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An Empirical Analysis of The Factors Influencing China's Personal Insurance Premium Income

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Abstract: This paper presents an in-depth empirical investigation into the determinants of personal insurance premium income in China, scrutinizing the period from 2016 to 2021. Through the application of quantitative analysis methods, the study explores the influence of socio-economic factors such as GDP growth, urbanization rate, social welfare expenditure, per capita disposable income, the aging population, and education levels on the propensity of individuals to purchase personal insurance. Key findings reveal that while economic prosperity and increased social welfare expenditures positively influence personal insurance uptake, demographic shifts towards an aging population and higher educational attainment among the populace exhibit a deterrent effect on insurance consumption. The research contributes to the insurance literature by highlighting the nuanced interplay between economic development, demographic trends, and insurance market dynamics in China. It suggests policy implications for insurance companies and regulators to foster market growth, including the development of innovative insurance products that cater to the evolving needs of a diverse population and the implementation of educational initiatives to raise insurance awareness.

Keywords: China's Insurance Market, Empirical Analysis, Correlation Analysis, Hausman Test.

1. Motivation

Despite the rapid development of China's insurance industry in recent years, there are still gaps compared to some Western countries with developed insurance markets. According to CEIC data, in 2022, the global average insurance density is $1107 per person while China's is $550 per person. Insurance is an integral part of the modern economy, providing risk coverage and property protection to reduce the adverse impact of unknown factors on individuals or families. Ungur (2017), Cheng and Hou (2022) emphasize that the insurance sector is instrumental in promoting financial stability and enhancing welfare protection. Empirical evidences suggest a causal relationship between insurance and economic growth (Singhal, Goyal and Singhal, 2022). Therefore, it is of great significance to analyses the premium income, which serves as a criterion for the development of the insurance industry, in relation to several socio-economic influences.

A wide variety of studies have examined the factors influencing premium income over the years. Christophersen and Jakubik (2014) analyses from European panel data that gross written premiums for life insurance are more sensitive to key macroeconomic determinants. It is illustrated by Wang and Wang (2023) that through a two-way fixed effects model, the influence of the digital economy on the insurance industry from a demand perspective is largely disentangled, and it also highlights that the level of education has a significant impact on personal insurance income. Li, Teng and Wang (2022) discover that personal insurance premium income shows a significant negative relationship with the elderly dependency ratio based on the panel data of China from 2007 to 2019. Li et al. (2023) proves that the increase in GDP and per capita disposable income promotes the growth of premium income.

This shows the selection of factors influencing premium income matters most, whereas previous studies may have concentrated on relatively homogeneous aspects. Considering people are increasingly concerned about old-age care and health, this essay explores how gross domestic product, social welfare, elderly dependency ratio, per capita disposable income, education attainment and health expenditure affect personal insurance premium income through China's panel data from 2016 to 2021. Then, based on the empirical results, suggestions for improvement are made in the hope that the development of China's insurance industry will be in line with international standards and better contribute to social society.

2. Data Description

2.1. Source of Data

This essay empirically explores the relationship between six variables and personal insurance premium income based on the panel data, which contains the data of 31 provinces from 2016 to 2021. Data of premium income (PI), gross domestic product (GDP), social welfare (SW) and per capita disposable income (PCDI) were aggregated from China Insurance Yearbook. Data of elderly dependency ratio (EDR) and educational attainment (EA) were from National Bureau of Statistics and data of health expenditure (HE) was from Chinese National Knowledge Infrastructure.

2.2. Description of the Variables

Premium Income (PI)

The public is advised to register for insurance to transfer the risks (Alif, 2022). The prospective policyholder pays premiums to the insurer for coverage or protection, which constitutes a significant component of insurance companies' profits. As a result, this essay considers personal insurance premium income as the dependent variable.

Gross Domestic Product (GDP)

GDP explains the financial development of a country. Both Ward and Zurbruegg (2000) and Arena (2008) emphasize the strong relationship between GDP growth and the insurance market. Consequently, this research sets GDP as a control variable and suggests a positive relationship between GDP and premium income.

Social Welfare (SW)

Social Welfare is a means of regulating distributional relations, reducing property gaps, guaranteeing social equity and maintaining social stability. Increased social welfare makes a positive contribution to premium income (Li, 2006). Yi, Zhao and Zhou (2008) show that higher social welfare spending boosts demand for health insurance.

