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# Modeling Adequacy Ratio in Life Insurance Using Markov Switching Approach

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## *Abstract*

***Background:*** *The life insurance sector often experiences nonlinear fluctuations during macroeconomic shocks and disasters. To capture these dynamics, nonlinear methods such as the Markov switching model are appropriate.*
***Objective:*** *This study examines the effects of premium adequacy and investment returns on the claim payment ratio in Indonesia's life insurance sector using a Markov switching approach.*
***Methods:*** *This study analyzed 115 monthly observations of premium adequacy, investment returns, and claim payment ratios from January 2016 to July 2025, obtained from the Otoritas Jasa Keuangan (OJK). Three Markov switching models (MSM, MSV, and MSMV) were compared to identify the dominant source of regime-switching behavior. The two-regime Markov switching variance model was selected based on convergence and the lowest Akaike Information Criterion (AIC).*
***Results:*** *The optimal model identified a volatile regime and a stable regime. The volatile regime had a 75.87% persistence probability with an average duration of four months, whereas the stable regime showed a 90.52% persistence probability and an average duration of 10.5 months. The probability of transitioning from volatility to stability (24.13%) exceeded the probability of shifting from stability to volatility (9.48%).*
***Conclusion:*** *Indonesia's conventional life insurance sector demonstrates resilience by maintaining stable conditions and recovering from periods of volatility.*

***Keywords :*** *Life Insurance, Markov Switching Model, Nonlinear, Regime, Time Series.*



## Abstrak

**Latar Belakang**: Sektor asuransi jiwa sering mengalami fluktuasi nonlinier selama guncangan makroekonomi dan bencana. Untuk menangkap dinamika tersebut, metode nonlinier seperti model *Markov switching* merupakan pendekatan yang tepat.
**Tujuan**: Penelitian ini bertujuan menganalisis pengaruh kecukupan premi dan hasil investasi terhadap rasio pembayaran klaim pada sektor asuransi jiwa di Indonesia menggunakan pendekatan *Markov switching*.
**Metode:** Penelitian ini menganalisis 115 observasi bulanan mengenai kecukupan premi, hasil investasi, dan rasio pembayaran klaim dari Januari 2016 hingga Juli 2025 yang diperoleh dari Otoritas Jasa Keuangan (OJK). Tiga model *Markov switching* (MSM, MSV, dan MSMV) dibandingkan untuk mengidentifikasi sumber dominan perilaku perpindahan rezim. Model *Markov switching variance* dua rezim dipilih berdasarkan keberhasilan konvergensi dan nilai *Akaike Information Criterion* (AIC) terendah.
**Hasil:** Model terbaik mengidentifikasi rezim volatil dan rezim stabil. Rezim volatil memiliki probabilitas bertahan sebesar 75,87% dengan durasi rata-rata empat bulan, sedangkan rezim stabil memiliki probabilitas bertahan sebesar 90,52% dengan durasi rata-rata 10,5 bulan. Probabilitas transisi dari kondisi volatil ke kondisi stabil (24,13%) lebih tinggi dibandingkan probabilitas perpindahan dari kondisi stabil ke kondisi volatil (9,48%).
**Kesimpulan:** Sektor asuransi jiwa konvensional di Indonesia menunjukkan ketahanan yang kuat dengan kecenderungan mempertahankan kondisi stabil serta mampu pulih dari periode volatilitas dalam menghadapi ketidakpastian ekonomi secara berkelanjutan nasional efektif.

**Kata Kunci:** Asuransi Jiwa, Model Markov Switching, Nonlinear, Rezim, Runtun Waktu.

## INTRODUCTION

The life insurance industry in Indonesia has recorded significant growth over the past decade, in line with increased public awareness of the importance of long-term financial protection. However, amid fluctuating global economic dynamics, insurance companies face serious challenges in maintaining a balance between adequate premiums, investment returns, and the ability to pay claims on time. Based on data from the Otoritas Jasa Keuangan (OJK), from January to November 2022, total claims paid reached IDR 144.46 trillion with premium income of IDR 153.55 trillion (Putri, 2023). Fluctuations in this ratio indicate pressure on the financial stability of companies, especially when there is uncertainty about investment returns, thus requiring a modeling approach that is able to capture changes in data behavior adaptively. However, conventional time-series models assume constant parameters and cannot handle structural breaks. With 115 months of data spanning the COVID-19 pandemic, such models are inadequate for this dataset because they cannot distinguish between different volatility regimes. Therefore, a Markov switching approach is necessary.

