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Volatility Transmission: Evidence from U.K. REIT & Stock Market Implied Volatility

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ABSTRACT
This paper investigates volatility transmission in the U.K. REIT market. It considers how REIT volatility is related to implied volatility in both the overall stock market as well as that derived from traded options on REIT stocks. The multivariate analysis utilizes both Constant Conditional Correlation (CCC) and Dynamic Conditional Correlation (DCC) GARCH specifications to analyse the interdependence of the data. The findings confirm the presence of volatility transmission across the implied volatility of U.K. REITs, the U.K. implied volatility index, and the U.K. REIT index. The study also applies the variance decomposition approach proposed by Diebold and Yilmaz to examine spillover effects.

KEYWORDS
REIT volatility transmission; implied volatility; variance decomposition

1. Introduction

The last two decades have seen a large literature development that has considered various issues concerning volatility in public real estate vehicles such as Real Estate Investment Trusts (REITs). Most of that literature has focused on either modelling and/or forecasting REIT volatility or studying the relationship with volatility in either the broader stock market or across international REIT markets. Little work has been undertaken that has considered implied volatility drawn from the derivative market, the primary exceptions being Diavatopoulos et al. (2010) and Chung et al. (2016), who both consider the U.S. market. A major factor behind that omission is the comparative lack of traded derivative markets that are specifically focused on REITs, whether that be at a sector or individual firm level. In many respects, this highlights the still relative youth of public real estate, and in particular REITs. While the REIT market in the United States now dates back over six decades to its establishment in 1960, it is at times forgotten how much this growth has been relatively recent.

During the first three decades of their existence, the U.S. market remained a small niche sector, especially if one considered Equity REITs. In 1987, for example, despite many REIT IPOs (Initial Public Offerings) in the preceding years, there were 53 Equity REITs with a market capitalization of less than $5 billion. This comprised less than half of the overall REIT market in terms of both the number of firms and the market capitalization. Changes in the second half of the eighties and the early nineties, such as the development of the UPREIT (Umbrella Partnership) structure, helped

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the market develop and by 1995 there were 178 Equity REITs with a combined market cap of \$49bn.[1] Furthermore, this relatively recent growth in maturity in the sector is echoed internationally. Until the mid-nineties, very few countries had introduced a tax-efficient vehicle similar to REITs, Australia being the most notable exception. Even then, while countries such as Canada did introduce REITs in the nineties most of the major global capital markets did not see a REIT market introduced until after the millennium.[2]

The comparative youth, and for many years the relative immaturity, of REIT markets also impacted upon the availability of derivative instruments based on REITs. Even today very few individual REITs have traded options based on their stock. In addition, in many markets, the majority of REITs are small stocks which in turn further limits the likelihood of traded options being available. In addition, even at a sector level, the number of index derivatives is relatively sparse. The first REIT-specific index futures contract was established in Australia in 2002, followed by the U.S. (2007) and Japan (2008), in addition to European-wide contracts introduced in 2007. The lack of a wide array of alternative traded hedging instruments also adds to the challenges present in the effective risk management of REIT portfolios (Cotter & Stevenson, 2006, 2007; Diavatopoulos et al., 2010, Lee et al., 2014).

This paper extends the existing literature by considering how volatility in the U.K. REIT market is related to implied volatility. The advantage of implied volatility is that it isn't either a historical or quantitatively forecasted measure of volatility but rather it is derived from the market pricing of traded options. It can therefore be viewed as capturing market sentiment and expectations regarding volatility and market risk and can therefore be a valuable metric to investigate the relationship between market risk and return (e.g., Canina & Figlewski, 1993; Chiang, 2012; Mayhew, 1995). The paper uses two measures of implied volatility. The first is derived from stock options traded on the three largest U.K. REITs; British Land, Hammerson and Land Securities. The second is a non-REIT-specific measure, the market-wide FTSE Implied Volatility Index (FTSE-IVI), which is based on index options for the FTSE100 benchmark index (Emna & Myriam, 2017, Whaley, 2009). Whilst this isn't a REIT-specific measure it does provide a measure of market-wide sentiment, and there is also empirical evidence that such measures provide information on the performance of both individual companies as well as the overall market.[3]

The U.K. public real estate market differs in several ways from other REIT markets. While REITs were only introduced in the U.K. in January 2007 the U.K. already had a well-established public real estate sector, that had been one of the largest public real estate sectors globally, with firms structured in a conventional corporate form. This pre-existing market also meant that the 2007 introduction of REITs involved the conversion of existing publicly listed property companies into REITs, rather than the creation of new firms as was common in most markets. This in turn meant that from the start the market consisted of mature and well-established companies, many of whom had been publicly listed for decades. Hammerson, for example, has been listed on the London Stock Exchange since 1953. Furthermore, a number of the largest U.K. REITs have been long-established members of U.K. benchmark indices such as the FTSE100. This meant that they immediately had a level of maturity, institutional investment and market trading that was not observed in many other markets. This does provide an advantage in the availability of data for the U.K. sector and also that the underlying characteristics of U.K. REITs are distinct from some other markets. The remainder of the paper is structured as follows: The following section discusses some of the relevant previous literature and empirical evidence. Section 3 details the data and methodological framework adopted. Sections 4 and 5 present the empirical findings, while the final section provides concluding comments.

