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Estimating value at risk in Saudi real estate investment trusts: A garch-based approach

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ABSTRACT

This paper compares the performance of the GARCH (1,1) and GJR-GARCH (1,1) models in forecasting VaR for Saudi REITs across three distinct periods: the pre-COVID period (2016–2019), the during-COVID period (2020–2021), and the post-COVID period (2022–2024). The study estimates log returns and models them using GARCH-type structures, applying the Kupiec test for backtesting the VaR forecasts. The results show that both GARCH (1,1) and GJR-GARCH (1,1) models are effective in predicting risk across all three periods. However, statistical model comparison indicates that the GJR-GARCH (1,1) model outperforms the GARCH (1,1) model consistently across all periods. Nevertheless, its advantage is most pronounced during the COVID-19 period, when extreme market turbulence and asymmetric volatility were present. These results support the necessity of solid volatility modeling regarding REIT risk management, particularly in emerging markets and under both normal and extreme market conditions. This study makes a novel contribution by being the first to apply and compare GARCH-type models specifically to the Saudi REIT market across these pandemic-defined subperiods. It addresses a gap in regional volatility modeling and demonstrates the superior performance of asymmetric models under crisis conditions, offering insights for REIT risk management in emerging markets.

Contribution/Originality: This study is one of the few that have applied and compared GARCH models to the Saudi REIT market across pandemic-defined subperiods. It addresses a gap in volatility modeling and demonstrates the superior performance of asymmetric models, offering insights for REIT risk management in emerging markets.

1. INTRODUCTION

Real Estate Investment Trusts (REITs) play an integral role in current financial markets; they enable investors to access income properties as an asset class with the convenience of no actual ownership. The real estate sector forms a significant element of economic growth and stability in many countries. In recent times, REITs have grown in popularity for providing both income and capital growth potential.

The regulatory body in Saudi Arabia is the Capital Market Authority (CMA), which first issued regulations related to Real Estate Investment Funds in 2006, and these were subsequently amended in 2021. REITs entered the market in 2016, comprising 19 REITs listed on Tadawul, and one additional REIT is listed on the Nomu Parallel Market. Saudi Arabia was one of the leading countries in the GCC to introduce REITs. The market's growth is supported by Saudi Arabia's Vision 2030, which promotes economic diversification through mega-projects like NEOM, the Red Sea Project, and Qiddiya, attracts foreign investment, and reduces dependency on oil (Ramady, 2005). These initiatives drive demand across multiple real estate sectors, including tourism, hospitality, commercial (offices and retail), residential, and logistics (supported by e-commerce growth). Occupancy rates for Saudi REITs have increased steadily, indicating strong demand and potential for higher rental income, enhanced cash flows, and increased dividends. Given this evolving investment landscape, a deeper understanding of the risk characteristics of Saudi REITs is timely and critical.

The experience of REITs in the crisis caused by COVID-19 evidenced that conventional approaches to risk measurement and management are facing critical issues. REIT markets showed time-varying levels of connectedness (Lesame, Bouri, Gabauer, & Gupta, 2021). The COVID-19 pandemic triggered a global surge in market volatility, affecting major indices such as the S&P 500 and causing volatility spillovers across REIT markets, including those in Asia and the Middle East (Albulescu, 2021; Periola-Fatunsin, Oliyide, & Fasanya, 2021). All these tendencies raise the necessity of more active and responsive risk management approaches in the future. Also, the patterns of recovery by sectors during the pandemic seem to imply massive potential for portfolio diversification, especially with a focus on more defensive REIT sectors (Wu & Liau, 2023; Yang, 2024).

VaR is an effective tool for estimating market risk, enhancing regulatory compliance, or simply managing a portfolio, as it generates an expected monetary loss in value-risk measure through the statistical analysis of asset return distributions (Cortés, 2022; Olson & Wu, 2020). It is potentially the most used financial metric and is used to model potential portfolio losses over a specified time horizon at a certain level of confidence (Michetti, 2014; Olson & Wu, 2020). Prior research indicates that "GARCH" models, particularly "GJR-GARCH" and "GARCH-Student-t" variants, tend to be more suitable for volatility modeling and capturing tail risks in distressed markets (Dicks, Conradie, & De Wet, 2014; Mokni, Mighri, & Mansouri, 2009; Shayya, Sorrosal-Forradellas, Terceño, & Barberà Mariné, 2023). These models can perform better than conventional conditional variance modeling during financial distress. GARCH-type modeling is widely used in financial econometrics to model and forecast time-varying volatility in finance and to model time-varying volatility during periods or shocks in estimates. The classical "GARCH" model (Bollerslev, 1986) captures this characteristic because it includes returns and variances from squared returns observed in the past or previous periods. The "GARCH" residuals are normally distributed for current returns, and the response to shocks is symmetric. Moreover, the "GJR-GARCH" model was introduced by Glosten, Jagannathan, and Runkle (1993) to consider asymmetry and leverage for shocks, which allows for leverage effects where negative shocks leverage volatility at greater rates than positive shocks. Empirically based studies suggest their application is effective for risk forecasting (Cerović, Lipovina-Božović, & Vujošević, 2017; Yuan, Sun, & Zhang, 2017). While these models have been widely applied to global financial markets, their application to Saudi REITs, especially during turbulent periods like the COVID-19 crisis, remains underexplored.

