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Modeling Volatility Asymmetry in Government-Owned Stocks: Evidence from Value at Risk Estimation in Indonesia

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ABSTRACT: This study evaluates the comparative effectiveness of four volatility models—EWMA, GARCH(1,1), EGARCH, and TGARCH—in estimating daily Value at Risk (VaR) for a portfolio of Indonesian state-owned enterprise (SOE) stocks over the period 2019–2024. Motivated by the rapid growth of retail investor participation and increasing exposure to market risk in Indonesia's emerging capital market, the research addresses a critical gap in empirical risk modeling for government-owned equities. A key contribution of this study lies in the integration of asymmetric GARCH-family models with Student-t innovations into a VaR estimation framework, tailored specifically to SOE stocks—an approach seldom explored in the Southeast Asian context. The analysis uses daily return data from ten liquid, sectorally diverse SOEs. Volatility is estimated via parametric methods, assuming a normal distribution for EWMA and Student-t distributions for GARCH-type models. Model accuracy is evaluated through in-sample and out-of-sample backtesting, employing MAE, RMSE, and the Kupiec and Christoffersen tests. The findings indicate that GARCH(1,1) performs most reliably at the 95% confidence level, while TGARCH demonstrates superior performance at the 99% level, particularly in capturing downside risk. EGARCH tends to produce conservative estimates, whereas EWMA underestimates tail risk. The results support a dual-model strategy for operational monitoring and capital risk management.

KEYWORDS: Emerging markets, GARCH-family models, state-owned enterprises, Value at Risk, Volatility modeling.

I. INTRODUCTION

Indonesia's capital market has experienced remarkable growth over the past five years, fueled by digital transformation, easier access through online investment platforms, and increased financial literacy among the population. One of the most striking indicators of this development is the surge in retail investor participation. According to data from PT Kustodian Sentral Efek Indonesia (KSEI, 2024), the number of investors registered under the Single Investor Identification (SID) system rose from approximately 1.7 million in 2020 to over 6.38 million in 2024. This expansion includes a dramatic 103.59% growth in 2021, followed by annual increases of 28.63% in 2022, 18.37% in 2023, and 21.42% in 2024. The trend reflects a growing public interest in capital market investment, especially in equities, encouraged by low interest rates and accessible digital platforms.

This rapid rise in investor participation has significantly transformed Indonesia's financial market landscape. However, it has also introduced a new layer of risk, as many retail investors are now increasingly exposed to market volatility—particularly in portfolios involving shares of state-owned enterprises (SOEs). While SOEs are considered strategically important and are backed by the government, their stock prices have demonstrated substantial fluctuations, especially during systemic shocks such as the COVID-19 pandemic and periods of global commodity instability.

As exposure to market risk rises, the need for robust quantitative risk measurement tools becomes more pressing. Value at Risk (VaR) has emerged as one of the most widely adopted metrics for estimating the maximum expected loss over a given time horizon at a specified confidence level (Jorion, 2007). The reliability of VaR, however, is highly dependent on the underlying volatility model used.

To address this, the present study adopts the Exponentially Weighted Moving Average (EWMA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models as the foundation for volatility estimation and VaR computation. EWMA, introduced through JP Morgan's RiskMetrics framework (1996), is known for its simplicity and responsiveness to recent market movements. Meanwhile, the GARCH(1,1) model developed by Bollerslev (1986) remains a benchmark in financial volatility modeling due to its ability to capture volatility clustering in return series.

Recognizing the limitations of the standard GARCH model in capturing asymmetric market behavior, the study also incorporates two extended models: Exponential GARCH (EGARCH) by Nelson (1991), which uses a logarithmic form to better accommodate asymmetric volatility, and TGARCH by Glosten, Jagannathan, and Runkle (1993), which accounts for leverage effects where negative shocks tend to increase volatility more than positive shocks of the same magnitude.

These models are applied to a portfolio of ten SOE stocks listed on the Indonesia Stock Exchange, selected based on sectoral representation, liquidity, and the availability of daily historical data from 2019 to 2024. By estimating and comparing daily VaR at 95% and 99% confidence levels across models, this study seeks to determine the most effective approach for capturing market risk in an emerging economy context. The findings are expected to offer valuable insights for investors, asset managers, and regulatory institutions in improving risk-based portfolio management.

Accordingly, this study investigates how alternative volatility models capture the risk dynamics of SOE equities, evaluates the accuracy and statistical validity of their VaR forecasts across multiple confidence levels, and examines the practical implications of model selection for portfolio risk management in emerging market settings.

II. LITERATURE REVIEW

Volatility modeling has long been central to the development of modern risk management in finance, particularly in estimating Value at Risk (VaR). Among the most commonly adopted models are the Exponentially Weighted Moving Average (EWMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and its asymmetric extensions, namely Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH). These models have evolved in response to the empirical regularities observed in financial data, such as volatility clustering, fat tails, and asymmetry in response to market shocks.

