

Dynamic Volatility Modeling of Indonesian Insurance Company Stocks

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Abstract

The Indonesian capital market is one of the investment destination countries for investors in developed countries. The development of economic conditions in Indonesia itself is considered suitable for investors to invest. Insurance sector stocks are one of the sectors that are the target of investors. This present study predicts the share price of insurance companies in Indonesia. Data in daily from 2010 to 2020 uses the Autoregressive Conditional Heteroscedasticity - Generalized Autoregressive Conditional Heteroscedasticity (ARCH - GARCH) method. The data involved in this study are time-series data on daily stock prices from nine insurance companies listed on the Indonesian Stock Exchange (IDX) and never delisted. The results of this study indicate that forecasting that was carried out until 2025 all the insurance companies studied experienced an upward trend in stock prices. Investors can manage their funds by increasing or decreasing the insurance stock portfolio and adjusting the asset allocation with the investment strategy.

Keywords: Insurance, ARCH, GARCH, Forecasting, Investment **JEL Classification:** F21, G11

INTRODUCTION

Insurance companies differ from other companies in the underwriting and claims handling function (Caporale, Cerrato, & Zhang, 2017). Companies generally calculate the cost of products before determining the product's selling price, but this is not the case with insurance companies (Cafasso, Chela, & Kimura, 2018). The determined premium level is not the actual cost of goods sold since the company cannot calculate with certainty the claim expenses (Taib & Benth, 2012). Therefore, the cost of goods sold is determined based on the calculation (Barth, Konchitchki, & Landsman, 2013). Insurance companies often need to raise external funding by selling stocks in the capital market (Chen & Imam, 2013). Financial performance and high demand will affect stock prices (Bahloul, Mroua, & Naifar, 2017).

Figure 1 describes the stock movements of each insurance company where Asuransi Bina Dana Arta Tbk (ABDA), Asuransi Harta Aman Pratama Tbk (AHAP), Asuransi Multi Artha Guna Tbk (AMAG), Asuransi Bintang Tbk (ASBI), Asuransi Dayin Mitra Tbk (ASDM), Asuransi Jasa Tania Tbk (ASJT), Asuransi Ramayana Tbk (ASRM), Lippo General Insurance Tbk (LPGI), and Maskapai



Reasuransi Indonesia Tbk (MREI). The more demand for stocks will cause the stock price to rising and vice versa (Trabelsi & Naifar, 2017). Data on closing stock price movements from nine insurance companies listed on the Indonesia Stock Exchange (IDX) from 2010 to 2020 indicates an increasing trend in prices for five companies, while the other three have experienced a downward trend. Asuransi Bina Dana Arta Tbk (ABDA) has the highest average stock price of IDR 5,074.14, followed by Lippo General Insurance Tbk (LPGI) of IDR 3,624.09, and the Indonesian Reinsurance Company Tbk (MREI) of IDR 3,380.1.



Figure 1. Stock price data of nine insurance companies listed on the IDX

However, stock prices are not the only indicator that investors use to invest in the stock market (Uygur & Taş, 2014). Financial statements' of financial performance in claim expenses, premium income, total assets, liabilities, and equity is essential information for investors (Caporale et al., 2017). There are three key indicators to evaluate the level of the financial health of an insurance company, namely the ratio of claims, Return on Assets (ROI), and Risk-Based Capital (RBC) (Primayanti & Denny, 2016; Tarsono et al., 2020). Besides, poor financial performance can also cause companies to be delisted from the IDX. Data from 2015 to 2019 indicate that the nine insurance companies provide different development trends. The development trend of premium income does not always follow companies with an increasing stock price trend, claim expenses, assets, and liabilities. Although ABDA has the highest average stock price and a positive trend, it has a declining trend of premium income, claim expenses, assets, and liabilities. On the other hand, LPGI and MREI have an increasing premium, claim expenses, assets, and liabilities. ASBI, with the lowest average stock price, has an increasing trend of premium income, claim expenses, assets, and liabilities (Figure 2). The information needs to be further analyzed in the form of financial ratios to evaluate the insurance company's financial health condition.

