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VOLATILITY SPILLOVERS AND REIT HEDGING ACROSS SECTORS: EVIDENCE FROM US AND UK MARKETS

Jongseok RIM *

Department of Accounting, Finance and Informatics, Kingston University, London, UK

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Abstract. This study rigorously investigates volatility spillovers between REITs and stock markets in the US and UK, specifically differentiating between market and sector-specific interactions. Utilising a robust multivariate GARCH framework with data from 2000 to 2021, the research meticulously examines how these dynamics shift during periods of market distress, including the Global Financial Crisis and the COVID-19 pandemic. Findings reveal that volatility spillovers are generally weaker at the industry level compared to the broad market level, highlighting enhanced diversification potential when real estate is strategically paired with select equity sectors. Crucially, real estate's hedging effectiveness is highly contingent on the nature of the crisis: it significantly eroded during the GFC, an endogenous property-led shock, but remarkably improved during COVID-19, an exogenous health shock. These insights underscore the critical importance of sector-level risk dynamics and context-specific hedging strategies for real estate portfolio management. For investors, this implies the need for dynamic, sector-tailored allocations and hedge ratios to optimise risk-adjusted returns. For policymakers, the study highlights real estate's dual role in systemic resilience, advocating for refined macroprudential oversight that accounts for both property-led contagion and external-shock stabilisation scenarios. The actionable guidance offered is vital for optimising multi-asset portfolios and enhancing financial stability.

Keywords: Real Estate Investment Trusts (REITs), volatility spillovers, asset allocation, crisis resilience, portfolio risk management.

* Corresponding author. E-mail: *j.rim@kingston.ac.uk*

1. Introduction

Understanding volatility spillovers – the transmission of shocks and uncertainty across diverse asset classes and market segments – is paramount in contemporary financial markets due to their profound implications for portfolio diversification, asset allocation, and the assessment of systemic risk (e.g., Dungey & Martin, 2007; Meng & Chen, 2023; Yang & Zhou, 2017). In today's highly interconnected global financial system, disturbances originating in one market segment possess the capacity for swift propagation, potentially eroding diversification benefits and significantly complicating effective risk management strategies. Consequently, for both investors and policymakers, a comprehensive understanding of the structure and intensity of these spillovers is indispensable for fostering resilience against episodes of systemic instability.

Historically, real estate has been perceived as a stabilising anchor within multi-asset portfolios, offering the distinct advantages of historically low correlations with equities and serving as a potential hedge against inflation and broader macroeconomic shocks (e.g., Hartzell et al., 1987; Hoesli et al., 2008). While Real Estate Investment Trusts (REITs), as a property-related sector, might intuitively be expected to exhibit strong cyclicality and significant co-movement with other cyclical sectors like Financials, Industrials, and Consumer-related industries, reflecting shared business cycle sensitivities and interest rate exposure, their actual behaviour can be more nuanced and, at times, appear counter-intuitive. This complexity arises from factors such as REITs' mandatory dividend payouts, which ensure a stable income flow, and the nature of their leases, which can limit income falls during economic downturns, while also potentially capping growth. For instance, historical evidence from the US during the late 1990s and early 2000s illustrates this: REITs initially underperformed high-growth tech sectors but then acted counter-cyclically during the tech crash of 2000, being viewed as a relatively strong and stable sector. However, the increasing financialisation of property markets, most notably evidenced by the significant expansion of REITs in the US, has undeniably deepened their integration with the broader capital markets (Chiang et al., 2016; Chong et al., 2009; Glascock et al., 2000; Li & Wang, 1995). This heightened

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interconnectedness compels a critical re-evaluation: under modern market conditions, do real estate assets retain the defensive attributes that previously underpinned their integral role in portfolio construction, particularly during periods of financial stress?

While a substantial body of research has explored the linkages between real estate and equities, a notable limitation is the prevalent reliance on market-level indices. This aggregated analytical perspective carries an inherent risk of obscuring critical sector-specific relationships, which are often the true locus of investment decisions, and may consequently misrepresent the actual scope for diversification. Sector-level dynamics are profoundly influenced by heterogeneity in factors such as cyclicality, capital intensity, and sensitivity to interest rates, all of which can generate distinct patterns of volatility transmission. Therefore, a more granular examination is empirically critical to accurately assess real estate's genuine contribution to portfolio stability.

This study systematically addresses these identified research gaps by undertaking a detailed examination of volatility spillovers between REITs and both market-wide indices and major equity sectors within the US and the UK. The analysis spans distinct periods of market conditions, specifically differentiating between relative stability and financial turbulence. The research investigates four core themes to provide nuanced insights: whether spillovers exhibit systematic differences between market-level and sector-level pairings; the extent to which spillover structures vary across national financial architectures; the economic significance of these observed patterns for portfolio diversification and strategic asset allocation; and how these spillovers behave under varying types of market stress, providing a specific comparison between the Global Financial Crisis (GFC) and the COVID-19 pandemic.

The deliberate comparison between the GFC and the COVID-19 crises offers a rare and valuable opportunity. These crises differ fundamentally in their origins and transmission channels: the GFC was an endogenous shock, primarily rooted in property and credit markets, thereby positioning real estate at the very epicentre of systemic instability. In stark contrast, COVID-19 represented an exogenous health shock, influencing property markets indirectly through widespread macroeconomic disruption and extensive policy interventions. This stark contrast permits an assessment of whether real estate's diversification and hedging roles are stable across different crisis types or are instead contingent upon the specific nature of the underlying shock. Such an assessment offers deeper insight into the precise conditions under which real estate most effectively contributes to portfolio resilience.

Utilising a GARCH framework with three complementary specifications, the study yields several material findings. Firstly, volatility spillovers are generally weaker at the sector level than at the market level, indicating that sector-based allocations hold the potential to enhance diversification benefits. Secondly, the study uncovers structural differences in spillover patterns between the US and the UK, likely reflecting variances in their respective financial market architectures. Most crucially, real estate's hedging performance is found to be contingent on the specific crisis type. Its diversification benefits significantly diminish when shocks are endogenous, as exemplified by the GFC, but conversely, these benefits strengthen under exogenous shocks, such as the COVID-19 pandemic, particularly when augmented by supportive policy responses.

These findings reveal that real estate's exposure to equity market volatility is shaped not only by broad macroeconomic shocks but also by specific sectoral linkages, driven by shared underlying factors such as business cycles and credit market conditions. Notably, sectors such as Industrial, Consumer, Retail, and, at times, Financials, exhibit strong co-movements with real estate. This pronounced comovement can diminish real estate's defensiveness within portfolios heavily exposed to these particular industries, necessitating more deliberate allocation and active hedging strategies in such instances.

Ultimately, the crisis-specific dynamics illuminated by this study demonstrate that real estate's portfolio value is not static but is instead highly dependent on the nature of the shock and its specific transmission channels. The observation of weaker and more differentiated spillovers at the sector level challenges the efficacy of traditional market-level models and underscores the tangible benefits of adopting targeted equity exposures. This research thus concludes that real estate serves not as a broad, universal hedge, but rather as a precision instrument for effectively managing sector-specific risks, thereby requiring dynamic allocation strategies that are responsive to evolving market conditions and systemic events.

2. Literature review

The relationship between listed real estate and equities has been a long-standing topic in financial research, evolving from early studies on return comovement to more sophisticated analyses of volatility transmission. Early work provided mixed evidence. Some studies documented meaningful comovement, particularly following structural reforms in the US REIT sector, suggesting increasing equity market integration (Glascock et al., 2000; Li & Wang, 1995). Others argued that REITs remained more closely aligned with direct property than with the broader stock market, emphasising segmentation (Clayton & MacKinnon, 2001; Wilson & Okunev, 1996). Early research also questioned the adequacy of traditional time-domain correlation methods in capturing REIT-equity comovement. Oppenheimer and Grissom (1998) applied cross-spectral analysis to examine frequency-space correlations between REITs and capital market indices, documenting significant co-movement at specific frequencies that conventional regression approaches failed to detect. Their findings highlighted that REIT-stock relationships may vary across cyclical horizons, thereby motivating later work employing more sophisticated dynamic volatility frameworks.

Methodological advances in the early 2000s, particularly the adoption of ARCH and GARCH models, shifted the focus from static correlations to dynamic measures of volatility transmission. Stevenson (2002) reported significant volatility spillovers among US asset classes, while subsequent international studies documented cross-border propagation between US, UK, and Asia-Pacific property markets (Liow et al., 2009; Michayluk et al., 2006). Later research confirmed strong volatility linkages between real estate and equities, and between housing and stock sectors across European markets (Vardar, 2018; Yunus, 2012).

Another strand of literature has examined the diversification benefits of real estate in mixed-asset portfolios. Several studies noted that rising correlations with equities have reduced diversification gains (Chiang et al., 2016; Chong et al., 2009), though time-varying conditional correlation models indicated that real estate can still provide hedging opportunities when strategically paired with other asset classes (Case et al., 2012; Fei et al., 2010). Periods of market stress tend to erode these benefits. Evidence from the GFC showed intensified REIT-equity comovement and diminished hedging capacity (Chen et al., 2015; Liow, 2012; Luchtenberg & Seiler, 2014; Yang et al., 2012). Similar patterns were observed during the European debt crisis, where REIT-equity connectedness increased and diversification potential declined (Abuzayed et al., 2020). This crisis sensitivity has motivated the development of models that can capture regime changes and shifts in spillover intensity over time.

More recent studies have moved beyond describing the presence of spillovers to examining the mechanisms that drive them. Three key channels have emerged in the literature. The first is investor sentiment and risk aversion. Market-based and news-based sentiment measures influence cross-market linkages by altering investor behaviour, including herding and changes in risk appetite. Mensi et al. (2023) show that positive sentiment dampens G7 REIT spillovers in normal times, while negative sentiment significantly amplifies them during market stress. Using a quantile connectedness framework, Hadad et al. (2024a) find that spillovers between REIT returns, stock-market sentiment, and home-purchase sentiment are modest in the middle of the distribution but surge in the tails, with REITs switching from net receivers in normal conditions to net transmitters in extremes, highlighting sentiment-driven tail risk.

The second channel is economic policy uncertainty and broader global risk. Elevated uncertainty alters discount rates and precautionary saving behaviour, producing flight-to-quality dynamics. Fasanya and Oyewole (2023) find that economic policy uncertainty conditions the REIT-oil price nexus, with stronger short-run connectedness during periods of high uncertainty, particularly in oil-exporting countries. Mensi et al. (2023) also report that economic policy uncertainty, geopolitical risk, interest rates, and equity volatility shape REIT connectedness, with uncertainty having the strongest effects during crises.

The third channel is housing sector risk and macro-financial conditions. Alam (2024) constructs a housing risk index based on the volatility of ten housing indicators and shows that it is priced in REIT returns, implying that housing-specific risk transmits to non-residential REITs and commands a risk premium. Wu and Wang (2024) document nonlinear and state-dependent causality from GDP growth and the broad stock market to US REIT returns, while expected inflation remains weak, indicating time-varying sensitivity to macroeconomic and financing conditions. Behavioural indicators also have a role: in the housing market, local Google search activity predicts prices, while global search interest does not, reinforcing the role of local sentiment and attention as drivers of price dynamics (Vasileiou et al., 2024).

