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Episodic Volatility Dynamics of U.S. REITs and Conventional Stocks: Evidence from Crisis and Tranquil Periods**Kazeem O. Isah***

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This study examines the episodic volatility dynamics of U.S. real estate investment trusts (REITs) relative to conventional equities across turbulent and tranquil market conditions. Using daily returns from the Wilshire U.S. REIT Index and S&P 500 from 2000 to 2003, the analysis separates the Global Financial Crisis and COVID-19 pandemic from the remaining lower stress periods. Standard GARCH, EGARCH, and GJR-GARCH models are used to capture persistence and asymmetric responses. The results show that volatility behaviour is strongly state-dependent and differs across asset classes. For REITs, positive shocks generate stronger volatility responses during the two crisis episodes, while negative shocks dominate during tranquil periods. Conventional equities also exhibit asymmetric volatility, although the magnitude and persistence of shocks vary across regimes. Half-life estimates indicate that volatility shocks dissipate rapidly during crises but persist longer in tranquil markets, particularly for conventional stocks. Overall, the findings challenge the view of REITs as uniformly low-risk assets and show that their risk characteristics depend on market conditions. The results support regime-sensitive volatility modelling for portfolio allocation, diversification, risk management, and financial-stability assessments.

Keywords

REITs, Volatility, GARCH, EGARCH, Asymmetric effects, Episodic dynamics

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1. Introduction

Real estate investment trusts (REITs) have become increasingly influential in global capital markets by offering investors liquid exposure to real estate while avoiding the high transaction costs and illiquidity associated with direct property ownership. Their hybrid nature, which is a combination of the characteristics of both equities and tangible assets, makes REITs an essential vehicle for portfolio diversification, inflation hedging, and long-term risk management (Akinsomi et al., 2016; Mensi et al., 2023). As of early 2023, the global commercial real estate market, represented by the Financial Times Stock Exchange European Public Real Estate Association National Association of Real Estate Investment Trusts (Nareit) Real Estate Index, was valued at approximately USD 34.9 trillion, with listed real estate accounting for USD 3.1 trillion and total market capitalisation of USD 2.1 trillion¹. The rapid expansion of the REIT markets underscores their strategic importance for institutional and retail investors, as well as their growing role in global financial stability and asset allocation (Umar and Olson, 2022; Fasanya and Oyewole, 2023).

Despite their appeal, REITs exhibit complex, time-varying volatility patterns that differentiate them from conventional equities. Their prices are not only influenced by broader financial market dynamics but also by property-specific fundamentals, heterogeneous investor behaviour, and liquidity constraints, thus resulting in multi-frequency and nonlinear return processes (Assaf, 2015; Odusami, 2021). Earlier studies have often portrayed REITs as relatively defensive and low-risk investments (Tsai, 2013; Marfatia et al, 2021). However, empirical evidence from the Global Financial Crisis (GFC) and COVID-19 pandemic challenges this perception: the NAREIT All-Equity Index fell by nearly 48% during 2007–2008 and REITs again ranked among the weakest-performing S&P 500 sectors during 2020 (Odusami, 2021). These episodes suggest that REIT volatility is episodic—sensitive to the nature, source, and intensity of macro-financial shocks.

A substantial body of research has examined the volatility behaviour of REITs, with particular attention given to their responses to market shocks, financial integration, and changing macroeconomic conditions. Early studies emphasise the unique volatility characteristics of REITs relative to conventional equities. For example, Cotter and Stevenson (2008) document significant time-varying volatility and contagion effects within REIT markets, particularly during periods of financial stress. Similarly, Liow (2012) shows that international securitised real estate markets exhibit strong volatility spillovers and heightened sensitivity to global risk factors, thereby suggesting that REITs are increasingly integrated with the broader financial markets. Hoesli and

¹ See:

https://www.epra.com/application/files/8916/9357/7010/EPRA_Global_REIT_Survey_2023_ONLINE_v1_1.pdf

Oikarinen (2012) further demonstrate that even though REITs retain diversification benefits, these benefits may weaken during periods of elevated market uncertainty due to increased co-movement with equity markets. In the United States (U.S.) setting, Sing et al. (2016) show that REIT betas vary substantially over time, which implies that REIT sensitivity to broad equity-market risk is regime-dependent rather than fixed. Lantushenko and Nelling (2022) further link institutional ownership volatility to REIT investment behaviour, which suggests that ownership structure and trading composition can influence REIT risk dynamics.

More recent studies have explored the role of crises and macro-financial uncertainty in shaping REIT volatility. Lee et al. (2022) report that REIT markets show substantial regime-dependent volatility dynamics, with financial crises significantly altering risk transmission mechanisms. Likewise, Milcheva (2022) highlights the importance of uncertainty shocks in driving the performance and volatility of real estate securities, particularly during periods of economic disruption. During the COVID-19 episode, Aboluwodi et al. (2025) show that real estate performance forecasting depends on model choice, with statistical and machine-learning approaches capturing crisis-period dynamics differently. Other studies, including Assaf (2015), Odusami (2021), and Mensi et al. (2023), have documented nonlinearities, structural breaks, and volatility spillovers in REIT returns respectively, thus reinforcing the view that REIT volatility is neither constant nor purely driven by real estate fundamentals.

Collectively, these studies establish that REIT volatility is dynamic, asymmetric, and sensitive to changing economic conditions. However, the existing literature remains largely focused on REIT markets in isolation or their interactions with selected financial variables, with relatively less emphasis on direct comparisons between REITs and broad conventional equity markets across multiple crisis episodes with the use of a common modelling framework.