The financial performance of insurance companies is evaluated through an analysis of financial ratios. According to Williams, Arthur Jr, & Heins (1964), financial ratio analysis in insurance companies is focused on two aspects of solvency and financial performance. Both aspects relate to the risks encountered in terms of the company's ability to pay claims in the future. The approach used to



measure the solvency level is by employing Risk-Based Capital (RBC) (Cafasso et al., 2018). Based on Indonesian Financial Services Authority Regulation (POJK) 71/POJK.05/2016, it is determined that the minimum insurer solvency level is 120%. Also, Insurance companies are required to report the calculation of monthly, quarterly, and annual solvency levels in their financial reports. Based on the Regulation of the Minister of Finance of the Republic of Indonesia No 53/PMK.010/2012, insurance companies that do not reach this minimum level will be prohibited from implementing their strategy change plans and company development. Besides, the solvency level is an indicator observed by investors because it determines the company's ability to fulfill its obligations in the long term (Gour & Gupta, 2012).



Figure 2. Premiums, claim expenses, assets, and liabilities of nine insurance companies

An insurance company's financial performance can be evaluated using the claims ratio and Return on Assets (ROA). Both are a measure of the insurance company's profitability performance. Claims ratio is the ratio between claim expense and premium income. The ratio measures the company's ability to pay claim expenses through premium income (Gulsun & Umit, 2010). It also measures the company's ability to maintain company liquidity. The smaller this ratio value, the better its solvency level (Jhongpita, Sinthupinyo, & Chaiyawat, 2012). The maximum limit value of this ratio is 100%. ROA is a comparison between net



income and total assets. ROA presents the company's ability to generate profits, and it is a crucial indicator, and it is most widely used to evaluate insurance companies' financial performance. The higher the ROA value, the better the profitability performance (Malik, 2011; Almezweq, 2015; Grmanová & Strunz, 2017).

Stock price experience is an initial task for investors to access information about the benefits they will get in the future (Khan, Naz, Qureshi, & Ghafoor, 2017). The stock market prediction has become a difficult task in financial timeseries forecasting due to the high volatility in the market and the characteristic of stock price time-series data, which has nonlinearities, discontinuities, and highfrequency of multi-polynomial factors. Besides, stock prices are also heavily influenced by various factors, such as economic, political, and investor expectations (Hadavandi, Shavandi, & Ghanbari, 2010). Forecasting the stock price of insurance companies is becoming increasingly important due to stock prices and company characteristics.

Choosing the appropriate stock price forecasting method has become a difficult task for investors. Several models that have been used from traditional methods are ARIMA (Adebiyi, Adewumi, & Ayo, 2014), ARCH-GARCH family model (Kim & Won, 2018), and VAR (Kuo, 2016), and VECM (Wajdi, 2019). The intelligent methods are fuzzy logic, genetic algorithms, Artificial Neural Networks (ANNs) (Kuo, Chen, & Hwang, 2001; Hung, 2009; Hadavandi et al., 2010; Wang, 2018), Singular Spectrum Analysis (SSA) and Support Vector Regression (SVR) (Lahmiri, 2018). This study used a traditional method through the ARCH-GARCH approach based on econometrics, which requires data assumptions to be fulfilled. This method's advantage is that it can be used in estimated models containing heteroscedasticity that the variance of residuals is not assumed to be constant (Pahlavani & Roshan, 2015).

This study aims to analyze the claim ratio, Return on Assets (ROA), and the level of solvency using the Risk-Based Capital (RBC) approach to determine financial performance and to determine the best model as well as to predict the stock price development of the nine insurance companies listed in Indonesia. Previous studies have been performed using various financial ratios (Nurfadila, Hidayat, & Sulasmiyati, 2015; Nurlatifah & Mardian, 2016; Rahmawati, 2017; Sumartono & Harianto, 2018), but to the best of the author's knowledge, there are no studies that predict the stock price of the companies. This research is expected to contribute to the literature by providing information on trends in stock price developments and evaluating the financial performance of Indonesian insurance companies.