2. Literature Review

A considerable number of papers have in recent years examined various aspects of volatility in public real estate, with particular emphasis on volatility spillovers. This work initially built upon the empirical research in mainstream finance that utilized the ARCH (Autoregressive Conditional

Heteroscedasticity) and GARCH models developed by Engle (1982) and Bollerslev (1986). Much of the early research in finance generally focused on international markets and complemented and expanded the research to have considered causal relationships in returns (e.g., Bae & Karolyi, 1994; Baele, 2005; Bekaert & Harvey, 1997; Christiansen, 2007; Hamao et al., 1990; King et al., 1994; Ng, 2000; Skintzi & Refenes, 2006; Theodossiou & Lee, 1993). This focus was echoed in the early papers to specifically examine REITs, many of which considered either the volatility relationship between REITs and other domestic assets or between international public real estate markets. Stevenson (2002) examined the interaction between REITs and the equity and fixed-income sectors in the U.S. In contrast to much of the later literature, which has generally examined daily data, this paper focused instead on monthly data. Whilst this was primarily due to data limitations at the time, it does also provide an interesting comparison when retrospectively looking back. The results highlight the intuitive relationship between Equity REITs, small-cap stocks and value stocks, which is in contrast to the lack of a significant spillover relationship noted between the fixed-income sector and Mortgage REITs. The intuitive findings with respect to Equity REITs are generally not however supported when higher frequency data is considered. For example, Cotter and Stevenson (2006, 2008) provide evidence that would imply that overall stock market volatility, and sentiment, play a more central role when daily data is examined.[4]

Papers that have considered volatility spillovers across global REIT markets have to consider not only the relationship across public real estate markets but also the domestic interaction between REITs and the broader stock market. Hoesli and Reka (2013) assess whether there are different dynamics underlying co-movement in the entire distribution, including extreme events. They investigate market contagion in both public real estate and the broader equity markets by testing for tail-dependence structural changes within a time-varying copula framework. The results reveal that the U.S. is frequently the base of spillover effects and highlight the importance of co-movements in tail distributions between markets. More recently, Milcheva and Zhu (2018) distinguish between co-movement due to market risk exposure and that due to linkages between markets, as measured via a Spatial Multi-Factor Model (SMFM). The SMFM model is estimated from indices of 14 developed countries' public real estate markets and assesses' the systematic implications for REIT returns. The authors find that during the global financial crisis, spillover risk increased dramatically and explained up to 60% of total asset variation. In contrast, unsystematic risks dominated during the remainder of the sample period. Furthermore, the results reveal that in comparison to traditional linkages such as geographical distance, economic integration performs a pronounced role in the interconnectedness among markets. Liow and Huang (2018) investigate ten established markets and find that a significant source of REIT volatility integration shocks, in 80% of the cases, is the local stock market. Consistent with other papers, they find that this effect is more pronounced during periods of crisis and extreme volatility. In a non-volatility context, Stevenson (2016) not only notes that economic variables are important factors when considering the degree of integration across international public real estate markets, but that the relationship between a public real estate market and its domestic equity market also influences the degree of integration and co-movement. The paper notes that factors such as the relative domestic size of the REIT sector and the extent to which the overall stock market is integrated with the global market are key determinants in how integrated public real estate is.

The vast majority of REIT volatility research has relied upon either historical estimates or has utilized modeling approaches, such as GARCH, to provide estimates of volatility.[5] While implied volatility has been extensively investigated in mainstream finance there have been relatively few papers to have considered it in a real estate specific context, primarily due to data limitations. Diavatopoulos et al. (2010) was the first paper to examine REIT implied volatility. The results illustrated that REIT implied volatility and implied idiosyncratic volatility distributions are similar to those of other listed equities and that the future realized volatility for REITs is related to both future and implied volatility. Chung et al. (2016) focused on the Global Financial Crisis (GFC) and considered the relationship between REIT volatility and future returns. The results show a negative relationship between implied volatility and contemporaneous returns. The paper also reports a significant positive relationship between implied volatility and future volatility, while the relationship between implied volatility and future returns is significantly negative. Akinsomi et al. (2018) investigate the impact of implied volatility and equity market uncertainty on herding behavior in the U.K. REIT market through different market regimes, as estimated via a Markov regime-switching model. In this paper, the implied volatility measure is based upon a market-wide measure, as measured by the FTSE-IVI. The static model rejects the existence of herding in U.K. REITs, while the regime-switching model shows significant evidence of herding and anti-herding behavior in the low and high-volatility regimes, respectively. This suggests that the level of the equity market's volatility may provide a signal of herding-related risk in REITs, although this is dependent on the market condition, or regime, in which the analysis is undertaken.

3. Data and Methodological Framework

A challenge in any analysis of implied volatility is the need for an actively traded options market on individual firms or at an index level. While the U.K. has a long-established public real estate sector, currently there are over fifty REITs traded in London, only three of them have stock options traded on them, namely, British Land, Hammerson and Land Securities. These firms are, however, three of the oldest and largest U.K. REITs. They have consistently been among the five largest U.K. REITs, or pre-2007 property companies, and constitute on average approximately 30% of the market. Furthermore, they have also frequently been constituent members of the FTSE100. While stock options on Land Securities and British Land have been traded since May 2005 and May 2008, respectively, in order to have a common sample period we opt to start the empirical analysis in October 2013 when options on Hammerson stock were first traded. The analysis, therefore, extends from October 2013 to February 2018. During this period all three firms were constituents of the FTSE-100, with Hammerson being downgraded to become a member of the FTSE-250 in March 2018.

All of the data, which is of a daily frequency, was sourced from Bloomberg. The firm-specific 30-day implied volatility data were obtained from the Bloomberg Option Monitor (OMON). As a departure from most of the research associated with implied volatility in REITs, this research follows the approach of Siriopoulos and Fassas (2013) by taking the absolute log of the daily changes in the implied volatility levels of the implied volatilities and the REIT index. Table 1 reports the descriptive statistics of the log of the implied volatility changes in the various series, while graphs of the implied volatility series and the REIT index are displayed in Figure 1. The data is characterized by positive skew, high kurtosis and high Jarque-Bera statistics, suggesting that the data is not normally distributed and has fat tails. The changes in the implied volatilities and the REIT index are stationary, as supported by significant Augmented Dickey-Fuller (ADF) tests for all variables. The

Table 1. Descriptive Statistics

	FTSE-IVI	REIT Index	British Land	Hammerson	Land Securities
Mean	0.0034	0.0003	0.0013	0.0026	0.0014
Median	0.0000	0.0001	0.0000	0.0000	−0.0011
Maximum	0.5375	0.0585	0.5557	0.4044	0.3612
Minimum	−0.3628	−0.1448	−0.3001	−0.3062	−0.2250
Std. Dev.	0.0828	0.0110	0.0516	0.0660	0.0493
Skewness	0.8138	−2.3568	1.5029	0.7324	1.0798
Kurtosis	8.0113	34.3510	23.2227	8.4751	10.7330
Jarque-Bera	1306***	47282***	19663***	1511***	3032***
Observations	1129	1129	1129	1129	1129
ADF	−27.1349***	−20.5443***	−20.5443***	−25.7087***	−27.4866***
Arch Test	25.9614***	159.6116***	30.5839***	52.1379***	70.2863***

Note. ADF is the Augmented Dickey-Fuller Test that test for stationarity. *** represents statistical significance at the 1% level, ** represents statistical significance at the 5% level and * represents statistical significance at the 10% level.