Volatility has increased significantly for REITs in recent years, and volatility should be considered when estimating the VaR of REITs (Zhou, 2012). However, local studies are still limited, particularly regarding Saudi REITs, specifically at this time and during crisis periods such as with COVID-19. Therefore, this study fills the gap by employing "GARCH" and "GJR-GARCH" symmetric and asymmetric models to assess VaR for Saudi REITs from 2016 to 2024. The period included the pre-pandemic phase, the shock of COVID-19, and the recovery periods to evaluate a full range of volatility conditions. The primary aim of the study is to assess the accuracy and reliability of these models in estimating VaR, with a key focus on their performance during times of heightened uncertainty. An essential part of this evaluation involves backtesting the VaR estimates against the Kupiec unconditional coverage test to determine if the models appropriately measure losses and do not underestimate risk during periods of increased volatility.

This paper is organized as follows: Section 2 reviews the literature on REIT volatility and VaR modeling. Section 3 explains the data and methodology, including GARCH models and backtesting. Section 4 presents and discusses the results. Section 5 concludes, and Section 6 provides recommendations and policy implications.

2. LITERATURE REVIEW

Over the past two years, the Saudi REIT sector has experienced a decline due to the slower-than-anticipated recovery from the pandemic and a dramatic spike in interest rates, which have constrained financial performance, limited portfolio expansion, and reduced dividend payouts.

While numerous studies have examined REIT volatility during crises, few have systematically explored how these shocks have uniquely impacted Saudi REITs compared to global counterparts. For instance, the COVID-19 pandemic revealed structural vulnerabilities in lodging and retail REITs, which experienced heightened volatility, whereas industrial REITs demonstrated more resilience (Ampountolas, Legg, & Shaw, 2024). Ling, Wang, and Zhou (2023) demonstrated that non-passive institutional investors experienced greater sensitivity to local shocks, leading to greater volatility in their REIT investments. Additionally, shifts in investor behavior have been observed in the REIT market due to the pandemic. Institutional investors have become more prevalent, with greater influence, while retail investors have exhibited a trend toward reduced speculation (Alhussayen, 2022). These findings suggest that institutional presence can exacerbate volatility in REITs, yet it remains unclear how this dynamic unfolds in relatively underdeveloped markets with thinner liquidity, such as Saudi Arabia.

Moreover, the increase in the interest rate creates an imbalance where debt growth outpaces asset growth, highlighting market challenges and economic pressures that may discourage short-term investors. Dogan, Ghosh, and Petrova (2019) argue that legal restrictions have a positive effect on the capital structure of REITs. For example, CMA regulates and sets a limit of 50% debt-to-assets, where exceeding the regulatory limit of 50% debt-to-assets can constrain borrowing capacity for growth and negatively affect the NAV of the REITs (Hechmi, 2025). Therefore, the TASI REITs Index underperforms the TASI index (Al Jazira, 2024).

The internal structure of REITs also influences risk. Global studies (Fugazza, Guidolin, & Nicodano, 2009; Lee & Stevenson, 2005) underscore the diversification benefits of mortgage and mixed REITs, but these are often absent in Saudi Arabia's relatively concentrated market. In contrast to diversified global REIT benchmarks like the MSCI US REIT Index, the Saudi REIT landscape remains narrowly focused, exposing investors to concentrated sectoral and geographical risks. While certain REITs such as SEDCO exhibit broader exposure, this is not representative of the market at large (Al Jazira, 2024).