Elderly Dependency Ratio (EDR)

EDR measures the proportion of working-age individuals (15-64 years) to the elderly population (65+ years). Chen (2022) reports that a 1% increase in EDR can cause a substantial 28.14% rise in health insurance premiums, showing its profound impact.

Per Capita Disposable Income (PCDI)

PCDI, the individual income post-taxes, is vital for insurance markets. Wang (2011) points out the direct effect on insurance sales, with each yuan of PCDI growth leading to a 0.023 billion yuan hike in life insurance premiums.

Educational Attainment (EA)

EA is defined as the percentage of people aged over six who have received education at a high school level or above. He (2019) suggests that higher EA is linked to greater insurance investment, as education enhances risk awareness and the capacity to purchase insurance.

Health Expenditure (HE)

HE, the total healthcare spending, is key to insurance sector growth. Wang (2020) emphasizes the importance of cost management between insurers and healthcare providers to support the development of health insurance.

Table 1. Description of the Variables

Variable	Definition	Unit
Premium Income (PI)	The fee charged by insurance companies for insuring the life and body of a person, including life insurance, annuities, health insurance and personal accident insurance.	Yuan in Hundred Million
Gross Domestic Product (GDP)	The total value of all the goods and services produced by a country in one year.	Yuan in Hundred Million
Social Welfare (SW)	A form of expenditure is used for the operation of the social security system to provide a minimum standard of living for the population.	Yuan in Hundred Million
Elderly Dependency Ratio (EDR)	The proportion of population aged 65 and over to working-age population aged 15-64.	Percentage
Per Capita Disposable Income (PCDI)	Balance of personal income after deduction of tax.	Yuan
Education Attainment (EA)	The percentage of people aged over six who have received education at a high school level or above.	Percentage
Health Expenditure (HE)	The total amount of money consumed by the whole society for health services in a region.	Yuan in Hundred Million

Source: Author-compiled

2.3. Descriptive Statistics

The descriptive statistics for initial data and the relative frequency of the variables are shown in Table 2 and Figure 1.

Table 2. Descriptive Statistics for Initial Data

	PI	GDP	SW	EDR	PCDI	EA	HE
Observation	186	186	186	186	186	186	186
Mean	1196.86	30279.1	874.39	16.760	29264.47	0.329	1993.94
SD	942.84	25018.8	444.91	4.278	12249	0.970	1346.98
Minimum	22.25	1173	107.92	7.01	13639	0.111	124.98
Median	891.85	23773.9	842.748	16.375	25743	0.317	1670.70
Maximum	4199.34	124720	2165.82	26.7	78026.6	0.699	7622.19

Source: Author-compiled

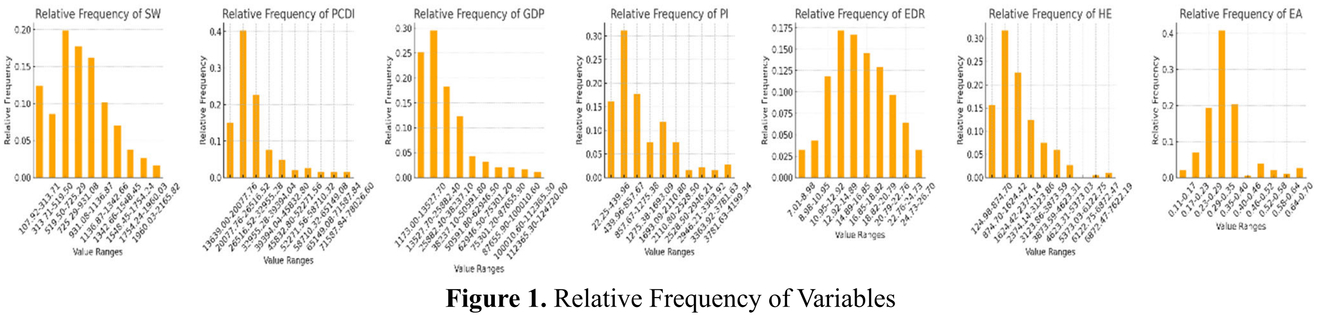

Figure 1. Relative Frequency of Variables

2.4. Data Processing

Due to the absence of 2021 health expenditure data in the CNKI database, MATLAB's 'polyfit' and 'polyval' functions were used to predict the figure from previous years' data (MathWorks, 2022). Given the differences in units and magnitudes of various variables, this research has normalized the data using the Min-Max Normalization technique. This approach ensures all feature values are mapped within the [0, 1] range, crucial for maintaining uniformity across varied datasets (Muhammad Ali, 2022). Furthermore, as O'Reilly (2022) discusses, Min-Max normalization not only scales the data but also preserves the original relationships among data values, albeit with smaller standard deviations which can reduce the impact of outliers. The mathematical formulation of Min-Max Normalization is expressed as follows:

