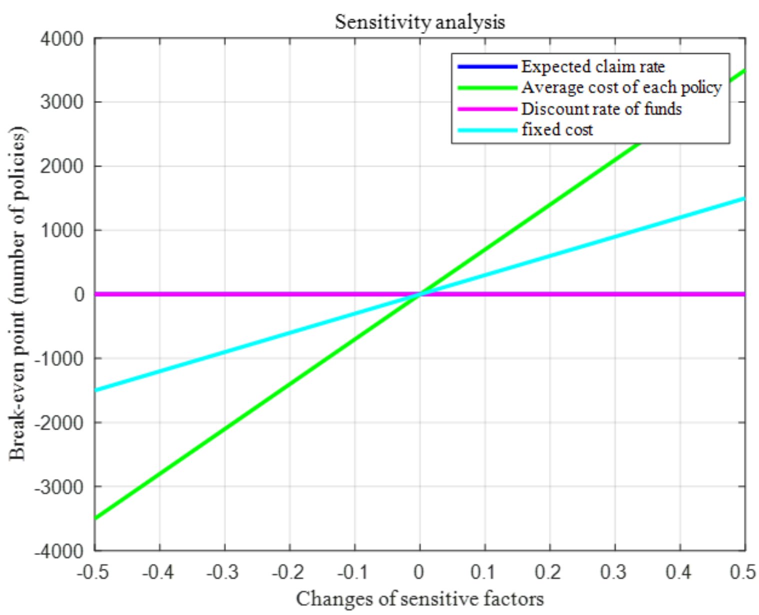

Figure 3. Refinement of sensitivity analysis results

According to Figure 3, it is intuitively obvious that the average cost per policy, fixed cost, discount rate of time value of money, and expected claim rate, in that order, are more sensitive to the breakeven point, and that changes in the discount rate of time value of money and the expected claim rate have little effect on the number of policies at the breakeven point.

To summarize, the factors that insurance companies consider when choosing to underwrite are, in descending order, the average amount of money per claim, the average cost per policy, fixed costs, the discount rate of the time value of money, and the expected claim rate.

2.4 Community Resilience System Model

Table 3. Indicator weights for community resilience systems

Benchmark indicators	Information entropy	Information utility value	Weights
Green space area (10,000 square meters)	0.872	0.128	31.693
Number of infrastructures (10,000)	0.916	0.084	20.907
Size of population	0.874	0.126	31.296
Annual average air quality index	0.97	0.03	7.358
Number of natural disasters	0.965	0.035	8.745

In this paper, by establishing a community resilience system, the five indicators affecting the community's resilience are divided into positive indicators (area of green space, number of infrastructures, and level of education of the public), and negative indicators (average annual quality index of the air, and number of natural disasters occurring), and an increase in the positive indicators will lead to an increase in the community's resilience, and an increase in the negative indicators will lead to a decrease in the community's resilience.

As can be seen from Table 3, the weight of the green space area is 31.693%, the weight of the number of infrastructures is 20.907%, the weight of the level of education of the population is 31.296%, the weight of the average annual quality index of the air is 7.358%, and the weight of the number of natural disasters is 8.745%, in which the maximum value of the weight of the indicator is the area of the green space, whose weight is 31.693%, and the minimum value is the average annual quality index of the air, whose weight is 7.358%. The minimum value is the annual average quality index of air and its weight is 7.358%. This indicates that the area of green space, the level of education of the population, and the amount of infrastructure have a greater impact on the system of community resilience to disasters.

Table 4. TOPSIS Evaluation Method Calculations TOP 10

Year	Positive ideal solution distance (D+)	Negative ideal solution distance (D-)	Composite score index	Rank
2023	0.157	0.919	0.854	1
2022	0.260	0.816	0.759	2
2021	0.260	0.796	0.754	3
2018	0.272	0.741	0.731	4
2019	0.300	0.787	0.724	5
2020	0.292	0.758	0.722	6
2017	0.391	0.681	0.635	7
2016	0.397	0.643	0.618	8
2015	0.436	0.623	0.588	9
2014	0.520	0.517	0.498	10