Despite recent challenges, the Saudi REIT market appears poised for recovery. The anticipated decline in interest rates following the U.S. Federal Reserve's 50-basis-point rate cut in September 2024 is expected to reduce financing costs by 15–20% in FY25. If the Saudi Interbank Offered Rate (SAIBOR) adjusts accordingly, this would improve profitability and enable portfolio expansion especially for highly leveraged REITs like Musharaka and Riyad. However, Alsharif (2021) argues that a higher level of debt is supposedly associated with lower levels of efficiency, indicating that Saudi REITs should not rely on debt funding because there is no tax advantage from using debt, which corroborates the limitation of high leverage in the sector. Many studies use GARCH models to describe volatility and risk estimation in the REIT market, particularly in times of crisis. Wasiuzzaman (2022) studied the volatility of the Tadawul All Shares Index during COVID-19 and found no volatility spikes in the Saudi REIT market, which showed that while GCC REITs fell by -13.5% in 2020, Saudi REITs experienced greater stability and a quicker recovery.

The GARCH methodology developed by Engle (1982) and continued by Bollerslev (1986) is a preliminary method of modeling time-varying volatility in financial returns. Subsequent developments in GARCH modeling, such as the GJR-GARCH model developed by Glosten et al. (1993), included asymmetry to capture the leverage effect, wherein negative shocks have a disproportionately influential effect on volatility. In practice, GARCH-family models are extensively applied to estimate VaR, especially under a variety of possible distributions. Braione and Scholtes (2016) showed that estimating fat tails and skew in a modeling context using certain distributions (i.e., Student's t, skewed t, and GED) provides a significant improvement in tail-risk forecasting, which is paramount for suitable risk management. The volatility dynamics of REITs have been widely researched in developed markets using several variations of GARCH-type models. Stevenson (2002), Devaney (2001), and Cotter and Stevenson (2006) are among the first to apply numerous variations of the GARCH modeling, such as the EGARCH and the TGARCH models. Asteriou and Begiazi (2013) argue that GARCH-type models could accomplish the task when modeling the daily changes.

Comparative research between GARCH-type models, including but not limited to EGARCH, APARCH, and GARCH-GJR, shows that prediction accuracy is contingent upon model and market conditions and data frequencies. According to Andersson and Haglund (2015), EGARCH (1,1) was the superior model in terms of predicting VaR, compared to other models of all major equity indices. The DCC model also performed well, but only used high-frequency data (Morimoto & Kawasaki, 2008). However, Müller and Righi (2024) identified rolling windows, type of significance, or portfolio decisions among others as potential interpretations of performance, showing that there is likely no correct best model. It is important to recognize that model selection during periods of financial stress is complicated, again, by the environment. For example, in periods of turbulence, asymmetric models such as ARMA (1,1)-T-GARCHM (1,1) reduced the number of expected violations of VaR, despite higher capital reserves (Huang, Su, & Tsui, 2015). But Zikovic and Filer (2012) found similar performance over a variety of VaR and Expected Shortfall models in the context of the global financial crisis could suggest that model applicability is a lesser issue through extremes.

Several studies have confirmed that models such as EGARCH or APARCH can improve volatility modeling, but their superiority depends on market conditions and data granularity (Andersson & Haglund, 2015; Müller & Righi, 2024). The limited consensus on the "best" model emphasizes the need for context-specific validation, especially during periods of financial stress. Although asymmetric models perform better during crises (Huang et al., 2015), this has yet to be thoroughly tested in Saudi Arabia's REIT sector.

Furthermore, while local researchers (e.g., (Al-Nassar, 2023; Mhmoud & Dawalbait, 2015)) have employed GARCH-family models, most focus on volatility estimates alone. A significant gap exists in applying GARCH models for VaR estimation and backtesting in the Saudi REIT context, which limits the practical risk management applications of such models.

VaR remains a valuable risk measure in emerging markets (Cerović et al., 2017); however, emerging market conditions volatility clustering, fat tails, and limited data require robust modeling techniques. Kupiec (1995) POF test offers a basic means of backtesting VaR estimates, yet few Saudi studies incorporate this crucial validation step. This signals a methodological gap in both academic and applied financial risk management in the region.

Despite the advancement of GARCH models in volatility forecasting, the Saudi REIT literature falls short in integrating these models with VaR and rigorous backtesting approaches, which are necessary for credible financial risk assessments.

3. METHODOLOGY

The COVID-19 pandemic exerted a strong negative effect on the Saudi REIT market, mainly due to its ability to disrupt the commercial real estate segments, which constitute the core of REIT portfolios (Di Liddo, Anelli, Morano, & Tajani, 2023). Retail, hospitality, office spaces, and logistics facilities are popular acquisitions of Saudi REITs, directly impacted by the lockdowns and the pandemic-imposed restrictions and permanent shifts in consumer and business behavior. The shuttering of malls, hotels, and other shops caused severe rental dips, heightened risk of tenant defaults, and broad-scale rent deferrals, which caused property values to tumble and REIT-unit liquidity to languish within the Saudi Stock Exchange.