Methodological developments that focus on the extremes of return distributions have further deepened understanding of crisis-time dynamics. Tong et al. (2024) show that in twelve major REIT markets, connectedness is high in normal states but markedly stronger in extreme downturns and upturns. During the COVID-19 pandemic, linkages remained elevated and became unstable during the recovery phase, undermining cross-country diversification. In the G7, Mensi et al. (2023) and related time-varying VAR studies identify sharp increases in connectedness during early 2020 as sentiment and uncertainty surged. The combined evidence suggests that both the magnitude and the direction of REIT spillovers are sensitive to market regimes, with behavioural and uncertainty channels central to crisis dynamics.

Despite these advances, there remain important gaps in the literature. Most studies focus on market-level dynamics, leaving sector-level interactions underexplored. Yet portfolio allocation and risk management decisions are frequently made at the industry level, where transmission channels such as sentiment, policy uncertainty, housing risk, and funding costs may operate differently across sectors. In addition, there is limited research that jointly examines these drivers within models capable of tracking volatility transmission across both stable periods and major crises such as the GFC and COVID-19. Addressing these gaps requires a framework that integrates market, sector, and channel-specific perspectives to explain why spillovers strengthen, reverse, or persist across different economic conditions and market regimes.

3. Methodology

The empirical analysis employs a robust econometric framework to examine volatility transmission between real estate and equity sectors and its implications for portfolio performance. This framework integrates a bivariate vector autoregression (VAR) model with three multivariate GARCH variants: Constant Conditional Correlation (CCC), Dynamic Conditional Correlation (DCC), and diagonal BEKK (DBEKK). Each model captures different aspects of volatility dynamics, enabling a comprehensive and robust analysis.

The CCC-GARCH model (Bollerslev, 1990) assumes constant correlations, providing a baseline for understanding static volatility relationships. In contrast, the DCC-GARCH model (Engle, 2002) allows correlations to evolve over time, which is particularly relevant for capturing changes during periods of market turbulence. The diagonal BEKK model (Engle & Kroner, 1995) extends this analysis by directly modelling the conditional covariance structure, while restricting parameter matrices to be diagonal. This restriction preserves the ability to model own-market and cross-market volatility spillovers, but substantially reduces the number of parameters and mitigates estimation issues associated with the full BEKK specification.

The DBEKK model is employed instead of the full BEKK following well documented concerns over the latter's statistical validity. The full BEKK specification has been shown to lack proven stochastic processes, regularity conditions and asymptotic properties, which can bias volatility transmission estimates (Allen & McAleer, 2018; Chang et al., 2019). In contrast, DBEKK imposes diagonal parameter matrices, greatly reducing the number of parameters, ensuring positive definiteness and, crucially, satisfying the regularity conditions needed for consistent and asymptotically normal estimation (Comte & Lieberman, 2003; Jeantheau, 1998). This makes DBEKK a statistically reliable choice for modelling sector level REIT spillovers while retaining the ability to capture own and cross market volatility effects with clearer interpretation.

The rationale for using multiple GARCH specifications lies in their complementary strengths. The CCC model serves as a baseline to gauge whether correlations are, in fact, time-varying. The DCC model captures short-term shifts in market comovement, especially during stress periods when correlations tend to spike. The DBEKK model, by explicitly including cross-terms in the variance–covariance equations, quantifies the magnitude and persistence of volatility spillovers in a statistically reliable way. This combination allows for robust conclusions that do not hinge on the assumptions of a single specification.

All models are estimated within a VAR (1)-GARCH framework. The VAR component captures linear interdependencies between real estate and stock sector returns, while GARCH components model volatility dynamics. A lag length of one in the VAR equations is selected based on information criteria to parsimoniously capture spillovers without overfitting[1]. Although variance equations differ according to model type, each includes terms representing ARCH (short-run shocks) and GARCH (long-run persistence) effects, alongside cross terms indicating volatility spillovers between paired return series.

Comparative analysis across CCC, DCC, and DBEKK specifications enables assessment of robustness. As expected, the DCC model generally provides a better fit (higher log-likelihood values) when correlations are highly time-varying. The DBEKK model produces qualitatively consistent spillover patterns, while offering the advantage of valid statistical inference and reduced parameter estimation bias. Together, these models provide a methodologically rigorous approach for investigating sector-level REIT volatility spillovers and their evolution across different market conditions.

3.1. Volatility spillover effect

The econometric specification for volatility transmission between real estate and industry sectors consists of two components. First, a bivariate vector autoregression (VAR) with one lag is adopted to specify the conditional mean as follows:

$$r_{i,t} = \mu_{i,o} + \sum_{j=1}^{2} \phi_{ij} r_{j,t-1} + \varepsilon_{i,t},$$
$$\varepsilon_{i,t} \left| \mathrm{I}_{i,t-1} \sim N\left(0, h_{i,t}\right), \quad i = 1,2; \right. \tag{1}$$

$$\varepsilon_{i,t} = v_{i,t} h_{i,t}^{1/2}, \; v_{i,t} \sim N\left(0,1\right), \tag{2}$$

where: $r_{i,t}$ is the return for series i; $\varepsilon_{i,t}$ the random error term; $h_{i,t}$ the conditional variance; $I_{i,t-1}$ the market information available at time t–1, and $v_{i,t}$ a sequence of independently and identically distributed (i.i.d) random errors.

Second, the VAR (1)-GARCH approach, with three multivariate GARCH models, is used to investigate the volatility transmission effect between the real estate and industry sectors. For a bivariate case, the VAR (1)-GARCH model can be represented as:

$$h_{ii,t} = c_{ii} + \sum_{j=1}^{2} a_{ij} \varepsilon_{j,t-1}^2 + \sum_{j=1}^{2} b_{ij} h_{jj,t-1}, \qquad i = 1,2, \tag{3}$$

where: h_t are the elements of the conditional variance matrix, and ε_t the vector of the error terms in the conditional mean equations for each series. Eq. (3) can be parameterised as:

$$h_{11,t} = c_{11} + a_{11}\varepsilon_{1,t-1}^2 + a_{12}\varepsilon_{2,t-1}^2 + b_{11}h_{11,t-1} + b_{12}h_{22,t-1}; \tag{4}$$

$$h_{22,t} = c_{22} + a_{21}\varepsilon_{1,t-1}^2 + a_{22}\varepsilon_{2,t-1}^2 + b_{21}h_{11,t-1} + b_{22}h_{22,t-1}, \tag{5}$$

where each ε_{t-1}^2 and h_{t-1} term denotes the lagged error term or unexpected market shocks (ARCH effect) and long-term volatility persistence (GARCH effect) respectively. Given the conditional variances, the CCC model formulates the conditional covariance matrix as:

$$H_t = D_t R D_t \quad D_t = diag\left(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}\right), \tag{6}$$

where: D_t denotes the 2 × 2 diagonal matrix with elements $\sqrt{h_{11,t}}$ and $\sqrt{h_{22,t}}$ in a bivariate case; R is the unconditional correlation matrix of the standardised residuals. Thus, if the element of matrix R is ρ_{ij}(ρ_{ij} = 1 when $i = j$) the conditional covariance can simply be derived as:

$$h_{12,t} = \rho_{12}\sqrt{h_{11,t}h_{22,t}}. \tag{7}$$

[1] Schwarz's Bayesian Criterion (SBC) chooses 0 lags, and Akaike's Information Criterion (AIC) chooses different lags for each variable. This study chooses VAR (1) in the interest of parsimony.

In the DCC model, the correlation matrix is time-varying, and thus the conditional covariance matrix is specified as:

$$H_t = D_t R_t D_t, \quad D_t = diag\left(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}\right); \tag{8}$$

$$R_t = diag(1/\sqrt{q_{11,t}}, 1/\sqrt{q_{22,t}}) Q_t \, diag(1/\sqrt{q_{11,t}}, 1/\sqrt{q_{22,t}}); \tag{9}$$

$$Q_t = \left(1-\theta_1-\theta_2\right)\bar{Q} + \theta_1 u_{t-1} u'_{t-1} + \theta_2 Q_{t-1}, \tag{10}$$

where: Q_t denotes a symmetric positive definite matrix with elements q_{11} and q_{22} in a bivariate case; $\bar{Q}$ is a 2 × 2 unconditional covariance matrix, and u_{t-1} a matrix of model residuals. As shown, Q is not the sequence of covariance matrices but is used mainly to provide the correlation matrix through Eq. (9). The conditional variance-covariance matrix H_t is constructed using variances in Eqs. (4)–(5), and the correlation matrix in Eqs. (9)–(10). Therefore, the conditional covariance in a bivariate case can be obtained as:

$$h_{12,t} = q_{12,t}\sqrt{h_{11,t}h_{22,t}} \,/\, \sqrt{q_{11,t}q_{22,t}}. \tag{11}$$

On the other hand, the DBEKK model produces conditional covariance matrices using direct recursions in both lagged variance-covariance matrices (H_{t-1}) and lagged residuals (ε_{t-1}). In the DBEKK (1,1) specification, the conditional variance-covariance matrix of the residuals, H_t, for the bivariate GARCH model can be written as:

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B, \tag{12}$$

where: C is a 2 × 2 lower triangular matrix of constants for the pair of series, and A and B are diagonal 2 × 2 square parameter matrices. In the DBEKK model, only the own-lagged residuals and own-lagged conditional variances influence each series, thereby simplifying the model structure while retaining essential dynamic features. The diagonal structure of matrices A and B restricts the cross-product terms and reduces the number of parameters, thereby improving estimation efficiency and interpretability. Specifically, the elements of matrix A represent the effects of own shocks, while matrix B captures the volatility persistence from own past conditional variances.

The bivariate representation of model (12) can be expressed as:

$$\begin{aligned} H_t = &\begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}\begin{bmatrix} c_{11} & c_{21} \\ 0 & c_{22} \end{bmatrix} + \\ &\begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix}\begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix}\begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix} + \\ &\begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}\begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{12,t-1} & h_{22,t-1} \end{bmatrix}\begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}. \end{aligned} \tag{13}$$

Hence, conditional variance and covariance of each series can be parameterised as:

$$h_{11,t} = c_{11}^2 + a_{11}^2\varepsilon^2_{1,t-1} + b_{11}^2 h_{11,t-1}; \tag{14}$$

$$h_{22,t} = c_{21}{}^2 + c_{22}{}^2 + a_{22}^2\varepsilon^2_{2,t-1} + b_{22}^2 h_{22,t-1}; \tag{15}$$

$$h_{12,t} = c_{11}c_{21} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{11}b_{22}h_{12,t-1}. \tag{16}$$

Compared to the unrestricted BEKK model, the DBEKK specification excludes cross-product terms involving past residuals and conditional covariances, focusing solely on own-market effects and direct spillovers via the constant matrix C. This parsimonious structure simplifies estimation and reduces the risk of overfitting.

All multivariate GARCH models, including DBEKK, are estimated by the Quasi-Maximum Likelihood Estimation (QMLE) approach and an iteration technique suggested by Engle and Kroner (1995) is used for the nonlinear maximisation in estimating the parameters. The final estimations are then obtained by the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm[2].