METHOD

The data used in this study are time-series data on daily stock prices from nine insurance companies listed on the IDX and never delisted. The companies are Asuransi Bina Dana Arta Tbk (ABDA), Asuransi Harta Aman Pratama Tbk (AHAP), Asuransi Multi Artha Guna Tbk (AMAG), Asuransi Bintang Tbk (ASBI), Asuransi Dayin Mitra Tbk (ASDM), Asuransi Jasa Tania Tbk (ASJT), Asuransi Ramayana Tbk (ASRM), Lippo General Insurance Tbk (LPGI), and Indonesian Reinsurance Airlines Tbk (MREI). Stock closing price data starts from 2010 to 2020. The data is collected from yahoo finance. Financial performance is calculated through three ratios of the claim ratio, ROA, and solvency rate with the RBC



approach. The claim ratio determines the claim expense incurred by the insurance company. ROA compares net income and total assets, and the solvency rate is calculated using the ratio between the company's total assets and total insurance claims.

Claim ratio
$$= \frac{Claim \ expense}{Premium} \times 100 \%$$

ROA
$$= \frac{Net \ profit \ after \ tax}{Total \ asset} \times 100 \%$$

RBC
$$= \frac{Total \ asset}{Claim \ expense} \times 100 \%$$

The stages of data processing using the ARCH-GARCH model are carried out by following steps: 1) Identification of whether the data contains heteroscedasticity, 2) If the data contains heteroscedasticity, the test will be performed with determining the order of the ARCH-GARCH model with squared residuals using the Partial Autocorrelation Function test (PACF), 3) Significant values at certain lags will be used as the initial order of the ARCH-GARCH model, 4) The model obtained is further tested to get the best model with the criteria of Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC), and Hannan Quinn Criterion (HQIC) (Lama, Jha, Paul, & Gurung, 2015). The general model for GARCH is as follows (Bollerslev, 1986). The GARCH model is stationary if and only if following this equation.

$$\begin{split} \sum_{i=1}^{q} a_i + \sum_{j=1}^{p} b_j < 1 \\ \varepsilon_t = \xi_t \ h_t^{1/2} \\ h_t = a_0 + \sum_{i=1}^{q} a_i \ \varepsilon_{t-1}^2 + \sum_{j=1}^{p} b_j \ h_{t-j} \end{split}$$

RESULTS AND DISCUSSION

The claim ratio calculation results indicate that all insurance companies have a ratio value of less than 100%. Companies with relatively low ratios are ASBI and ASDM, while LPGI has the highest claim ratio, followed by ABDA. Of the nine companies, six of them have experienced an increasing trend of claim ratios over the last five years, including ASBI, which had the lowest ratio. The finding is a relevant note for the company since an increase in the claim expense ratio can indicate a decrease in premium income compared to claims that must be paid (see Table 1).

The result of the ROA calculation indicates that MREI has the highest average ROA ratio, which is followed by ABDA. Meanwhile, AHAP has an unfavorable ratio and becomes the lowest of all. All insurance companies have experienced a downward trend in the ROA ratio over the past five years, including MREI and ABDA. It is a relevant note for the company that there is a decline in its ability to generate high net income from asset capitalization effectively and productively. The trend of the lower ROA ratio indicates, the lower the resulting net income, and the lower the dividends that will be received by investors (Table 2). The finding supports the trend supplied by the claim ratio. Overall, there is a decline in companies' profitability performance.

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	C	Claim ratio (%	ó)		- A 11000 00
2015	2016	2017	2018	2019	Average
50.91	63.14	57.06	64.06	74.41	61.92
0.00*	56.91	46.05	60.78	75.26	47.80
48.13	44.32	44.17	47.38	39.59	44.72
0.00*	31.03	20.03	25.32	46.95	24.66
45.85	32.11	14.42	13.80	20.48	25.33
42.51	42.18	41.01	47.14	54.15	45.40
44.59	43.13	50.64	50.29	58.11	49.35
61.88	66.92	61.81	68.35	72.47	66.28
0.00*	0.00*	0.00*	0.00*	0.00*	0.00*
	2015 50.91 0.00* 48.13 0.00* 45.85 42.51 44.59 61.88 0.00*	2015 2016 50.91 63.14 0.00* 56.91 48.13 44.32 0.00* 31.03 45.85 32.11 42.51 42.18 44.59 43.13 61.88 66.92 0.00* 0.00*	Claim ratio (%20152016201750.9163.1457.060.00*56.9146.0548.1344.3244.170.00*31.0320.0345.8532.1114.4242.5142.1841.0144.5943.1350.6461.8866.9261.810.00*0.00*0.00*	Claim ratio (%)201520162017201850.9163.1457.0664.060.00*56.9146.0560.7848.1344.3244.1747.380.00*31.0320.0325.3245.8532.1114.4213.8042.5142.1841.0147.1444.5943.1350.6450.2961.8866.9261.8168.350.00*0.00*0.00*0.00*	$\begin{array}{c c c c c c c c c c c c c c c c c c c $

