The Influence of Interest Rates, Life Expectancy and Inflation Rates on Changes in Social Insurance Premium Costs in Indonesia

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Abstract- This research aims to analyze the influence of inflation, interest rates, and life expectancy on Indonesia's mortality rate on insurance premium costs. The data used in this research is secondary data obtained from the Indonesian Statistic (BPS), Indonesian Bank Publishing, PT Jasa Raharja in Sumbawa Regency, BPJS Employment of Sumbawa Regency, and BPJS Health of Sumbawa Regency. The data analysis method used is panel data regression analysis. Based on the research results, the best model was obtained, which is a random effect model with cross-section effects. The research results show that interest rates have a negative influence on the cost of social insurance premiums in Indonesia, life expectancy rates have a positive influence on the cost of social insurance premiums in Indonesia, and inflation does not significantly affect the cost of social insurance premiums in Indonesia.

Indexed Terms- Inflation, Interest rates, Insurance premium, Life expectancy, Panel data regression

I. INTRODUCTION

In the last five years, namely the 2018-2023 period, the global and domestic economies have faced various dynamics that have affected various sectors, including the insurance sector. Macroeconomic factors such as inflation, interest rates, and life expectancy have a significant impact on the cost structure of insurance premiums. A deep understanding of the relationship between these variables and premium costs is very important for government policies in adapting fair and sustainable insurance strategies.

Inflation is an economic indicator that reflects the general increase in prices of goods and services within a certain period. Inflation is one of the classic problems in an economy which can result in a decline in people's real income which continuously has a negative impact on the macroeconomy (Santosa, 2017). An increase in inflation can increase the cost of insurance claims because the prices of health services, treatment costs, and living necessities are increasingly higher. This forces insurance companies to adjust premiums to maintain the continuity of their operations. Therefore, inflation is an important factor that needs to be considered in determining insurance premiums.

Interest rates also play a role in determining the cost of insurance premiums. Low interest rates can reduce investment income from premium funds collected by insurance companies. As a result, companies have to increase premiums to cover the shortfall in investment income. On the other hand, high interest rates can provide better investment profits so that insurance companies have more flexibility in setting higher premiums.

Life expectancy continues to increase, reflecting improvements in public health conditions and advances in the medical field. However, increasing life expectancy also means that health and life insurance claim periods will be longer, which can increase the total cost of claims. Mortality tables used by insurance companies to calculate mortality risk and longevity must be updated periodically to reflect changes in demographics and health conditions.
Governments are often involved in providing social insurance or national health insurance programs designed to protect their citizens. Policies in determining the cost of government insurance premiums must consider the dynamics of inflation, interest rates, and life expectancy to ensure the

program remains sustainable and able to provide protection.

This research aims to examine the influence of inflation, interest rates, and life expectancy in the mortality table on changes in government insurance premium costs during the 2018-2023 period. It is hoped that the results of this research will provide useful insights for policymakers in designing insurance policies that are more responsive to changes in economic and demographic conditions.

II. THEOTERICAL REVIEW

A. The Effect of Interest Rates on Insurance Premium Costs

In this research, the interest rate variable has a negative effect on insurance premium costs. This is in accordance with research conducted by Pradipta et al [28] regarding the effect of changes in interest rates on the calculation of the annual net premium for individual health insurance, showing that changes in interest rates are inversely proportional to the calculation of the annual net premium. This shows that if there is an increase in interest rates, the premium value will decrease. This is in line with research conducted by Susanti [35] that if the premium is paid at the beginning of the period, then every increase in interest rates will cause a decrease in the premium paid. However, if the premium is paid at the end of the period, an increase in interest rates will result in an increase in the premium. This is also in accordance with research conducted by Widaya [36] that interest rates will cause insurance costs to decrease. For an increase in interest rates of 1%, insurance costs decrease by less than 3%. Meanwhile, if interest rates rise by 2%, insurance costs will decrease by less than 16%. Similar results were also obtained for participants aged less than 30 years.