3.2. Portfolio implications

3.2.1. Portfolio weights

Assuming mean zero returns and a no-shorting constraint, a variance-minimising portfolio without reducing expected returns can be constructed as follows (Kroner & Ng, 1998).

$$w_{1,t} = \frac{h_{22,t} - h_{12,t}}{h_{11,t} - 2h_{12,t} + h_{22,t}},$$

where: $w_{1,t}$ denotes the weight of asset 1 in a portfolio at time t (*asset* 1= *real estate*, *asset* 2= *stock index*); $h_{11,t}$ and $h_{22,t}$ represent the conditional variance of return for each asset, and $h_{12,t}$ refers to the conditional covariance of returns between the two assets. Therefore, the optimal portfolio weights of real estate are determined as follows, with the optimal holdings of a stock market index/industry sector being $1-w^*_{1,t}$.

$$w^*_{1,t} = \begin{cases} 0 & if\ w_{1,t} < 0 \\ w_{1,t} & if\ 0 \le w_{1,t} \le 1 \\ 1 & if\ w_{1,t} > 1 \end{cases}.$$

3.2.2. Hedge ratios

Following Ederington (1979), the dynamic risk minimising hedge ratio at time t (β_t) can be obtained as:

$$\beta_t = \frac{h_{12,t}}{h_{22,t}}. \tag{17}$$

To illustrate, a long position of one dollar on asset 1 should be hedged by a short position of β dollars on asset 2 in the same market at time t to minimise risk.

3.2.3. Hedging effectiveness

Minimum-variance hedge ratios (β_t) indicate the proportion of one asset required to hedge another but do not capture the economic value of that hedge. To address this limitation, hedging effectiveness is calculated to measure the percentage reduction in portfolio variance achieved

[2] All calculations were conducted using RATS version 10.0.

by including real estate in market- and sector-level portfolios. Hedging effectiveness is widely employed to quantify realised variance reduction from hedging strategies in multi-asset portfolio contexts, across international markets, and under different market conditions (Antonakakis et al., 2020; Hadad et al., 2024b; Mensi et al., 2022). These studies demonstrate that hedging effectiveness not only reveals cross-market and sectoral differences in hedging performance but also supports dynamic portfolio allocation by identifying asset pairings that deliver the most effective risk mitigation under prevailing conditions.

In line with this literature, the analysis of hedging effectiveness aims to provide insights into the practical implications of hedging strategies informed by dynamic volatility spillovers. This approach is intended to assist investors and policymakers in evaluating real estate's risk-reduction potential, to facilitate consistent comparisons between US and UK markets and between market- and sector-level portfolios, and to assess whether there are any changes in the hedging role of real estate under different episodes of market distress, such as the Global Financial Crisis and the COVID-19 pandemic.

The methodology follows the widely adopted procedure of Ederington (1979) and Ku et al. (2007). Hedged portfolios are constructed with two assets (*asset* 1= *real estate*, *asset* 2= *stock index*) and the return for each hedged portfolio is defined as $r_{2,t} - \bar{\beta} r_{1,t}$, where r_1, r_2 is the return on each asset, and $\bar{\beta}$ is the average hedge ratios computed from the conditional variance-covariance estimates for each paired portfolio. The variance of an unhedged portfolio, *VAR* (*U*), and that of a hedged portfolio, *VAR* (*H*), are calculated as:

$$VAR\ (U) = VAR\ (r_2);$$

$$VAR\ (H) = VAR\ (r_{2,t} - \bar{\beta} r_{1,t}).$$

Hedging effectiveness (HE) is then measured by calculating the percentage reduction in the variance as follows, and a higher *HE* ratio indicates greater hedging effectiveness in terms of the portfolio's variance reduction.

$$HE = 1 - \frac{VAR(H)}{VAR(U)}. \quad (18)$$

4. Data

To investigate the relationship between listed real estate and stock markets, this study focuses on REIT-oriented indices in the US and UK, given their substantial market capitalisation and long, continuous performance histories. Numerous empirical studies have demonstrated that REIT indices closely reflect the return and risk characteristics of the direct real estate market, with listed real estate returns often aligning with broader real estate market trends (Pagliari et al., 2005; Hoesli & Oikarinen, 2012, 2016, 2021).

For the US, the FTSE Nareit Equity REIT Index and FTSE Nareit Mortgage REIT Index are utilised to measure real estate investment performance. The FTSE Nareit Equity REIT Index specifically tracks the performance of US REITs and serves as a benchmark for investment products within this sector. As of December 2021, the National Association of Real Estate Investment Trusts (NAREIT) comprised 217 publicly traded REITs, with a total market capitalisation of approximately USD 1,740 billion. Among these, equity and mortgage REITs account for USD 1,344 billion and USD 74 billion, respectively. For the UK market, the FTSE EPRA Nareit UK Index (FTELUK) is used to monitor the performance of listed real estate companies and REITs, with REITs representing over 90% of the index's total market capitalisation. The FTSE EPRA Nareit UK Index (FTELUK) is a widely recognised benchmark for UK REITs, reflecting the performance of the overall real estate sector in the UK.

Equity market performance is represented by broad benchmarks (S&P500 and FTSE100) alongside five major industry sectors in each country. For the US, the selected sectors are Financials, Industrials, Consumer, Energy, and Information Technology (IT). For the UK, the Banking, Industrials, Consumer, Energy (Oil, Gas, and Coal), and Retail sectors are used. The sector selection is motivated by two factors: data availability over the full sample period for both countries, and the inclusion of sectors with varying cyclical characteristics, ranging from interest rate sensitive financials to defensive consumer sectors, to assess heterogeneity in volatility spillovers.

The dataset consists of weekly observations from January 2000 to December 2021 (1,149 observations per series). Weekly frequency is chosen to balance two objectives: capturing sufficient time variation in volatility and correlations without the excessive noise present in daily returns, while retaining enough observations to ensure robust estimation in multivariate GARCH models. All data were obtained from Bloomberg. The return series are then calculated as $100 \times \ln\left(I_t / I_{t-1}\right)$, where I_t represents the weekly closing index.

To examine regime-dependent dynamics, the sample is divided into four subperiods. The pre-GFC period, from January 2000 to December 2006, represents a relatively stable expansionary phase. The GFC period, from January 2007 to December 2009, captures the global property-led financial crisis. The post-GFC period, from January 2010 to December 2019, reflects a prolonged recovery phase under accommodative monetary policy. Finally, the COVID-19 period, from January 2020 to December 2021, corresponds to an exogenous global health shock that triggered severe but short-lived market dislocations.

5. Empirical results and discussion

5.1. The results of descriptive statistics

Table 1 presents selected descriptive statistics for each return series in the US and UK markets. The statistics indicate that the US market experienced higher returns than the UK market across all corresponding industry sectors, while also exhibiting relatively greater volatil-

Table 1. Descriptive statistics of return series

		Mean	Median	Maximum	Minimum	Std. dev.	ADF	PP	JB	ARCH (6)
US	EREIT	0.1173	0.2782	21.6023	–29.8619	3.4475	–17.7262***	–37.2525***	8413.78 ***	398.85***
	MREIT	–0.0744	0.1951	42.5742	–47.4642	3.9105	–13.9299 ***	–38.1234***	134353.70 ***	325.86***
	S&P500	0.1043	0.2406	11.4237	–20.0838	2.5035	–18.4593 ***	–36.6316***	3176.46 ***	167.22***
	Financial	0.0644	0.2331	29.1559	–27.0549	3.8195	–20.8757 ***	–38.0929***	7196.02 ***	254.55***
	Industrial	0.1044	0.2279	14.3512	–20.3104	2.9756	–20.1375 ***	–35.6762***	1800.11 ***	246.96***
	Consumer	0.1493	0.2227	15.7549	–20.1905	2.9724	–14.2528 ***	–35.9000***	1374.09 ***	249.44***
	Energy	0.0566	0.3152	15.2345	–28.8140	3.6195	–20.7469 ***	–33.4964***	3901.63 ***	152.27***
	IT	0.1217	0.3544	14.5828	–24.1969	3.5153	–35.9033 ***	–35.9330***	1046.77 ***	130.04***
UK	FTELUK	0.0595	0.2102	14.3140	–18.7891	2.9918	–34.1328 ***	–34.1725***	2940.12 ***	234.13***
	FTSE100	0.0111	0.1917	12.5845	–23.6317	2.4500	–14.3718 ***	–36.5697***	7847.53 ***	73.77***
	Banking	–0.0838	0.0348	17.1172	–34.5228	3.7917	–12.7718 ***	–35.5515***	5169.41 ***	130.17***
	Industrial	0.0729	0.2719	12.7130	–19.9672	2.6413	–23.0213 ***	–35.0131***	1566.49 ***	182.14***
	Consumer	0.0482	0.2402	23.3275	–20.5370	2.7087	–17.3078 ***	–34.9210***	6664.76 ***	84.14***
	Energy	–0.0111	0.0835	18.7314	–36.5536	3.6235	–22.7032 ***	–33.6118***	6807.68 ***	112.83***
	Retail	0.0382	0.2027	19.3087	–21.5475	3.1872	–34.2480 ***	–34.3680***	1688.23 ***	190.93***

Notes: The table presents the basic statistics of the return series. The dataset is composed of weekly sector returns from 7 January 2000 to 31 December 2021 (1,149 observations). ADF and PP are test statistics for stationarity (H_0: The series has a unit root). The lag length for the ADF test is selected using the Akaike Information Criterion (AIC), while the PP test is conducted with a lag length of 12. JB is the Jarque-Bera test statistic for normality (H_0: The series is normally distributed). ARCH (6) is the Lagrange multiplier test statistic for ARCH effects (Engle, 1982) of lag order six (H_0: The series is mean zero, not serially correlated and has constant variance). The symbol *** denotes rejection of the null hypothesis at the 1% level of significance.

ity. In both markets, the consumer and industrial sectors outperformed other industries, whereas the financial/banking and energy sectors demonstrated comparatively weaker performance.

Across all return series, the mean values are consistently lower than the medians, suggesting negative skewness and highlighting the asymmetric distribution of returns. Beyond the distributional characteristics, additional tests were conducted to examine the time-series properties of the data.

First, the stationarity of each return series was assessed using the augmented Dickey-Fuller (ADF) test (Said & Dickey, 1984) and Phillips-Perron (PP) test (Phillips & Perron, 1988). Both tests examine the null hypothesis that a unit root is present, indicating non-stationarity. In all cases, the null hypothesis was rejected at the 1% significance level, suggesting that the return series exhibit mean stationarity.

Second, the Jarque-Bera (JB) test statistics confirmed that the null hypothesis of normal distribution was rejected at the 1% level across all series. Additionally, the test for autoregressive conditional heteroskedasticity (ARCH) effects was rejected at the 1% significance level for all series, indicating the presence of time-varying volatility. This finding suggests that the return series exhibit conditional heteroskedasticity, a feature more appropriately captured by GARCH-type models. Consequently, the results support the empirical application of GARCH models to analyse volatility transmission dynamics within the return series of real estate and industry sectors, as these models effectively accommodate the intricate and persistent volatility patterns present in the data.

5.2. Volatility spillover between real estate and stock markets

The DCC estimates in Tables 2 to 4 indicate that volatility spillovers are consistently stronger in broad market pairs than in industry specific combinations in both the US and the UK. In the broad market case, the cross shock and cross persistence terms from the equity index to the real estate series are both significant, while the reverse effects are generally weak or absent. This suggests that market wide conditions, encompassing macroeconomic, policy, and sentiment driven influences, serve as the dominant drivers of volatility transmission into real estate.