The ratio that reflects the balance between premium adequacy, investment returns, and claim payments is an important indicator in assessing the health of life insurance companies (Park & Shin, 2022). The number of claims is very important to the company because a significant increase in claims has a positive impact on financial sustainability (Lestari, 2022). As time series data, this financial stability indicator is influenced by various dynamic factors that can change suddenly. This condition creates nonlinear dynamics in the data that require analysis methods capable of adapting to changes in the economic regime. Theoretically, under normal conditions, the ratio between premium adequacy, investment returns, and claim payments should ideally remain within a stable range that reflects the company's health. However, in practice, this stability is disrupted by structural breaks that can be triggered by several conditions, one of which is a pandemic that significantly affects conditions (Ulyah et al., 2022). This shift in the economic regime fundamentally changes policyholder behavior and investment performance, creating discontinuities in time series data that cannot be captured by conventional econometric models such as linear regression or ARCH/GARCH, which assume fixed parameters over time (Hernández et al., 2025).

Previous empirical research has validated the superiority of Markov switching in financial econometrics, but few studies have critically evaluated its limitations. Ozdemir (2020) employed a Markov switching model to analyze regime shifts in interest rate movements across several Asian countries, finding that the regime-switching behavior significantly explains economic conditions (Ozdemir, 2020). However, the study was limited to interest rates and did not examine insurance or claim-related ratios, leaving a gap in understanding regime shifts in insurance stability indicators. Blazheska and Ivanovski (2021) applied a similar Markov switching approach to model policyholder behavior in Motor Third Party Liability insurance in North Macedonia, revealing that claim frequency changes across regimes (Blazheska & Ivanovski, 2021). Nevertheless, their study focused solely on claims frequency without considering premium adequacy or investment returns, and they did not compare alternative Markov switching specifications. Surya et al. (2025) used a Markov switching model to capture time-varying claim risks in community-based disaster insurance in West Java, Indonesia (Surya et al., 2025). Their results confirmed the presence of regime-dependent claim severity. A key limitation is that they only modeled claim risk, not the balance between premiums, investments, and claims. Ulyah et al. (2026) adopted an alternative methodology by employing Support Vector Regression (SVR) with a radial basis kernel to forecast both the premium-to-claim ratio and the ratio of premiums plus investments to claims for life and general insurance, attaining the highest level of accuracy (Ulyah et al., 2026). However, as a non-probabilistic machine learning method, SVR does not provide regime transition probabilities nor accommodate state-dependent dynamics, making it unsuitable for identifying the dominant source of regime-switching behavior. Consequently, specific applications that simultaneously compare various types of Markov switching in modeling the ratios between premium adequacy, investment returns, and claim payments in conventional life insurance in Indonesia remain absent. This study fills that gap by systematically comparing these three Markov switching specifications and evaluating which type of regime shift is the dominant source of nonlinearity in this dataset.

This study aims to model nonlinear dynamics in the financial ratios of conventional life insurance in Indonesia using a Markov switching approach. This method accommodates the possibility of regime switching, allowing model parameters to change according to prevailing conditions (Degras et al., 2022). In this approach, data are assumed to transition between different regimes based on Markov transition probabilities. To account for various sources of nonlinearity, this study compares three model specifications: Markov Switching Mean (MSM), Markov Switching Variance (MSV), and Markov Switching Mean and Variance (MSMV). The fundamental difference among these three models lies in the parameter components allowed to change between regimes. The MSM specification only allows changes in the mean value between regimes with constant variance. The MSV specification, conversely, allows the variance to change while the mean remains constant. The MSMV specification combines both characteristics, allowing both the mean and variance to change simultaneously. By comparing these specifications, the study can identify the most dominant type of regime shift in Indonesian life insurance financial ratio data. The selection of the best model will be based on the lowest Akaike Information Criterion (AIC) value, which will then be analyzed more comprehensively. The findings of this analysis are expected to serve as a foundation for adaptive risk management strategies and early warning systems, for both companies and regulators. Furthermore, these results also contribute to the achievement of the Sustainable Development Goals (SDGs), particularly SDG 8 (Decent Work and Economic Growth) through strengthening the stability of the financial services sector, and SDG 9 (Industry, Innovation, and Infrastructure) in the context of resilient long-term investment planning.