This episodic behaviour arises from the dual exposure of REITs to financial system shocks and real-sector disturbances. The GFC, rooted in credit and leverage channels, magnified systemic financial risk, whereas the COVID-19 crisis disrupted real-estate cash flows and occupancy rates through exogenous shocks. Theoretically, these distinct mechanisms imply heterogeneous volatility transmission paths—financial shocks are transmitted through balance-sheet effects, while real-sector shocks propagate through income and liquidity channels. Understanding how REITs behave under these divergent regimes is therefore crucial for determining whether their “low-risk” status persists across economic cycles or merely reflects temporary conditions.

To address this, the study explicitly compares the volatility dynamics of REITs and conventional equities. Although both are publicly traded and subject to general market sentiment, they differ fundamentally in asset backing, cash-flow structures, and exposure to real-sector risks. This comparison allows us to

assess whether REITs truly represent a distinct, more stable asset class or only mirror the volatility of equity markets during stress periods. Theoretically, this analysis informs asset-pricing and portfolio-diversification debates; that is, whether REITs deliver structural segmentation benefits or increasing market integration has eroded these advantages (Hoesli et al., 2020). Empirically, the work contributes to the understanding of contagion and volatility spillovers between property-linked and non-property assets across financial regimes.

Furthermore, previous studies show that REIT volatility often responds asymmetrically to market shocks, consistent with the leverage and overreaction hypotheses (Black, 1976; Christie, 1982). Negative shocks typically induce more volatility than positive ones due to liquidity constraints and financing frictions. However, recent evidence also reveals nonlinear co-movements and asymmetric volatility persistence between REITs and macro-financial variables, particularly during crises (Mensi et al., 2023; Ozcelebi and Yoon, 2025). Although the literature provides substantial evidence on REIT volatility, contagion, and market integration, several important issues remain unresolved. First, much of the existing research focuses exclusively on REIT markets or their interactions with selected macro-financial variables, without directly comparing their volatility dynamics with those of broad conventional equity markets under a common empirical framework. Second, while regime dependence has received increasing attention, previous studies typically focus on a single crisis episode or a specific source of uncertainty, which makes it difficult to determine whether REIT volatility responds differently to crises of fundamentally different origins. Third, limited evidence exists on whether volatility asymmetry, persistence, and shock reversion differ systematically between REITs and conventional equities across both turbulent and tranquil market states.

This study addresses these gaps by providing a comparative analysis of REIT and conventional stock volatility across two major crises: the GFC and COVID-19 pandemic, and a tranquil market phase, by using a consistent family of asymmetric generalised autoregressive conditional heteroskedasticity (GARCH) models. By examining volatility asymmetry, persistence, and half-life dynamics across heterogeneous market regimes, the study offers new evidence on whether REITs maintain distinct risk characteristics relative to conventional equities or these distinctions diminish under periods of market stress. The findings are expected to have significant implications. For investors and portfolio managers, distinguishing structural from episodic volatility improves diversification and hedging strategies, especially during market stress. For institutional investors such as pension funds and insurers, understanding when REITs behave more like equities than real assets inform liability management and dividend policy. For policymakers and regulators, recognising volatility asymmetries enhances the macroprudential monitoring of real-estate-linked financial instruments.

In summary, this study contributes to the literature by systematically analysing the state-dependent, asymmetric, and comparative volatility dynamics of REITs

and non-REIT equities across financial regimes. By integrating crisis heterogeneity, asset-type differentiation, and nonlinear volatility modelling, the work enhances understanding of how real-estate securities transmit and absorb shocks, thus offering new insights for both financial stability research and investment practices.

In addition to this introductory section, the remainder of the paper is structured as follows. Section 2 explains the data and offers some preliminary analysis to determine the inherent statistical features of the data as prerequisites to justify the appropriateness of estimation techniques considered in the study. Section 3 presents the methodology and techniques used in the study and discusses their applicability in line with various specific objectives of this study. Section 4 presents the empirical results in line with each study objective. We conclude the paper in Section 5 and offer some remarks.

2. Data and Preliminary Analysis

This study employs daily price series for REITs and conventional U.S. equities to examine the episodic dynamics of volatility. The focus on the U.S. is motivated by the fact that the country hosts the largest, most liquid, and most mature REIT market in the world, which accounts for a substantial share of global listed real estate capitalisation. The long history, depth, and institutional development of the U.S. REIT market provides a suitable setting for examining volatility dynamics across multiple economic and financial episodes. The REIT market is represented by the Wilshire U.S. REIT Index, which provides broad coverage of publicly traded U.S. equity REITs and is widely used to capture aggregate REIT market performance. Its comprehensive market representation makes it particularly suitable for examining economy-wide REIT volatility behaviour. The S&P 500 Index serves as a proxy for conventional stocks because it is widely regarded as the benchmark indicator of the overall U.S. equity market performance. Although some REIT firms may be constituents of the S&P 500, their aggregate weight is relatively small, which makes the S&P 500 index an appropriate comparator for assessing differences in volatility behaviour between REITs and conventional equities.

All of the data were collected from Investing.com, and cover the period from January 3, 2000, to December 29, 2023, thus yielding a total of 6,237 observations. The daily frequency is selected to capture high-resolution volatility dynamics, which is essential for identifying episodic patterns across crisis and non-crisis periods. In line with the objective of investigating whether REIT volatility is state-dependent, the full sample is partitioned into two sub-samples: a turbulent period which captures the crises and a tranquillity period which represents relatively calm markets. The turbulent period combines two major economic shocks of differing origin. First, the GFC, which took place from September 3, 2007 to February 27, 2009, is considered the longest

economic downturn since World War II, triggered by housing-market collapses and systemic financial stress. Second, the COVID-19 episode started March 11, 2020, when the World Health Organization officially declared COVID-19 to be a global pandemic, to May 5, 2023, when the World Health Organization terminated this public health emergency of international concern. From a market perspective, this endpoint also corresponds to the period in which pandemic-related uncertainty, mobility restrictions, and emergency policy interventions had largely subsided, thus marking a transition toward post-pandemic normalisation.