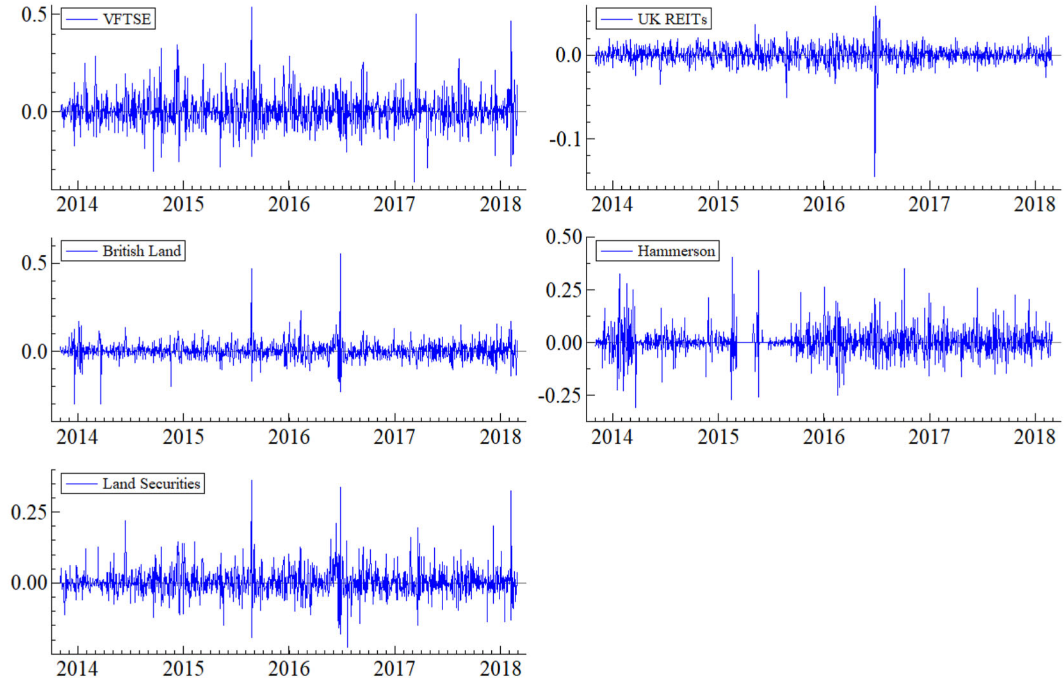

Figure 1. Changes of Implied Volatility and U.K. REIT Index.
Note. Figure 1 displays the log changes for the FTSE-IVI and U.K. REIT Index and the implied volatility for British Land, Hammerson and Land Securities.

ARCH test is also significant, indicating that there are ARCH effects present in the data. Therefore, ARCH family models like GARCH are suitable for use despite the Jarque-Bera test not suggesting that the data is non-normal.

In common with papers such as Anderson et al. (2018), Case et al. (2012), Chong et al. (2012) and Cotter and Stevenson (2006) this paper employs multivariate GARCH (MGARCH) specifications. Specifically, the paper uses Bollerslev's (1990) Constant Conditional Correlation (CCC) GARCH model and the Dynamic Conditional Correlation (DCC) GARCH specification of Engle (2002). Such models are structured in such a way that the variances and covariances are linear functions of the squares and cross-products of the data. In so doing the aim is to specify the conditional variance matrix. However, the parameters for these matrices increase at a rapid rate as the dimension increases. The covariance matrix has to be invertible but this becomes challenging in terms of computation when the number of assets, *n*, exceeds the number of the time series, *t*. It is therefore important that a multivariate GARCH model is parsimonious enough, while still maintaining flexibility at the same time and the conditional covariance matrix must be positive definite. It is possible to consider MGARCH specifications based on the following four groups.

i. Models of the conditional covariance matrix, i.e., the VEC-GARCH (Bollerslev et al., 1988) and BEKK parametric models.
ii. Factor models, i.e., Generalized Orthogonal GARCH proposed by van der Weide (2002).
iii. Conditional variances and correlations, i.e., CCC and DCC GARCH, as used in the current study.
iv. Nonparametric and semiparametric approaches. These provide an alternative to the parametric estimation of the conditional covariance structure. In contrast to the parametric models, the nonparametric and semiparametric models do not impose a particular structure on the data.

This study employs the CCC and DCC multivariate GARCH models. The conditional variance and correlation permit one to specify separately the individual conditional variances on the one hand, and the conditional correlation matrix on the other. Put differently; the conditional covariance is decomposed into *k* conditional variances and conditional correlations. Even though theoretical results on stationarity, ergodicity and moments may not be that straightforward to obtain compared to the models in the other groups, they are parsimonious and therefore much easier to estimate. The conditional variance matrix for this class of models (CCC and DCC GARCH) is specified hierarchically. Firstly, one chooses a GARCH specification for each conditional variance. Secondly, the conditional correlation matrix is then modelled based on the conditional variances. The CCC GARCH model assumes that these correlations are constant and hence the conditional covariances are proportional to the product of the corresponding standard deviations. The effect of this restriction is that it highly reduces the number of unknown parameters. The assumption that the conditional correlations are constant seems unrealistic in many empirical applications and for this reason, a generalization of the CCC GARCH model was developed by making the conditional correlation matrix time-dependent, hence the Dynamic Conditional Correlation (DCC) GARCH model. The DCC GARCH model, as proposed by Engle (2002) and Tse and Tsui (2002), extends the CCC GARCH specification by introducing simple scalar BEKK-like dynamics to the conditional correlations.[6]