## METHOD

### Research Design

This study employs a quantitative research design with a time series observational approach. The research design is non-experimental as it uses secondary data obtained from official reports without any intervention or treatment. The statistical methods applied include time series analysis covering the Augmented Dickey-Fuller (ADF) test for stationarity, the Terasvirta test for linearity, and Markov Switching modeling with three specifications (MSM, MSV, MSMV). Parameter estimation is conducted using the Maximum Likelihood Estimation (MLE) method with the Expectation-Maximization (EM) algorithm. Model selection is based on the Akaike Information Criterion (AIC), followed by parameter significance testing (z-test) and residual diagnostics, including the Jarque-Bera normality test, Ljung-Box autocorrelation test, and ARCH-LM heteroscedasticity test.

### Population and Sample

The population of this study comprises all monthly observation points of the premium adequacy and investment returns to claim payment ratio in conventional life insurance companies in Indonesia. The samples are 115 monthly observations taken from January 2016 to July 2025. This period was deliberately selected because it covers a complete economic cycle and includes the necessary transition period relevant to the research objectives, ensuring that the sample captures the dynamic behavior of the ratio under various economic regimes.

Formal statistical tests indicated that the selected period (January 2016–July 2025) satisfies the assumption of parameter constancy for a stationary time series, ensuring that the sample is suitable for Markov-switching estimation.

### Sampling Techniques

This study employs a purposive sampling technique. The sample is not drawn randomly but is deliberately selected based on specific criteria. The criteria applied in this study are that the observation period must include a complete economic cycle to capture various regime conditions, and the period must cover the necessary transition time to ensure data stability and relevance to the Markov Switching analysis. Based on these criteria, the sample was limited to the period from January 2016 to July 2025, even though the full population data is available from January 2011. This purposive approach ensures that the sample is representative of the population under the specific conditions required for modeling regime shifts in life insurance financial ratios.

### Research Subjects

This study uses secondary data obtained from the Financial Services Authority insurance statistics reports. The data are a monthly time series covering the period from January 2016 to July 2025. The research subject is the premium adequacy and investment returns to claim payment ratio of conventional life insurance companies in Indonesia. The exact formula used to calculate this ratio is:

$$Y_t = \frac{P_t + I_t}{C_t + E_t} \qquad (1)$$

Where $Y_t$ is the ratio at month $t$, $P_t$ represents total premium adequacy, $I_t$ is total investment returns from the company's portfolio, $C_t$ is total claim payments made during month $t$, and $E_t$ is general expenses during month $t$ (OJK, 2020). This ratio is a continuous variable measured on an interval scale. The definition and measurement of the research variable are summarized in Table 1 below.

**Table 1.** Research Variable

| Variable | Description | Unit | Variable Type |
|---|---|---|---|
| $Y_t$ | Ratio of premium adequacy and investment returns to claims payments at month *t*. | Ratio | Continuous |

### Data Analysis Techniques

This section describes the sequential steps in building the Markov switching model, starting from stationarity testing, linearity testing, model formulation, parameter estimation, model selection, significance testing, and residual diagnostics.

1. Augmented Dickey-Fuller Test

   Stationarity testing is the first step in time series data analysis. Stationary data is defined as data that has a constant mean and variance over time. The stationarity test for conventional life insurance ratio data in this study was conducted using the Augmented Dickey-Fuller (ADF) test. The hypotheses used in this test are as follows:

$H_0$: The data contains a unit root (non-stationary)
$H_1$: The data does not contain a unit root
The following regression model estimates were used to obtain the ADF test statistics (Fowler et al., 2024)

$$\Delta y_t = \alpha + \beta_t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{2}$$

The criteria for rejection $H_0$ are when the ADF statistic value is smaller than the critical value or when the *p-value* < $\alpha$. If the data is not stationary at the level, the next step is to perform first-order differencing, then retest the transformed data until a stationary condition is obtained.

2. Tsay Test

The Tsay linearity test is used to detect nonlinearity in time series data. Conducting this test constitutes a prerequisite for the application of the Markov switching model, as the model is only pertinent when the data have been empirically demonstrated to exhibit nonlinear characteristics. The Tsay test is based on the Taylor series expansion of the nonlinear model. The hypotheses used are:
$H_0$: Linear relationship
$H_1$: Nonlinear relationship

The test procedure is carried out by regressing the dependent variable against its lags and the cross-products of these lags. The test statistic follows an F distribution, with the decision to reject $H_0$ if *p-value* < $\alpha$ (Tsay, 1986).