$$Normalized\_Value = \frac{(Original\_Value - Min\_Value)}{(Max\_Value - Min\_Value)} \times 100$$

The correlation between the variables is shown in Table 3. All six variables have a strong positive correlation with PI, particularly HE and GDP, exceeding 0.9. This allows us to preliminarily deduce the relationships between the variables and affirm that ceteris paribus, all variables in the model are statistically significant.

Table 3. Correlation

		PI	SW	PCDI	GDP	EDR	HE
SW	Correlation	0.800***					
	P-value	0.000					
PCDI	Correlation	0.492***	0.289***				
	P-value	0.000	0.000				
GDP	Correlation	0.953***	0.757***	0.429***			
	P-value	0.000	0.000	0.000			
EDR	Correlation	0.404***	0.661***	0.328***	0.359***		
	P-value	0.000	0.000	0.000	0.000		
HE	Correlation	0.954***	0.868***	0.421***	0.952***	0.439***	
	P-value	0.000	0.000	0.000	0.000	0.000	
EA	Correlation	0.323***	0.186***	0.828***	0.200***	0.254***	0.228**
	P-value	0.000	0.011	0.000	0.006	0.000	0.002

Source: Author-compiled

Table 4. VIF

Variable	**VIF**	**1/VIF**
HE	26.02	0.038
GDP	13.90	0.072
SW	9.36	0.107
EDR	4.69	0.213
PCDI	3.68	0.272
EA	2.41	0.416
Mean VIF	10.01	

Source: Author-compiled

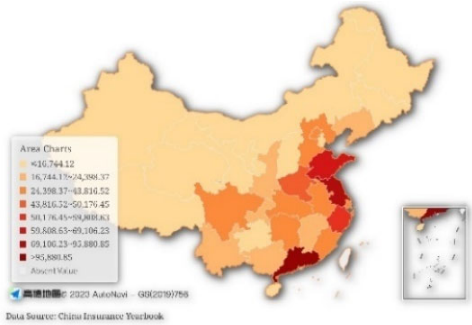

Figure 2. Average GDP Distribution

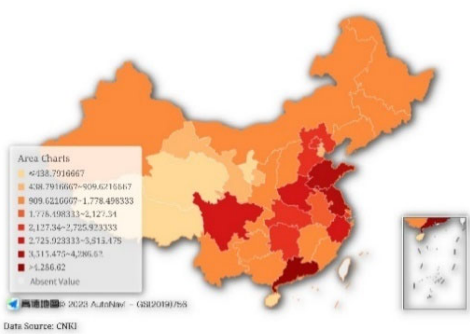

Figure 3. Average HE Distribution

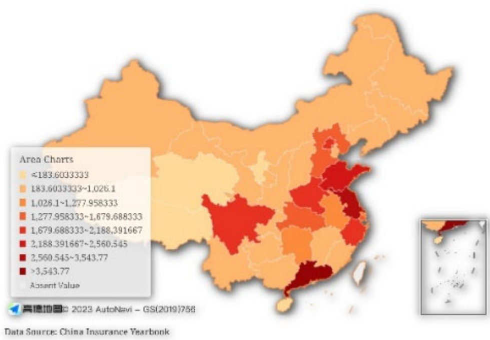

Figure 4. Average PI Distribution

In order to test multicollinearity more precisely, we check the variance inflation factor (VIF). According to Table 3 and Table 4, GDP and HE exhibit exceedingly high VIF values of 13.90 and 26.02, respectively, and high correlation coefficients of 0.9530 and 0.9540 with PI, indicating a substantial linear relationship with other variables. Meanwhile, based on Figure 2 to Figure 4, the distribution of GDP, HE and PI are similar to large extent. Furthermore, for SW, although the VIF is 9.36, the considerable correlation coefficient of 0.800 with PI suggests underlying collinearity concerns. Therefore, we exclude HE and GDP from the model. The following Table 5 shows the adjusted VIF after excluding HE and GDP, which are all below 5. The descriptive statistics for processed data are displayed in Table 6.