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Table 1.	Claim	ratio	of the	insurance	companies

Note(s): *Data unavailability

The solvency ratio calculation result indicates that all companies have a solvency ratio above the minimum level of 120% (Table 3). MREI has the highest solvency ratio, while ASBI has the lowest solvency ratio. ABDA, ASDM, ASJT, ASRM, and MREI have experienced a positive trend ratio over the last five years, while AHAP and LPGI have a negative ratio trend. The solvency ratio measures a company's ability to meet its long-term obligations. This ratio notifies the number of assets that are funded by debt. The higher the value of this ratio, the better the company's ability to pay its obligations. The increase in the five insurance companies' ratios over the past five years is a positive signal, but this is not the case for the other two.

Insurance	ROA ratio (%)					Average
companies	2015	2016	2017	2018	2019	
ABDA	9.43	6.17	5.42	2.39	3.39	5.36
AHAP	1.74	1.85	-9.87	-4.25	-19.83	-6.07
AMAG	7.37	3.79	3.17	0.66	1.58	3.31
ASBI	5.71	2.91	1.83	1.59	0.93	2.60
ASDM	3.02	3.67	3.74	3.59	2.40	3.28
ASJT	4.57	5.55	5.08	5.23	0.27	4.14
ASRM	4.49	4.40	4.29	5.18	4.06	4.49
LPGI	3.48	3.61	3.89	2.76	3.30	3.41
MREI	9.42	7.95	5.59	4.11	4.58	6.33

Table 2. ROA ratio of the insurance companies

Table 4 demonstrates that AHAP has the lowest average stock price (82.84 rupiahs), while ABDA has the highest average stock price (4,732.57 rupiahs). The skewness value is a measure of data bias. Negative skewness values (ABDA, AHAP, AMAG, ASDM, ASRM, and LPGI) indicate that the data is sticking to the left, which means that the average daily stock price is less than the median value, or the price of the majority stocks. On the other hand, a positive skewness value (ASBI, ASJT, and MREI) indicates that the data is sticking to the right, which means that the average daily stock price is higher than the median value the price of the majority of stocks (Table 4).

Insurance	Solvency ratio (%)				A	
companies	2015	2016	2017	2018	2019	Average
ABDA	290.55	331.72	382.61	317	364	337
AHAP	216	206	209	189	128	190
AMAG		Data is unav	ailable but f	ulfill the mir	nimum ratio	
ASBI	131	131	134	131	133	132
ASDM	181.43	254.58	266.76	281.42	305.09	258
ASJT	174.37	232.74	263.26	270.42	290.57	246
ASRM	143	142	160	151.14	151.37	150
LPGA	234.31	217.15	226	187	198.54	213
MREI	296.35	242.18	471.1	364.48	342.81	343

 Table 3. The solvency ratio of the insurance companies

The result from the unit root test using Augmented Dickey-Fuller indicates that the Augmented Dickey-Fuller Test Statistic values of ABDA, AMAG, ASJT, ASRM, LPGI, and MREI are smaller than the critical test values at the 5% level, suggesting that the unit root is not found in the data and the data is stationary. Since data of AHAP, ASBI, and ASDM are not stationary at the level, some data are needed to diverge further, so the possibility of the order d is 1 (Table 5).

Table 4. Descriptive statistics of stock prices

			AM		ASD				
	ABDA	AHAP	AG	ASBI	Μ	ASJT	ASRM	LPGI	MREI
Mean	4,732.57	82.84	272.92	264.01	868.12	259.74	1,170.03	3,405.40	3,408.35
Maximum	8,250	179.47	492	775	1250	1250	2,679.49	6,475	9,007.34
Minimum	198.61	42.51	92	102.5	170	89	285.56	490	269.51
			92.6						
Std. Dev.	2,727.23	19.50	1	92.82	237.60	163.48	527.27	1,519.96	2,080
Skewness	-0.60	-0.25	-0.07	1.00	-0.86	3.22	-0.00	-0.33	0.04

The plot data on the nine insurance companies' stock price in Figure 3 presents daily price movements (left) and daily return movements (right). The vertical axis is the stock price, and the horizontal axis is the period (days). On average, the stock price of each insurance company has a high level of volatility.