In view of the foregoing, the study considers two distinct crisis episodes: the GFC and COVID-19 pandemic. Although both episodes are categorised as turbulent market conditions, they are analysed separately throughout the empirical investigation because they originated from fundamentally different economic mechanisms. The GFC was primarily driven by financial-sector fragilities, leverage, and credit-market disruptions, whereas the COVID-19 pandemic represented an exogenous health shock with substantial implications for real economic activity and property-market fundamentals. Treating these episodes separately allows the study to examine whether REIT and conventional stock volatilities respond differently to crises of differing origin and transmission channels.

Thus, the tranquillity period is defined as the complement of the identified crisis windows. While the other market disturbances occurred during the sample period, the GFC and COVID-19 pandemic are widely regarded as the two most severe and globally synchronised shocks that affected the U.S. financial and real estate markets during the study horizon. Defining tranquillity as the residual sample follows an event-based classification approach commonly adopted in crisis-oriented financial research and allows for a clear comparison between periods characterised by systemic stress and periods that reflect relatively normal market functioning. Consequently, the tranquillity regime is herein interpreted as a benchmark or lower-stress period rather than a state entirely free from market disturbances.

Technically, daily returns for REITs and non-REITs are calculated as continuously compounded log returns, for example, $R_t^{REIT} = \ln(P_t^{REIT}) - \ln(P_{t-1}^{REIT})$ and $R_t^{Stock} = \ln(P_t^{Stock}) - \ln(P_{t-1}^{Stock})$, where P_t denotes the daily index level for REITs and conventional stocks, respectively. This standard transformation ensures stationarity and stabilises the variance for volatility modelling. Table 1 presents the summary statistics for the full sample, turbulent periods (GFC and COVID-19), and tranquillity period. Several patterns emerge. Across the entire sample, REIT returns exhibit higher skewness and kurtosis relative to conventional equities, thus indicating fatter tails and occasional extreme movements consistent with episodic volatility. During the turbulent periods, both REIT and stock returns show elevated standard deviations and increased negative skewness, which reflect pronounced downside risks. Notably, REIT volatility was higher during COVID-19 than the GFC, thereby

suggesting episodic behaviour that is dependent on the nature of the shock. While REITs generally record higher average returns during crises, the magnitude of positive and negative returns is also more pronounced compared to conventional equities. In contrast, during the tranquillity period, conventional stocks have a higher standard deviation than the REITs (Salisu et al., 2024), thus supporting the hypothesis of state-dependent volatility.

Table 1 Descriptive Statistics

	Full Sample [FS]	Turbulent Periods [TUP]		Tranquil Periods [Full Less TUP]
		GFC	COVID	
REIT Stock Returns				
Mean	0.0180	0.0224	-0.2855	0.0031
Std. Dev.	1.7467	2.0944	4.6088	4.2536
Skewness	-0.5207	-31.0073	0.0226	14.4858
Kurtosis	25.4739	57.0080	5.8480	81.4055
No. Obs.	6237	5025	389	1211
Conventional Stock Returns				
Mean	0.0224	0.0278	-0.1817	0.0861
Std. Dev.	1.2322	1.6138	2.2996	4.3944
Skewness	-0.3234	-17.5773	-0.0756	28.0547
Kurtosis	13.3480	44.5057	7.3053	9.8654
No. Obs.	6237	5025	389	1211

Source: Author's own work

A cursory inspection of these descriptive statistics already indicates early conformity with our hypothesis of episodic volatility. For example, while the REITs recorded positive average returns during the GFC, they experienced negative returns during the COVID-19 period. Similarly, the standard deviation of REIT returns is higher during COVID-19 than the GFC, and exceeds that of conventional stocks during turbulent periods, thus highlighting the potential episodic nature of the widely assumed low-risk profile of REITs. By contrast, conventional stock returns exhibit higher dispersion than REITs in calm periods, which further reinforces the state-dependence of volatility.

To formally assess the presence of conditional heteroskedasticity, we apply the ARCH-Lagrange multiplier (ARCH-LM) test, which regresses the squared residuals from an AR(1) process on their own lags. As evident in Table 2, the null hypothesis of no ARCH effect is consistently rejected for both the REIT and conventional stock returns in the full and turbulent sub-samples, whereas it is not rejected for the tranquillity period. These results confirm significant volatility clustering during crises, which is absent in the calm periods, thus providing empirical justification for the use of GARCH-type models to capture nonlinear and asymmetric volatility dynamics. Overall, the preliminary analysis demonstrates that REIT returns exhibit episodic volatility patterns relative to conventional stocks, particularly in response to shocks of differing origin.

These findings motivate the subsequent GARCH-based modelling framework, which allows for rigorous estimation of state-dependent and asymmetric volatility dynamics.

Table 2 ARCH Test for REITs and Conventional Stock Returns

Period/Sample	K=5		K=10		K=20	
	REITs	S&P500	REITs	S&P500	REITs	S&P500
Full Sample	427.64***	428.48***	263.63***	241.95***	143.48***	130.72***
TUP [GFC]	19.97***	26.12***	13.31***	14.87***	7.47***	9.29***
TUP [COVID]	2.72**	10.29***	2.78***	7.12***	1.82**	4.45***
Tranquil Period	0.10	0.04	0.16	0.05	0.12	0.04

Notes: The ARCH test is performed based on the AR(1) process with $k=5$, $k=10$, and $k=20$ which represent the lag lengths for the test statistic, while ***, ** and * denote significance at 1%, 5% and 10%, respectively.