Table 5. Adjusted VIF

Variable	**VIF**	**1/VIF**
SW	1.81	0.551484
EDR	1.85	0.541987
PCDI	3.40	0.293854
EA	3.21	0.311168
Mean VIF	2.57	

Source: Author-compiled

Table 6. Descriptive Statistics for Processed Data

	PI	SW	EDR	PCDI	EA
Observation	186	186	186	186	186
Mean	28.120	37.245	49.516	24.268	37.121
SD	22.572	21.620	21.727	19.025	16.493
Minimum	0	0	0	0	0
Median	20.818	35.708	47.562	18.799	35.117
Maximum	100	100	100	100	100

Source: Author-compiled

3. Empirical Model and Hypotheses

3.1. Model Selection

Reflecting on scholarly precedents in insurance data analysis, we adopt the double fixed effects model, a robust approach for dissecting the intricate dynamics in our panel data.

Model 1

$$PI_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 SW_{it} + \beta_3 EDR_{it} + \beta_4 PCDI_{it} + \beta_5 EA_{it} + \beta_6 HE_{it} + \mu_i + \gamma_t + \varepsilon_{it}$$

PI_{it} is the dependent variable representing Premium Income.

GDP_{it} 、 SW_{it} 、 EDR_{it} 、 $PCDI_{it}$ 、 EA_{it} 、 HE_{it} : represent, respectively, the Gross Domestic Product, Social Welfare expenditure, Elderly Dependency Ratio, Per Capita Disposable Income, Education Attainment, and Health Expenditure for the i^{th} observation unit at time t .

μ_i : captures the individual fixed effects, unique to each observation unit and constant over time

γ_t : captures the time fixed effects, common to all units but vary over time

ε_{it} : error term

β_0 : intercept

β_1 , β_2 , β_3 , β_4 , β_5 , β_6 are the coefficients for the respective independent variables

Model 2

Based on the previous data processing and analysis, we derive an improved model:

$$PI_{it} = \beta_0 + \beta_1 SW_{it} + \beta_2 EDR_{it} + \beta_3 PCDI_{it} + \beta_4 EA_{it} + \mu_i + \gamma_t + \varepsilon_{it}$$

In the realm of econometric analysis, particularly with panel data, the Hausman test is pivotal for determining the appropriate model—fixed effects (FE) or random effects (RE). This test scrutinizes the correlation between the explanatory variables of the model and the error terms unique to each entity in the dataset.

3.2. Hypothesis

H0 (Null Hypothesis): The random effects model is assumed appropriate. This hypothesis posits no correlation between the individual-specific error terms and the explanatory variables.

H1 (Alternative Hypothesis): The fixed effects model is considered more suitable. This hypothesis suggests there is a correlation between these individual-specific error terms and the explanatory variables.

3.3. Hypothesis Testing for Model Validation

In this study, the Hausman test yields a χ^2 value of 75.22 and a p-value of 0.000, significantly lower than conventional thresholds such as 0.05, leading to a robust rejection of the null hypothesis. This outcome indicates that key variables in the analysis — like SW, PCDI and EDR — exhibit notable discrepancies in coefficients between the fixed and random effects models. Such disparities underscore the presence of correlations between the individual-specific error terms and the explanatory variables.

Given these results, opting for the fixed effects model aligns well with the fundamental principles of econometrics, where controlling for unobservable heterogeneity across entities is pivotal to preserving the integrity and validity of the model's estimations. This approach enriches the analytical rigor of the study and enhances the reliability of the findings, providing deeper insights into the intricate interplays among the examined socioeconomic variables.