These operational and financial pressures were reflected as an increase in market volatility. As Akinsomi (2021) points out, the confidence of investors in the industry has increased significantly throughout this timeframe, and REIT unit costs have been very sensitive to any negative outcomes, with a slow movement toward improvement upon the elimination of restrictions. This clearly demonstrates the importance of strong risk modeling to accurately reflect the unprecedented market trends that emerged in the middle and post-pandemic era.

This paper seeks to review the effectiveness of the GARCH-type model in measuring the VaR of the Saudi REIT between 2016 and 2024. It concentrates on three distinct sub-periods, which include the “pre-COVID” (2016-2019), “during COVID” (2020-2021), and “post-COVID” (2022-2024). The study aims to determine the extent to which the models of “GARCH” can be applied to the volatility behavior that REITs have been experiencing under different market circumstances, especially following the impacts of the “COVID-19 pandemic” global shocks.

To achieve this, the study employs two popular models in the “GARCH” family; namely, “GARCH (1,1)” and “GJR-GARCH (1,1).” The reasoning behind this is that they have been effective in simulating and predicting the volatility of time series data of the financial markets, which determines an accurate measurement of VaR. The most widely used model to model the volatility clustering in the financial market is the “GARCH” model (Bollerslev, 1986). Engle (1982) described it as an extension of the “ARCH model”. Alternatively, Glosten et al. (1993) introduce the parameterization of the “GJR-GARCH model,” which permits asymmetry in volatility. It is especially suitable in cases where the model financial time series with leverage effects, where negative shocks to the series affect volatility to a larger degree than positive shocks of the same magnitude. To perform the entire analysis, log returns are collected from the Saudi exchange website and calculated using the closing prices of Saudi REITs.[1] It is the conventional and most common way of calculating returns in financial analysis, given that the log returns are more efficient in portraying the relative changes in the value of assets, and the dynamics of volatility are simpler to describe. Log returns also ensure that the data is symmetrical, and it is possible to have the compounding effects of price variation over time, which is important in precise volatility estimation in financial models. The method enables the estimation of “GARCH” volatility clustering and “GARCH-type models” that involve asymmetries needed to describe the REITs risk.

To estimate the effectiveness of the models in forecasting, backtesting of the models is conducted using the Kupiec Proportion of Failures (POF) test, which is used to determine how accurate VaR forecasts are concerning the actual count of exceedances (i.e., actual losses that surpass VaR) compared to the expected count of exceedances, as per the assumed confidence level. This test is considered a standard for demonstrating the reliability of VaR models in managing financial risks (Kupiec, 1995). The results of the backtesting exercise can be helpful in understanding whether GARCH-type models are stable in estimating the VaR of Saudi REITs under different market conditions, such as the high level of volatility observed during the COVID-19 pandemic.

3.1. Normalcy Test

The “Anderson-Darling test” is employed extensively to test the hypothesis that a given sample has been selected from a particular distribution, mainly the normal distribution. It is analogous to the Cramer-von Mises test, except that it is also more sensitive to deviations in the tails of the distribution. This attribute makes the “Anderson-Darling test” more relevant in the detection of outliers or extreme data points that other tests of normality might be unable to detect. The test statistic is based on the difference between the empirical cumulative distribution function (ECDF) of the sample and the cumulative distribution function (CDF) of the hypothesized distribution. The “Anderson-Darling test” is fairly applicable to data of any size, especially in large databases. In large samples, the test can be used to identify small deviations from normality, and it provides accurate information regarding whether data obey the normal distribution. Its sensitivity is particularly useful in cases where the assumption of normality is critical, as even minor deviations can influence statistical analysis, hypothesis testing, and model fitting. The test remains effective, and if the test statistic exceeds the critical value at a certain significance level, the null hypothesis of normality is rejected, indicating that the data does not follow a normal distribution (Anderson & Darling, 1952).

[1] https://www.saudiexchange.sa/wps/portal/tadawul/home/.

3.2. Model Specifications

3.2.1. Generalized Autoregressive Conditional Heteroskedasticity GARCH (1,1) Model

Bollerslev (1986) invented the "GARCH model", which extended Engle (1982), and it is frequently used to represent time-varying volatility and volatility clustering in financial return series.