3. Methodology

The study adopts a GARCH framework to model the conditional volatility of daily returns for REITs and conventional stocks. Our preference for the GARCH family of models in the context of this study is technically motivated by the preliminary ARCH-LM results that confirm the presence of conditional heteroskedasticity and volatility clustering in both REIT and conventional stock returns. While alternative approaches such as Markov-switching GARCH and heterogeneous autoregressive realised volatility (HAR-RV) models can accommodate regime transitions and realised-volatility dynamics, respectively, the objective of this study is to compare volatility behaviour across exogenously identified market episodes rather than estimate latent regime changes. Consequently, conventional and asymmetric GARCH specifications provide a parsimonious and empirically appropriate framework for examining volatility persistence and asymmetry across crisis and tranquil periods.

Following the standard practice in the volatility literature, the GARCH(1,1) model is employed as the benchmark specification because it has been shown to capture the persistence characteristics of financial return volatility effectively while avoiding unnecessary parameterisation (Bollerslev, 1986). Moreover, a number of studies in the REIT literature have adopted the GARCH(1,1) framework as a baseline model to facilitate comparison with existing evidence. Accordingly, the conditional mean equation is specified as an AR(1) process to account for potential short-run serial dependence in daily returns. The choice of an AR(1) structure follows standard practice in financial volatility modelling and helps to ensure that the estimated volatility dynamics are not contaminated by residual linear dependence in the conditional mean process.

Let r_t denote the daily return on financial assets, which in this study represents either REIT or non-REIT (S&P 500) returns. The conditional mean of the return process is given as follows:

$$r_t = \lambda + \sum_{i=1}^k \delta_i r_{t-i} + \varepsilon_t \quad (1)$$

where r_t is the return from holding financial assets or securities, which, in the context of this study, is captured separately for REIT and conventional stock returns. The term λ represents the risk premium for investing in long-term assets, while (δ) captures the short-term persistence in returns, and ε_t is a mean-zero error term. Given that r_t in Equation (1) is presumed to be conditional on the immediate past information set (Ω) , the conditional mean is therefore expressed as:

$$E(r_t | \Omega) = \lambda + \sum_{i=1}^k \delta_i r_{t-i} + \varepsilon_i \quad (2)$$

Equation (2) shows that the conditional mean of r_t is time-varying, which aligns with the statistical characteristics typically observed in financial return series. Assuming that the error term follows the approach in Engle (2002), we obtain:

$$\varepsilon_t = \mu_t \left(\beta_0 + \sum_{j=1}^q \beta_j \varepsilon_{t-j}^2 \right)^{\frac{1}{2}} ; j = 1, \dots, q \quad (3)$$

where $\mu: ID(0,1)$ and to ensure that the conditional variance is positive, it is assumed that $\beta_0 > 0$ and $0 < \beta < 1$, which is in line with the non-negative constraint imposed on the ARCH model of Engle (1982). Accordingly, the ARCH(q) model in Equation (3) can be rewritten as follows:

$$\varepsilon_t^2 = \mu_t^2 \left(\beta_0 + \sum_{j=1}^q \beta_j \varepsilon_{t-j}^2 \right) \quad (4)$$

Taken the expectation of Equation (4) with respect to the relevant information set (ζ_{t-1}) , for instance, $E(\mu^2 | \zeta_{t-1}) = 1$, we derive the conditional variance equation as follows:

$$\text{var}(\varepsilon_t | \zeta_{t-1}) = \beta_0 + \sum_{j=1}^q \beta_j \varepsilon_{t-j}^2 \quad (5)$$

Since

$$E(\mu_t^2 | \zeta_{t-1}) = 1$$

Equation (5) represents the conditional variance model, and using the lag operator (L), the unconditional variance model can be respecified as:

$$\sigma_t^2 = E(\varepsilon_t^2) = \frac{\beta_0}{1 = \beta(L)} \quad (6)$$

where $\sum_{j=1}^q \beta_j \varepsilon_{t-j}^2 = \beta(L) \varepsilon_t^2$ and by extension $\beta_1 + \beta_2 L^2 + \dots + \beta_q L^q$ given that $\beta(L)$ is defined as a polynomial lag operator.

The ARCH (q) model in Equation (4) is defined in a way that the value of conditional variance [$\text{var}(\varepsilon_t | \zeta_{t-1})$] is treated as a function of the squared error term of the past periods (ε_{t-j}^2). As established in the preliminary analysis, the hypothesis of no ARCH effect is strongly rejected, which implies that the variance is time-dependent and likely higher in the presence of volatility clustering.

Bollerslev (1986) extends the ARCH model in Engle (1982) (see Equation (5)) by incorporating lagged conditional variances, thereby yielding the well-known GARCH(p, q) model in the literature:

$$\sigma_t^2 = \beta_0 + \sum_{j=1}^q \beta_j \varepsilon_{t-j}^2 + \sum_{i=1}^p \gamma_i \sigma_{t-i}^2 \quad (7)$$

Equation (7) represents our baseline GARCH model, where p denotes the lag order of the conditional variance and q represents the lag order of the squared error term. For $j = 1, \dots, q$ and $i = 1, \dots, p$, it is expected that $p \geq 0, q > 0, \beta_0 > 0, \beta_j \geq 0, \gamma_i \geq 0$.

The GARCH model in Equation (7) comprises two important components. The first is $\sum_{j=1}^q \beta_j \varepsilon_{t-j}^2$ which captures the ARCH effect while the second is $\sum_{i=1}^p \gamma_i \sigma_{t-i}^2$ and captures the GARCH effect. Again, we can use the lag operator (L) method to rewrite the GARCH (p, q) model in the following form:

$$\sigma_t^2 = \beta_0 + \beta(L) \varepsilon_t^2 + \gamma(L) \sigma_t^2 \quad (8)$$

where $\gamma(L) \sigma_t^2 = \sum_{i=1}^p \gamma_i \sigma_{t-i}^2$ and $r(L)$ is the polynomial lag operator $\gamma_1 L + \gamma_2 L^2 + \dots + \gamma_p L^p$. After further simplification, Equation (8) can be written as:

$$\sigma^2 = \beta_0 [1 - \gamma(L)]^{-1} + \beta(L) [1 - \gamma(L)]^{-1} \varepsilon_t^2 \quad (9)$$

However, the unconditional variance is smaller where there is no evidence of volatility.

$$\sigma^2 = [1 - \beta(L) - \gamma(L)]^{-1} \beta_0 \quad (10)$$

The GARCH(1,1) specification is adopted as the benchmark because it has been shown to adequately capture volatility persistence in financial return series while maintaining parsimony (Bollerslev, 1986). A number of REIT studies

also employ GARCH(1,1) as the baseline specification, so that the study results are directly comparable with those of the literature.