B. The Influence of Life Expectancy on Insurance Premium Costs

In this study, the life expectancy variable influences the cost of insurance premiums. Premium rates are determined by several factors related to the insured, such as age, gender, medical history, type of work and policy contract period. Life expectancy also influences insurance premium adjustments. The higher the life expectancy, the longer the protection period, and this can affect the premium amount.

C. The Effect of Inflation on Insurance Premium Costs

In this study, the inflation variable had no effect on insurance premium costs. These results are in line with research conducted by Buana [2], namely that based on simulation results for a period of six years, it shows that for every change in the magnitude of the inflation rate, there is only a slight difference in the premium value obtained. This shows that differences in inflation rates do not have a large enough influence on single premium calculations; net term life insurance

III. METHODS

The data used in this research is secondary data sourced from the Indonesian Statistics (BPS), Indonesian Bank Publishing, PT Jasa Raharja Sumbawa Regency, BPJS Employment of Sumbawa Regency, and BPJS Health of Sumbawa Regency. The data obtained are interest rates, life expectancy, inflation rates, and social insurance premium costs that apply in Indonesia in 2018-2023. The definitions of the variables used in this research are as follows:

1) Monthly premium costs for government social insurance that apply to insurance companies directly under the Indonesian government from 2018 - 2023, through secondary data provided by PT Jasa Raharja, BPJS Health and BPJS Employment.
2) The interest rate is the price of using money for a certain period of time. The data used is data valid in Indonesia from 2018 – 2023 published by Bank Indonesia.
3) The life expectancy in the mortality table is the average age estimated for a person based on the death rate at that time which tends not to change in the future. This data was obtained from the publication of the Indonesian Central Statistics Agency in 2018 – 2023.
4) Inflation that occurred in Indonesia from 2018 – 2023 through publications from the Indonesian Central Statistics Agency.

Summary of variables used in this research as follows:

Table 1. research variable

Variable	Information
Y	Cost of Social Insurance Premiums
X1	Interest Rates
X2	Life expectancy
X3	Inflation Rate

In this research, the method used is panel data regression, which is a combination of time series and cross-section data. Data analysis in this research used R Studio software. The stages of data analysis in this research are:

1. Classic Assumption Test

The Classical Assumption Test is a statistical requirement that must be met in multiple linear regression analysis based on Ordinary Least Squares (OLS). To ensure that the regression model obtained is the best model, in terms of estimation accuracy, unbiased, and consistent, it is necessary to test classical assumptions (Juliandi et al., 2014).

a. normality test

Normality tests are commonly used in quantitative research to ensure that observed data meets the assumptions required by some statistical analysis methods, such as regression analysis or t tests. Apart from detecting whether the data is normally distributed or not, it can also be done by looking at the normal probability plot.

b. Homoscedasticity Test

Homoscedasticity has the opposite, namely heteroscedasticity. Heteroscedasticity is the unequal variance of the residuals for all observations in the regression model. Another way to detect the presence or absence of heteroscedasticity is by carrying out several tests, including the Breusch pagan (BP) test, the Non-Constant Error Variance Test (ncvtest), and others.

c. Multicollinearity Test

Multicollinearity is a situation where there is correlation between independent variables (X1, X2, X3, etc.). In regression analysis, independent variables must not be correlated with each other because the correlation between independent variables causes the alleged coefficient to be unstable and will cause other independent variables to change. This causes the conclusion to tend to state that they accept H0 or that the influence of the independent variable is not significant even though the value of $RR2$ is very high.

d. Autocorrelation Test

Autocorrelation is the existence of correlation between observation members that are ordered according to time (such as time series data) or space (such as cross-sectional data). To detect autocorrelation in the regression model, the Durbin-Watson method can be used.