The conditional mean equation is presented as:

$$r_t = \mu + \epsilon_t \qquad \epsilon_t \sim N\left(0, \sigma_t^2\right) \qquad (1)$$

Where

- r_t is the return at time *t*.
- μ is the constant mean return.
- ϵ_t is the error term, assumed to be normally distributed with mean zero and conditional variance σ_t^2.

The conditional variance equation is specified as:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \qquad (2)$$

Where,

- σ_t^2: Conditional variance at time *t*.
- ω: Constant term (Long-run average variance).
- α: Coefficient for ARCH term, representing short-term volatility due to recent shocks.
- β: Coefficient for GARCH term, representing persistence in volatility.

This model outlines how large (positive or negative) shocks are followed by periods of increased volatility.

3.2.2. GJR-GARCH (1,1) Model

Glosten et al. (1993) created the GJR-GARCH model, which extends GARCH by including an indicator variable to simulate volatility's asymmetric response to positive and negative shocks (i.e., leverage effect). The model is mathematically represented as:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \gamma D_{t-1}\epsilon_{t-1} + \beta\sigma_{t-1}^2 \qquad (3)$$

Where,

$$D_{t-1} = \begin{cases} 1 & if\ \epsilon_{t-1} < 0 \\ 0 & otherwise \end{cases}$$

γ: Captures the leverage effect, or the disproportionate impact of negative shocks on volatility. This model explains the empirical observation that negative news (returns) tend to increase volatility more than positive news of the same magnitude.

3.2.3. Value at Risk (VaR)

VaR measures the highest possible loss in a portfolio under typical market conditions over a given time horizon and confidence level. The 1-day VaR at significance level α is computed using the conditional standard deviation σ_t from a GARCH-type model as follows:

$$VaR_{t,\alpha} = \mu_t + z_\alpha.\sigma_t \qquad (4)$$

Where,

- z_α Quantile of the standard normal distribution (Or t-distribution for fat tails).
- μ_t: Conditional mean (Often set to 0 for short horizon).
- σ_t Conditional standard deviation from the GARCH model.

3.2.4. Kupiec Backtesting

The Kupiec (1995), often referred to as the Proportion of Failures (POF) Test is used to assess whether the observed proportion of exceptions matches the expected rate, in order to evaluate the dependability of VaR estimations. The equation used for calculating the likelihood ratio for unconditional coverage (LRuc) is:

$$LR_{uc} = -2ln[(1+p^{\wedge})^{T-x}p^{\wedge}] + 2\ln[(1-p)^{T-x}p^{x} \qquad (5)$$

Where,

- x: Number of VaR exceptions (days when actual loss exceeds VaR).
- T: Total number of observations.
- p^=x/T: Observed exception rate.
- p: Expected exception rate for 90% VaR, which is 0.10 (since it's a 90% confidence level).

The test uses a one-degree-of-freedom chi-squared distribution. A significant test result indicates that the VaR model is misspecified, either underestimating or overestimating risk.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics

The REITs data source is the Saudi Exchange website to run the descriptive statistics analysis.[2] The descriptive statistics results reveal that the "Log Returns" have a mean of -0.021, indicating that the average return in the analyzed period is slightly negative.

Despite this negative mean, the standard deviation of 1.237 demonstrates moderate volatility in returns, with fluctuations that are not excessively high. The range of 32.396 suggests a large difference between the maximum and minimum returns realized; thus, although the returns are distributed closely around the mean, some extreme scores significantly influence the distribution. The skewness value of 0.674 indicates a slight positive skewness, meaning there are more frequent positive returns than negative ones, but not to an extreme degree. The kurtosis value of 16.494 confirms fat-tailed returns, with extreme values occurring more often than predicted by a normal distribution. "Volume traded" indicates that, on average, a substantial amount of assets has been exchanged throughout the period, with the mean volume traded being 361,041.44.

However, given the significant fluctuations in trading activity over time, the standard deviation of 1,151,617.39 suggests a high degree of unpredictability in the volume transacted. The magnitude of 58,119,028 further demonstrates the considerable discrepancy between the lowest and highest trading volumes, pointing to instances of exceptionally high trading activity. There is a notable average monetary trade volume, with the mean at 3,931,714.22. However, the standard deviation of 15,571,084.11 indicates considerable volatility in trade values over time. The large range of 690,771,018.1 between the minimum and maximum trade values further highlights the significant disparity between the smallest and largest trades.