Given the potential for asymmetric volatility behaviour in REIT and conventional stock returns, we further consider GARCH variants that capture such dynamics. Specifically, we employ the exponential GARCH (EGARCH) model proposed by Nelson (1991), which effectively models leverage effects, which are situations where negative shocks exert a larger impact on volatility than positive shocks of equal magnitude. The EGARCH(p, q) model is specified as:

$$\text{Log}(\sigma_t^2) = \Psi + [1 - \gamma(L)]^{-1}[1 - \beta(L)]f\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) \quad (11)$$

and

$$f\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) = \alpha\varepsilon_{t-1} + \vartheta\left(\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - E\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right|\right) \quad (12)$$

Compared to the standard ARCH and GARCH models, the log of the conditional variance in the EGARCH is a function of the logged error terms. As a result, the asymmetric effect is captured by the parameter α in Equation (12) (i.e., the function $f\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right)$). The null hypothesis of no asymmetry is rejected when $\alpha < 0$ and there is no asymmetric effect if $\alpha = 0$. For the sake of robustness and consistency, we also consider the asymmetric GARCH model in Glosten et al. (1993), which modifies Equation (7) to include a dummy variable I_{t-j} :

$$\sigma_t^2 = \beta_0 + \sum_{j=1}^q \beta_j \varepsilon_{t-j}^2 \varepsilon_{t-j}^2 + \sum_{i=1}^p \gamma_i \sigma_{t-i}^2 + \sum_{j=1}^q \varphi_j \varepsilon_{t-j}^2 I_{t-j} \quad (13)$$

where $I_{t-j} = 1$ if $\varepsilon_{t-j} > 0$ (positive shocks) and $I_{t-j} = 0$ otherwise. Therefore, there is evidence of an asymmetric effect if $\varphi_j < 0$ which implies that positive shocks reduce the volatility of Z_t more than negative shocks of the same magnitude.

To further assess the volatility dynamics, the study calculates shock persistence and volatility half-life measures. Shock persistence captures the proportion of a volatility shock that is transmitted into subsequent periods and is calculated as the sum of the ARCH and GARCH coefficients ($\beta_j + \gamma$), where β_j denotes the ARCH effect and γ_i represents the GARCH effect. Values that are closer to unity indicate highly persistent volatility processes, whereas smaller values imply rapid mean reversion. Following the standard practice in the volatility literature, the half-life (HL) of a volatility shock is calculated as: $\frac{\ln(0.5)}{\ln(\beta_1 + \gamma)}$, where HL denotes the number of trading days required for half of a volatility shock to dissipate. A longer HL indicates slower reversion of volatility and greater persistence of market disturbances.

4. Empirical Result

4.1 Best fit GARCH modelling framework

The intuition here is to identify the most appropriate GARCH framework for capturing the episodic and asymmetric volatility dynamics of U.S. REITs and conventional equities across different market regimes. Given the heterogeneous nature of financial shocks during crisis and tranquil periods, selecting the correct model specification is critical for obtaining consistent and interpretable volatility estimates. A model that fails to account for asymmetry or regime sensitivity may underestimate volatility persistence or misrepresent the true risk profile of each asset class. Therefore, before discussing the substantive results, this section begins by determining the best-fitting GARCH model based on established information criteria. Lower Akaike information criterion (AIC) or Schwarz information criterion (SIC) values for an estimated GARCH model means a better statistical fit. However, where AIC and SIC rankings diverge, the SIC is typically preferred because it penalises over-parameterisation more strongly (see Salisu and Oloko (2015)). Starting with the REITs in Table 3a, convergence is achieved for all of the GARCH specifications. The GJGJR, Jagannathan, and Runkle (GJR)-GARCH(1,1) model ranks first for the full sample and non-crisis period, while EGARCH(1,1) emerges as the best-fitting model during the GFC and COVID-19 episodes. Similarly, Table 3b shows that asymmetric GARCH variants provide superior fit for conventional stock volatility, although the specific optimal model differs across market regimes.

From an economic perspective, these results confirm the asymmetric nature of volatility in both REITs and conventional stocks, thus implying that markets react differently to good and bad news. The preference for asymmetric models supports the leverage hypothesis and information asymmetry theory, which suggests that the direction of shocks matters for volatility behaviour. Moreover, the dominance of EGARCH during the GFC and COVID-19 underscores the nonlinear and regime-dependent behaviour of volatility, where crises amplify the sensitivity of returns to information flows. These findings are consistent with previous studies such as Huang and Lee (2009), Fasanya et al. (2021), and Mensi et al. (2023), who document similar asymmetries in the real estate and equity markets. For practitioners, these results imply that assuming symmetric volatility (as in standard GARCH models) may understate actual risk exposure. Investors and risk managers should thus adopt regime-sensitive volatility frameworks that accommodate asymmetric and nonlinear responses to shocks. Such models are better suited for stress testing, value at risk (VaR) calculation, and portfolio optimisation, particularly under varying market conditions.