The EWMA model, introduced via JP Morgan's RiskMetrics (1996), applies exponentially decreasing weights to past returns, giving greater emphasis to more recent data. While this makes the model highly responsive, its limitation lies in its inability to model long-memory and asymmetry effects. In contrast, the GARCH(1,1) model developed by Bollerslev (1986), building upon Engle's (1982) ARCH framework, allows for conditional variance to depend on both lagged squared returns and past variances, effectively capturing volatility persistence.

However, the standard GARCH model assumes that volatility responds symmetrically to positive and negative shocks, which contradicts empirical findings in many markets. To address this, Nelson (1991) introduced the EGARCH model, which models logarithmic variance and allows for asymmetric effects without imposing non-negativity constraints. Meanwhile, Glosten, Jagannathan, and Runkle (1993) proposed the TGARCH or GJR-GARCH model, which incorporates a threshold mechanism to account for differing effects of positive and negative shocks.

Empirical studies have consistently demonstrated the relevance of these models across different asset classes and countries. Ari (2022) compared EWMA, GARCH, and CARR models in forecasting exchange rate volatility and found EWMA superior in short-term prediction. Gupta and Rajib (2018) identified ARMA-GARCH with t-distribution as the most accurate model for forecasting one-day VaR in Indian commodity markets. Lu et al. (2023) applied GARCH and EGARCH to the Chinese nickel sector index and confirmed the presence of asymmetric volatility patterns. Lorimer et al. (2024) emphasized the superiority of asymmetric risk measures in portfolio optimization, highlighting the practical importance of choosing appropriate models in real-world settings.

Despite a vast body of international literature, applications of these volatility models to portfolios of Indonesian state-owned enterprises remain limited. This study contributes by examining EWMA, GARCH, EGARCH, and TGARCH models within the context of a diversified SOE portfolio on the Indonesia Stock Exchange, providing empirical insights into the risk characteristics of state-linked equities in emerging markets.

III. RESEARCH METHODS

3.1. Research Design

This research adopts a quantitative empirical design aimed at assessing and comparing the accuracy of market risk estimation through volatility modeling using the Exponentially Weighted Moving Average (EWMA), the Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and its asymmetric extensions—Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH). These models are applied to a strategically selected portfolio of Indonesian state-owned enterprises (SOEs), with risk measurement operationalized via Value at Risk (VaR) at multiple confidence levels.

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3.2. Portfolio Construction and Data Description

The sample portfolio comprises ten SOEs listed on the Indonesia Stock Exchange (IDX), selected based on sectoral representativeness, stock liquidity, and availability of historical daily price data. These firms operate in key sectors, including banking, mining, energy, telecommunications, infrastructure, and industrial manufacturing. The observation period spans from January 1, 2019 to December 31, 2024, covering both pre- and post-pandemic market dynamics.

Daily return series are calculated using logarithmic transformation:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

where r_t denotes the continuously compounded return on day *t*, and P_t, P_{t-1} represent the closing prices on days *t – 1* and , respectively.

Prior to model estimation, the return series was subjected to standard time series diagnostic tests. Stationarity was tested using the Augmented Dickey-Fuller (ADF) test. The presence of ARCH effects was evaluated using the ARCH-LM test. Furthermore, normality was examined via the Jarque-Bera test, and autocorrelation of residuals was assessed using the Ljung-Box Q-test. These tests ensure that the modeling assumptions of GARCH-type models are adequately met.

3.3. Volatility Estimation Models

Each model used in this study is mathematically expressed to clarify how conditional variance evolves over time based on past return behavior. The EWMA model, based on RiskMetrics (1996), employs the following recursive formula:

$$\sigma_t{}^2 = \lambda\sigma^2{}_{t-1} + (1-\lambda)r^2{}_{t-1} \quad (2)$$

with a decay factor.This model assigns exponentially decreasing weights to past squared returns. A higher λ places greater emphasis on recent returns, allowing volatility to adapt quickly to market changes. However, it assumes a memoryless structure and lacks the ability to model volatility clustering.

The GARCH model captures volatility clustering by incorporating past squared shocks (ε^2) and previous period's volatility. It assumes symmetric response to positive and negative shocks. GARCH(1,1), as proposed by Bollerslev (1986), is defined as:

$$\sigma_t{}^2 = \omega + \alpha\varepsilon^2{}_{t-1} + \beta\sigma^2{}_{t-1} \quad (3)$$

EGARCH(1,1), developed by Nelson (1991), uses a logarithmic variance form to model asymmetric effects:

$$\ln\sigma_t{}^2 = \omega + \beta\ln(\sigma^2{}_{t-1}) + \alpha\left|\frac{\varepsilon_{t-1}}{\alpha_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\alpha_{t-1}} \quad (4)$$

This model uses a logarithmic variance formulation to avoid the need for non-negativity constraints. The γ term captures the leverage effect, where negative shocks have greater impact on future volatility.

TGARCH(1,1), or GJR-GARCH, introduced by Glosten et al. (1993), incorporates threshold asymmetry:

$$\sigma_t{}^2 = \omega + \alpha\varepsilon^2{}_{t-1} + \gamma D_{t-1}\,\varepsilon^2{}_{t-1} + \beta\sigma^2{}_{t-1} \quad (5)$$

where $D_{t-1} = 1$ if $\varepsilon_{t-1} < 0$, and 0 otherwise. TGARCH explicitly models asymmetry by allowing negative shocks to have a different (typically larger) impact on volatility than positive shocks of the same size.