2. Model Selection

In panel data regression analysis, model selection is carried out first to determine panel data regression assumptions. The selection of the best model to be used includes the common effect model, fixed effect model, and random effect model. Obtained from 2 tests, which are:

a. Chow Test

This is done to choose between the common effect model (CEM) or the fixed effect model (FEM). If the p-value > alpha = 0.05 then the selected model is CEM, and if the p-value < alpha = 0.05 then the selected model is FEM.
H0: Common Effect Model
H1: Fixed Effect Model

b. Hausman test

Conducted to compare between the Fixed effect model (FEM) and the Random effect model (REM). If the p-value > alpha = 0.05 then the selected model is REM, and if the p-value < alpha = 0.05 then the selected model is FEM.
H0: random effect model
H1: fixed effect model

3. Panel Data Regression Analysis

In this research, the method used is panel data regression analysis. Namely a combination of time series and cross section. Data collected at one time on many observation units is cross-individual data, while data collected over time [19]

In panel data regression analysis there is a panel data regression model which consists of:

a) *Common Effect Model (CEM)*

It assumes that the intercept and slope values for each variable are the same for all cross-section and time series units.

b) *Fixed Effect Model (FEM)*

It assumes that the slope coefficient of each variable is constant but the intercept varies for each cross-section unit. To differentiate the intercept, dummy variables can be used, so this model is also known as the Least Square Dummy Variable (LSDV) model. The estimation technique for panel data regression models with fixed effect models uses the Least Square Dummy Variable (LSDV) estimation approach as follows.

c) *Random Effect Model*

Assumes that differences in individual characteristics and time are accommodated in the error of the model. Considering that there are two components that contribute to the formation of error, namely individual and time, the random error in random effects also needs to be broken down into error for the time component and combined error.

4. Test Simultaneously

Shows whether the independent variables included in the model have a simultaneous influence on the dependent variable. The provisions used are as follows;

a. If Prob. < 0.05 then $H0$ is rejected, meaning that simultaneously the independent variable has a significant influence on the dependent variable.
b. if Prob. > 0.05 then $H0$ is accepted, meaning that simultaneously the independent variable does not have a significant influence on the dependent variable

5. Test Partially

Used to find out whether each independent variable partially has a significant influence on the dependent variable. This test is carried out by looking at the degree of significance of each independent variable. The provisions are as follows:

a. If Prob. < 0.05 then $H0$ is rejected, meaning that each independent variable has a significant effect on the dependent variable.
b. If Prob. > 0.05 then $H0$ is accepted, meaning that each independent variable has no significant effect on the dependent variable.

IV. RESULTS AND DISCUSSION

classic assumption test

a. Normality test

The normality test is useful for proving that the data from the sample comes from a normally distributed population or that the population data is normally distributed. This can be proven by the results of the Kolmogorov-Smirnov test carried out in Table 2 below:

Table 2. Kolmograv-Smimov Test

Data : res
D = 0.013889 , p-value = 1
Alternative hypothesis : teo-sided

Based on the test results, it was found that the residuals were normally distributed because the p-value was > alpha 0.05.

b. Homoscedasticity

This test is used to determine whether the residual variance-covariance structure is homoscedastic or heteroscedastic. This can be proven by the results of the Breusch-Pagan test carried out in Table 3 below:

Table 3. Breusch-Pagan Test

Data : m1
BP = 0.7014 , df = 3, p-value = 0.8729

Based on the test results, it was found that there were no symptoms of homoscedasticity in the data because the p-value was > alpha 0.05 in the test.

c. Multicollinearity Test

This was done with the aim of finding out whether in a regression model a correlation was found between independent variables [20]. Testing can be done by looking at the Tolerance and Variance Inflation Factor (VIF) values in the regression model. The test results can be presented in table 4.

Table 4. Multicollinearity Test

Variables	Tolerance	VIF

X1	0.7924672	1.262882
X2	0.5675161	1.762065
X3	0.4855343	2.059587

Based on the test results, it was found that the VIF value was <10 and the tolerance value was >0.01, so there was no multicollinearity between the independent variables, namely the interest rate, life expectancy and inflation rate variables.

d. Autocorrelation Test

The term autocorrelation can be interpreted as the correlation between observation members ordered by time (time series) or place (cross-section) [22].

Table 5. Autocorrelation Test

Breusch-Godfrey/wooldrige test for serial correlation in panel models
Data: BP~X1+X2+X3 Chisq = 2.946, df = 1, p-value = 0.08609 Alternative hypothesis : serial correlation in idiosyncratic erors

Model Selection

a) Chow Test

The Chow test or Likelihood Test Ratio can be used to select one of the models in panel data regression, namely the Fixed Effect Model (FEM) and the Common Effect Model (CEM). This test can be carried out by looking at the significance of the FEM model using the F statistical test.