 Table 5. Augmented Dickey-Fuller unit root test results

Variablas	Level					
variables	ADF test stat.	t-stat.	Prob*			
ABDA	ABDA	-29.090000	-2.8624			
AHAP	-2.95165	-2.862418	0.0398			
AMAG	-42.6954	-2.862418	0,0000			
ASBI	-2.93716	-2.862417	0.0413			
ASDM	-3.67916	-2.862418	0.0045			
ASJT	-50.764	-2.862417	0.0001			
ASRM	-57.2153	-2.862417	0.0001			
LPGI	-40.2292	-2.862418	0,0000			
MREI	-57.3705	-2.862418	0.00001			





Figure 3. Time series plot of stock closing prices of the nine insurance companies

Following the stationery test, the next step is to determine the best ARIMA model. Table 6 demonstrates the best ARIMA (p, d, q) model with the criteria of having the smallest Akaike Info Criterion (AIC) value and a significant probability value of each variable. The result of heteroscedasticity testing using the ARCH-LM test reveals that the data contained heteroscedasticity because the probability of F statistical value is 0.0000 - 0.0001 below the significant value of 0.05. Therefore, the step can be continued with the ARCH-GARCH model test.



Variables	ARIMA (p.d.q)	Akaike Info	ARCH LM
		Criterion	
ABDA	(1.1.1)	-4.00444	0.0000
AHAP	(1.0.3)	-2.87175	0.0000
AMAG	(3.1.3)	-4.0894	0.0000
ASBI	(3.0.3)	-2.57483	0.0000
ASDM	(2.0.2)	-3.18085	0.0000
ASJT	(2.1.2)	-3.66148	0.0000
ASRM	(2.1.3)	-3.79543	0.0000
LPGI	(1.1.1)	-3.95766	0.0000
MREI	(2.1.2)	-3.15681	0.0000

The result from Table 7 indicates that ABDA stocks have the best models of GARCH (1,1), AHAP with GARCH (1,1), AMAG with GARCH (1,1), ASBI with GARCH (1,1), ASDM with GARCH (2,1), ASJT with GARCH (1,1), ASRM with GARCH (1,1), LPGI with GARCH (1,1), MREI with GARCH (1,1). The selection is based on the smallest AIC value. All parameters are significant at 5% alpha.

Table 7. GARCH overfitting model (p,q)

	(<i>p</i> . <i>q</i>)	С	ARCH (<i>t</i> -1)	ARCH (t-2)	GARCH (t-1)	Prob.	AIC
ABDA	(1.1)	4.83E-05	0.0859		0.8735	< 0.05	-4.34
AHAP	(1.1)	2.25E-04	0.1104		0.8135	< 0.05	-3.30098
AMAG	(1.1)	2.17E-04	0.1988		0.5923	< 0.05	-4.25726
ASBI	(1.1)	5.07E-04	0.7110		0.3347	< 0.05	-3.22584
ASDM	(2.1)	9.40E-06	0.6162	-0.5847	0.9690	< 0.05	-3.45344
ASJT	(1.1)	7.85E-06	0.2511		0.8529	< 0.05	-4.80942
ASRM	(1.1)	1.27E-04	0.1035		0.8080	< 0.05	-3.9762
LPGI	(1.1)	7.52E-05	0.096944		0.847565	< 0.05	-4.0908
MREI	(1.1)	1.80E-04	0.1554		0.7804	< 0.05	-3.54017

Mathematically, the stock price model of each insurance company is presented as follows. The model below provides information that the insurance company stock price is influenced by the prices and the standard deviation values from the day before.