Table 3a Optimal GARCH Model Selection for REIT Return Volatility

Full Sample				
Model Type	Convergence Status	Selection Criteria		
		AIC	SIC	Rank
GARCH (1,1)	Achieved	3.0639	3.0693	2nd
EGARCH (1,1)	Achieved	3.0658	3.0723	3rd
GJR-GARCH (1,1)	Achieved	3.0574	3.0639	1st
TUP [GFC]				
GARCH (1, 1)	Achieved	5.3404	5.3914	3rd
EGARCH (1,1)	Achieved	5.3089	5.3702	1st
GJR-GARCH (1,1)	Achieved	5.3139	5.3751	2nd
TUP [COVID]				
GARCH (1, 1)	Achieved	3.3017	3.3304	3rd
EGARCH (1,1)	Achieved	3.2700	3.3045	1st
GJR-GARCH (1,1)	Achieved	3.2865	3.3210	2nd
Tranquillity [Full Sample less TUP]				
GARCH (1,1)	Achieved	3.4416	3.4481	3rd
EGARCH (1,1)	Achieved	3.4268	3.4346	2nd
GJR-GARCH (1,1)	Achieved	3.3549	3.3627	1st

Source: Compiled by authors

Table 3b Optimal GARCH Model Selection for Conventional Stock Return Volatility

Full Sample				
Model Type	Convergence Status	Selection Criteria		
		AIC	SIC	Rank
GARCH (1,1)	Achieved	2.7084	2.7138	3rd
EGARCH (1,1)	Achieved	2.6808	2.6873	1st
GJR-GARCH (1,1)	Achieved	2.6825	2.6890	2nd
TUP [GFC]				
GARCH (1,1)	Achieved	4.0433	4.0944	2nd
EGARCH (1,1)	Achieved	3.9931	4.0544	1st
GJR-GARCH (1,1)	No Convergence	N/A		
TUP [COVID]				
GARCH (1,1)	Achieved	2.3008	2.3295	3rd
EGARCH (1,1)	Achieved	2.2996	2.3340	2nd
GJR-GARCH (1,1)	Achieved	2.2973	2.3317	1st
Tranquillity [Full Sample less TUP]				
GARCH (1, 1)	Achieved	3.1124	3.1188	2nd
EGARCH (1,1)	Achieved	3.3722	3.3799	3rd
GJR-GARCH (1,1)	Achieved	3.0520	3.0597	1st

Notes: N/A means not applicable. Compiled by authors

4.2 Volatility Dynamics and Conditional Variance Estimates

Table 4 reports the empirical estimates from the selected asymmetric-based GARCH models for REITs across the crisis and non-crisis periods. Although the primary focus is on volatility dynamics, the risk premium coefficient of the mean equation also provides valuable insight. Consistent with the finance theory, this coefficient is expected to be positive if risk is compensated with return. However, the estimates reveal a negative sign during the GFC, an insignificant effect during COVID-19, and a positive, statistically significant value during tranquil periods. Economically, this pattern highlights a risk-return inversion during crises, where heightened uncertainty and liquidity constraints may cause investors to accept lower returns for perceived safety, consistent with the flight-to-quality behaviour reported in the crisis-finance literature.

Turning to volatility behaviour, the conditional variance results (Table 4) reveal that the asymmetry parameter is positive and statistically significant during the GFC and COVID-19 periods. This finding suggests that positive shocks (good news) are associated with larger volatility responses than negative shocks (bad news) during crisis periods. However, this interpretation should be treated with caution. While the GARCH framework identifies the presence and direction of statistical asymmetry, it does not directly reveal the underlying behavioural or market mechanisms responsible for this pattern. One possible explanation is that favourable developments during periods of turmoil, such as policy stimulus measures, monetary easing, or early signs of economic recovery, may encourage investors to reallocate capital toward real estate securities, thereby increasing short-term trading activity and volatility. Nevertheless, alternative explanations are also plausible. For example, short-covering behaviour, liquidity adjustments, derivatives-market positioning, or changing risk perceptions may generate similar volatility responses. In addition, heightened information asymmetry and heterogeneous investor expectations during crisis periods can amplify market reactions to positive news as participants reassess asset valuations under conditions of heightened uncertainty.

By contrast, the asymmetry parameter is negative during tranquil periods, which indicates that bad news dominates volatility in stable markets. This aligns with the traditional leverage effect, where negative shocks increase perceived risk and thus volatility. This dual behaviour underscores the episodic nature of REIT volatility, which suggests that the dominance of good or bad news depends on the prevailing market regime. These findings extend those of Fasanya and Akinwale (2022), who document similar asymmetric and time-varying patterns in REIT volatility, and lend support to the view that REITs exhibit hybrid behaviour—part real asset, part financial security.

Table 4 GARCH-based Volatility Estimates for REITs across Market Episodes

Episode	Mean Equation		Variance Equation			
	λ	$\delta = \text{AR}(1)$	β_0	β_j	γ_i	Asym (α or φ)
Full	0.0361***	0.0014	0.0220***	0.0665***	0.0796***	0.0828***
Sample	(0.0119)	(0.0131)	(0.0021)	(0.0083)	(0.0061)	(0.0100)
TUP	-0.3174**	-0.2062***	-0.0277	0.0913***	-0.1284***	0.9851***
[GFC]	(0.1436)	(0.0541)	(0.0277)	(0.0297)	(0.0321)	(0.0060)
TUP	-0.0052	-0.0164	-0.0261*	0.0453**	0.0844***	0.9802***
[COVID]	(0.0424)	(0.0343)	(0.0152)	(0.0190)	(0.0194)	(0.0051)
Tranquility	0.1490***	-0.2037***	0.1310***	0.5262***	0.0434***	-1.8794***
[Full	(0.0122)	(0.0157)	(0.0096)	(0.0702)	(0.0093)	(0.0742)
Sample						
less						
TUP]						
Diagnostic / Post-estimation Test						
	Full Sample	GFC	COVID	Tranquility		
ARCH-LM (5)	0.0744	0.0849	0.0912	0.0728		
	(0.964)	(0.958)	(0.9554)	(0.9643)		
ARCH-LM (10)	1.9264	0.6994	0.8174	2.0067		
	(0.859)	(0.983)	(0.9759)	(0.8482)		
Ljung-Box Q-Stat	1.0497	0.9195	2.6471	2.7295		
(5)	(0.5916)	(0.632)	(0.266)	(0.2554)		
Ljung-Box Q-Stat	6.3865	6.0283	5.5833	5.6834		
(10)	(0.2704)	(0.304)	(0.349)	(0.3382)		