Table 7. Hausman Test

Variables	FE	RE	Coefficient Difference	Standard Error
SW	0.453***	0.525***	-0.072	0.021
PCDI	0.349**	0.370***	-0.021	0.031
EDR	-0.074*	-0.123**	0.049	0.009
EA	-0.270**	-0.213*	-0.057	0.039
		χ^2 value 75.22		
		Hausman		
		P-value 0.000		

*p< 0.05, **p< 0.01, ***p< 0.001

Source: Author-compiled

Table 8. Comparison of Single and Two-Way Fixed Effects Models

Metric	Single Fixed Effects Model	Two-Way Fixed Effects Model
R-squared (Within)	0.6354	0.6593
R-squared (Between)	0.7710	0.7505
R-squared (Overall)	0.7333	0.7335
F-Statistic	F(4,151) = 65.80	F(9,146) = 31.39
Prob > F	<0.001	<0.001
	LR Test Comparison	
LR χ^2 Value		12.58
P-value		0.0276

Source: Author-compiled

After deciding to use a fixed effects model, the subsequent critical question involves the consideration of heterogeneity due to time. The single fixed effects model addresses inter-individual heterogeneity by assigning a unique intercept to each entity, such as firms or countries. This model excels in scenarios where the primary focus is on variations observed across different entities, with time-related heterogeneity being of secondary concern or assumed invariant. However, the two-way fixed effects model takes a step further by incorporating not only inter-individual differences but also variations across the temporal dimension, adeptly capturing the dynamic influences of time on the dependent variable by introducing specific fixed effects for each time period.

To ascertain which model better fits our data - single or two-way fixed effects, we resort to the likelihood ratio test (LR test).

H0 (Null Hypothesis): The single fixed effects model is sufficient for explaining the data, and the inclusion of time-fixed effects does not significantly improve the model's fit.

H1 (Alternative Hypothesis): The double fixed effects model, incorporating both individual and time-fixed effects, is necessary as it provides a significantly better fit to the data.

The LR test evaluates the necessity of including both individual and time-fixed effects by comparing the fit of the single fixed effects model against that of the double fixed effects model. This test derives a χ^2 statistic from the comparison of their likelihood function values and computes a p-value. The result, indicating a χ^2 value of 12.58 with a p-value of 0.0276, significantly below the conventional significance threshold (e.g., 0.05), robustly rejects the null hypothesis in favor of the alternative hypothesis. It suggests that the inclusion of time-fixed effects in a double fixed effects model significantly enhances the data fit.

This outcome underscores the substantial impact of temporal factors within the model, validating the use of a two-way fixed effects framework in capturing the intricacies of data where both entity-specific and time-specific variations play crucial roles. Therefore, in light of these statistical findings, the two-way fixed effects model will be selected for the examination of premium income and its determinants.

4. Regression Results and Inferences

The regression results from the double fixed effects model provide insightful observations into SW, PCDI, EDR and EA influencing PI. The model's fit and effectiveness are indicated by the R-squared values: within (0.6593), between (0.7505), and overall (0.7335), signifying a robust explanatory power for both individual and time variations across the 186 observations from 31 provinces.

Table 9. Regression Result

Variable	Coefficient	t-Statistic	P-value
SW	0.445***	7.63	<0.001
PCDI	0.474**	3.79	<0.001
EDR	-0.016*	-1.98	0.049
EA	-0.180**	-2.11	0.008
Constant	8.750	1.57	0.119
	R-squared		
Within		0.6593	
Between		0.7505	
Overall		0.7335	

Observations186

No. of provinces 31

*p< 0.05, **p< 0.01, ***p< 0.001

Source: Author-compiled

A deeper look into the coefficients reveals the nuanced dynamics within the insurance market. The positive and significant coefficient of social welfare (0.445, p<0.001) suggests a strong link between government investment in welfare and the demand for personal insurance. National financial support for workers who terminate their employment due to old age or illness promotes insurance awareness and increases the demand for personal insurance. Similarly, per capita disposable income positively correlates with premium income (coefficient of 0.474, $p<0.01$). It is possible that people's ability to pay has increased, so they spend more on expenses other than daily consumption, leading to a higher demand for insurance protection. Beyond mere risk mitigation and self-interest protection, contemporary insurance offerings such as certain whole life insurance policies, with financial management and wealth accumulation features. With the rise in disposable income, such multifaceted insurance products naturally gain traction. Concurrently, the more surplus income people have, the more individuals tend to become conscious of their health and life protection needs. Thus, the dual role of modern insurance products not only aligns with the increasing financial acumen of consumers, but also satisfies the need for health protection, leading to an expanded market demand.