3. Markov Switching Model Formulation

Hamilton (1989) introduced the Markov Switching Model as an approach to modeling time series data whose characteristics change according to regime switching (Hwu & Kim, 2024). In this study, conventional life insurance financial ratio data are modeled as a process that can switch between several regimes based on transition probabilities that follow a first-order Markov process.

In general, the Markov Switching model for univariate time series data can be written as:

$$y_t = \mu_{S_t} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, \sigma_{S_t}^2\right) \tag{3}$$

where $y_t$ is the ratio value at time $t$, $S_t$ is the unobserved state variable, $\mu_{S_t}$ is the regime-dependent mean, $\sigma_{S_t}^2$ is the regime-dependent variance, and $\varepsilon_t$ is the residual distributed normally with mean 0 and variance $\sigma_{S_t}^2$. This study assumes the existence of two regimes ($S_t = 0 \; and \; 1$ to represent stable and volatile conditions in life insurance financial ratios, in accordance with initial indications of observed data fluctuations. The transition probability between regimes is represented in matrix form as follows:

$$\boldsymbol{P} = \begin{bmatrix} p_{00} & p_{01} \\ p_{10} & p_{11} \end{bmatrix} \tag{4}$$

where $p_{ij} = P(S_t = j \mid S_{t-1} = i)$ with $\sum_{j=0}^{1} p_{ij} = 1$. This probability indicates the chance of transition from regime $i$ in period t-1 to regime $j$ in period t. In this study, the author compares three Markov Switching model specifications as follows:

a. Markov Switching Mean (MSM) Model

This model assumes that only the mean parameter changes between regimes, while the variance is considered constant. After the data undergoes a stationarity process, the MSM model is formulated as:

$$y_t = \mu_{S_t} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, \sigma^2\right) \tag{5}$$

where $\mu_{S_t}$ is the mean depending on the regime and $\sigma^2$ is the constant variance.

b. Markov Switching Variance (MSV) Model

This model assumes that only the variance parameter changes between regimes, while the mean is considered constant. After the data undergoes a stationarity process, the MSV model is formulated as:

$$y_t = \mu + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, \sigma^2_{S_t}\right) \qquad (6)$$

where $\mu$ is the constant mean and $\sigma^2_{S_t}$ is the variance depending on the regime.

c. Markov Switching Mean and Variance (MSMV) Model

This model assumes that both the mean and variance change between regimes. After the data undergoes a stationarity process, the MSMV model is formulated as:

$$y_t = \mu_{S_t} + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, \sigma^2_{S_t}\right) \qquad (7)$$

where $\mu_{S_t}$ is the mean that depends on the regime, and $\sigma^2_{S_t}$ is the variance that also depends on the regime.

Parameter estimation for the three models was performed using the Maximum Likelihood (MLE) method with the Expectation-Maximization (EM) algorithm [9]. The EM algorithm was used because of its ability to estimate model parameters with latent variables iteratively until convergence is achieved.

4. Criteria for Selecting the Best Model

In this study, the selection of the best model among the three Markov Switching specifications was performed using the Akaike Information Criterion (AIC). AIC was chosen for its ability to balance model goodness of fit with model complexity. A model with a lower AIC value indicates a superior model. The AIC formula is as follows.

$$AIC = -2\ln(L) + 2k \qquad (8)$$

where $L$ is the maximum likelihood value of the model and $k$ is the number of estimated parameters (Lesnoff et al., 2021).

5. Parameter Significance Test

Significance testing of parameters is performed on the selected model to evaluate whether the parameters in the model have a significant effect. This test is performed using a z-test based on the asymptotic normal distribution of MLE with the following hypotheses.

$H_0: \theta_j = 0$ (parameter is not significant)
$H_1: \theta_j \neq 0$ (parameter is significant)

This test uses a test statistic formulated as follows(Li & Liu, 2023).

$$z = \frac{\hat{\theta}_j}{SE(\hat{\theta}_j)} \qquad (9)$$

where $\hat{\theta}_j$ is the estimate of parameter $j$ and $SE(\hat{\theta}_j)$ is the standard error of the estimate. The rejection criterion for $H_0$ is when $|z| > z_{\alpha/2}$ or *p-value* $< \alpha$, which indicates the statistical significance of the tested parameter.

6. Residual Diagnostics

In this study, diagnostic tests are performed using filtered residuals obtained from the selected Markov switching model. Filtered residuals are computed based on one-step-ahead predictions and the filtered probabilities at each time point, reflecting the model's real-time prediction errors. Residual assumption testing is performed on the selected model to ensure that the model meets the classical assumptions. There are three residual assumption tests used:

a. Jarque-Bera Normality Test

The normality test is used to test whether the residuals are normally distributed. The hypotheses used in the residual normality test are as follows.