4. GARCH Models

This section initially examines the result and analysis of the CCC and DCC GARCH models. Table 2 displays a summary of the estimated coefficients, and p-values, of the two multivariate GARCH models. Of the two models, the CCC GARCH does have lower values for both the AIC and BIC criteria. While both models display conditional correlations that are significantly different from zero, the DCC GARCH model reports consistently lower correlations. Both models show that the highest correlation is between Land Securities and British Land, implying heightened interconnection between the implied volatilities of these REITs. This is intuitive as not only are they the two largest UK REITs, but their investment focus is similar, both predominantly focused on the office sector, with some shopping centers. In contrast, Hammerson is virtually exclusively focused on retail. While the implied volatility index for the FTSE-IVI shows statistically significant correlations with the three REIT companies, there are small spillover effects with the U.K. REIT market. Both models show evidence of interconnectedness between the implied volatility changes of the three REITs with Land Securities and British Land having the highest correlation. Figure 2 displays the conditional variance plots estimated by both the CCC and DCC GARCH. It is clear that Hammerson experienced marked volatility during the sample period. Given the firm's retail focus and the challenges that have faced the retail sector in recent years, this heightened volatility is perhaps not surprising. In addition, in 2018 the firm also pulled out of a proposed takeover bid of fellow UK Retail REIT INTU, and shortly afterwards in the second quarter of 2018, Hammerson was dropped from the FTSE100 benchmark Index. The FTSE-IVI has the second-highest conditional volatility, and the U.K. REIT index has the least volatility while the pattern for the conditional volatility of British Land and Land Securities is similar.

Table 3 presents the unconditional correlation matrix for the implied volatility changes in FTSE-IVI, U.K. REIT Index, British Land, Hammerson, and Land Securities; measured using Pearson's correlation coefficient. The null hypothesis of no relationship between the variables is rejected, as the correlation coefficients are all not equal to zero. There appears to be a moderate positive correlation between the overall U.K. REIT index and both British Land and Land Securities. Again, Hammerson is the outlier, with a weak positive correlation with the FTSE-IVI, British Land and Land Securities. Land Securities and British Land have the highest unconditional correlations, though moderate. Their similar focus in office markets again makes this an intuitive finding. Unlike the conditional correlations which have several negative correlations, the unconditional correlations

Table 2. Summary of the Multivariate GARCH Models

		CCC GARCH		DCC GARCH	
		Coefficient	p-value	Coefficient	p-value
Panel A: GARCH Results					
ω	FTSE-IVI	0.0015***	0.0001	0.0015***	0.0001
α	FTSE-IVI	0.1250***	0.0063	0.1250***	0.0063
β	FTSE-IVI	0.6531***	0.0000	0.6531***	0.0000
ω	REITs	0.0000**	0.0278	0.0000**	0.0278
α	REITs	0.1724***	0.0012	0.1724***	0.0012
β	REITs	0.7632***	0.0000	0.7632***	0.0000
ω	British Land	0.0004**	0.0205	0.0004*	0.0684
α	British Land	0.3193***	0.0083	0.2696***	0.0001
β	British Land	0.5470***	0.0001	0.7042***	0.0000
ω	Hammerson	0.0003*	0.0684	0.0003*	0.0633
α	Hammerson	0.2696***	0.0001	0.2441***	0.0058
β	Hammerson	0.7042***	0.0000	0.6397***	0.0000
ω	Land Securities	0.0001***	0.0001	0.0001***	0.0001
α	Land Securities	0.3087**	0.0211	0.3087**	0.0211
β	Land Securities	0.2158	0.1697	0.2158	0.1697
Panel B: Conditional Correlation Results					
	ρUR_VF	−0.4269***	0.0000	−0.3839***	0.0000
	ρBL_VF	0.4314***	0.0000	0.3884***	0.0000
	ρHS_VF	0.2170***	0.0000	0.1892***	0.0002
	ρLS_VF	0.4900***	0.0000	0.4508***	0.0000
	ρBL_UR	−0.4876***	0.0000	−0.4500***	0.0000
	ρHS_UR	−0.3406***	0.0000	−0.3185***	0.0000
	ρLS_UR	−0.4718***	0.0000	−0.4499***	0.0000
	ρHS_BL	0.2717***	0.0000	0.2275***	0.0000
	ρLS_BL	0.5363***	0.0000	0.4943***	0.0000
	ρLS_HS	0.2666***	0.0000	0.2649***	0.0000
Panel C: Diagnostics					
	df	4.5062	0.0000	4.4801	0.0000
	AIC	−20.2299		−20.2921	
	BIC	−20.0250		−20.0783	

Note. Table 2 provides the summary for the multivariate models, i.e., the estimated coefficients and p-values for the CCC and DCC GARCH models. The GARCH univariate parameters (ω, α and β) are estimated for the FTSE-IVI, U.K. REIT index, British Land, Hammerson and Land Securities. The conditional correlations are also provided, and the abbreviations are VF = FTSE-IVI, UR = UK REITs, BL = British Land, HS = Hammerson and LS = Land Securities. Df is the degree of freedom, and the AIC and BIC are the Akaike Information Criterion and Schwartz Criterion, respectively. *** Represents statistical significance at the 1% level, ** Represents statistical significance at the 5% level and * Represents statistical significance at the 10% level.

are all positive. Figure 3 plots the conditional correlations estimated from the DCC model. The correlations vary over time, with the biggest range observed being that between FTSE-IVI and British Land, while the smallest range is perhaps not surprising that of the two index related measures the FTSE-IVI and the REIT index. These conditional correlations vary, on average, between -0.26 to 0.71 over the sample period (see Table 4), and this is significantly different from the average conditional correlations shown in Figure 1. The average conditional correlations are all not equal to zero, and hence the null hypothesis that there is no association amongst the changes in implied volatilities and the price of the U.K. REIT index is rejected. This suggests that there is integration or transmission amongst the implied volatilities of the FTSE-IVI, REIT and the implied volatilities of the three individual REITs, albeit very little in some instances. Although there is some transmission it is moderate with the highest average conditional correlation being 0.53 between Land Securities and British Land as shown by the CCC GARCH model. In some periods, as shown in Table 4, this conditional correlation is quite high, meaning there is a positive relationship among the FTSE-IVI, British Land, Hammerson and Land Securities, as suggested by their implied volatilities changes. A comparison between the conditional correlation and the unconditional correlation reveals discrepancies that are almost uniform as all but one conditional correlation, i.e., that between Hammerson and FTSE-IVI; are marginally higher than the unconditional correlations.