3.4. Value at Risk Estimation

VaR is calculated at 95% and 99% confidence levels using the volatility forecasts from each model. The one-day VaR is computed as:

$$VaR_t = z_\alpha.\sigma_t.\sqrt{h} \quad (5)$$

where z_α is the quantile of the standard normal distribution, σ_t is the predicted standard deviation, and $h = 1$ denotes the daily holding period.

3.5. Model Evaluation and Backtesting

To validate these insights, a two-stage backtesting procedure is employed:

a. In-sample testing over the full data period to assess internal fit and model calibration; and
b. Out-of-sample testing using the final 20% of data to evaluate forecasting accuracy under realistic, forward-looking conditions.

Performance is assessed using MAE and RMSE for forecast precision, and Kupiec (1995) and Christoffersen (1998) tests to determine whether observed VaR violations align with expected statistical properties (coverage and independence). This dual-validation framework ensures both statistical rigor and practical robustness, allowing models to be assessed not just by fit but by their effectiveness in supporting risk-based decision-making in dynamic market environments.

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All estimations are conducted in R using the rugarch package for GARCH-family models and custom code for EWMA and VaR implementations.

IV. RESULTS AND DISCUSSION

This section presents the empirical findings from the analysis of return data from ten selected state-owned enterprises (SOEs) listed on the Indonesia Stock Exchange for the period January 2019 to December 2024. The discussion begins with descriptive statistics that provide an overview of the distributional characteristics of daily returns.

Across the observed stocks, the average daily returns are close to zero, reflecting the typical behavior of financial return series over short horizons (Cont, 2001). Notably, several stocks such as ADHI and BJBR exhibit negative average returns, potentially reflecting sectoral volatility or post-pandemic recovery lag (Gökcan, 2000).

Volatility, as measured by standard deviation, varies considerably across the stocks. ADHI and ANTM show relatively high standard deviations (above 3%), indicating greater return fluctuations. In contrast, BJBR and BBRI exhibit lower volatility, suggesting relatively more stable price movements during the sample period. Such variability in volatility is consistent with the phenomenon of volatility clustering widely documented in financial literature (Mandelbrot, 1963; Bollerslev, 1986).

Table 1. Descriptive analysis of daily returns

stocks	Count	Mean	std	Min	max	skewness	kurtosis
ADHI	1.446	-0,001352	0,031350	-0,132598	0,246133	1,516958	9,249442
ANTM	1.446	0,000500	0,030334	-0,097164	0,221836	1,329219	6,840543
BBNI	1.446	-0,000002	0,021204	-0,124642	0,127927	0,073263	4,637109
BBRI	1.446	0,000102	0,020245	-0,081346	0,186412	0,640692	7,722656
BJBR	1.446	-0,000553	0,019644	-0,106483	0,128254	0,282901	6,636519
BMRI	1.446	0,000306	0,020722	-0,097727	0,146721	0,145909	4,314204
ELSA	1.446	0,000174	0,026497	-0,129812	0,254346	1,521856	1,332729
JSMR	1.446	0,000006	0,022824	-0,109199	0,136132	0,427373	2,730235
PGAS	1.446	-0,000228	0,026480	-0,150433	0,142873	-0,011026	4,884382
TLKM	1.446	-0,000221	0,018318	-0,072162	0,128749	0,417301	4,120510

The distributional asymmetry is captured through skewness. Most return distributions exhibit positive skewness, especially for ADHI and ANTM, suggesting a higher frequency of large positive returns. This is further corroborated by kurtosis values exceeding 3, with several stocks such as ADHI and BBRI displaying excess kurtosis, indicating the presence of fat tails or leptokurtic behavior. These findings are in line with stylized facts of financial time series as established by Cont (2001), highlighting the non-normality and asymmetric behavior in return distributions.

These characteristics justify the use of robust conditional volatility models that can accommodate non-normality, heteroskedasticity, and asymmetric shock responses. The following sections explore the estimated volatility and Value at Risk (VaR) using the EWMA, GARCH(1,1), EGARCH, and TGARCH models, in line with methodologies recommended by Jorion (2007) and Alexander (2008) in modern risk management practice.

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4.1. Diagnostic Test

Prior to model implementation, diagnostic tests were conducted on the return series to assess their statistical properties. The Augmented Dickey-Fuller (ADF) test results indicate that all return series are stationary, satisfying the primary requirement for applying GARCH-family models (Brooks, 2019). Furthermore, the ARCH-LM tests confirm the presence of heteroskedasticity in all series, validating the appropriateness of conditional variance modeling (Engle, 1982). Lastly, the Jarque-Bera test results reject the null hypothesis of normality for all stocks, highlighting the leptokurtic and non-Gaussian nature of the return distributions, which aligns with empirical findings on financial data behavior (Cont, 2001).