$H_0$: Residuals are normally distributed
$H_1$: Residuals are not normally distributed

The Jarque-Bera test statistic is as follows.

$$JB = \frac{n}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \qquad (10)$$

where $n$ is the number of observations, $S$ is the skewness coefficient, and $K$ is the kurtosis coefficient. Reject $H_0$ if $JB > \chi^2_{\alpha,2}$ or *p-value* $< \alpha$ *(Glinskiy et al., 2024).*

b. Ljung-Box Autocorrelation Test

The autocorrelation test is used to detect the presence of autocorrelation in the residuals. The hypotheses used are:

$H_0$: There is no autocorrelation in the residuals up to lag m

$H_1$: There is autocorrelation in the residuals up to lag m

The Ljung-Box test statistic is expressed by the following equation.

$$Q = n(n+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{n-k} \quad (11)$$

where $\hat{\rho}_k$ is the residual autocorrelation at lag $k$. Reject $H_0$ if $Q > \chi^2_{\alpha,m}$ or *p-value* $< \alpha$ *(Lee, 2022)*.

c. ARCH Effect Test

The ARCH effect test is used to detect conditional heteroscedasticity in the residuals. The hypotheses used are:

$H_0$: There is no ARCH effect (constant residual variance)

$H_1$: There is an ARCH effect (non-constant residual variance)

The ARCH-LM (Lagrange Multiplier) test statistic is formulated as follows.

$$LM = nR^2 \quad (12)$$

where $n$ is the number of observations, and $R^2$ is obtained from the residuals of the regression against its lags. Reject $H_0$ if $LM > \chi^2_{\alpha,q}$ or *p-value* $< \alpha$ *(Gong, 2021)*.

The research flowchart is shown in Figure 1.

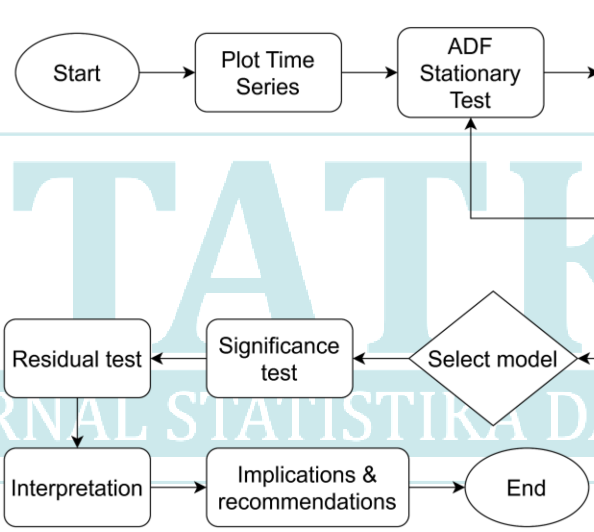


**Figure 1.** Research Flowchart



## RESULTS AND DISCUSSION

### Characteristics of the Data

The descriptive statistic data and time series plot is presented in Figure 2 and Table 2 as follows.

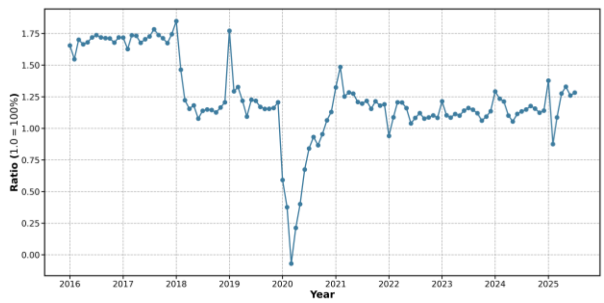


**Figure 2.** Time Series Plot of Ratio of premium adequacy and investment returns to claims payments

**Table 2.** Descriptive Statistic Data

| Variable | N | Std. Dev. | Mean | Min. | Median | Max. | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| Ratio of premium adequacy and investment returns to claims payments | 115 | 0.3292 | 1.2408 | -0.0695 | 1.1802 | 1.8480 | -0.6424 | 2.3196 |

Based on the plot in Figure 1, it can be seen that the premium adequacy and investment returns to claim payments ratio showed a fluctuating trend throughout the period. Based on Table 2, the lowest ratio of premium adequacy and investment returns to claim payments occurred in March 2020 at -0.0695, while the highest ratio occurred in August 2017 at 1.8480, with the ratio mean of 1.2408. Additionally, the descriptive statistics show a total of 115 observations (N), with a standard deviation of 0.3292, a median of 1.1802, a skewness of -0.6424, and a kurtosis of 2.3196.