The observed negative correlation between the elderly dependency ratio and insurance premium income, as indicated by a coefficient of -0.016 ($p<0.05$), could be attributed to a constellation of socio-economic and policy-related factors. Primarily, the comparatively low insurance awareness among the elderly population influenced by traditional mindsets may significantly diminish their participation in insurance markets. This trend is particularly pronounced in the context of China's intensifying aging problem. Besides, a critical aspect contributing to this phenomenon is the insurance industry's policy framework. Many personal insurance products, especially life insurance, impose stringent health and age-related eligibility criteria, which may increase difficulty in obtaining insurance for older individuals, sometimes by outright rejection. This exclusionary trend in the insurance market could inadvertently reinforce the lower insurance uptake among the elderly. Moreover, the increasing elderly population is paralleled by a relative decrease in the labor force, as evidenced by recent policy shifts like delayed retirement and changes in maternity policies. This contraction in the labor force could lead to a reduction in the overall creation of social wealth, subsequently dampening the general propensity to invest in personal insurance. The interplay of these factors – diminishing insurance awareness among the elderly, restrictive insurance industry policies and a shrinking labor force – collectively shapes the dynamics of insurance premium income, underscoring the complex relationship between demographic trends and market behavior in the insurance sector.

The negative relationship between the level of education ratio and premium income (coefficient of -0.180, $p<0.01$) could be interpreted as a reflection of the educated population's nuanced approach to risk management. Higher education levels might correlate with a comprehensive understanding of risk and alternative risk management strategies, leading to a decreased dependency on traditional insurance products. They may accumulate wealth through other financial investment behaviors with more significant benefits. Furthermore, this demographic might exhibit a selective preference for insurance products, opting for those offering better value or aligning closely with their specific needs.

The regression model's robust R-squared values across different measures indicate a strong fit, capturing the variation in premium income effectively across provinces and over time. The significance of the coefficients, along with their directions, paints a complex picture of the socio-economic and demographic factors influencing the insurance sector. These insights are crucial for the insurers, offering a deeper understanding of market dynamics and guiding strategic decision-making in product offerings and market engagement.

5. Conclusion and Discussion

This essay analyzes the impact of gross domestic product, social welfare, elderly dependency ratio (EDR), per capita disposable income, education attainment and health expenditure on premium income in China's 31 provincial administrative regions from 2016 to 2021. Variance inflation factor (VIF) is used to remove HE and GDP to minimize their impact on the experiment. Since panel data was used, the Hausman test was applied to determine the use of a fixed effects model and the LR test confirmed the optimal solution as a special multivariate linear regression formed by a double fixed model. Regression results show that SW and PCDI have a positive correlation, which aligns with basic understanding. However, the coefficients for EDR and EA are negative, possibly indicating that highly educated groups and elderly people are less willing to purchase insurance.

The limitation of our study is associated with variables. Firstly, Table 4 and Table 9 show that the correlation coefficients of EDR, HE with PI are positive, however, the regression coefficients are indeed negative, respectively. Thus, it cannot be ruled out the possibility that these two variables may have a non-linear relationship with premium income. Moreover, this study only analyzed the relationship between six variables and premium income. In the future, more variables will be taken into consideration, for instance, pricing index.

The statistical insights from Table 9 provide a nuanced understanding of the factors influencing personal premium income in China's insurance industry. The positive correlation of SW and PCDI with PI underscores the impact of economic well-being on insurance uptake. In addition, the negative correlation with EDR and EA highlights diverse insurance needs across demographics.

These findings advocate for targeted policies and initiatives to bolster the insurance sector. From the economic point of view, it is necessary to raise the level of economic development. Since economic conditions are the material basis for insurance, an increase in the per capita disposable income helps to directly enhance people's ability to purchase insurance, thus expanding the insurance market. At the level of cultural perspective, there is a need to raise people's awareness of insurance. To the population, especially the elderly, an attempt is made to improve their perception of insurance by stressing the importance of insurance, which encompasses both protection and investment functions. Finally, product innovations should be made from the perspective of insurance companies. For the elderly, restrictions on the purchase of life insurance can be appropriately reduced due to improved health conditions. At the same time, broaden the channels for them to buy insurance. For some highly educated people, it is possible to tailor several flexible new insurances that combine the functions of efficient investment.

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