In the US, volatility transmission into real estate is most pronounced from the Industrial and Consumer sectors, particularly through both cross shock and cross persistence channels. By contrast, the Energy and Financial sectors exhibit relatively weak spillovers: Energy shows some meaningful but limited transmission, while Finance displays a smaller and less consistent effect. The IT sector demonstrates the weakest link overall, with cross terms rarely reaching statistical significance. The pattern for Mortgage REITs in Table 3 is broadly consistent with that for Equity REITs in Table 2, with the notable exception that the Financial sector displays weaker transmission when paired with Mortgage REITs. This is consistent with the extensive use of securitisation in the US, which channels property related risks into capital markets and reduces the direct influence of financial sector volatility on REIT performance.

In the UK, the Industrial and Retail sectors display the most evident volatility spillovers into real estate. An important feature of the UK results is the reverse transmission from real estate into the Banking sector, where the

Table 2. Estimates of the DCC-GARCH model in the US market (EREITs)

	EREIT	S&P500	EREIT	Financial	EREIT	Industrial	EREIT	Consumer	EREIT	Energy	EREIT	IT
Mean model: VAR (1)												
Constant	0.2851***	0.2552***	0.2413***	0.1782**	0.2459***	0.2145***	0.2457***	0.2771***	0.2418***	0.1548*	0.2635***	0.3198***
EREIT (1)	–0.0353	0.0009	–0.0436	–0.0091	–0.0415	–0.0142	–0.0430	–0.0184	–0.0382	0.0107	–0.0404	0.0069
Industry (1)	–0.0319	–0.0754**	–0.0092	–0.0488	0.0190	–0.0450	0.0098	–0.0375	–0.0278	–0.0237	0.0045	–0.0556
Variance equation												
Constant	0.7064***	0.3760***	0.5280***	0.4390**	0.6637***	0.3697***	0.6390***	0.5356***	0.6434***	0.5407***	0.7290***	0.2585***
$\varepsilon^2_{1,\,t-1}$	0.1521**	0.0130	0.1577***	0.0554	0.1501***	0.0431	0.1495**	0.0006	0.1488***	0.0574	0.2078***	0.0188
$\varepsilon^2_{2,\,t-1}$	0.0868*	0.1841***	0.0337	0.1324***	0.0356	0.0819***	0.0370	0.1826***	0.0385**	0.1169***	0.0000	0.0880***
$h_{11,\,t-1}$	0.7870***	–0.0184	0.8140***	–0.0409	0.8106***	–0.0520	0.8075***	0.0004	0.7985***	–0.0733*	0.7241***	–0.0265
$h_{22,\,t-1}$	–0.1021***	0.7740***	–0.0448*	0.8306***	–0.0645***	0.8882***	–0.0608*	0.7567***	–0.0490**	0.8601***	–0.0100	0.8928***
θ_1	0.0344		0.0737***		0.0788***		0.0215*		0.0344		0.0418	
θ_2	0.9347***		0.9081***		0.8863***		0.9666***		0.9406***		0.9243***	
Q (20)r	13.6374	15.7484	13.9412	15.6737	13.5288	25.3572	15.0214	17.0127	13.5660	27.0281	14.2565	14.1088
	[0.8484]	[0.7321]	[0.8335]	[0.7367]	[0.8536]	[0.2271]	[0.7752]	[0.6522]	[0.8518]	[0.1345]	[0.8173]	[0.8249]
Q (20)r^2	17.2002	10.7452	18.2926	7.2506	17.0439	9.9901	16.8553	19.3506	15.6072	15.9723	19.8780	19.2344
	[0.6399]	[0.9526]	[0.5681]	[0.9958]	[0.6501]	[0.9684]	[0.6624]	[0.4992]	[0.7407]	[0.7183]	[0.4656]	[0.5066]
Log Likelihood	–4885.19		–5284.51		–5139.95		–5114.39		–5523.19		–5400.08	
H_Q (12)	34.43 [0.9296]		32.49 [0.9577]		44.13 [0.6320]		40.80 [0.7598]		35.57 [0.9081]		35.82 [0.9028]	

Notes: This table shows the results of parameterisation for Equations (4) and (5) using the DCC-GARCH model in the US market. ε_1 and ε_2 denotes the lagged residuals for EREITs and the stock return series respectively, and h_{11}, h_{22} denotes the conditional variance of EREITs and the stock return series respectively. To illustrate, the short-term shock and volatility transmissions between EREITs and S&P500 are parameterised as $h_{11,t} = 0.7064 + 0.1521\varepsilon^2_{1,t-1} + 0.0868\varepsilon^2_{2,\,t-1} + 0.7870h_{11,t-1} - 0.1021h_{22,t-1}$, $h_{22,t} = 0.3760 + 0.0130\varepsilon^2_{1,t-1} + 0.1841\varepsilon^2_{2,t-1} - 0.0184h_{11,t-1} + 0.7740h_{22,t-1}$. For the former equation, the coefficient for $\varepsilon^2_{1,t-1}$, $h_{11,t-1}$ represents the effect of the short-term shock and volatility persistence on the time-varying variance of EREIT respectively, and the coefficient for $\varepsilon^2_{2,t-1}$, $h_{22,t-1}$ represents the short-term shock and volatility transmissions of the overall stock market (S&P500) on EREITs respectively. For the latter equation, the coefficient for $\varepsilon^2_{2,t-1}$, $h_{22,t-1}$ represents the effect of the short-term shock and volatility persistence on the time-varying variance of the stock market (S&P500) respectively, and the coefficient for $\varepsilon^2_{1,t-1}$, $h_{11,t-1}$ represents the short-term shock and volatility transmissions of EREITs on the overall stock market (S&P500) respectively. Q (20)r and Q (20) r^2 are the Ljung-Box Q statistics for standardised and standardised squared residuals, respectively, for up to 20 lags. H_Q (12) is the Q statistic for jointly standardised residuals (Hosking, 1981) for up to 12 lags. The symbols *, ** and *** denote significance at 10%, 5% and 1% levels respectively, and the p-values of the diagnostic tests are given in brackets.

Table 3. Estimates of the DCC-GARCH model in the US market (MREITs)

	MREIT	S&P500	MREIT	Financial	MREIT	Industrial	MREIT	Consumer	MREIT	Energy	MREIT	IT
Mean model: VAR (1)												
Constant	0.0450	0.2790***	0.0447	0.2607***	0.0208	0.2472***	0.0205	0.2770***	0.0420	0.1641*	0.0229	0.3285***
MREIT (1)	–0.0587	–0.0346	–0.0668	–0.0552	–0.0765	–0.0618*	–0.0509	–0.0736**	–0.0869*	–0.0215	–0.0547	–0.0243
Industry (1)	–0.0082	–0.0516	0.0110	–0.0485	0.0137	–0.0223	–0.0132	–0.0095	0.0188	–0.0090	–0.0190	–0.0447
Variance equation												
Constant	0.4694***	0.2715***	0.5676	0.3442	0.4912**	0.2438	0.4550**	0.4095***	0.6415***	0.4291***	0.4098**	0.2363***
$\varepsilon^2_{1,\,t-1}$	0.2269***	0.0141	0.2378***	0.0435	0.2401***	0.0129	0.2448***	0.0257	0.2499***	0.0539	0.2564***	0.0097
$\varepsilon^2_{2,\,t-1}$	0.1532***	0.2074***	0.0491	0.1107*	0.0429*	0.0964**	0.0642**	0.1736***	0.0477	0.1095***	0.0416*	0.1158***
$h_{11,\,t-1}$	0.7529***	–0.0068	0.7048***	–0.0399	0.7436***	–0.0109	0.7473***	–0.0097	0.7339***	–0.0451	0.7303***	–0.0064
$h_{22,\,t-1}$	–0.1180**	0.7546***	–0.0146	0.8615***	–0.0331	0.8752***	–0.0537	0.7654***	–0.0543*	0.8586***	–0.0291***	0.8610***
θ_1	0.0187*		0.0206*		0.0262**		0.0201		0.0171**		0.0168	
θ_2	0.9725***		0.9721***		0.9667***		0.9519***		0.9807***		0.9786***	
Q (20)r	16.4287	22.8800	11.3424	17.3803	13.7271	24.7825	9.9933	17.7310	14.3377	36.1949	10.0338	13.7981
	[0.6897]	[0.2947]	[0.9369]	[0.6282]	[0.8441]	[0.2099]	[0.9683]	[0.6051]	[0.8130]	[0.0146]	[0.9676]	[0.8406]
Q (20)r^2	17.5725	53.4914	13.4670	21.1851	12.8987	18.9002	13.4954	35.1616	13.0560	91.1777	11.9522	28.3367
	[0.6156]	[0.0001]	[0.8565]	[0.3863]	[0.8817]	[0.5283]	[0.8551]	[0.0193]	[0.8750]	[0.0000]	[0.9177]	[0.1017]
Log Likelihood	–5031.02		–5411.96		–5279.66		–5251.39		–5603.90		–5505.27	
H_Q (12)	41.66 [0.7290]		34.41 [0.9288]		39.57 [0.8015]		33.62 [0.9425]		43.94 [0.6399]		48.40 [0.4566]	

Notes: This table shows the results of parameterisation for Eqs. (4)–(5) using the DCC-GARCH model in the US market. ε_1 and ε_2 denotes the lagged residuals for MREITs and the stock return series respectively, and h_{11}, h_{22} denotes the conditional variance of each return series. For the illustration of parameterisation, see the notes in Table 2. Q (20)r and Q (20) r^2 are the Ljung-Box Q statistics for standardised and standardised squared residuals, respectively, for up to 20 lags. H_Q (12) is the Q statistic for jointly standardised residuals (Hosking, 1981) for up to 12 lags. The symbols *, ** and *** denote significance at 10%, 5% and 1% levels respectively, and the p-values of the diagnostic tests are given in brackets.