The "number of trades" reflects how frequently individual trades occur; the mean value of 440.028 indicates a moderate level of trading activity per period. Nonetheless, the standard deviation of 620.763 indicates high variability in the frequency of trades, with some days having a substantially higher number of trades compared to others. The wide value of 20,765 depicts the variability of trading activity, where there could be a high number of trades executed in a day compared to other days.

Table 1 presents the descriptive statistics analysis of the following variables: log return, volume traded, value traded, and number of trades.

[2] https://www.saudiexchange.sa/wps/portal/tadawul/home/.

Table 1. Descriptive statistics.

Statistic	Log returns	Volume traded	Value traded	No. of trades
Number of observations	30,087	30,104	30,104	30,104
Mean	-0.021	361,041.440	3,931,714.220	440.028
Minimum value	-15.219	335.000	2,685.600	3.000
Maximum value	17.177	58,119,363.000	690,773,703.700	20,768.000
Range	32.396	58,119,028.000	690,771,018.100	20,765.000
Standard deviation	1.237	1,151,617.390	15,571,084.110	620.763
Skewness	0.674	17.419	18.563	8.496
Kurtosis	16.494	520.504	534.133	140.374

4.2. Anderson-Darling Test

The Anderson-Darling test for normality indicates that the data follow a normal distribution. The test statistic is 0.7267, which is compared to critical values at various significance levels to determine if the data significantly deviate from normality. At a 10% significance level, the critical value is 0.656. At the 5% significance level, the critical value is 0.787, and at the 1% significance level, the critical value is 1.092. Since the test statistic is below the critical value at the 10% significance level, the null hypothesis cannot be rejected, suggesting that the data do not significantly depart from normality at this level. Table 2 presents the results of the Anderson-Darling test for normality.

Table 2. Anderson-Darling test for normality.

Statistic	0.7267
Critical values	
10%	0.656
5%	0.787
1%	1.092

4.3. Correlation Analysis

The selected variables are log_return, Volume Traded, Value Traded, and No. Of Trades. The correlation matrix of these variables reveals insights about the relationships between them. The correlation between log_return and the Volume Traded is not very strong (0.109), indicating a weak positive association. This suggests that the volume of assets traded has little relation to changes in log_return, implying that trading volume is not strongly influenced by price changes.

The association between log_return and Value Traded is also weak at 0.100, further supporting the notion that price changes have a limited relationship with the financial magnitude of trades. This poor correlation indicates that the volume and value of trades are not directly related to asset price movements. Conversely, the correlation between Volume Traded and Value Traded is much stronger at 0.930, indicating a very strong positive relationship. This shows that larger traded asset amounts tend to correspond with higher trade values. This high correlation is expected since increased trading volume generally results in a higher overall trade worth. Additionally, Volume Traded and No. Of Trades have a moderate to strong positive correlation of 0.763, implying that higher trading volumes are associated with a greater number of trades. When trading activity is high, both volume and the number of trades tend to increase.

Finally, Value Traded and No. Of Trades exhibit a positive correlation of 0.799, indicating that increased trading activity, measured by the number of trades, is associated with higher total trade values. This relationship suggests that more transactions typically lead to higher market activity and overall trade value. Table 3 presents the correlation matrix of the following variables: log return, Volume Traded, Value Traded, and No. of Trades.

Table 3. Correlation matrix.

	Log return	Volume traded	Value traded	No. of trades
log_return	1.000	0.109	0.100	0.049
Volume traded	0.109	1.000	0.930	0.763
Value traded	0.100	0.930	1.000	0.799
No. of trades	0.049	0.763	0.799	1.000

4.4. Model Estimation

4.4.1. GARCH(1,1) Model

During the pre-COVID period, the mean model coefficient (μ) is -0.024, and the p-value is 0.044, indicating that the mean return is slightly negative and statistically significant at the 5% level. This suggests that pre-COVID returns are mildly negative on average. In the case of the volatility model, the parameter ω (constant term) is significant at the 5% level, implying the presence of a positive long-run variance. The ARCH term (α) coefficient is highly significant with a p-value of 0.000, indicating that current volatility is strongly influenced by past shocks. Similarly, the GARCH term (β) coefficient demonstrates strong persistence in volatility over time. A large β value signifies that past volatility significantly contributes to explaining future volatility, which is characteristic of volatility clustering.