Notes: Values in parentheses are standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. λ denotes the mean-equation intercept, while $\delta = \text{AR}(1)$ represents the first-order autoregressive coefficient. In the variance equation, β_0 denotes the variance intercept (constant term), β_i represents the ARCH coefficient, γ_i represents the GARCH coefficient, and Asym (α or φ) denotes the asymmetry (leverage) parameter.

In addition, the coefficient on past shocks (the ARCH term) is positive across all regimes but larger in magnitude during tranquil periods. This suggests that in calm markets, volatility reacts more persistently to new information, consistent with the view that stable trading environments encourage more continuous price discovery and speculation. Conversely, during crises, market illiquidity and trading constraints dampen persistence even as volatility spikes in the short term.

For investors and fund managers, these findings imply that they should not treat REIT volatility as uniformly low or stable. In tranquil times, high trading intensity and search for yield may increase volatility persistence, whereas in crises, shocks may dissipate quickly but with a larger amplitude. Consequently, risk models should be dynamically updated across regimes, and portfolio rebalancing should reflect the conditional behaviour of volatility.

The results for conventional stocks in Table 5 reinforce this view. Positive shocks consistently increase volatility across all regimes, thus highlighting that equity markets react more strongly to good news than bad news—possibly due to momentum trading and algorithmic strategies that amplify positive market sentiment. The effect of past shocks remains positive and significant in all cases, but the magnitude varies across periods, which suggest that volatility persistence is both time- and asset-dependent.

Table 5 GARCH-based Volatility Estimates for Conventional Stocks across Market Episodes

Episode	Mean Equation		Variance Equation			
	λ	$\delta=AR(1)$	β_0	β_i	γ_i	Asym (α or φ)
Full	0.0229**	0.1668***	-0.1280***	0.1613***	-0.1162***	0.9756***
Sample	(0.0100)	(0.0069)	(0.0057)	(0.0072)	(0.0044)	(0.0015)
TUP	-0.1801**	-0.0291	-0.0283	0.0828*	0.1981***	0.9709***
[GFC]	(0.0783)	(0.0204)	(0.0411)	(0.0493)	(0.0397)	(0.0080)
TUP [COVID]	0.0243	0.5717***	0.0062**	0.0007	0.9655***	0.0459***
	(0.0262)	(0.0194)	(0.0031)	(0.0133)	(0.0115)	(0.0154)
Tranquility	-0.0242**	0.1006***	0.0084***	0.0053***	0.8934***	0.4165***
[Full Sample less TUP]	(0.0115)	(0.0058)	(0.0008)	(0.0003)	(0.0026)	(0.0130)
Diagnostic/Post-estimation Test						
	Full Sample	GFC	COVID	Tranquility		
ARCH-LM (5)	0.0807	0.0851	0.0771	0.0915		
	(0.9604)	(0.9584)	(0.9622)	(0.9553)		
ARCH-LM (10)	1.8999	0.6949	1.9796	0.8156		
	(0.8628)	(0.9832)	(0.8520)	(0.9760)		
Ljung-Box Q-Stat	2.6614	0.8996	2.7437	1.0315		
(5)	(0.2643)	(0.6378)	(0.2536)	(0.5970)		
Ljung-Box Q-Stat	5.5961	5.9919	5.6954	6.3578		
(10)	(0.3475)	(0.3070)	(0.3370)	(0.2729)		

Notes: Values in parentheses are standard errors. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. λ denotes the mean-equation intercept, while $\delta=AR(1)$ represents the first-order autoregressive coefficient. In the variance equation, β_0 denotes the variance intercept (constant term), β_i represents the ARCH coefficient, γ_i represents the GARCH coefficient, and Asym (α or φ) denotes the asymmetry (leverage) parameter.

More importantly, the comparison between REITs and conventional stocks reveals key behavioural differences. During crises, conventional stock volatility is more persistent than REIT volatility, which implies that stock market shocks take longer to dissipate. This finding indicates that REITs may revert to equilibrium more quickly during distress, thus reflecting their income-based structure and regulated payout requirements. However, in calm markets, REIT

volatility becomes more persistent, thereby suggesting that active trading and yield-chasing can heighten short-term uncertainty. These findings challenge the traditional notion that REITs are uniformly defensive assets and underscore the importance of contextual, regime-aware risk assessment.

4.3 Measures of persistence and half-life

Table 6 presents the estimated persistence and HL of volatility shocks for REIT and conventional stocks across different market episodes. A clear pattern emerges: volatility shocks are the least persistent during crisis episodes; specifically, the GFC and COVID-19, and most persistent during tranquil market conditions. At first glance, this may appear counterintuitive; however, it aligns well with the market microstructure theory. Crisis periods tend to generate sharp and abrupt volatility spikes that unwind quickly following policy interventions, liquidity injections, or rapid dissemination of new information. By contrast, tranquil markets exhibit slow-moving, autocorrelated volatility driven by continuous trading and gradual information diffusion, thus resulting in higher persistence. The table shows that for REITs, shock persistence is 0.2809 during the GFC and 0.1297 during COVID-19, which correspond to relatively short HLs of 0.5459 and 0.3394 days, respectively. Conventional equities show even lower persistence during COVID-19 (0.0007), with an HL of only 0.0954 days, which implies almost immediate shock dissipation. During the GFC, their persistence is 0.0828 with an HL of 0.2782 days. These results confirm the rapid reversion of volatility under stressed conditions across both asset classes. In tranquil periods, however, both markets exhibit much higher persistence, with REITs showing a persistence estimate of 0.5696 (HL $\approx$ 1.23 days) and conventional stocks demonstrating extremely high persistence at 0.8987, which translates into a remarkably long HL of approximately 6.49 days. This stark contrast underscores the regime-dependent nature of volatility dynamics: shocks dissipate quickly during crises yet linger substantially longer when the markets are calm.