Table 4. Estimates of the DCC-GARCH model in the UK market

	Real Estate	FTSE100	Real Estate	Banking	Real Estate	Industrial	Real Estate	Consumer	Real Estate	Energy	Real Estate	Retail
Mean model: VAR (1)												
Constant	0.2927***	0.1400**	0.2670***	0.0569	0.2498***	0.2440***	0.2482***	0.1604***	0.2466***	0.0863	0.2343***	0.1543**
Real Estate (1)	0.0286	–0.0055	0.0054	0.0142	0.0079	–0.0512	0.0028	0.0003	0.0353	–0.0044	–0.0163	–0.0112
Industry (1)	–0.0071	–0.0163	0.0252	–0.0332	0.0122	–0.0041	0.0315	–0.0153	–0.0202	0.0477	0.0623**	0.0056
Variance equation												
Constant	0.3402***	0.2879**	0.2137***	0.1913**	0.4595***	0.4343***	0.2549***	0.2085**	0.3493***	0.6656***	0.3997***	0.4090**
$\varepsilon^2_{1,\,t-1}$	0.0955***	0.0204	0.1041***	0.0739**	0.1030***	0.0309*	0.1055***	0.0339	0.1051***	0.0364	0.0927***	0.0470*
$\varepsilon^2_{2,\,t-1}$	0.1057***	0.1599***	0.0321**	0.1023***	0.0722**	0.1248***	0.0338	0.1080***	0.0412**	0.1758***	0.0552***	0.0963***
$h_{11,\,t-1}$	0.9088***	0.0139	0.8798***	–0.0669*	0.8706***	–0.0292**	0.8736***	–0.0290	0.8747***	–0.0225	0.8728***	–0.0581*
$h_{22,\,t-1}$	–0.1546***	0.7603***	–0.0307**	0.8914***	–0.1052**	0.8136***	–0.0404**	0.8672***	–0.0524***	0.7739***	–0.0683**	0.8709***
Θ_1	0.0222		0.0241*		0.0487***		0.0383**		0.0282*		0.0378**	
Θ_2	0.9581***		0.9657***		0.8367***		0.9246***		0.9523***		0.8750***	
Q (20)r	16.7199	29.8031	18.0420	18.4962	17.0028	19.6521	17.4077	13.8352	16.3607	33.5053	15.9136	12.4604
	[0.6711]	[0.0731]	[0.5846]	[0.5548]	[0.6528]	[0.4799]	[0.6264]	[0.8388]	[0.6940]	[0.0297]	[0.7220]	[0.8993]
Q (20)r^2	14.7070	13.2598	12.6805	8.9755	11.1904	22.8554	13.4667	15.0508	12.1204	18.1382	10.9942	44.3828
	[0.7929]	[0.8660]	[0.8907]	[0.9832]	[0.9411]	[0.2960]	[0.8565]	[0.7735]	[0.9119]	[0.5783]	[0.9464]	[0.0013]
Log Likelihood	–4833.53		–5314.49		–4974.44		–4940.62		–5471.56		–5206.84	
H_Q (12)	44.98 [0.5973]		44.63 [0.6119]		39.51 [0.8035]		38.97 [0.8204]		41.40 [0.7384]		37.15 [0.8717]	

Notes: This table shows the results of parameterisation for Eqs. (4)–(5) using the DCC-GARCH model in the UK market. ε_1 and ε_2 denotes the lagged residuals for the securitised real estate and stock return series respectively, and h_{11}, h_{22} denotes the conditional variance of each return series. For the illustration of parameterisation, see the notes in Table 2. Q (20)r and Q (20) r^2 are the Ljung-Box Q statistics for standardised and standardised squared residuals, respectively, for up to 20 lags. *H_Q* (12) is the Q statistic for jointly standardised residuals (Hosking, 1981) for up to 12 lags. The symbols *, ** and *** denote significance at 10%, 5% and 1% levels respectively, and the *p*-values of the diagnostic tests are given in brackets.

banking variance equation places substantial weight on real estate cross terms. This suggests that property market shocks can transmit meaningfully into the banking sector in the UK, consistent with a system where securitisation is less prevalent and banks hold greater direct exposure to property related lending and collateral values.

Regarding empirical model specifications, the coefficients on θ_1 and θ_2 are statistically significant at the 1% level, and $\theta_1+\theta_2<1$, (with $\theta_1+\theta_2\approx 1$) hold consistently. This parameter structure reflects mean-reverting dynamic conditional correlations, indicating persistent relationships between paired returns (Engle, 2002). Diagnostic tests for standardised and squared residuals, both univariate and multivariate, confirm the absence of serial correlation at the 1% significance level. These diagnostics affirm the robustness and appropriate specification of all pairwise DCC-GARCH models used in this analysis.

From an economic standpoint, these findings indicate that the exposure of real estate to equity market volatility is shaped not only by broad macroeconomic shocks but also by sector specific linkages that reflect common demand and financing conditions. These results further underscore the complex and context-dependent behaviour of real estate in multi-asset portfolios, aligning with the nuanced expectations outlined in the Introduction. Industries such as Industrial, Consumer, Retail, and in some contexts Financial services, share underlying drivers with real estate, including sensitivity to the business cycle, credit market conditions, and investment activity. Volatility originating in these sectors therefore propagates into real estate with relatively little attenuation, limiting its ability to provide defensive characteristics in portfolios where such sectors are heavily represented. In these circumstances, portfolio construction requires a more deliberate allocation and active hedging strategy to offset the higher comovement in returns.

The weaker spillovers from sectors such as IT – and, to a lesser extent, Energy – indicate a greater degree of independence in risk drivers, suggesting stronger potential for diversification when these sectors are combined with real estate. The structural differences between the US and the UK also have strategic implications. In the US, securitisation dampens direct real estate to bank linkages, while in the UK, the banking system remains more directly tied to property cycles. These structural and sectoral patterns influence the potential role of real estate within mixed asset portfolios and provide the basis for the allocation and hedging analysis in the next section.

5.3. Portfolio considerations

Figures 1–2 illustrate the time-varying conditional correlations between real estate and stock markets in the US and UK, respectively. These figures reveal varying correlation strengths across industry sectors, highlighting the appropriateness of the time-varying covariance approach for estimating optimal portfolio weights and hedge ratios, as it accurately reflects changing asset correlations and volatilities over time.

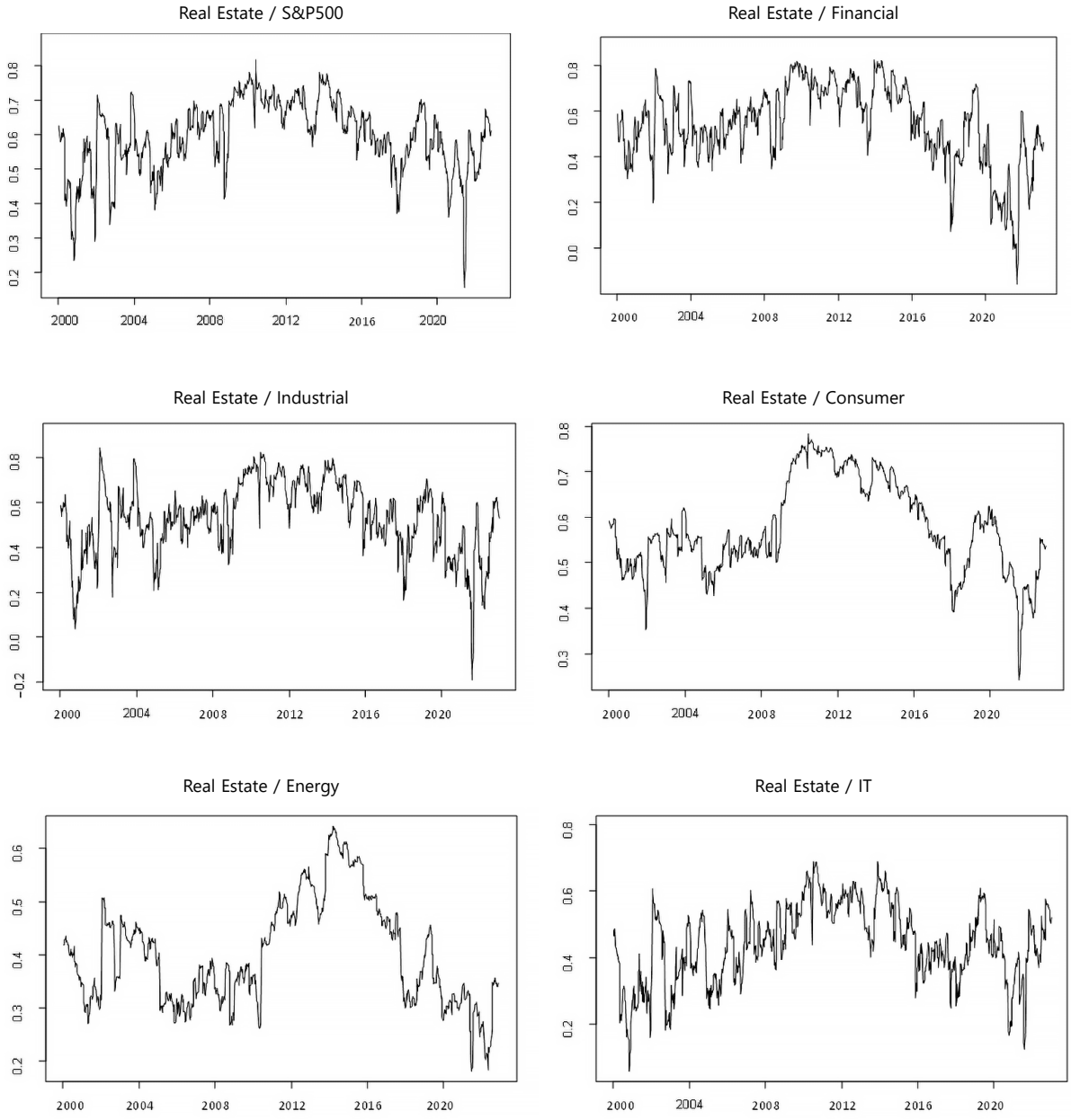


Figure 1. Time-varying conditional correlations from the DCC-GARCH model (US)

The portfolio implications of the observed volatility spillovers have been examined using the three GARCH specifications outlined earlier. As shown in Table 5, the results differ slightly across models due to variation in the estimation of dynamic variance covariance matrices. The discussion here draws on the DCC estimates, given their ability to capture time varying correlations in a parsimonious structure that is well suited to interpreting both market and sector level relationships.

In the broad market setting, the optimal allocation to real estate is moderate, and the hedge ratio is of similar magnitude. This outcome reflects the strong correlation and persistence in risk between real estate and the market index, which limits the scope for diversification but still allows for measurable reductions in portfolio variance. The persistence of correlations in this pairing means that risk reduction is possible, but it comes at the cost of constraining the proportion of real estate in the optimal mix.

At the sector level, the relationship between volatility spillovers and portfolio parameters is more nuanced. Sectors such as Industrial, Consumer, and Retail, where volatility transmission into real estate is relatively strong, are associated with smaller optimal real estate weights compared to sectors like Financials, Banking, Energy, and IT, where spillovers are weaker. However, the higher-spillover sectors exhibit larger hedge ratios, reflecting the need for