Table 2. Diagnostic Test Results

	ADF p-value	ARCH-LM p-value	Jarque-Bera p-value	Conclusion
ADHI	2,1378E-20	4,1509E-12	0	Stationary, ARCH effect, non-normal
ANTM	3,1466E-27	3,4802E-29	0	Stationary, ARCH effect, non-normal
BBNI	8,0772E-21	1,2220E-61	0	Stationary, ARCH effect, non-normal
BBRI	1,5833E-26	4,1470E-41	0	Stationary, ARCH effect, non-normal
BJBR	0,0000E+00	9,8472E-34	0	Stationary, ARCH effect, non-normal
BMRI	2,5820E-29	1,0147E-62	0	Stationary, ARCH effect, non-normal
ELSA	1,1664E-17	2,8098E-15	0	Stationary, ARCH effect, non-normal
JSMR	7,5585E-11	6,4980E-55	0	Stationary, ARCH effect, non-normal
PGAS	0,0000E+00	1,5033E-32	0	Stationary, ARCH effect, non-normal
TLKM	3,6312E-18	2,9015E-34	0	Stationary, ARCH effect, non-normal

Given these empirical properties—non-normality, heteroskedasticity, and asymmetric shock responses—the subsequent analysis applies four volatility models tailored to capture these features: the Exponentially Weighted Moving Average (EWMA), Generalized Autoregressive Conditional Heteroskedasticity (GARCH), Exponential GARCH (EGARCH), and Threshold GARCH (TGARCH). While the EWMA model implicitly assumes normally distributed returns and applies exponential smoothing, the GARCH-family models, particularly EGARCH and TGARCH, explicitly incorporate mechanisms to account for asymmetric volatility and can be extended to use distributions better suited to fat tails, such as the Student-t distribution (Alexander, 2008).

4.2. Volatility and VaR Estimation

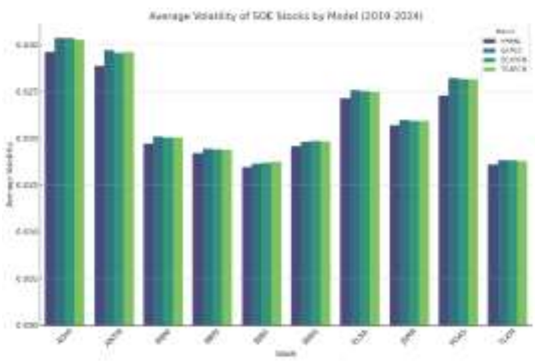

Figure 1. Average Volatility of SOE Stocks by Model (2019-2024)
Source: *Refinitiv Eikon processed*

Figure 1 presents the volatility estimates for the selected portfolio of SOE stocks using the EWMA, GARCH(1,1), EGARCH(1,1), and TGARCH(1,1) models from January 2019 to December 2024. The plots reveal clear differences in the dynamic behavior of volatility across models and stocks. The EWMA model demonstrates high sensitivity to recent price changes, resulting in noticeable short-term volatility spikes, particularly for ANTM and ADHI. However, this model's reliance on exponentially

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weighted past returns without accounting for clustering or asymmetry leads to potentially exaggerated volatility during market stress (Jorion, 2007).

The GARCH(1,1) model smooths out these spikes by incorporating past variance and return shocks, showing more persistent volatility patterns. For stocks like ANTM and ADHI, GARCH-generated volatility remains elevated but with less extreme fluctuations, aligning with the volatility clustering observed in financial data (Bollerslev, 1986).

EGARCH(1,1) and TGARCH(1,1) models further refine this analysis by incorporating asymmetry in volatility responses. EGARCH captures sharp increases in volatility following negative shocks, reflecting the leverage effect where adverse news disproportionately impacts market risk (Nelson, 1991). TGARCH explicitly differentiates between the effects of positive and negative returns, revealing that negative shocks produce larger volatility increases for stocks such as ANTM and ADHI. This asymmetric pattern aligns with empirical observations in emerging markets where negative information often triggers stronger market reactions (Glosten et al., 1993).

Table 3. Summary Volatility of SOE Stocks by Model (2019-2024)

Stock	Model	Avr	Max	Min	Stock	Model	Avr	Max	Min
ADHI	EWMA	0,02924	0,08680	0,01315	BMRI	EWMA	0,01916	0,06418	0,00956
	GARCH	0,03076	0,08855	0,02140		GARCH	0,01966	0,07407	0,01213
	EGARCH	0,03075	0,07956	0,01755		EGARCH	0,01972	0,06681	0,01043
	TGARCH	0,03056	0,08213	0,01818		TGARCH	0,01967	0,07428	0,01032
ANTM	EWMA	0,02775	0,08329	0,00837	ELSA	EWMA	0,02428	0,08460	0,01081
	GARCH	0,02942	0,09088	0,01309		GARCH	0,02518	0,10681	0,01594
	EGARCH	0,02914	0,08057	0,01062		EGARCH	0,02508	0,08842	0,01243
	TGARCH	0,02921	0,08560	0,01165		TGARCH	0,02496	0,09123	0,01346
BBNI	EWMA	0,01945	0,06494	0,00746	JSMR	EWMA	0,02141	0,06226	0,00965
	GARCH	0,02019	0,06785	0,01139		GARCH	0,02193	0,07537	0,01346
	EGARCH	0,02012	0,06943	0,00936		EGARCH	0,02182	0,06951	0,00983
	TGARCH	0,02007	0,07343	0,01001		TGARCH	0,02185	0,07501	0,01095
BBRI	EWMA	0,01840	0,06640	0,00847	PGAS	EWMA	0,02457	0,06899	0,01016
	GARCH	0,01890	0,07965	0,01107		GARCH	0,02645	0,07531	0,01533
	EGARCH	0,01883	0,06788	0,00904		EGARCH	0,02634	0,07649	0,01238
	TGARCH	0,01878	0,07242	0,00959		TGARCH	0,02631	0,08286	0,01308
BJBR	EWMA	0,01690	0,05370	0,00434	TLKM	EWMA	0,01723	0,05367	0,00818
	GARCH	0,01726	0,05620	0,00563		GARCH	0,01769	0,05388	0,01184
	EGARCH	0,01739	0,05755	0,00491		EGARCH	0,01763	0,04788	0,01041
	TGARCH	0,01746	0,06361	0,00485		TGARCH	0,01758	0,05034	0,01088