## Stationary Test

Stationary test was performed with the Augmented Dickey–Fuller (ADF) test at 5% significance level. Based on data processing, the results are shown in Table 3.

**Table 3.** Stationary Test Result

| Level | | Differencing 1 | |
|---|---|---|---|
| t-statistics | p-value | t-statistics | p-value |
| -2.637 | 0.086 | -11.474 | 0.000 |

Based on Table 3, the data sets are not stationary at the level with p-values (0.086) greater than $\alpha$ = 5%. Therefore, a differencing process is carried out to make the data stationary. The first differencing result shows that the data does not contain unit roots or is already stationary with p-value (0.000) < $\alpha$ at the 5% significance level. Thus, the data is already stationary in the first differencing, so the model identification process can be continued.

## Nonlinearity Test

Nonlinearity tests were conducted to check whether the data had nonlinear elements that could not be captured by ordinary linear models. In this time series, nonlinearity tests were conducted using Tsay's test. A lag order of 2 was chosen based on the lowest AICc value and to adequately capture the higher-order temporal dependencies and nonlinear dynamics present in the data. The results of the tests are shown in Table 4.

**Table 4.** Nonlinearity Test Result

| $F$-Statistic | p-value |
|---|---|
| 4.3370 | 0.0063 |

Based on Table 4, the nonlinearity test results using Tsay's test show $F$-Statistic value of 4.3370 with a p-value (0.0063) less than alpha 5%, which means rejecting $H_0$, that means the data has a nonlinear pattern that cannot be captured using ordinary linear methods, so that nonlinear methods such as Markov switching can be used.

## Optimum Methods Selection

Optimum method selection was performed by comparing the smallest AIC in each Markov switching method and ensuring that the estimation process successfully converged. The model with the lowest AIC is chosen as it represents the best balance between goodness of fit and model simplicity while avoiding overfitting. Furthermore, achieving convergence is a strict prerequisite to ensure that the Maximum Likelihood Estimation (MLE) algorithm has reached a stable and valid global maximum. The comparison results of each method used are shown at Table 5 below.

**Table 5.** Optimum Methods Selection

| Method | Regime | Convergency Status | AIC | BIC | Log-Likelihood |
|---|---|---|---|---|---|
| Markov Switching Mean | 2 | Convergent | -135.031 | -121.350 | 72.515 |
| Markov Switching Variance | 2 | Convergent | -180.788 | -167.107 | 95.394 |
| Markov Switching Mean and Variance | 2 | Convergent | -178.902 | -162.485 | 95.451 |

Based on the Table 5 above, the method with the smallest AIC value and convergent result is Markov switching variance method with 2 regimes and an AIC value of -180.788. From this, the data will be estimated using Markov switching variance with 2 regimes.

### Markov Switching Variance 2 Regimes Estimation

The parameter estimation results were obtained with 100 trials to find the initial value to avoid local maxima. The estimation results are shown in Table 6.

**Table 6.** Markov Switching Estimation Result

| Lag | Coefficient | Std. error (SE) | Z Statistic | p-value | 95% Confidence Interval |
|---|---|---|---|---|---|
| Constant ($\mu$) | 0.0008 | 0.007 | 0.118 | 0.906 | [-0.013, 0.014] |
| Regime 0 Variance ($\sigma_0^2$) | 0.0713 | 0.023 | 3.08 | 0.002 | [0.026, 0.117] |
| Regime 1 Variance ($\sigma_1^2$) | 0.003 | 0.001 | 3.55 | 0.000 | [0.001, 0.005] |
| Probability $p[0 \to 0](P_{00})$ | 0.7587 | 0.102 | 3.55 | 0.000 | [0.559, 0.959] |
| Probability $p[1 \to 0](P_{10})$ | 0.0948 | 0.043 | 2.203 | 0.028 | [0.010, 0.179] |

Based on Table 6, the final fitted models obtained are as follows.

$$y_t = 0.0008 + \varepsilon_t, \varepsilon_t \sim N\left(0, \sigma_{s_t}^2\right)$$

With state value:

$$\sigma_{s_t}^2 = \begin{cases} 0.0713, & \text{for } s_t = 0 \text{ (Volatile State)} \\ 0.003, & \text{for } s_t = 1 \text{(Stable State)} \end{cases}$$