A further look at Table 6 reveals nuanced differences between REITs and conventional stocks. During crises, the HL values of REITs (0.34–0.55 days) are slightly larger than those of conventional equities (0.09–0.38 days), thus implying that conventional stocks tend to revert marginally faster in turbulent conditions. However, in tranquil periods, this relationship reverses dramatically with conventional equities showing far greater persistence (6.49 days) compared to REITs (1.23 days). This indicates that volatility in conventional markets becomes highly entrenched during calm episodes, whereas REIT volatility remains more moderate and less sticky. These patterns are consistent with the hybrid asset hypothesis, which posits that REITs incorporate characteristics of both equities and fixed-income securities, thus producing volatility behaviours that vary systematically across states of the economy. The empirical evidence also aligns with earlier findings by Gentry et al. (2003), Huang and Lee (2009), and Rahman (2024), who report that REIT volatility

dynamics are sensitive to macroeconomic regimes and underlying market conditions.

Table 6 Shock Persistence and Half-Life Estimates

Episode	REIT Stocks		Conventional Stocks	
	Shock Persistence $(\beta_1 + \gamma)$	Half-Life	Shock Persistence $(\beta_1 + \gamma)$	Half-Life
Full Sample	0.1461	0.3604	0.1613	0.3799
TUP [GFC]	0.2809	0.5459	0.0828	0.2782
TUP [COVID]	0.1297	0.3394	0.0007	0.0954
Tranquility [Full Sample less TUP]	0.5696	1.2315	0.8987	6.4897

Notes: While the shock persistence is calculated as $(\beta_1 + \gamma)$, HL is calculated as $\frac{\ln(0.5)}{\ln(\beta_1 + \gamma)}$.

From a practical standpoint, these persistence dynamics carry important implications. For investors and portfolio managers, the relatively short HL of volatility during crises suggests that REITs recover from shocks at a predictable pace, thus offering potential diversification benefits when systemic risk is elevated. Conversely, the longer persistence observed in tranquil periods signals that volatility clustering in conventional equities can accumulate more deeply, which potentially increases medium-term risk exposures. Understanding these distinctions allows for improved volatility forecasting, dynamic hedging strategies, and more informed portfolio rebalancing. For regulators and policymakers, the asymmetric persistence across episodes underscores the need for regime-aware stress testing frameworks and the calibration of countercyclical capital buffers that account for the differing speed at which volatility dissipates under varying market conditions. Overall, the findings reinforce the view that REIT volatility is not uniformly low or stable, but rather episodic and state-dependent. Recognising this behaviour enhances our understanding of the role of REITs in mixed-asset portfolios, particularly for institutional investors such as pension funds and insurance companies who are seeking assets that offer stable income but demonstrate distinct volatility behaviour across market cycles.

5. Conclusion

This study has re-examined the volatility dynamics of U.S. REITs relative to conventional equities across distinct market regimes. Using symmetric and asymmetric GARCH models and separating the sample into the GFC, COVID-19, and tranquil market episodes, the analysis demonstrates that REIT volatility is neither constant nor uniformly lower than that of conventional stocks.

Instead, volatility behaviour is strongly regime-dependent. The findings show that REITs exhibit relatively higher short-term volatility during tranquil periods, whereas conventional equities experience more pronounced volatility escalation during crisis episodes. In addition, volatility persistence and asymmetry vary systematically across market states, thereby indicating that the risk characteristics of REITs evolve with changing economic and financial conditions. These results reinforce the view that REITs occupy a hybrid position between traditional real estate assets and conventional financial securities, and exhibit characteristics of both markets depending on the prevailing conditions. Beyond documenting these dynamics, the findings have several practical implications. For institutional investors, pension funds, insurance companies, and REIT-focused fund managers, the results suggest that strategic asset allocation decisions should account for regime-dependent volatility rather than treating REITs as uniformly defensive assets. During crisis periods, the relatively rapid dissipation of REIT volatility shocks may enhance their usefulness as portfolio diversifiers and tactical allocation instruments. Conversely, the higher persistence observed during tranquil periods implies that risk management models, VaR calculations, and portfolio rebalancing strategies should incorporate the possibility of prolonged volatility clustering even in seemingly stable market environments. The evidence also supports the use of regime-sensitive volatility forecasts when designing hedging strategies that involve listed real estate securities.

From a regulatory perspective, the results suggest that REIT market stability cannot be adequately assessed with static risk measures. Regulatory authorities and market supervisors should incorporate regime-specific volatility characteristics into stress-testing exercises, particularly during periods of financial disruption. The finding that volatility asymmetry changes across market states further implies that positive and negative market developments may have differing implications for REIT market risk. Consequently, liquidity surveillance frameworks, macroprudential monitoring, and sector-specific risk assessments should explicitly account for the state-dependent nature of REIT volatility. Such an approach would enhance the ability of regulators to identify emerging vulnerabilities and support financial stability in real estate capital markets. Overall, the study contributes to the growing literature on REIT risk dynamics by demonstrating that volatility behaviour is episodic, asymmetric, and contingent on market conditions. Recognising these characteristics can improve volatility forecasting, portfolio construction, risk management, and regulatory oversight, thereby fostering more resilient real estate investment and financial systems.

Competing Interests

The authors declare that there are no competing interests related to this work.

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