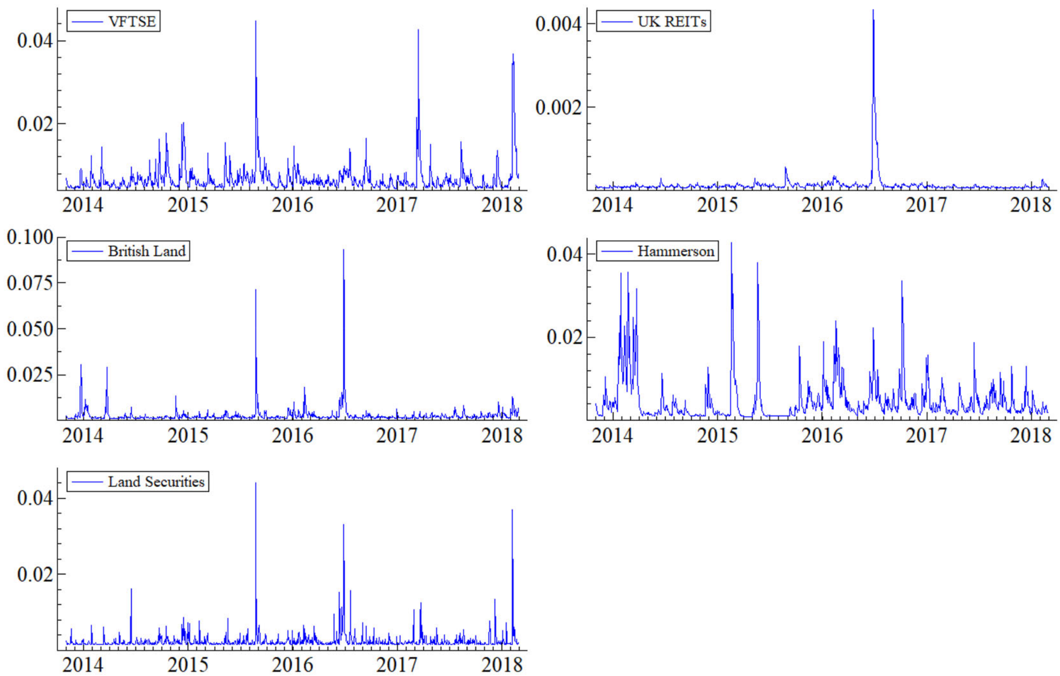

Figure 2. Conditional Variances.
Note. Figure 2 displays the conditional variances estimated by the DCC GARCH. Both the CCC and DCC GARCH show the same estimates for the conditional variances.

Table 3. Unconditional Correlations

	FTSE-IVI	REIT Index	British Land	Hammerson	Land Securities
FTSE-IVI	1.0000				
REIT Index	0.2982	1.0000			
British Land	0.3473	0.4427	1.0000		
Hammerson	0.0373	0.2161	0.1742	1.0000	
Land Securities	0.3942	0.4447	0.4917	0.1059	1.0000

5. Volatility Transmission

While the multivariate GARCH models provide information about the relationship regarding the correlation of volatilities across the assets and markets under investigation, the next section extends the analysis by utilizing a Generalized Vector Autoregressive (VAR) framework to assess volatility spillovers. The purpose of the Generalized VAR, and the variance decomposition approach proposed by Diebold and Yilmaz (2012), is to measure total and directional spillovers. In contrast to their earlier model (Diebold & Yilmaz, 2009) which relies on Cholesky factor decomposition but is order dependent, Diebold and Yilmaz (2012) propose a new approach that eliminates the possible dependence of the results on ordering. Based on a Generalized VAR framework the approach computes the forecast error variance decomposition without the orthogonalization of shocks. This is achieved by exploiting the framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) which they refer to as KPPS. The Diebold and Yilmaz (2012) approach has been used in this paper because it results in the measurement of the total spillovers which culminates in a spillover index that can provide information as to the net contributor and net recipient of the spillovers (Batten et al., 2019; Diebold & Yilmaz, 2012; Mensi et al., 2018).

The variance decompositions are defined as the fractions of the $\boldsymbol{H}$-step-ahead error variances in forecasting $\boldsymbol{x_i}$ that come about due to shocks to $\boldsymbol{x_i}$ for $\boldsymbol{i} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{N}$, and spillovers, or cross

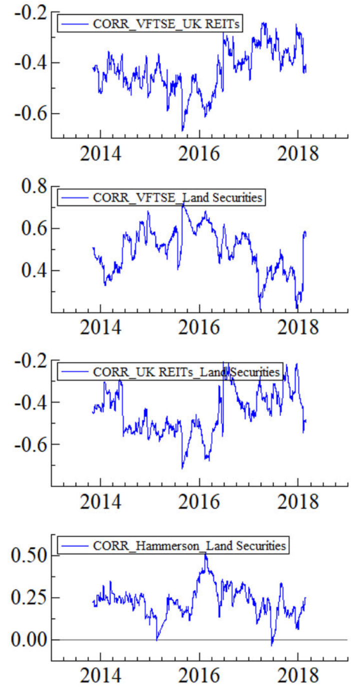

Figure 3. Conditional Correlation Plots.

Table 4. Conditional Correlation Ranges.

	ρUR-VF	ρBL-VF	ρHS-VF	ρLS-VF	ρBL-UR	ρHS-UR	ρLS-UR	ρHS-BL	ρLS-BL	ρLS-HS
Maximum	−0.2560	0.6253	0.4333	0.6399	−0.2585	−0.1015	−0.2630	0.4826	0.7148	0.4521
Minimum	−0.5880	0.1625	0.0252	0.2522	−0.6493	−0.4977	−0.6470	0.0885	0.2325	0.0747
Range	0.3319	0.4627	0.4081	0.3876	0.3908	0.3961	0.3839	0.3940	0.4823	0.3774

variance shares, are the fractions of the $\boldsymbol{H}$-step-ahead error variances in forecasting $\boldsymbol{x_i}$ due to shocks to $\boldsymbol{x_i}$, for $\boldsymbol{i,j} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{N}$, such that $\boldsymbol{i} \neq \boldsymbol{j}$. Utilizing the Generalized VAR framework the $\boldsymbol{H}$-step-ahead generalized forecasts-error variance decomposition can be expressed as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=o}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=o}^{H-1} \left(e_i' A_h \sum A_h' e_j\right)} \tag{1}$$