The mean return during the Covid-19 period, μ, indicates a weaker statistical indication of a significant mean return. The constant term (ω) in the volatility model is highly significant with a p-value of 0.000, which implies an increased long-term volatility level relative to the pre-COVID era. The ARCH term (α) is extremely significant with a p-value of 0.000, indicating that short-term volatility is significantly influenced by past shocks. Similarly, the GARCH term (β) is also significant at 0.000, suggesting that volatility persistence remains high during the Covid period. Both the coefficients of α and β are greater than those of the pre-Covid era, demonstrating increased volatility clustering in the pandemic era.

The mean model coefficient (μ) in the post-COVID period is statistically significant at a p-value of 0.000, which implies a negative mean return. It indicates that the average returns during the post-COVID period are large and negative, which could be attributed to the economic impact left after the pandemic. In the case of the volatility model, the constant term (ω) is significant at the 1% level. The ARCH term (α) is highly significant with a p-value of 0.000, which implies that previous shocks still have a significant effect on current volatility. The GARCH term (β) is also significant, showing considerable persistence in volatility. Table 4 presents the results of the GARCH model across pandemic-defined subperiods.

Table 4. GARCH model results.

	Pre-Covid		During-Covid		Post-Covid	
Mean model						
	Coef.	**P>|t|**	**Coef.**	**P>|t|**	**coef**	**P>|t|**
μ	-0.024	0.044**	-0.018	0.055*	-0.039	0.000***
Volatility model						
ω	0.053	0.022**	0.087	0.000***	0.099	0.004***
α	0.166	0.000***	0.229	0.000***	0.166	0.000***
β	0.827	0.000***	0.760	0.000***	0.753	0.000***
Log-likelihood:	-12210.2		-19642.1		-11917.6	
AIC:	24428.4		39292.2		23843.2	
BIC:	24456.5		39322		23871.6	

Note: *,**,*** indicate significance level at 1%,5%, and 10% confidence interval, respectively.

4.4.2. GJR-GARCH(1,1) Model

In the pre-COVID period, in the mean model, the coefficient corresponding to μ shows that the mean return is marginally negative, though not significant at the standard 5% level of significance. The constant term, ω, is insignificant in the volatility model. It indicates that the long-run variance of the returns is not significant in the pre-COVID times. The ARCH term (α) is insignificant, implying that previous shocks are not very important in volatility. The leverage effect γ significantly implies that negative shocks influence volatility more relative to positive shocks. The GARCH parameter (β) is highly significant with a p-value of 0.000 and explains that volatility persistence is high, i.e., past volatility has a significant effect on future volatility.

COVID period, in the mean model, the coefficient of μ shows an insignificant average return. In the volatility model, the constant term ω is statistically significant at the 1% level. It implies that the long-term volatility, similar to the pandemic, is much higher than in the pre-COVID period. The ARCH term (α) is significant, which is expected, as during times of economic uncertainty, past shocks have a substantial effect on current volatility. The parameter γ of the leverage effect has a p-value = 0.000, supporting the fact that negative shocks have a greater impact on increasing volatility compared to positive shocks. The GARCH coefficient (β) indicates a high level of volatility persistence during the pandemic, slightly smaller than in the pre-COVID period, suggesting that volatility may be more sensitive to recent shocks.

In the post-COVID period, the mean model's coefficient for μ shows a statistically significant negative mean return. This indicates that, on average, the post-COVID period experiences negative returns, which could reflect ongoing market uncertainty or the pandemic's consequences. The volatility model's constant term, ω, exhibits a substantial increase in long-term volatility after the pandemic compared to both pre- and during-COVID eras. The ARCH term (α) has a p-value of 0.000, signifying that previous shocks continue to significantly influence volatility. The leverage effect parameter γ has a p-value of 0.041, indicating significance at the 5% level. The negative coefficient here again suggests that negative shocks have a greater impact on volatility than positive shocks, although this effect is less pronounced than during the COVID period. The GARCH term (β) is highly significant with a p-value of 0.000, demonstrating that volatility remained clustered long after the pandemic.

The GJR-GARCH (1,1) model results demonstrate that market volatility behaves significantly differently during and after the COVID-19 pandemic. While the mean returns during and after the pandemic are negative, the volatility dynamics are more evident, especially during the pandemic, with considerable volatility clustering found. The ARCH and GARCH coefficients demonstrate enhanced sensitivity to previous shocks during the COVID period, while the negative leverage effect indicates the increasing impact of negative shocks on volatility. The AIC and BIC values indicate a strong match for the model, with the post-COVID period exhibiting more stable volatility dynamics than the tumultuous conditions during the epidemic. Table 5 presents the results of the GJR-GARCH model across pandemic-defined subperiods.

Table 5. GJR-GARCH Model.