Based on the table, it can be seen that the movement of the insurance ratio regime is divided into two regimes, with regime 0 characterized as a fluctuating phase marked by a high variance value ($\sigma_0^2$ ) of 0.0713 (SE = 0.023) and significant with a p-value of 0.002. Conversely, regime 1 is a stable phase with a small variance value ($\sigma_1^2$) of 0.003 (SE = 0.001) and a significance of 0.000. The model constant is 0.0008 (SE = 0.007), but not significant with a p-value of 0.960. This indicates that the movement of the ratio is more dominated by the movement of variance between regimes and not due to changes in the average value trend.

### Normality of Residual Test

The Jarque-Bera test is used to determine the normality of residual data. Jarque-Bera test results are as follows.

**Table 7.** Normality of Residual Test Result

| Regime | $\chi^2$ Statistic | p-value |
|---|---|---|
| 0 | 1.5223 | 0.4671 |
| 1 | 1.4968 | 0.4731 |

Based on Table 7, the normality of residual test result shown both regime 0 (p-value 0.4671) and regime 1 (p-value 0.4631) have p-value greater than 0.05, so the residual of regime 0 and regime 1 is normally distributed.

### Autocorrelation Test

The autocorrelation test is performed to examine whether the model's residuals are correlated over time. The Ljung-Box test is utilized to confirm if the residuals behave as white noise, indicating the absence of autocorrelation. The results of the test are presented below.

**Table 8.** Ljung-Box Test Result

| Lag | Q Statistic | p-value |
|---|---|---|
| 10 | 5.850353 | 0.827675 |
| 20 | 9.370861 | 0.9782 |

Based on Table 8, the residual p-value at lag 10 with a Q statistic of 5.850353 and lag 20 with a Q statistic of 9.370861 is greater than alpha 0.05, which means accepting $H_0$, so it can be concluded that there is no autocorrelation between lag or the residual data are already white noise.

### Heteroskedasticity Test

This test is conducted to assess whether the variance of errors is the same across all observations (homoscedasticity). A good model should have errors with homogeneous variance. The ARCH effect test results are as follows.

**Table 9.** ARCH Test Result

| $\chi^2$ Statistic | p-value |
|---|---|
| 9.5196 | 0.4836 |

Based on the test results on Table 9, the $\chi^2$ test statistic obtained was 9.5196 and the p-value was 0.4836. Since this value is greater than $\alpha$ = 0.05, $H_0$ is not rejected. Therefore, it can be concluded that the variance of error in the model is homoscedastic.

## Regime Transition Probability Analysis

After residual diagnostic concluded, the transition probability matrix model is obtained as follows.

$$\boldsymbol{P} = \begin{bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{bmatrix} = \begin{bmatrix} 0.7587 & 0.2413 \\ 0.0948 & 0.9052 \end{bmatrix}$$

Analysis of the regime transition probability matrix shows that the probability of the system remaining in a fluctuating state ($P_{00}$) is 75.87%, while the probability of transitioning to a stable regime ($P_{01}$) is 24.13%. while the probability of the system remaining in a stable state ($P_{11}$) is also strong at 90.52%, and the probability of the system shifting to a fluctuating state ($P_{10}$) is 9.48%. The regime 0 duration then obtained as follows.

$$Regime\ 0\ duration = \frac{1}{1 - P_{00}} = \frac{1}{1 - 0.7587} \approx 4.14\ months$$

The regime 0 duration is then obtained as follows. The regime 0 (Volatile State) lasts only about 4 months on average. This shows that shocks in the life insurance industry are usually short-term phenomena before the market eventually adjusts. Furthermore, the regime 1 duration is obtained as follows.

$$Regime\ 1\ duration = \frac{1}{1 - p_{11}} = \frac{1}{1 - 0.9052} \approx 10.55\ months$$

Regime 1 (Stable State) lasted much longer, averaging 10.5 months. This means that the conventional life insurance industry actually has sufficient resilience to remain stable in the long term. The probability graph for each regime is presented in Figure 3 as follows.


**Figure 3.** Smoothed Marginal Probability Plot Data

Next, the movement of each regime data point in the above data is illustrated in the following graph.