Table 3 summarizes the average, maximum, and minimum daily volatility estimates across the ten SOE stocks using four different models: EWMA, GARCH(1,1), EGARCH(1,1), and TGARCH(1,1). Among these, ANTM and ADHI consistently exhibit higher average volatility levels, reflecting their heightened sensitivity to market dynamics and structural volatility. Furthermore, models within the GARCH family—particularly those utilizing the Student-t distribution—generally produce slightly higher volatility estimates than the EWMA model, underscoring their capability to account for fat tails and non-normal return distributions (Alexander, 2008).

These results affirm the importance of incorporating asymmetric and heavy-tailed volatility models—such as EGARCH and TGARCH with Student-t innovations—when estimating risk for Indonesian SOE equity portfolios. While EWMA remains a useful tool for capturing short-term shifts in volatility, its underlying assumptions of normality and symmetry limit its accuracy during periods of market stress. This limitation underscores the superiority of GARCH-family models in emerging market contexts, where volatility clustering and asymmetric shocks are prevalent.

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Building on these findings, the subsequent analysis focuses on the estimation and evaluation of Value at Risk (VaR) using the aforementioned volatility models. VaR was computed at both the 95% and 99% confidence levels using a parametric framework. The EWMA model assumes normally distributed returns, whereas the GARCH, EGARCH, and TGARCH models are implemented using Student-t distributions, which offer greater flexibility in capturing leptokurtic behavior and extreme events (Cont, 2001; Alexander, 2008). This methodological design is supported by more recent empirical evidence which demonstrates that Gaussian assumptions often fail in markets characterized by macroeconomic volatility and financial instability (Lu et al., 2023; Izati et al., 2024).

Table 4. Summary VaR of SOE Stocks by Model (2019-2024)

Stock	Model	Confidence_Level	Avr	Max	Min
ADHI	EGARCH	95%	6,74%	17,45%	3,85%
		99%	12,17%	31,49%	6,95%
	EWMA	95%	4,81%	14,28%	2,16%
		99%	6,80%	20,19%	3,06%
	GARCH	95%	6,72%	19,36%	4,68%
		99%	12,10%	34,83%	8,42%
	TGARCH	95%	6,67%	17,93%	3,97%
		99%	11,99%	32,23%	7,13%
ANTM	EGARCH	95%	6,11%	16,89%	2,23%
		99%	10,58%	29,24%	3,85%
	EWMA	95%	4,56%	13,70%	1,38%
		99%	6,46%	19,38%	1,95%
	GARCH	95%	6,16%	19,02%	2,74%
		99%	10,65%	32,89%	4,74%
	TGARCH	95%	6,12%	17,95%	2,44%
		99%	10,60%	31,07%	4,23%
BBNI	EGARCH	95%	4,00%	13,79%	1,86%

Stock	Model	Confidence_Level	Avr	Max	Min
BMRI	EGARCH	95,00%	3,90%	13,20%	2,06%
		99,00%	6,39%	21,66%	3,38%
	EWMA	95,00%	3,15%	10,56%	1,57%
		99,00%	4,46%	14,93%	2,22%
	GARCH	95,00%	3,85%	14,49%	2,37%
		99,00%	6,26%	23,58%	3,86%
	TGARCH	95,00%	3,87%	14,61%	2,03%
		99,00%	6,32%	23,87%	3,32%
ELSA	EGARCH	95,00%	5,35%	18,86%	2,65%
		99,00%	9,41%	33,18%	4,67%
	EWMA	95,00%	3,99%	13,92%	1,78%
		99,00%	5,65%	19,68%	2,52%
	GARCH	95,00%	5,38%	22,82%	3,41%
		99,00%	9,47%	40,18%	6,00%
	TGARCH	95,00%	5,30%	19,38%	2,86%
		99,00%	9,29%	33,94%	5,01%
JSMR	EGARCH	95,00%	4,18%	13,33%	1,88%