where Σ denotes the covariance matrix for the error vector ε; σ_{jj} is the standard deviation of the error term for the j^{th} equation; e_j is the selection vector, with one of the j^{th} element and zero otherwise. The sum of the elements in each row of the variance decomposition table is not equal to 1, i.e., $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. Each entry of the variance decomposition matrix by row sum is normalized as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{2}$$

where $\sum_{j=1}^{N} \theta_{ij}^{g}(H) = 1$ and $\sum_{ij=1}^{N} \theta_{ij}^{g}(H) = N$ by construction. Diebold and Yilmaz (2012) construct the total volatility spillover index as below, by utilizing the volatility contributions from the KPPS variance decomposition. The total spillover index measures the contribution of spillovers of volatility shocks across all the markets to the total forecast error variance.

Table 5. Volatility Spillovers across VFTSE, UK REITs, British Land, Hammerson, and Land Securities.

	FTSE-IVI	REIT Index	British Land	Hammerson	Land Securities	From Others	Net	Conclusion
FTSE-IVI	58.41	10.61	11.83	2.66	16.49	41.59	−2.56	Net recipient
REIT Index	10.15	57.45	13.34	7.47	11.59	42.55	3.21	Net contributor
British Land	10.63	13.91	53.52	4.12	17.82	46.48	2.19	Net contributor
Hammerson	3.41	10.21	5.69	77.45	3.23	22.54	−5.95	Net recipient
Land Securities	14.84	11.03	17.81	2.34	53.99	46.02	3.11	Net contributor
To Others	39.03	45.76	48.67	16.59	49.13	199.18		
Including Own	97.44	103.21	102.19	94.04	103.12	39.8%		

Note. From others – directional measure of spillovers from all markets$_j$ to market$_i$.
To others – directional measure of spillovers from all markets$_i$ to market$_j$.
Including own – directional measure of spillovers from market$_i$ to all markets$_j$ including from own market$_i$.
Other columns contain net pairwise (i, j)-th spillover indices.

Figure 4. Total Volatility Spillover Index.

$$S^P(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \; x \; 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \; x \; 100 \tag{3}$$

It is also possible to identify which markets play the dominant role in volatility spillovers by considering directional spillovers (Mensi et al., 2018). This is done by examining spillovers from one market to another, e.g., market *i* to market *j* and vice versa. The two categories of direction volatility spillovers are "from" and "to" and are calculated using Equations (4) and (5), respectively.

$$S_i^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \; x \; 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \; x \; 100 \tag{4}$$

$$S_i^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \; x \; 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \; x \; 100 \tag{5}$$

The net spillovers can also be calculated by considering the difference between the gross volatility shocks transmitted "to" and those received "from" all the markets, i.e.:

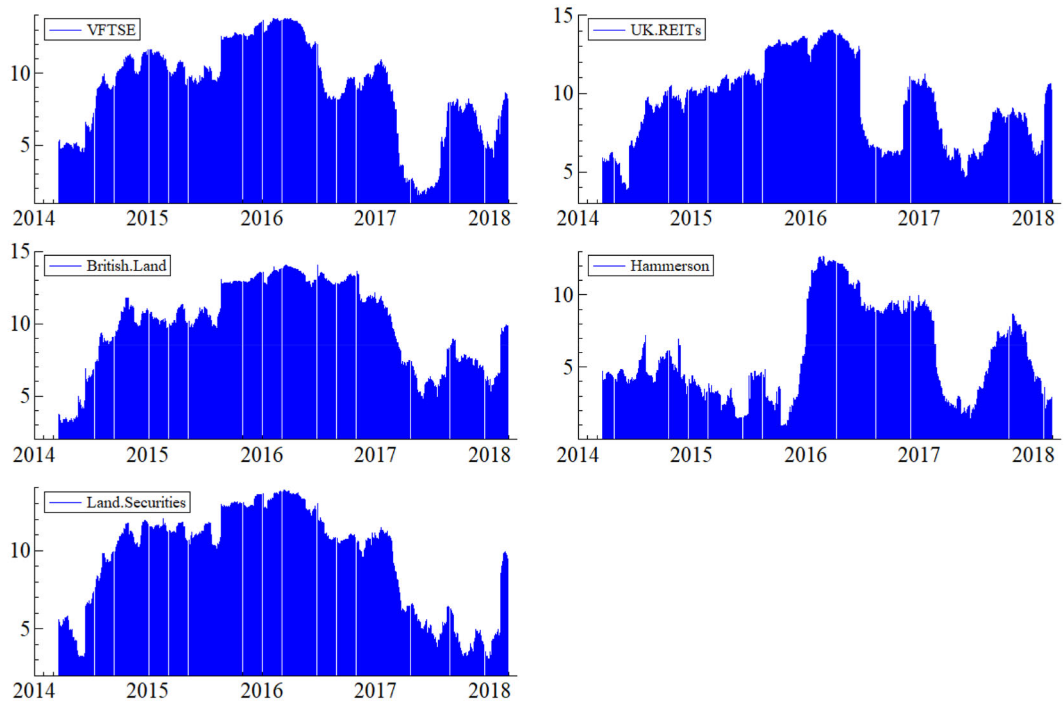

Figure 5. Directional Volatility Spillovers – From Others.