Table 6. Chow Test

F Statistic
Data: BP~X1+X2+X3 F = 72.862, df1 = 19, df2 = 49, p-value < 2.2e-16 Alternative hypothesis: Unstability

b) Hausman Test

The results of the Hausman test are presented in Table 7 below.

Table 7. Chow Test

F Statistic
Data: BP~X1+X2+X3 chisq = 0.0032694, df = 3, p-value =1 Alternative hypothesis : one model is inconsistent

Table 7 shows that p-value > alpha (0.05), so the decision for this hypothesis is to accept H0. So, a good model to use is the *random effect model.*

Table 8. Selection of the Best Model

Test	Result
Chow Test	FEM better than CEM
Uji hausman	REM better than FEM

Based on table 8, the best model used in this research is the *random effect model*.

Two-Way Effect Test in Panel Data Analysis

The two-way effect test in this study can be seen in table 9 below.

Table 9. Two-Way Effect Test

Langrange Multiplier Test–two-ways Effect (Breusch-pagan)
Data: BP~X1+X2+X3 chisq = 144.42, df = 2, p-value <2.2e-16 Alternative hypothesis: significant effects

From the test results, it can be concluded that the random effect model has two-way effects, namely cross section and time series because the p-value < alpha (0.05).

Cross-section effect test

Table 10. Cross-section effect test

Langrange Multiplier Test – (Breusch-pagan)
Data: BP~X1+X2+X3 chisq = 111.38, df = 1, p-value <2.2e-16 Alternative hypothesis: significant effects

From the test results, it can be concluded that the random effect model has a cross section effect because the p-value < alpha.

Test the time effect

Table 11. Time Series Effect Test

Langrange Multiplier Test–Time Effect (Breusch-pagan)
Data: BP~X1+X2+X3 chisq = 3.0365, df = 1, p-value = 0.08141 Alternative hypothesis: significant effects

From the test results, it can be concluded that the random effect model does not have a time effect because p-value > alpha.

So, based on the three tests above, it can be concluded that in this random effect model only cross-section effects are formed.

Panel Data Regression Analysis

Based on the selection of the best model that has been carried out, the best model used in this research is the random effect model with cross-section effects. The regression equation from the model is as follows.

$Yit = \beta 0 - 3499.300X1it + 13613.080X2it + 17.885X3it + \mathrm{u}it$

Test Simultaneously

The results of the simultaneous test of the random effect model can be seen from the chi-square value and p-value. The test results are presented in table 12.

Table 12. Test Simultaneously

Chisq	p-value
10.4135	0.01536

[1]

Based on Table 12, it is known that the p-value < alpha (0.05), it can be concluded that the interest rate, life expectancy and inflation rate simultaneously have a significant influence on changes in the cost of social insurance premiums.

Test Partially

Partial test results are presented in Table 13 below.

Table 13. Test Partially

Variables	Koef	Z-value	Pr(>|z|)
X1	-3499.300	-	0.03997*
X2	13613.080	2.0541	0.02717*
X3	17.885	2.2091	0.98769
		0.0154	

Note: * not significant

Based on the partial test results in Table 13, it can be concluded that X1 (Interest Rate) and X2 (Life Expectancy) have a significant influence on changes in insurance premium costs, while variable X3 (inflation) does not have a significant influence on insurance premium costs.

Coefficient of Determination

The coefficient of determination can be seen from the R-Squared value, in this study the R-Squred value = 0.2306 or only around 23.06% of the independent variables can explain the dependent variable, and the remaining 73.94% is explained by other variables not included in the model.

CONCLUSION

Based on the results of the research that has been conducted, it can be concluded that interest rates have a negative effect on the cost of social insurance premiums, life expectancy has a positive effect on the cost of social insurance premiums, while the inflation rate has no significant effect on the cost of social insurance premiums.

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