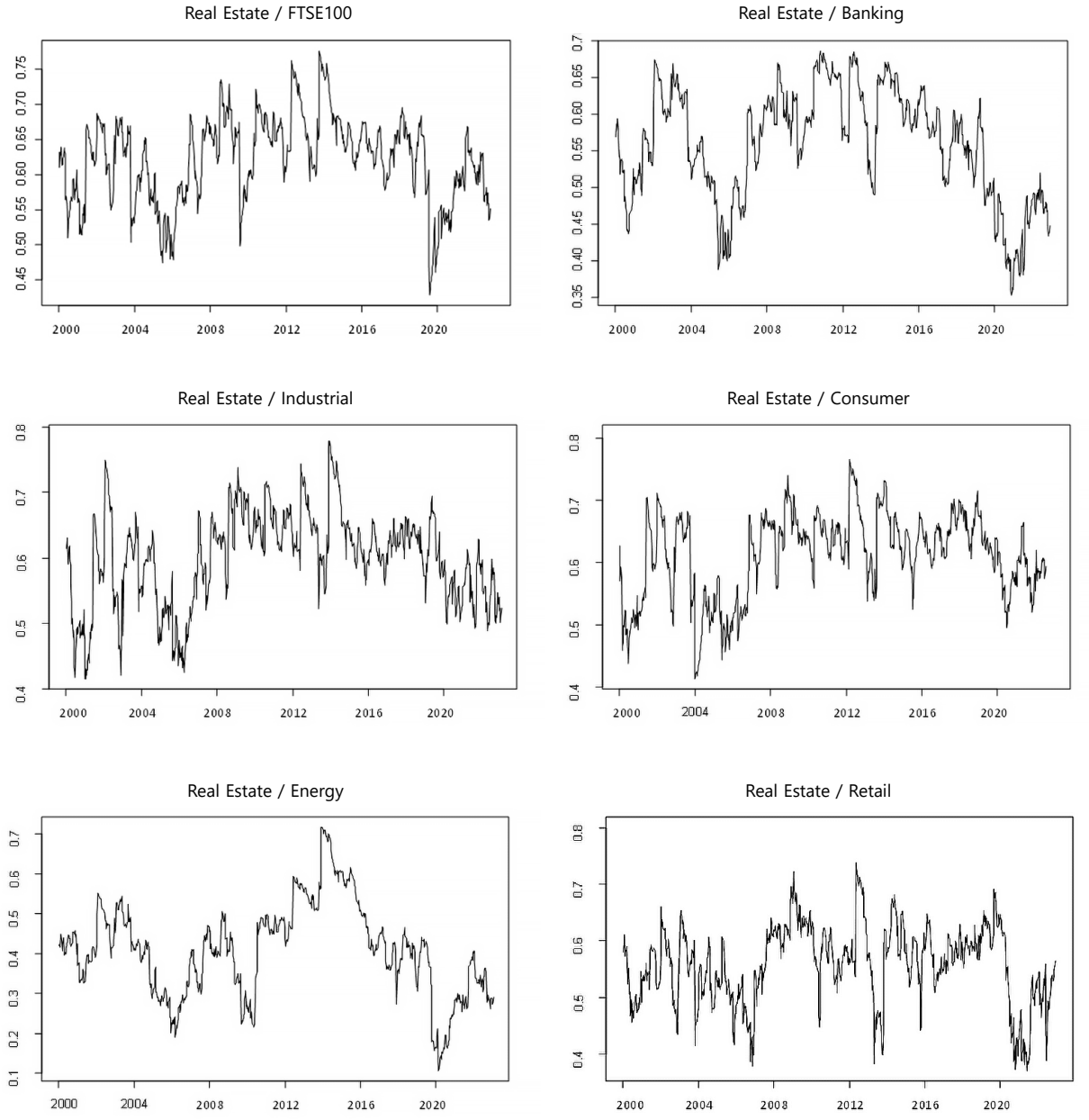


Figure 2. Time-varying conditional correlations from the DCC-GARCH model (UK)

greater offsetting positions due to stronger comovement. These smaller allocations to real estate suggest that while diversification benefits exist, they are limited by higher correlation costs, which constrain the ability to increase real estate's share in the portfolio.

In contrast, sectors such as Energy and IT, where spillovers are weaker, show comparatively larger optimal allocations to real estate but lower hedge ratios. While these combinations allow for greater inclusion of real estate without significantly increasing portfolio correlation, the capacity for variance reduction is limited. The hedging effectiveness measures presented in Table 6 confirm this, showing that these weaker spillover pairings deliver the smallest reductions in variance despite their higher allocations.

Overall, the results point to a trade-off between correlation management and variance reduction. Combinations involving stronger spillover sectors may require smaller real estate weights but can deliver greater relative gains in risk control through higher hedge ratios. Conversely, combinations with weaker spillover sectors may accommodate more real estate but achieve only modest hedging benefits. Recognising and managing this trade-off is central to effective portfolio construction, particularly in settings where spillover patterns evolve with market conditions.

Table 5. Optimal portfolio weights and hedge ratios

Portfolio (a = Real Estate, b = Stock Indices)	US			UK		
	DCC	CCC	DBEKK	DCC	CCC	DBEKK
Real Estate / S&P500 (FTSE100)						
Portfolio weight (a)	0.26	0.30	0.29	0.34	0.36	0.34
Hedge ratio (b/a)	0.55	0.54	0.46	0.59	0.57	0.53
Real Estate / Financial (Banks)						
Portfolio weight (a)	0.62	0.61	0.61	0.73	0.71	0.70
Hedge ratio (b/a)	0.71	0.67	0.61	0.78	0.73	0.67
Real Estate / Industrial						
Portfolio weight (a)	0.45	0.48	0.47	0.45	0.47	0.44
Hedge ratio (b/a)	0.63	0.61	0.53	0.63	0.60	0.55
Real Estate / Consumer						
Portfolio weight (a)	0.43	0.47	0.45	0.43	0.46	0.42
Hedge ratio (b/a)	0.64	0.84	0.53	0.62	0.63	0.59
Real Estate / Energy						
Portfolio weight (a)	0.66	0.65	0.64	0.70	0.69	0.68
Hedge ratio (b/a)	0.59	0.54	0.47	0.57	0.56	0.49
Real Estate / IT (Retail)						
Portfolio weight (a)	0.54	0.56	0.54	0.63	0.62	0.60
Hedge ratio (b/a)	0.53	0.63	0.47	0.68	0.65	0.60

Notes: The table presents the average optimal weight of real estate and hedge ratios/hedging effectiveness for the respective real estate-industry sector portfolios in the US and UK market using conditional variances and covariances estimated from bivariate GARCH models (DCC, CCC, DBEKK). Hedge ratio (b/a) indicates that a long position of one dollar (pound) on a paired industry sector should be hedged by a short position of hedge ratio (b/a) × one dollar (pound) on real estate.

Table 6. Hedging effectiveness

Portfolio		US		UK	
		Variance	Hedging Effectiveness	Variance	Hedging Effectiveness
S&P 500 (FTSE 100)		6.2618		5.9974	
Real Estate /	DCC	3.3758	46.09	3.3798	43.65
S&P 500 (FTSE 100)	CCC	3.3642	46.27	3.3666	43.87
	DBEKK	3.3565	46.40	3.3616	43.95
Financial (Banking)		14.5755		14.3648	
Real Estate /	DCC	7.4510	48.88	8.4172	41.40
Financial (Banking)	CCC	7.5342	48.31	8.4720	41.02
	DBEKK	7.7301	46.97	8.5968	40.15
Industrial		8.8465		6.9704	
Real Estate / Industrial	DCC	4.8174	45.54	4.1093	41.05
	CCC	4.8005	45.74	4.0845	41.40
	DBEKK	4.8276	45.43	4.0791	41.48
Consumer		8.8274		7.3304	
Real Estate / Consumer	DCC	4.9727	43.67	4.3150	41.14
	CCC	5.7631	34.71	4.3227	41.03
	DBEKK	4.9429	44.00	4.3026	41.31
Energy		13.0892		13.1182	
Real Estate / Energy	DCC	9.9933	23.65	10.6218	19.03
	CCC	9.9351	24.10	10.6155	19.08
	DBEKK	9.9533	23.96	10.6216	19.03
IT (Retail)		12.3464		10.1493	
Real Estate / IT (Retail)	DCC	9.8404	20.30	6.5349	35.61
	CCC	10.1157	18.07	6.5199	35.76
	DBEKK	9.7893	20.71	6.5308	35.65

Notes: The table presents the hedging effectiveness computed using Eq. (18). The variances of hedged and unhedged portfolios have been calculated using the realised returns over the period of 2000 to 2021, and hedged portfolios have been constructed using the average hedge ratios in Table 5.

5.4. Comparing crisis periods: GFC vs COVID-19

Given the evidence of volatility spillovers in normal market conditions, it is important to assess whether these relationships change during periods of systemic stress and how such changes affect portfolio allocation and hedging strategies. The analysis focuses on two distinct crises, the GFC and the COVID-19 pandemic, which differ in their origins and channels of transmission, allowing comparison between a financial system crisis rooted in real estate market disruptions and a broader economic contraction.

A clear contrast emerges in the volatility spillover dynamics involving real estate during the GFC and the COVID-19 pandemic. Volatility transmission between real estate and other equity sectors intensified significantly during the GFC. As a property centred financial crisis driven by the collapse of the subprime mortgage market, the GFC saw REITs experience severe volatility and heightened comovement with financial stocks. Tables 7–8 show a notable increase in cross volatility terms involving real estate, reflecting its deep integration into the crisis and the simultaneous collapse across REITs and broader equity markets.

By contrast, the COVID-19 crisis produced more moderate volatility spillovers. Although the pandemic initially triggered a widespread sell off, the shock originated externally, linked to a global health emergency rather than structural weaknesses in property or credit markets. Cross volatility terms involving real estate were lower during COVID-19 than during the GFC, indicating less intense risk transmission between real estate and equity markets.

These differences have important implications for portfolio construction and hedging. During the GFC, real estate's ability to reduce risk in mixed asset portfolios deteriorated markedly. Optimal allocations to real estate fell sharply, as seen in Table 9, reflecting reduced diversification benefits. Hedge ratios rose, yet actual hedging effectiveness was unclear due to the minimal weight of real estate in portfolios, illustrating the economic reality that when real estate becomes fully integrated into a broader financial shock, its role as a diversifier is eroded, leaving portfolios more vulnerable to correlated losses.

Conversely, during COVID-19, real estate's role within portfolios strengthened. Optimal allocations to REITs increased, and hedging effectiveness often exceeded pre pandemic levels. Table 9 shows significantly higher recommended REIT weights during the pandemic compared with the GFC, while hedge ratios reflected more stable relationships with equities. This improvement is consistent with a shock that did not originate in property or credit markets and with the rapid and large scale policy responses including low interest rates, quantitative easing, fiscal stimulus, and tenant protection measures, which helped stabilise property cash flows and valuations. From a portfolio management perspective, this suggests that ex-

Table 7. Estimates of the DBEKK-GARCH model in the US market (During the GFC and the COVID-19 pandemic)

	EREIT	S&P500	EREIT	Financial	EREIT	Industrial	EREIT	Consumer	EREIT	Energy	EREIT	IT
Variance equation: *GFC*												
Constant	6.6827***	4.2986	1.6335**	0.8879	6.5193***	7.3788	7.0554***	7.2657	4.0554***	7.1990**	5.1230***	6.7803
$\varepsilon^2_{1,\,t-1}$ / $\varepsilon^2_{2,\,t-1}$	0.2132***	0.6374***	0.1154	0.2758***	0.2442***	0.3819***	0.2223***	0.5724***	0.1896***	0.6628***	0.2540***	0.5261***
$h_{11,\,t-1}$ / $h_{22,\,t-1}$	0.5373***	0.0850**	0.8257***	0.7546***	0.5504***	0.1053***	0.5064***	0.0697***	0.6716***	0.0801*	0.5845***	0.0737*
Covariance												
Constant	5.3597***		1.1038***		6.9358***		7.1598***		3.8963**		5.8937***	
$\varepsilon_{1,\,t-1}\,\varepsilon_{2,\,t-1}$	0.3686***		0.1784		0.3054***		0.3567***		0.3545***		0.3656***	
$h_{12,\,t-1}$	0.2137**		0.7894***		0.2407***		0.1879***		0.2319*		0.2075*	
Log Likelihood	–794.62		–883.29		–823.01		–822.38		–884.83		–834.89	
H_Q (12)	47.69 [0.4852]		47.93 [0.4758]		67.68 [0.0320]		62.07 [0.0834]		45.26 [0.5876]		50.63 [0.3700]	
Variance equation: *COVID*												
Constant	0.3196***	0.1378	0.3901	0.0765	0.4020*	0.1737	0.4115	0.3964	0.2883*	0.0210	1.7665**	5.1587
$\varepsilon^2_{1,\,t-1}$ / $\varepsilon^2_{2,\,t-1}$	0.1467***	0.0545**	0.1292*	0.0588*	0.1584***	0.0676***	0.1534*	0.0333	0.1423**	0.0206***	0.2680***	0.4461***
$h_{11,\,t-1}$ / $h_{22,\,t-1}$	0.8016***	0.9017***	0.8102***	0.9155***	0.7836***	0.8923***	0.7916***	0.9195***	0.8127***	0.9643***	0.6158***	0.1126 *
Covariance												
Constant	0.1816**		0.0976		0.2087		0.2731		0.0777		2.9301**	
$\varepsilon_{1,\,t-1}\,\varepsilon_{2,\,t-1}$	0.0894**		0.0871*		0.1035***		0.0714		0.0541**		0.3458***	
$h_{12,\,t-1}$	0.8502***		0.8612***		0.8362***		0.8531***		0.8853***		0.2633*	
Log Likelihood	–465.67		–513.97		–489.52		–520.50		–580.72		–507.23	
H_Q (12)	29.68 [0.9825]		33.10 [0.9499]		25.96 [0.9961]		36.81 [0.8801]		38.45 [0.8361]		31.25 [0.9707]	