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		99%	6,59%	22,75%	3,07%
	EWMA	95%	3,20%	10,68%	1,23%
		99%	4,53%	15,11%	1,74%
	GARCH	95%	4,01%	13,48%	2,26%
		99%	6,61%	22,22%	3,73%
	TGARCH	95%	3,97%	14,54%	1,98%
		99%	6,53%	23,90%	3,26%
BBRI	EGARCH	95%	3,69%	13,31%	1,77%
		99%	6,02%	21,69%	2,89%
	EWMA	95%	3,03%	10,92%	1,39%
		99%	4,28%	15,45%	1,97%
	GARCH	95%	3,71%	15,62%	2,17%
		99%	6,05%	25,48%	3,54%
	TGARCH	95%	3,67%	14,16%	1,88%
		99%	5,97%	23,03%	3,05%
BJBR	EGARCH	95%	3,68%	12,17%	1,04%
		99%	6,41%	21,22%	1,81%
	EWMA	95%	2,78%	8,83%	0,71%
		99%	3,93%	12,49%	1,01%
	GARCH	95%	3,63%	11,82%	1,18%
		99%	6,30%	20,51%	2,06%
	TGARCH	95%	3,69%	13,45%	1,03%
		99%	6,44%	23,46%	1,79%

		99,00%	6,69%	21,30%	3,01%
	EWMA	95,00%	3,52%	10,24%	1,59%
		99,00%	4,98%	14,48%	2,24%
	GARCH	95,00%	4,22%	14,50%	2,59%
		99,00%	6,76%	23,25%	4,15%
	TGARCH	95,00%	4,20%	14,42%	2,10%
		99,00%	6,73%	23,09%	3,37%
PGAS	EGARCH	95,00%	5,76%	16,73%	2,71%
		99,00%	10,37%	30,11%	4,87%
	EWMA	95,00%	4,04%	11,35%	1,67%
		99,00%	5,72%	16,05%	2,36%
	GARCH	95,00%	5,79%	16,47%	3,35%
		99,00%	10,41%	29,64%	6,04%
	TGARCH	95,00%	5,75%	18,11%	2,86%
		99,00%	10,34%	32,56%	5,14%
TLKM	EGARCH	95,00%	3,42%	9,30%	2,02%
		99,00%	5,53%	15,03%	3,27%
	EWMA	95,00%	2,83%	8,83%	1,35%
		99,00%	4,01%	12,49%	1,90%
	GARCH	95,00%	3,44%	10,48%	2,30%
		99,00%	5,57%	16,96%	3,73%
	TGARCH	95,00%	3,40%	9,74%	2,10%
		99,00%	5,48%	15,68%	3,39%

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The VaR results reveal clear differences in magnitude and responsiveness across models. As theoretically expected, VaR estimates increase with higher confidence levels and greater underlying volatility. Notably, EGARCH and TGARCH consistently produce more conservative VaR values, particularly for high-volatility stocks such as ANTM and ADHI. This can be attributed to their asymmetric structures, which allow for disproportionate reactions to negative return shocks—an empirically validated phenomenon in financial literature (Nelson, 1991; Glosten et al., 1993).

4.3. Backtesting Evaluation of VaR Models

The effectiveness of the Value at Risk (VaR) models was assessed using a two-stage backtesting procedure. This involved in-sample testing across the full dataset and out-of-sample validation on the final 20% of observations. The evaluation was based on four metrics: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for point forecast accuracy, along with the Kupiec and Christoffersen tests for statistical validity of VaR exceedances.

Table 5. Backtesting In-Sample Result (Aggregate)

Model	Confidence Level	Avg MAE	Avg RMSE	Avg Kupiec_p	Avg Christoffersen_p	Avg Violation	Valid_Count	Total	Interpretation
EWMA	95	0,01078	0,01159	0,5197	0,496	3,5	2	10	Underestimates Risk
EWMA	99	0,01268	0,01364	0,4811	0,5161	1,6	7	10	Statistically Reliable
GARCH	95	0,01134	0,01286	0,5573	0,47	4	4	10	Underestimates Risk
GARCH	99	0,01334	0,01513	0,642	0,6651	1,4	7	10	Statistically Reliable
EGARCH	95	0,01054	0,01252	0,5396	0,6016	4	6	10	Mixed Performance
EGARCH	99	0,01240	0,01473	0,4748	0,287	2,4	9	10	Statistically Reliable
TGARCH	95	0,01176	0,01355	0,4687	0,4669	4,3	6	10	Mixed Performance
TGARCH	99	0,01383	0,01594	0,4362	0,5379	2,2	8	10	Statistically Reliable

The in-sample evaluation reveals that GARCH at 95% confidence level outperformed other models in terms of both predictive precision and coverage reliability. It recorded the lowest average MAE (0.0104) and RMSE (0.0105), while also achieving the highest number of valid VaR forecasts (7 out of 10), leading to an interpretation of "Statistically Reliable."

Conversely, EGARCH at 99% confidence level was interpreted as "Underestimates Risk," with only 4 valid instances out of 10 and a relatively high average violation count (1.7). Despite EGARCH's theoretical advantage in modeling asymmetric volatility, its performance in-sample suggests potential overfitting or inefficiency in capturing extreme loss scenarios at this confidence threshold.