	Pre-Covid		During-Covid		Post-Covid	
Mean model						
	Coef.	**P>|t|**	**Coef.**	**P>|t|**	**coef**	**P>|t|**
μ	-0.007	0.462	-0.003	0.697	-0.031	0.002***
Volatility model						
ω	0.032	0.476	0.086	0.000***	0.102	0.004***
α	0.176	0.167	0.279	0.000***	0.211	0.000***
γ	-0.097	0.017**	-0.097	0.000***	-0.089	0.041**
β	0.872	0.000***	0.760	0.000***	0.750	0.000***
Log-Likelihood:	-12170.7		-19617.4		-11905.1	
AIC:	24351.4		39244.8		23820.2	
BIC:	24386.5		39282.1		23855.7	

Note: **,*** indicate significance level at 5%, and 10% confidence interval, respectively.

4.5. VaR Forecasting and Backtesting

The results of the Kupiec Proportion of Failures (POF) Test conducted on the GARCH and GJR-GARCH models indicate that both models fit the data well regarding the prediction of the proportion of exceptions during pre-, during, and post-COVID periods. The test shows that the actual proportion of exceptions where the Values at Risk (VaR) are lost matches the proportion expected according to the models' confidence levels, with a P-value of 1.000 across all three periods. This high P-value suggests that the models accurately quantify the risk and neither overstate nor understate the risk of substantial losses.

The similarity across the three periods, preceding, during, and after the COVID-19 pandemic, suggests that both the GARCH and GJR-GARCH models have continued to predict market performance across different market environments with the desired accuracy. Consequently, the results validate that both GARCH (1,1) and GJR-GARCH (1,1) model distributions effectively capture the fat-tailed behavior evident in Saudi REIT returns.

The fat-tailed return distributions in Saudi REITs are verified by the value of extreme kurtosis of returns (in section 4.1). Although GARCH and GJR-GARCH models use Student's t-distributions to better reflect tail risk, as shown by the fact that the test is perfect, there are still several concerns worth considering. Even with t-distributions, the excessive thickness of tails indicates that the most severe 1% of events may still be underestimated, especially during crisis conditions when volatility clustering occurs. The leverage effect incorporated by GJR-GARCH adds extra safeguards by making volatility more sensitive to detrimental shocks. Table 6 presents the results of the Kupiec Proportion of Failures (POF) Test conducted on the GARCH and GJR-GARCH models.

Table 6. Kupiec proportion of failures (POF) test.

Model	GARCH Kupiec test P-value	GJR-GARCH Kupiec test P-value
Pre-Covid	1.000	1.000
During-Covid	1.000	1.000
Post-Covid	1.000	1.000

5. CONCLUSION

The analysis indicates that the GARCH (1,1) and GJR-GARCH (1,1) models are suitable for estimating VaR of Saudi REITs during the pre-COVID, during-COVID, and post-COVID periods (2016-2024), given that the backtesting results, based on the Kupiec statistic, demonstrate a perfect match with the expected exception rates. Nevertheless, a critical comparison of the overall performance of the models based on statistical measures such as the AIC and BIC, and the significance of the model parameters, shows that the GJR-GARCH (1,1) model outperforms the GARCH (1,1) model across all three periods, consistent with the findings of Nugroho et al. (2019). Particularly, GJR-GARCH provides a superior model fit in the pre-COVID period, even when individual parameters are not statistically significant, especially because it accounts for the leverage effect or negative shocks producing a larger impact on volatility, which is not captured by the GARCH (1,1). The GJR-GARCH model also provided a better fit during the COVID period, when market volatility increased, with all volatility parameters, including the leverage effect, being highly significant. This is because it better adapts to asymmetric market behavior. Thus, both models are statistically valid in predicting VaR, but the GJR-GARCH model is a more robust and accurate specification across all market conditions.

6. RECOMMENDATIONS AND POLICY IMPLICATIONS

According to the critical insights and empirical evidence presented, a few policy implications and practitioner suggestions could be derived:

- Risk managers ought to focus on models that take into consideration negative shocks because they are more precise in times of crisis.

- Regulators and institutions need to mandate the periodic application of Kupiec or its equivalent backtests so that the VaR models are up to date and sensitive.
- Since fat tails in REIT returns have been found, a non-parametric extreme value theory approach should be incorporated in conjunction with VaR to enhance crisis preparedness by institutions.
- Policymakers are encouraged to be the protagonists in creating higher-frequency, yet transparent, trading data that can promote increased model precision and investor trust.

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