From Table 4, it can be concluded that community resilience increases roughly with each passing year. Communities and real estate developers should consider the role of key indicators such as the area of green space, the level of education of the public, and the amount of infrastructure, and should choose better green areas that can play the role of wind protection and rock protection, sand prevention and soil consolidation, etc., in the case of extreme weather, thus reducing the damage of extreme weather to urban buildings and infrastructure; the increase in the level of education of the public, and the awareness of disaster prevention in general, is also increased with the simultaneous increase in awareness of protection against extreme weather occurrences; the improvement of infrastructure can achieve a certain degree of earthquake and disaster mitigation, and protect the community residents from disasters. The improvement of infrastructure can to a certain extent achieve the effect of earthquake and disaster mitigation, and protect the personal and property safety of community residents, so the community and real estate developers should focus on the above circumstances to consider the construction and development of the site.

In this paper, the comprehensive consideration of different regions of the building disaster resistance coefficient is different, so the introduction of disaster-resistant building disaster resistance coefficient, the coefficient range of 1-4, level 1 to 4, respectively, indicates that the degree of disaster is extremely serious, serious, more serious, general degree. According to Figure 4, it can be seen that the break-even point decreases with the increase of the disaster-resistant building resistance coefficient, which indicates that the higher the probability of the insurance company's profitability and the better its adaptability to changes in the owner in the area with a lower degree of disaster. Conversely, in very heavily impacted areas, insurers have the least probability of profitability and are least adaptable to changes in homeownership. Thus, choosing less affected areas will lead to higher insurance profitability.

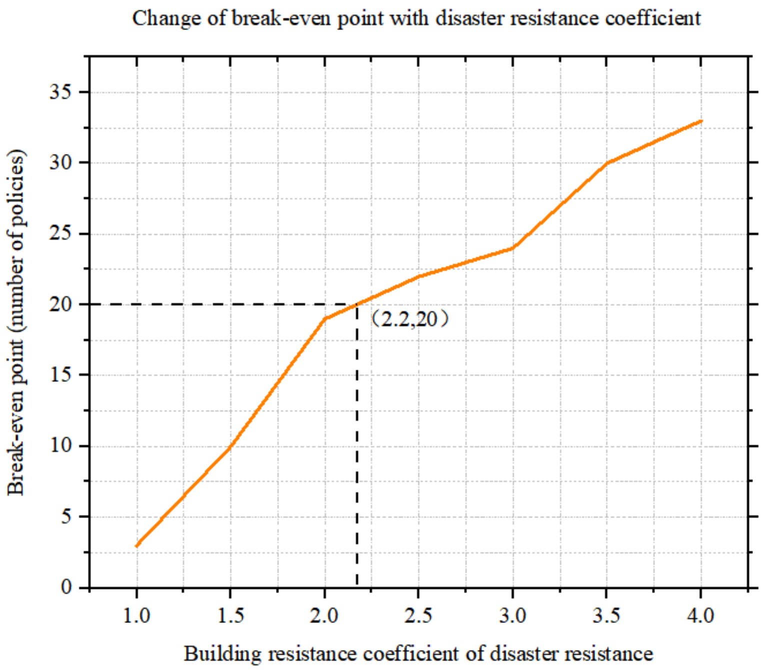

Figure 4. Variation of breakeven point with building resilience factor

3. Conclusion

When insurance companies choose to underwrite for disasters in extreme weather areas, they need to prioritize three indicators, namely, the total number of deaths in extreme weather, the total number of casualties in extreme weather, and the number of homeless people caused by extreme weather, because of their greater impact on the risk assessment system. Based on the results of the TOPSIS evaluation method, the underwriting risk profiles from 2000 to 2023 were sorted out, and insurance companies were advised to choose appropriate years for underwriting according to their profitability. On the basis of the risk assessment system, this paper selects five benchmark factors to quantify the total production cost, total claim amount, claim rate and sales revenue in the premium pricing strategy, and derives the changes of the break-even point of the insurance company with the five benchmark factors, and after further sensitivity analysis of the five benchmark indexes, it derives the degree of sensitivity of each benchmark index. Finally, this paper considers the disaster-resistant building resistance coefficient on the basis of exploring the influencing factors of building disaster resistance, and establishes a systematic model of community disaster resistance, so that developers can determine whether to build and develop according to the local disaster resistance indicators and disaster-resistant building resistance coefficient.

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