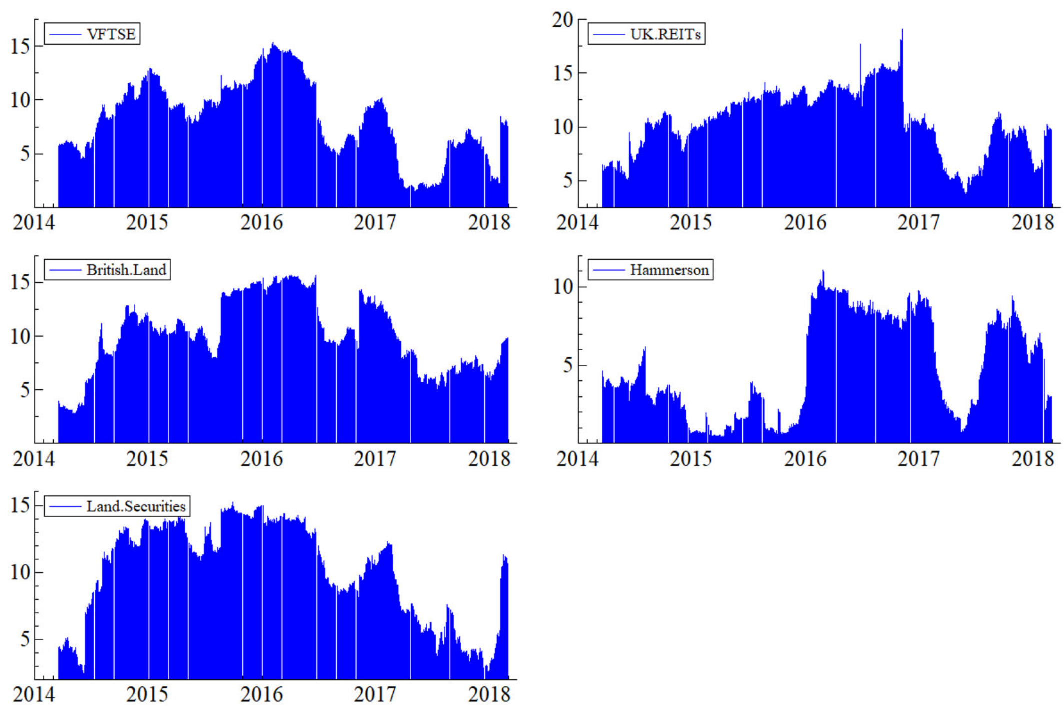

Figure 6. Directional Volatility Spillovers – To Others.

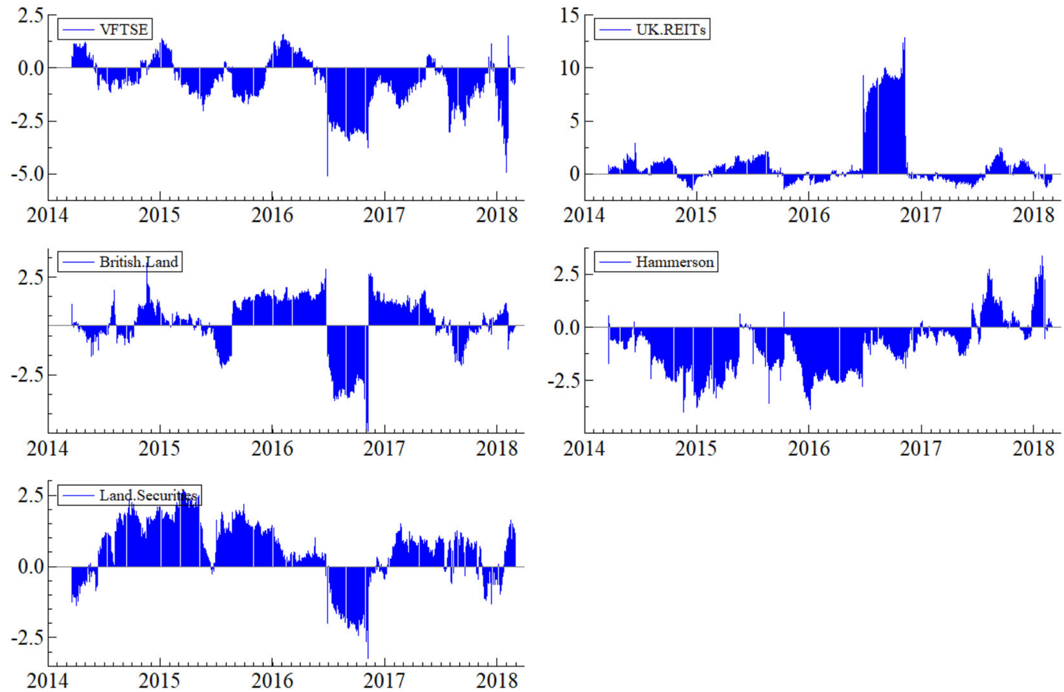

Figure 7. Net Volatility Spillovers.

$$S_i^g(H) = \left(= \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^g(H)} \ x \ 100 \right) - \left(\frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \ x \ 100 \right) \tag{6}$$

The net spillovers can be extended to enable one to calculate the net pairwise volatility spillovers. For example, the net pairwise volatility spillover between market i and market j is the difference between the gross volatility shock transmitted from market i to market j and those from market j to market i. This is illustrated in Equation (7);

$$S_i^g(H) = \left(\frac{\tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ik}^g(H)} - \frac{\tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{jk}^g(H)} \right) x \ 100 = \ - \left(\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \right) x \ 100 \tag{7}$$

Table 5 reveals that the total volatility spillover calculated using Equation (3) is about 39.8%. Land Securities contributes the most "to others" and therefore has the highest influence on the volatility contributing about 49%. This is, to some extent, expected as Land Securities has been the largest U.K. REIT, by market capitalization, for several decades. It is followed closely by British Land whose contribution "to others" is similar at 48.7%. This suggests that the transmission of risk to the other markets and companies under investigation is high for Land Securities and British Land; and the overall REIT index is at 45.8%. The volatility spillover between Land Securities and British Land is the highest for all off-diagonal values in the table. This is consistent with the findings in the MGARCH analysis which showed a generally high conditional correlation between these two companies. The contribution to others by the FTSE-IVI and Hammerson is relatively low, with Hammerson showing the least volatility spillovers to others. The three highest contributors to others all have positive net values and are therefore net contributors as more volatility spillover is going "to others" than they are receiving "from others". Further analysis shows that the total volatility spillover is not constant over time as illustrated in Figure 4 by considering 100-day rolling data. Total volatility spillover was initially at a value of approximately 25%, peaking close to 70%