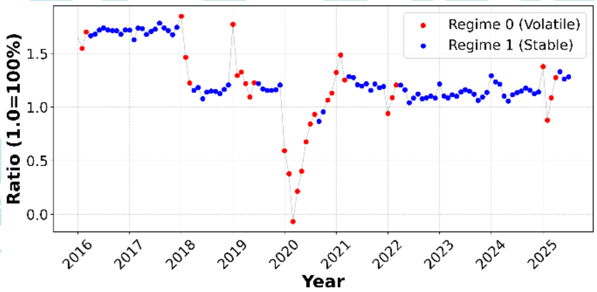


**Figure 4.** Dominant Regime Movement

Figure 4 above shows volatility from February to March 2016, which was then classified as regime 0. This volatility was likely suspected due to fluctuations in Indonesia's macroeconomic conditions and market sentiment. The trend stabilized again from April 2016 to December 2017, but volatility resurfaced from January to March 2018. A significant surge occurred in January 2018, resulting from the annual premium cycle and window dressing in the capital market, but the ratio fell sharply the following month amid global stock market turmoil. These dynamics indicate that the insurance adequacy ratio is highly vulnerable to a combination of seasonal business cycles and macroeconomic volatility.

Volatility resurfaced from January to June 2019, allegedly caused by window dressing practices in the capital market that inflated investment returns. The global stock market correction in February 2018 triggered a massive sell-off in global stock markets, which subsequently spread to Indonesia. This phenomenon caused the investment returns of insurance companies placed in stock and mutual funds to evaporate instantly, causing the ratio to plummet from its peak in January. The COVID-19 pandemic period coincided with significant volatility in the insurance ratio, which hit its lowest point in March 2020 when lockdowns occurred. This sharp decline is supported by empirical conditions in the indonesia financial sector, where the Jakarta Composite Index (IHSG) experienced severe srashes and multiple trading hlats in March 2020, drastically reducing the invesment portfolio value of life insurance companies (Otoritas Jasa Kauangan, 2020). Furthermore, the industry data during this period recorded a 4.1% spike in life insurance claims (Asosiasi Asuransi Jiwa Indonesia, 2020). This turmoil began in January 2020 and continued throughout most of 2020. During this period, macroeconomic pressures caused investment returns to turn negative and led to an increase in aggregate insurance claims. In 2021–2022, several fluctuations occurred during the post-COVID-19 economic recovery phase. The national vaccination program and surging commodity prices provided positive sentiment for insurance companies' investment portfolios, allowing the ratio to return to normal levels above 100%. Turbulence in 2025 is expected to be caused by a combination of an increase in the overall frequency of claims and medical cost inflation.

## CONCLUSION

### Conclusion

Based on the research findings, the best method for modeling the ratio of premium adequacy and investment returns to claim payments is the Markov switching variance (MSV) two-regime model. The findings indicate that the insurance ratio has a higher likelihood of persisting within a stable regime, characterized by a persistence probability of 90.52% and an expected duration of approximately 10.5 months, than within a volatile regime, which exhibits a persistence probability of 75.87% and an expected duration of roughly 4 months. The probability of recovering to a stable regime (24.13%) is significantly higher than the risk of deteriorating into a volatile regime (9.48%).

Theoretically, this study reveals that variance shifts, not mean or simultaneous shifts, are the dominant source of regime-switching in conventional life insurance financial ratios, refining the application of Markov switching models in insurance econometrics. Practically, for insurance companies, the results imply that monitoring claim payment volatility, focusing on maintaining sufficient premium and investment buffers during stable regimes, to prepare for sudden volatility spikes.

For OJK and regulators, the high persistence of the stable regime (90.52%) confirms fundamental sector resilience, but the 9.48% monthly transition risk necessitates an early warning system based on real-time filtered probabilities. Regulators can apply the MSV model to detect early signs of regime shifts and implement countercyclical measures, thereby supporting SDG 8 (financial sector stability) and SDG 9 (resilient long-term investment planning).

### Suggestions

Although the MSV model used in this study is effective, it relies on the assumption of static transition probabilities and does not incorporate macroeconomic variables or volatility clustering. Consequently, future studies are advised to extend the present model along three distinct directions. First, applying a Time-Varying Transition Probability Markov Switching (TVTP-MS) model to allow transition probabilities to change dynamically with macroeconomic conditions such as inflation or interest rate. Second, employing a Markov Switching model to capture both regime shifts in the mean/variance and persistent volatility clustering simultaneously, which is common in financial time series. Third, multivariate Markov switching models may be employed to analyze the contemporaneous interrelationships between the premium adequacy ratio and other financial performance indicators of insurance companies, including solvency margins, return on assets, or claim frequency.

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