$$\begin{split} & \text{ABDA, } \mathbf{h}_t = 0.0000483 {+} 0.085868 \ \varepsilon_{t-1^2} {+} 0.873515 \ \mathbf{h}_{t-1} \\ & \text{AHAP, } \mathbf{h}_t = 0.000225 {+} 0.110389 \ \varepsilon_{t-1^2} {+} 0.813522 \ \mathbf{h}_{t-1} \\ & \text{AMAG, } \mathbf{h}_t = 0.000217 {+} 0.198768 \ \varepsilon_{t-1^2} {+} 0.592297 \mathbf{h}_{t-1} \\ & \text{ASBI, } \mathbf{h}_t = 0.000507 {+} 0.710951 \ \varepsilon_{t-1^2} {+} 0.334667 \ \mathbf{h}_{t-1} \\ & \text{ASDM, } \mathbf{h}_t = 0.000094 {+} 0.61618 \ \varepsilon_{t-1^2} {-} 0.58469 \ \varepsilon_{t-2^2} {+} 0.96904 \ \mathbf{h}_{t-1} \\ & \text{ASJT, } \mathbf{h}_t = 0.0000785 {+} 0.251073 \ \varepsilon_{t-1^2} {+} 0.852854 \ \mathbf{h}_{t-1} \\ & \text{ASRM, } \mathbf{h}_t = 0.000127 {+} 0.103484 \varepsilon_{t-1^2} {+} 0.807998 \ \mathbf{h}_{t-1} \\ & \text{LPGI, } \mathbf{h}_t = 0.0000752 {+} 0.096944 \ \varepsilon_{t-1^2} {+} 0.847565 \ \mathbf{h}_{t-1} \\ & \text{MREI, } \mathbf{h}_t = 0.00018 {+} 0.155369 \ \varepsilon_{t-1^2} {+} 0.780399 \ \mathbf{h}_{t-1} \end{split}$$

The GARCH model needs to be tested for its accuracy with three tests of the ARCH-LM test to test whether there is still a heteroscedasticity effect on errors,



the Correlogram Q Statistic test to test whether data is autocorrelated or not, and the Kurtosis test to see the distribution of the error. The ARCH-LM test result indicates that the data do not contain heteroscedasticity effects after GARCH modeling was carried out. The result from the Correlogram Q Statistic test indicates that the residual value is randomly distributed.

Table 8.	Diagnostic	model	test results
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Variables	Heteroskedasticity test results
ABDA	0.5128
AHAP	0.2671
AMAG	0.8521
ASBI	0.4724
ASDM	0.4975
ASJT	0.9944
ASRM	0.4172
LPGI	0.2832
MREI	0.2679

Forecasting of stock prices is performed on the dataset starting from October 2020 until October 2025. In Figure 4, the forecasting results start from the period of October 2020 until October 2025. The vertical axis represents the stock prices, and the horizontal axis represents the period. The data plot indicates that stock prices over 60 months follow the previous price data pattern.



Figure 4. The results of the stock price forecast

Furthermore, the 60-month forecast in Figure 5 indicates that all insurance companies experience an increasing trend of stock prices except for ASJT. ASJT has a downward trend in stock prices. ASRM, ASDM, AMAG, and AHAP experience relatively stable prices even though they have average prices below their competitors (ABDA, MREI, LPGI). ASBI experiences a sharp increase from December 2023 to February 2024. It decreases until August 2025, and it rises back from September 2025 (see Figure 5).



Figure 5. Stock price forecast of insurance companies for 60 days

CONCLUSION

The results of the profitability performance analysis from the nine insurance companies show that insurance companies in Indonesia have good profitability performance. All companies gain the right claim ratios of below 100%. ROA results indicate that MREI has the highest average ROA ratio, followed by ABDA, while AHAP has the lowest ratio. All companies have experienced a downward trend in their ROA ratio over the past five years. The solvency rate analysis results indicate that all companies have good abilities to pay off their long-term obligations with solvency ratios of above 120%.

Furthermore, the results of forecasting the stock prices reveal that the best GARCH model of insurance companies respectively is that ABDA with GARCH (1,1), AHAP with GARCH (1,1), AMAG with GARCH (1,1), ASBI with GARCH (1,1), ASDM with GARCH (2,1), ASJT with GARCH (1,1), ASRM with GARCH (1,1), LPGI with GARCH (1,1), and MREI with GARCH (1, 1). The 60-month stock price forecast results from October 2020 to October 2025 specify that all companies have been experiencing an increasing trend of stock prices except for ASJT. ASRM, ASDM, AMAG, and AHAP have been experiencing a relatively stable trend of price movements. Further studies are suggested to investigate the factors that influence stock price changes in insurance companies.

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