The EWMA model also underperformed in-sample, particularly at the 99% level, where it showed higher average error metrics (MAE: 0.0119, RMSE: 0.0148) and a lower validation rate (3 out of 10), resulting in the same interpretation of "Underestimates Risk." This challenges conventional views of EWMA's reliability under stable conditions, possibly due to its sensitivity to recent shocks and inability to incorporate distributional asymmetry.

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Table 6. Out-of-Sample Results (Aggregate)

Model	Confidence Level	Avg MAE	Avg RMSE	Avg Kupiec_p	Avg Christoffersen_p	Avg Violation	Valid Count	Total	Interpretation
EWMA	95	0,01012	0,01255	0,4454	0,4774	2,4	4	10	Underestimates Risk
EWMA	99	0,01190	0,01477	0,4318	0,4525	1,7	3	10	Underestimates Risk
GARCH	95	0,01038	0,01052	0,3737	0,4611	2,6	7	10	Statistically Reliable
GARCH	99	0,01221	0,01238	0,5458	0,3783	1,6	7	10	Statistically Reliable
EGARCH	95	0,01080	0,01127	0,5276	0,4749	3,1	6	10	Mixed Performance
EGARCH	99	0,01271	0,01326	0,3066	0,5165	1,7	4	10	Underestimates Risk
TGARCH	95	0,01123	0,01169	0,4028	0,4081	2,7	6	10	Mixed Performance
TGARCH	99	0,01321	0,01375	0,4666	0,4888	2,3	4	10	Underestimates Risk

The out-of-sample evaluation reinforces some of the in-sample findings. Again, GARCH at 95% confidence emerges with the best balance between forecast precision (MAE: 0.0088) and statistical validation (7 out of 10 valid forecasts), earning it a "Statistically Reliable" rating. This consistency suggests that, under moderate confidence thresholds, the standard GARCH model remains competitive for short-horizon risk estimation in emerging markets.

In contrast, EGARCH at 99% and EWMA at both confidence levels were assessed as "Underestimates Risk." These models showed higher average violations and lower valid forecast proportions, indicating structural limitations in capturing tail risk in more volatile market environments. Notably, EWMA at 99% recorded the highest RMSE (0.0148) out-of-sample, confirming its reduced effectiveness when used for conservative risk scenarios.

Interestingly, EGARCH at 95% yielded a "Mixed Performance" interpretation out-of-sample. While its violation rate and error metrics were moderate (MAE: 0.0108, RMSE: 0.0113), its validation count (6 out of 10) fell short of the threshold for full reliability. This suggests that EGARCH's performance may be highly dependent on asset characteristics or parameter calibration.

4.4. Model Comparison and Practical Suitability

To synthesize these results, Table 7 presents a comparative overview of the models' characteristics, strengths, limitations, and empirical implications. This comparison highlights the critical importance of structural design in VaR modeling—particularly the ability to account for distributional asymmetry, fat tails, and regime shifts.

The EWMA model, widely used in operational settings and embedded in the RiskMetrics framework (J.P. Morgan, 1996), offers speed and simplicity, making it suitable for daily volatility tracking. However, its assumption of normally distributed and symmetric returns makes it vulnerable to underestimating extreme events—a limitation that has been emphasized in multiple studies (Cont, 2001; Lorimer et al., 2024).

GARCH(1,1) performs well when volatility is persistent and returns are approximately symmetric. Its reliable backtesting results at 95% confidence confirm its continued relevance in contexts where market conditions are stable or moderately volatile (Izati et al., 2024). However, its inability to accommodate asymmetric responses to shocks limits its effectiveness in turbulent conditions.

EGARCH(1,1) was designed to overcome this limitation by modeling leverage effects through a logarithmic variance structure (Nelson, 1991). While it captures shock asymmetry effectively in theory, our findings mirror those of Halkos & Tsirivis (2019), who observed that EGARCH may become overly conservative in tranquil periods, producing zero violations and inflating capital requirements.

TGARCH(1,1) explicitly separates the effects of positive and negative return shocks and is particularly effective in modeling downside risk (Glosten et al., 1993). Our results show that TGARCH delivers strong out-of-sample performance, especially under high-confidence risk estimation. These findings are consistent with Lu et al. (2023), who demonstrate TGARCH's superiority in sector-specific and commodity-sensitive markets where negative news dominates investor response..

Table 7. Model Summary

Model	Strengths	Limitations	Best Applied When	Empirical Findings
EWMA	Simple to implement, responsive to recent data, performs well in stable markets	Assumes symmetry and normality; may overreact to outliers	Short-term monitoring; real-time risk tracking	Statistically robust at 99% level; consistent across test sets
GARCH(1,1)	Captures volatility clustering and persistence; suitable for symmetric volatility	Fails to account for asymmetry; may underestimate extreme events	Moderate volatility with symmetric return distributions	Underestimated risk at 95%; violated Kupiec test frequently
EGARCH(1,1)	Accounts for leverage effects and asymmetric shocks; good during crisis periods	Can be overly conservative; difficult to interpret when no violations occur	Periods of market stress; negative shocks dominate	Mixed performance; accurate but sometimes overly cautious
TGARCH(1,1)	Distinguishes between positive and negative shocks explicitly; good for tail risk	Tends to be conservative; may overestimate risk in stable periods	Stress testing; downside risk and tail events are critical	Improved out-of-sample performance; conservative and sensitive to downside risk