Notes: This table shows the results of parameterisation for Eqs. (14)–(15) using the DBEKK-GARCH model for the US market during the GFC and the COVID-19 pandemic. ε_1 and ε_2 denote the lagged residuals for REITs and the stock return series, respectively, and h_{11} and h_{22} denote the conditional variances of each return series, while h_{12} denotes the covariance between REITs and the stock return series. H_Q (12) is the Q statistic for jointly standardised residuals (Hosking, 1981) for up to 12 lags. The symbols *, ** and *** denote significance at 10%, 5% and 1% levels respectively, and the p-values of the diagnostic tests are given in brackets.

Table 8. Estimates of the DBEKK-GARCH model in the UK market (During the GFC and the COVID-19 pandemic)

	Real Estate	FTSE100	Real Estate	Banking	Real Estate	Industrial	Real Estate	Consumer	Real Estate	Energy	Real Estate	Retail
Variance equation: *GFC*												
Constant	1.9263***	1.9377	1.0560***	1.1766	1.8772***	3.0162	1.1942***	0.6298**	1.3675*	2.9924*	1.1015***	0.7745
$\varepsilon^2_{1,\,t-1}$ / $\varepsilon^2_{2,\,t-1}$	0.0822***	0.4412***	0.0920***	0.1324***	0.0781***	0.1746**	0.1185***	0.1282***	0.0743***	0.3781***	0.0904***	0.1945
$h_{11,\,t-1}$ / $h_{22,\,t-1}$	0.8530***	0.5266***	0.8729***	0.8470***	0.8521***	0.5661***	0.8534***	0.8303***	0.8753***	0.4955***	0.8744***	0.8098***
Covariance												
Constant	1.9320***		0.5893		2.3614		0.6305**		1.5445*		0.7182	
$\varepsilon_{1,\,t-1}\,\varepsilon_{2,\,t-1}$	0.1904***		0.1104***		0.1168**		0.1233***		0.1676***		0.1326	
$h_{12,\,t-1}$	0.6703***		0.8598***		0.6945***		0.8418***		0.6586***		0.8415***	
Log Likelihood	–824.98		–901.19		–808.39		–820.27		–872.15		–882.09	
H_Q (12)	41.30 [0.7418]		51.37 [0.3428]		39.25 [0.8118]		30.96 [0.9732]		43.67 [0.6505]		36.17 [0.8949]	
Variance equation: *COVID*												
Constant	0.1408**	0.0160	0.1830	0.0560	0.2075**	0.1929	0.6106**	2.8104	0.1519*	0.0001	0.2577	0.1789
$\varepsilon^2_{1,\,t-1}$ / $\varepsilon^2_{2,\,t-1}$	0.0805***	0.0159*	0.1611**	0.0636***	0.1458**	0.0949	0.2355***	0.2318	0.1145*	0.0116*	0.1127	0.0360
$h_{11,\,t-1}$ / $h_{22,\,t-1}$	0.8642***	0.9563***	0.8059***	0.9185***	0.8141***	0.8694***	0.7066***	0.5423**	0.8411***	0.9704***	0.8237***	0.9268***
Covariance												
Constant	0.0474		0.0385		0.0789		1.1037		0.0037		0.1294	
$\varepsilon_{1,\,t-1}\,\varepsilon_{2,\,t-1}$	0.0358*		0.1012**		0.1176		0.2337		0.0364*		0.0637	
$h_{12,\,t-1}$	0.9091***		0.8604***		0.8413***		0.6190**		0.9034***		0.8737***	
Log Likelihood	–466.62		–525.26		–485.39		–480.09		–569.25		–497.93	
H_Q (12)	51.92 [0.3236]		39.59 [0.8007]		58.19 [0.1488]		38.44 [0.8362]		38.45 [0.8359]		44.95 [0.5982]	

Notes: This table shows the results of parameterisation for Eqs. (14)–(15) using the DBEKK-GARCH model for the UK market during the GFC and the COVID-19 pandemic. ε_1 and ε_2 denote the lagged residuals for REITs and the stock return series, respectively, and h_{11} and h_{22} denote the conditional variances of each return series, while h_{12} denotes the covariance between REITs and the stock return series. *H_Q* (12) is the Q statistic for jointly standardised residuals (Hosking, 1981) for up to 12 lags. The symbols *, ** and *** denote significance at 10%, 5% and 1% levels respectively, and the *p*-values of the diagnostic tests are given in brackets.

Table 9. Portfolio implications under different market conditions

Portfolio (a = Real Estate, b = Stock Indices)	US				UK			
	Pre GFC	Post GFC	GFC	COVID	Pre GFC	Post GFC	GFC	COVID
Real Estate / S&P500 (FTSE100)								
Portfolio weight (a)	0.49	0.23	0.05	0.20	0.45	0.36	0.11	0.36
Hedge ratio (b/a)	0.46	0.48	0.46	0.56	0.50	0.60	0.45	0.50
Hedging effectiveness (%)	20.40	55.07	59.34	73.55	32.48	49.25	48.25	54.47
Real Estate / Financial (Banking)								
Portfolio weight (a)	0.61	0.59	0.60	0.57	0.64	0.76	0.64	0.78
Hedge ratio (b/a)	0.53	0.55	0.88	0.61	0.61	0.69	0.75	0.72
Hedging effectiveness (%)	19.62	46.36	62.89	71.14	26.01	34.28	54.43	38.56
Real Estate / Industrial								
Portfolio weight (a)	0.61	0.46	0.05	0.44	0.64	0.44	0.04	0.59
Hedge ratio (b/a)	0.57	0.53	0.52	0.66	0.55	0.58	0.48	0.61
Hedging effectiveness (%)	18.46	50.68	64.87	77.17	27.45	47.74	51.27	57.55
Real Estate / Consumer								
Portfolio weight (a)	0.66	0.41	0.13	0.53	0.65	0.37	0.09	0.66
Hedge ratio (b/a)	0.52	0.50	0.59	0.57	0.56	0.61	0.47	0.86
Hedging effectiveness (%)	19.93	44.10	67.31	51.26	23.86	55.55	46.39	70.34
Real Estate / Energy								
Portfolio weight (a)	0.76	0.66	0.29	0.78	0.75	0.75	0.28	0.81
Hedge ratio (b/a)	0.44	0.52	0.34	0.58	0.46	0.58	0.33	0.44
Hedging effectiveness (%)	9.19	31.44	24.95	40.59	16.54	21.43	21.82	21.32

End of Table 9

Portfolio (a = Real Estate, b = Stock Indices)	US				UK			
	Pre GFC	Post GFC	GFC	COVID	Pre GFC	Post GFC	GFC	COVID
Real Estate / IT (Retail)								
Portfolio weight (a)	0.79	0.48	0.10	0.46	0.72	0.64	0.42	0.71
Hedge ratio (b/a)	0.44	0.45	0.46	0.60	0.60	0.63	0.63	0.72
Hedging effectiveness (%)	4.83	36.60	46.70	52.14	21.53	43.21	36.99	60.35

Notes: The table compares the average optimal weight of real estate and hedge ratios for the respective real estate-industry sector portfolios during four periods using the DBEKK-GARCH model: Pre-GFC (January 2000-December 2006), Post-GFC (January 2010-December 2021), GFC (January 2007-December 2009), and COVID-19 (January 2020-December 2021). The hedging effectiveness has been computed based on the realised variances of hedged and unhedged portfolios using Eq. (18), and hedged portfolios have been constructed using the average hedge ratios derived for each time period.

ternally driven crises can present opportunities to expand real estate exposure without sacrificing hedging performance, provided macroeconomic support is effective.

Overall, the findings confirm that real estate's portfolio value is highly dependent on the type of crisis and the nature of volatility transmission. In systemic downturns with strong and persistent connections between real estate and core financial sectors, as in the GFC, its diversification benefits diminish sharply, and the emphasis should shift toward active hedging and risk containment. In externally driven crises like COVID-19, real estate can play a more constructive role in both allocation and hedging. These differences have direct economic significance for portfolio management. The evidence suggests that in crises where real estate is at the centre of the shock, maintaining high exposure increases vulnerability to systemic losses, making reduction in allocation and active hedging essential. In contrast, when the crisis originates outside the property and credit systems, real estate can contribute to risk reduction and even enhance portfolio stability, particularly when paired with sectors less sensitive to the prevailing shock. Recognising the structural drivers of volatility and the role of policy responses is therefore crucial for dynamically adjusting real estate exposure, optimising hedging strategies, and preserving portfolio resilience in future periods of market stress.

5.5. Robustness check

To assess robustness, the benchmark DCC-GARCH results are compared with estimates from a DBEKK-GARCH model (Tables 10–11). Unlike the benchmark model, the DBEKK includes an explicit contemporaneous shock-transmission term ($\varepsilon_{1,t-1}\varepsilon_{2,t-1}$) and a lagged conditional covariance term ($h_{12,t-1}$), alongside the own ARCH and GARCH effects. These additions allow a clearer separation of the size of shock spillovers from the persistence of their comovement.