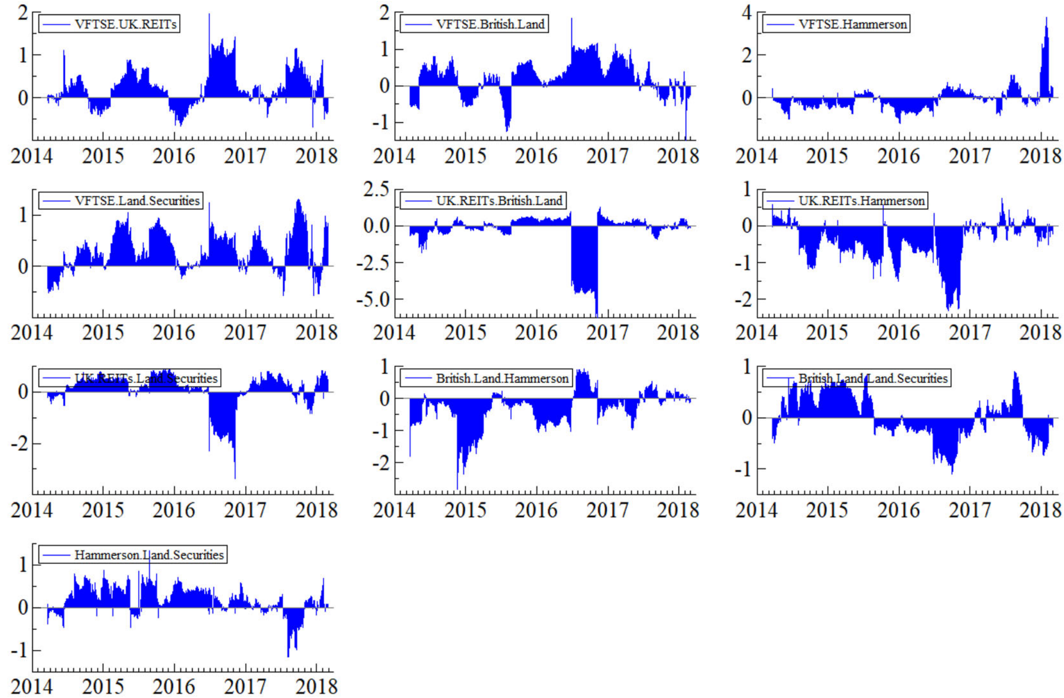

Figure 8. Pairwise Volatility Spillovers.

at the beginning of 2016 before starting to descend, reaching a low in the region of 10% toward the second quarter of 2017.

While the total spillover provides a pattern of the level of volatility spillovers, it does not show the direction of the spillovers. Figures 5 and 6 display the rolling data for directional "from others" and "to others", respectively. Like the total volatility spillover, the directional "from others" is time-varying though in a similar pattern, the exception being for Hammerson whose distribution is different. This is also observed for the directional "to others", with Hammerson again being quite distinct compared to the other series. It is interesting to note that both directional rolling volatility spillovers peaked in 2016. This not only could be attributed to the collapse in the European stock market (Mensi, 2018) but also the impact of the June 2016 Brexit referendum in the U.K. Figure 7 presents the changes in the net rolling volatility spillover and shows that the REIT index, Land Securities and British Land are all net transmitters, or contributors, of volatility spillover. In contrast, the FTSE-IVI and Hammerson are net recipients, and this is especially noticeable prior to mid-2017 when they display persistent negative net volatility spillovers. Finally, the spillover dynamics are examined by making use of the net pairwise spillovers displayed in Figure 8. It can be seen that these vary considerably over time. As expected, given the results already discussed, Hammerson and the REIT Index are recipients of volatility spillovers, while the FTSE-IVI is a contributor.

6. Conclusion

This study set to examine whether there is transmission or spillover effects between the U.K. stock market implied volatility index, FTSE-IVI, and the implied volatilities of British Land, Hammerson and Land Securities as well as the U.K. REIT index. Similar to Chung et al. (2016) and Diavatopoulos et al. (2010) who find relationships between the REIT implied volatility and future returns and other listed equities, respectively, both the multivariate GARCH and VAR results reveal volatility transmissions, although they are noticeably weaker in the case of the FTSE-IVI and for the retail

REIT Hammerson. While the GARCH provides information regarding the presence of volatility transmission, the models do not show the extent and direction of these spillovers. The analysis is extended by the VAR which reveal that British Land, Land Securities and the U.K. REIT sector are the net contributors to others while Hammerson and FTSE-IVI are the net recipients. This is in contrast to Liow and Huang (2018) who find that a significant source of REIT volatility integration shock in most cases is the local stock market. The generally low levels of transmission with respect to volatility in the overall U.K. stock market does indicate a degree of segmentation with respect to the U.K. REIT sector, implying potential diversification benefits for investors who have holdings in public real estate. The strong linkages observed between British Land and Land Securities is not unexpected given their similar portfolio holdings. Investors can, therefore, avoid allocating their money in the other if they already have a holding in one. If they do not have any holding in either, they should invest in one but not both at the same time. Likewise, it is not surprising that of the three individual firms it is the retail focused REIT Hammerson that is more distinct. Therefore, the level of implied volatility transmission or spillovers can help in asset allocation, diversification and risk management decisions. The findings in this paper extend the understanding of the implied volatility transmission within the U.K. REIT market and in the wider non-REIT market.

Notes

1. See studies such as Chan et al. (1998), Downs (1998), Feng et al. (2011) and Wang et al. (1995) for further discussions about various aspects of the development of the U.S. REIT market.
2. For example, REITs were only introduced in the following markets post 2000; France (2003), Germany (2007), Hong Kong (2003), Japan (2000), Korea (2001), Singapore (2002) and the UK (2007)
3. See Giot (2005); Whaley (2009); Chiang (2012); Emna and Myriam (2017); Bekaert and Hoerova (2014).
4. See also Bai et al. (2015) and Ertugrul et al. (2008) who consider interday data.
5. In addition to the REIT volatility papers already discussed there is also an extensive literature that has specifically considered forecasting REIT volatility, for example, Bonato et al. (2022), Zhou (2020) and Zhou and Kang (2011).
6. Check Sheppard (2013) and Silvennoinen and Teräsvirta (2007) for comprehensive details about the CCC GARCH and DCC GARCH.

Data Availability Statement

The data used for this research was accessed from a third party and is subject to commercial restrictions, so the supporting data are not available.

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