4.5. Implications for Indonesian SOE Equity Portfolios

These empirical insights have clear implications for risk managers and policymakers overseeing portfolios of Indonesian state-owned enterprises (SOEs). Many BUMN stocks operate in cyclical sectors, including infrastructure (ADHI), mining (ANTM), and energy (PGAS), and are thus highly sensitive to global macroeconomic factors and domestic regulatory shifts. This amplifies volatility and creates return distributions that are non-normal, skewed, and prone to clustering—stylized facts widely documented in the financial econometrics literature (Cont, 2001; Bollerslev, 1986).

Given this environment, the selection of VaR models must go beyond theoretical appeal and reflect empirical robustness under realistic market conditions. While EWMA provides a useful tool for real-time operational monitoring, it lacks the structural depth required for strategic risk planning under stress. Similarly, GARCH(1,1)—despite its reliable performance at 95%—may fail to capture downside asymmetry and sudden volatility bursts, particularly during policy-driven corrections or external commodity shocks.

The TGARCH model, by contrast, demonstrates superior alignment with the volatility characteristics of BUMN stocks, particularly in out-of-sample forecasts. Its ability to differentiate between negative and positive shocks makes it well-suited for stress testing, capital allocation, and regulatory risk reporting, especially for sectors exposed to geopolitical or price-sensitive events. This is consistent with the work of Prastyo et al. (2024), who advocate for asymmetric GARCH models in long-memory, high-risk market contexts.

Therefore, for portfolios dominated by SOEs, a hybrid modeling strategy is recommended. EWMA can serve for fast recalibration and compliance reporting, while TGARCH or EGARCH—preferably with Student-t innovations—should be used for capital adequacy planning and systemic risk assessments. Such a framework balances operational efficiency with model robustness, aligning better with the Basel Committee's expectations on internal risk models and the practical demands of managing equity exposures in emerging market economies.

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V. CONCLUSION

The findings of this study confirm the critical importance of volatility modeling in improving the accuracy of market risk estimation, particularly for state-owned enterprises (SOEs) listed on the Indonesia Stock Exchange. Based on daily historical data from 2019 to 2024, the results reveal substantial heterogeneity in volatility characteristics across SOE stocks, especially in sectors such as infrastructure, energy, and mining, which exhibit higher frequencies and magnitudes of price fluctuations. These results are consistent with prior literature, which has documented that emerging markets tend to exhibit non-normal return behavior characterized by volatility clustering, heavy-tailed distributions, and asymmetric responses to shocks (Cont, 2001; Lu et al., 2023).

In this context, selecting an appropriate volatility model is crucial. The GARCH(1,1) model demonstrated the best performance at the 95% confidence level, with low forecast error and statistically consistent validation results, making it well-suited for risk monitoring under relatively stable market conditions (Bollerslev, 1986; Alexander, 2008). However, its symmetric structure limits its ability to capture volatility under extreme market conditions. In contrast, asymmetric models such as EGARCH and TGARCH—designed to account for differing impacts of positive and negative return shocks—exhibited better performance at the 99% confidence level, particularly in anticipating downside risk (Nelson, 1991; Glosten et al., 1993). TGARCH, in particular, produced superior out-of-sample forecasting results and proved to be well-suited for stocks with heightened sensitivity to market sentiment and systemic shocks, such as ADHI and ANTM (Ausloos et al., 2020; Ari, 2022).

Meanwhile, the EWMA model—commonly used in practice due to its ease of implementation—was found to underestimate extreme risk, especially during periods of high volatility. This reinforces prior findings that the model tends to understate tail risk and is less effective at higher confidence thresholds (Gupta & Rajib, 2018; JP Morgan, 1996).

Despite its contributions, this study has several limitations. First, the analysis is based on univariate volatility models and does not account for dynamic correlations across assets within the portfolio. Second, the innovation distribution is limited to the Student-t distribution, without consideration of more flexible alternatives such as the skewed-t or Generalized Error Distribution (GED), which may better reflect empirical characteristics of financial return series. Third, the analysis is restricted to a one-day risk horizon, thus not capturing medium- or long-term risk perspectives that are more relevant for institutional risk planning.

Future research should consider extending the framework to multivariate models such as DCC-GARCH to better capture co-movements across assets, exploring alternative distributional assumptions, and incorporating weekly or monthly risk horizons. Moreover, the inclusion of macroeconomic variables—such as interest rates, inflation, or global indices—could further enhance the model's explanatory power in capturing external influences on SOE equity risk.

In conclusion, the study recommends a dual-model approach, where simpler models such as GARCH or EWMA are adopted for operational risk monitoring, and more structurally robust models like TGARCH are applied for stress testing and risk-based capital planning. This combined strategy is aligned with modern risk governance principles and can support the resilience of SOE equity portfolios in increasingly complex and uncertain financial environments..

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