Table 10. Estimates of the DBEKK-GARCH model in the US market

	REIT	S&P500	REIT	Financial	REIT	Industrial	REIT	Consumer	REIT	Energy	REIT	IT
EREITs: *Mean Model_ VAR* (1)												
Constant	0.2569***	0.2719***	0.2636***	0.1679**	0.2331***	0.2145***	0.2405***	0.2555***	0.2352***	0.1680**	0.2278***	0.3057***
Real Estate (1)	–0.0219	0.0324	–0.0289	0.0014	–0.0339	–0.0218	–0.0160	0.0026	–0.0113	0.0363	–0.0184	0.0242
Industry (1)	–0.0091	–0.0882**	–0.0065	–0.0364	0.0165	–0.0488	0.0011	–0.0416	–0.0164	–0.0330	0.0094	–0.0696*
EREITs: *Variance equation*												
Constant	0.4841***	0.3235***	0.5472***	0.3811***	0.4259***	0.2476***	0.5592***	0.3003***	0.5236***	0.4238***	0.4732***	0.2304***
$\varepsilon^2_{1,\,t-1}$ / $\varepsilon^2_{2,\,t-1}$	0.1707***	0.1792***	0.1570***	0.1427***	0.1443***	0.0877***	0.1828***	0.1098***	0.1648***	0.1136***	0.1634**	0.0921***
$h_{11,\,t-1}$ / $h_{22,\,t-1}$	0.7799***	0.7700***	0.7728***	0.8241***	0.8032***	0.8776***	0.7545***	0.8477***	0.7795***	0.8580***	0.7859***	0.8836***
Covariance												
Constant	0.2003***		0.2303***		0.1799***		0.2216***		0.1919***		0.1589***	
$\varepsilon_{1,\,t-1}\,\varepsilon_{2,\,t-1}$	0.1749***		0.1496***		0.1125***		0.1417***		0.1368***		0.1226**	
$h_{12,\,t-1}$	0.7749***		0.7980***		0.8396***		0.7997***		0.8178***		0.8333***	
Log Likelihood	–4928.98		–5294.47		–5155.67		–5150.88		–5561.85		–5422.27	
H_Q (12)	37.09 [0.8731]		35.89 [0.9012]		48.12 [0.4676]		42.95 [0.6791]		39.08 [0.8172]		35.41 [0.9112]	
MREITs: *Mean Model_ VAR* (1)												
Constant	0.0571	0.2299***	0.0214	0.2008**	0.0309	0.2196***	–0.0222	0.2040***	0.0610	0.1335	–0.0219	0.2874***
Real Estate (1)	–0.1084**	–0.0636*	–0.0780	–0.0413	–0.0755	–0.0368	–0.0364	–0.0424	–0.0739	0.0002	–0.0334	–0.0031
Industry (1)	0.0571	0.0007	0.0214	–0.0479	0.0107	–0.0367	–0.0072	–0.0197	0.0052	0.0102	0.0019	–0.0567

End of Table 10

	REIT	S&P500	REIT	Financial	REIT	Industrial	REIT	Consumer	REIT	Energy	REIT	IT
MREITs: *Variance equation*												
Constant	0.5738***	3.1723	0.5336***	0.2665***	0.4809***	0.2426***	0.3944***	0.2076***	0.5582***	0.4211***	0.4432***	0.1986***
$\varepsilon^2_{1,\,t-1}$ / $\varepsilon^2_{2,\,t-1}$	0.2202***	0.3223***	0.2693***	0.0909***	0.2435***	0.0836***	0.2493***	0.0767***	0.2481***	0.0825***	0.2493***	0.0580***
$h_{11,\,t-1}$ / $h_{22,\,t-1}$	0.7479***	0.1258*	0.7269***	0.8834***	0.7465***	0.8862***	0.7606***	0.8949***	0.7312***	0.8855***	0.7531***	0.9199***
Covariance												
Constant	1.3492***		0.2411***		0.2185***		0.1920***		0.2377***		0.2095***	
$\varepsilon_{1,\,t-1}\,\varepsilon_{2,\,t-1}$	0.2664***		0.1564***		0.1427***		0.1383***		0.1431***		0.1203***	
$h_{12,\,t-1}$	0.3067*		0.8014***		0.8134***		0.8250***		0.8046***		0.8323***	
Log Likelihood	–5150.72		–5456.71		–5304.44		–5296.28		–5648.86		–5542.01	
H_Q (12)	54.66 [0.2364]		43.76 [0.6471]		43.19 [0.6699]		36.28 [0.8926]		52.23 [0.3128]		54.63 [0.2371]	

Notes: This table shows the results of parameterisation for Eqs. (14)–(15) using the DBEKK-GARCH model for the US market. ε_1 and ε_2 denote the lagged residuals for REITs and the stock return series, respectively, and h_{11} and h_{22} denote the conditional variances of each return series, while h_{12} denotes the covariance between REITs and the stock return series. *H_Q* (12) is the Q statistic for jointly standardised residuals (Hosking, 1981) for up to 12 lags. The symbols *, ** and *** denote significance at 10%, 5% and 1% levels respectively, and the *p*-values of the diagnostic tests are given in brackets.

Table 11. Estimates of the DBEKK-GARCH model in the UK market

	Real Estate	FTSE100	Real Estate	Banking	Real Estate	Industrial	Real Estate	Consumer	Real Estate	Energy	Real Estate	Retail
Mean Model_ VAR (1)												
Constant	0.2171***	0.1171*	0.2150***	0.0321	0.2245***	0.2381***	0.2023***	0.1473***	0.2213***	0.0762	0.1794***	0.1300*
Real Estate (1)	0.0164	–0.0061	0.0093	0.0073	0.0079	–0.0484	–0.0085	0.0028	0.0432	0.0037	–0.0029	0.0069
Industry (1)	0.0478	–0.0027	0.0364	–0.0217	0.0249	0.0071	0.0717*	0.0028	0.0082	0.0581	0.0820**	0.0021
Variance equation												
Constant	0.2515***	0.1912**	0.3004***	0.1405***	0.2516***	0.3385***	0.2442***	0.1274***	0.2507***	0.6778**	0.2652***	0.1982***
$\varepsilon^2_{1,\,t-1}$ / $\varepsilon^2_{2,\,t-1}$	0.0960***	0.0952***	0.1264***	0.0890***	0.0932***	0.0979***	0.0944***	0.0805***	0.0923***	0.1722***	0.0826***	0.0772***
$h_{11,\,t-1}$ / $h_{22,\,t-1}$	0.8724***	0.8731***	0.8358***	0.9019***	0.8710***	0.8457***	0.8742***	0.9038***	0.8740***	0.7838***	0.8770***	0.9002***
Covariance												
Constant	0.1296**		0.1162***		0.1645***		0.1117***		0.1689**		0.1167***	
$\varepsilon_{1,\,t-1}\,\varepsilon_{2,\,t-1}$	0.0956***		0.1060***		0.0955***		0.0872***		0.1261***		0.0798***	
$h_{12,\,t-1}$	0.8727***		0.8682***		0.8583***		0.8889***		0.8277***		0.8886***	
Log Likelihood	–4893.04		–5353.56		–5007.11		–4976.53		–5510.09		–5243.46	
H_Q (12)	53.20 [0.2807]		57.24 [0.1695]		42.66 [0.6905]		43.77 [0.6466]		45.52 [0.5749]		39.94 [0.7892]	

Notes: This table shows the results of parameterisation for Eqs. (14)–(15) using the DBEKK-GARCH model for the UK market. ε_1 and ε_2 denote the lagged residuals for REITs and the stock return series, respectively, and h_{11} and h_{22} denote the conditional variances of each return series, while h_{12} denotes the covariance between REITs and the stock return series. H_Q (12) is the Q statistic for jointly standardised residuals (Hosking, 1981) for up to 12 lags. The symbols *, ** and *** denote significance at 10%, 5% and 1% levels respectively, and the p-values of the diagnostic tests are given in brackets.

The DBEKK estimates broadly confirm the benchmark conclusions. In the US, shock spillovers between REITs and the broad market (S&P500) are larger than those between REITs and individual sectors, reaffirming weaker sector-level spillovers on impact. However, persistence in conditional covariance is often greater for portfolios combining REITs with individual industries, suggesting that once shocks occur, sector comovement can be more sustained. In the UK, results indicate sectoral heterogeneity: Banking and Energy show stronger spillovers than the FTSE100, while Industrial, Consumer, and Retail are similar or lower. Persistence patterns are mixed, with some sectors above and others below the FTSE100 benchmark. These variations are modest and do not alter the benchmark inference that broad-market pairings typically exhibit stronger spillovers on impact.

Both models indicate that conditional variances are mainly driven by own-series ARCH and GARCH terms, with long-run volatility effects dominating short-run shocks. Log-likelihood comparisons generally favour the benchmark DCC-GARCH specification.

6. Conclusions

This study has significantly advanced the understanding of volatility spillovers between real estate (proxied by REITs) and equity markets, by meticulously examining both market-level and granular industry-level dynamics across the US and UK. The findings robustly demonstrate that volatility transmission is notably weaker at the industry level compared to the broad market level, a crucial insight that directly challenges the adequacy of conventional market-

wide models and underscores the greater diversification potential achievable when real estate is paired with targeted equity exposures. Furthermore, the analysis reveals that real estate's effectiveness as a hedge is not static but is profoundly contingent on the nature of the underlying crisis: its diversification benefits were significantly eroded during the GFC, which was an endogenous shock rooted in property and credit markets, but remarkably strengthened during the exogenously driven COVID-19 pandemic, particularly when supported by comprehensive policy responses.

The implications of these findings for investment practice are substantial and necessitate a more sophisticated approach to real estate allocation. For portfolio managers, the results confirm that the hedging benefits of real estate are most pronounced when exposures are strategically tailored to specific equity sectors. This positions real estate not as a broad, universal hedge, but rather as a precision instrument for effectively managing sector-specific risks. Crucially, the use of time-varying models, such as the DCC-GARCH, empowers managers to dynamically adapt hedge ratios as market conditions and spillover patterns evolve, thereby ensuring ongoing relevance and effectiveness of risk mitigation strategies.

From a policy perspective, the research highlights real estate's complex, dual role in systemic resilience. It can act as a stabilising force during broad macroeconomic disruptions, as witnessed during COVID-19, but can simultaneously become a significant channel of contagion in property-led financial crises, as exemplified by the GFC. This necessitates a more refined and dynamic macroprudential oversight that explicitly accounts for both scenarios. Policymakers and regulators should consider integrating sector-specific spillover monitoring into their frameworks, adjusting stress-testing methodologies to encompass scenarios where real estate prices collapse due to endogenous factors, as well as scenarios where real estate supports portfolio stability during external shocks. These insights can directly inform targeted interventions, such as bespoke liquidity provisions to REITs or broader asset purchase programmes, depending on the specific nature and origin of a crisis.

Nonetheless, the current research has several important limitations that warrant explicit acknowledgement and offer fertile ground for future investigation. Firstly, the study's scope is limited to two developed markets, the US and the UK, meaning the generalisability of these findings to other regions, particularly emerging markets with different institutional and economic contexts, remains to be determined. Secondly, the analysis relies on weekly frequency data, a choice made to balance time variation with estimation robustness. Future research could explore the dynamics using higher-frequency data, such as daily returns, which might reveal even finer, short-term volatility patterns, though this would need to account for increased noise. Thirdly, while the use of a robust multivariate GARCH framework (CCC, DCC, and diagonal BEKK) provides reliable insights into volatility transmission, future studies could explore alternative or more advanced econometric models to capture additional nuances. Specifically, this research does not explicitly incorporate broader macroeconomic variables, such as interest rates or monetary policy, as direct drivers of volatility spillovers. Subsequent work could integrate these critical factors using advanced models to clarify more intricate causal mechanisms. Finally, there is an opportunity to incorporate the influence of behavioural drivers, such as investor sentiment and economic policy uncertainty, more explicitly into models exploring real estate and equity linkages, building on existing literature that highlights their role in crisis dynamics. By addressing these limitations, future research can further enhance the precision and applicability of volatility spillover analysis in multi-asset portfolio management and financial stability oversight.

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