Diversification Benefits of U.S. REITs for Private Investors Holding Asian Stocks

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Abstract

This study endeavours to explore the potential diversification advantages stemming from the inclusion of United States Real Estate Investment Trusts (REITs) within investment portfolios heavily focused on Asian stock indices. Utilizing a robust framework comprising multivariate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) modelling and comprehensive Wavelet Transform analyses, this research investigates the intricate dynamics between US REITs and key Asian stock markets spanning the period from 2018 to 2023. This research contributes comprehensive empirical evidence, indicating that despite inherent volatility, US REITs showcase relatively weaker correlations with individual Asian stock indices. This highlights the possibility of diversification benefits, rendering US REITs potentially independent of the movements witnessed in Asian stock indices, particularly during select temporal intervals. Moreover, this study yields crucial insights for investors, offering guidance for optimized portfolio allocations and risk management strategies within a constantly evolving global financial landscape. The findings underscore the significance of considering US REITs as potential diversification assets for portfolios containing Asian stocks.

Keywords*:* Portfolio Diversification, Asian Stock Indices, United States REITs, Conditional Correlations, Maximum Overlap Discrete Wavelet Transform (MODWT), Continuous Wavelet Transform (CWT), Multivariate GARCH, Investment Analysis

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1.0 Introduction

In recent years, the investment landscape has witnessed increased interest and participation in Real Estate Investment Trusts (REITs) within the United States (US). (Orzano, M.) Simultaneously, private investors in Asian markets have been actively engaged in holding stocks within their regional markets. Against the backdrop of evolving global economic conditions and market dynamics between 2018 and 2023, this study aims to investigate the potential diversification benefits that US REITs offer to private investors who hold stocks within the Asian market, employing a robust multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Wavelet approach.

Diversification has long been recognized as a fundamental strategy for mitigating risk and enhancing portfolio performance. However, while the advantages of diversification are well-understood, comprehending the intricate interrelationships between US REITs and Asian stocks necessitates a meticulous investigation. This research, employing a multifaceted approach, endeavours to leverage both the robust multivariate Generalized Autoregressive Conditional Heteroskedasticity (M-GARCH) methodology and the discerning Wavelet Transform analysis.

Understanding the dynamics of these cross-market relationships, as determined by the multivariate GARCH analysis, is crucial for investors seeking to optimize portfolio allocation and manage risk effectively in an increasingly interconnected global financial landscape. The utilization of this advanced statistical approach enables a more comprehensive evaluation of the time-varying volatility and conditional correlations between US REITs and Asian stocks, thereby offering a deeper understanding of the diversification benefits achievable through these investment strategies.

Moreover, this study recognizes the imperative role of the Wavelet Transform analysis in unravelling complex interactions within the stock market. By employing the Wavelet Transform methodology, particularly the Continuous Wavelet Transform (CWT) and Maximum Overlap Discrete Wavelet Transform (MODWT), this research seeks to explore the correlation dynamics and co-movements between US REITs and Asian stocks across various temporal horizons. Understanding these dynamic relationships is crucial for investors striving to optimize portfolio allocation and manage risk effectively in an increasingly interconnected global financial landscape.

The utilization of these advanced statistical methodologies, encompassing GARCH and Wavelet Transform analyses, aims to provide a comprehensive understanding of the time-varying volatility, conditional correlations, and frequency domain insights between US REITs and Asian stocks. Through these methodologies, this study endeavours to shed light on the diversification benefits inherent in these investment strategies, thereby offering valuable insights to market participants navigating the complexities of global financial markets.

2.0 Data and Methodology

In this study, I've gathered daily closing prices from January 11, 2019, to October 27, 2023, sourced from Yahoo Finance. My dataset includes the stock indices encompassing several developed stock markets in Asia (China, Philippines, Korea, and Japan), along with the price of overall performance of the entire U.S. REITs market.

To examine the dynamic nature of volatilities and correlations between Asian stock indices and U.S. REITs, we are employing the multivariate GARCH DCC (MGARCH-DCC) model pioneered by Pesaran and Pesaran (2007), also wavelet tools such as wavelet coherency to effectively capture the correlation between two time series, namely Continuous Wavelet Transform (CWT) and Maximum Overlap Discrete Wavelet Transform (MODWT).

2.1 Multivariate GARCH – Dynamic Conditional Correlation (MGARCH-DCC)

This method enables us to pinpoint shifts in conditional correlations and volatilities over time, diverging from the conventional approach reliant on historical covariance estimation through a two-stage process. During the initial phase, the conditional variances of individual assets are calculated using the univariate GARCH (X, Y) model:

$$h_{it} = \omega_i + \sum_{x=1}^{X_i} \propto_{ix} r_{it-x}^2 + \sum_{y=1}^{Y_i} \beta_{iy} h_{it-y}\ , for\ i = 1, 2, \ldots, k \qquad (1)$$

Herein, ω_i, $\propto_{ix}$, and β_{iy} represent non-negative values and $\sum_{x=1}^{X_i} \propto_{ix} + \sum_{y=1}^{Y_i} \beta_{iy} < 1$. The parameter $\propto_{ix}$ signifies short-term persistence shocks affecting return X (ARCH effects), while β_{iy} denotes the impact of shocks on return Y in terms of long-term persistence (GARCH effects). Additionally, k stands for the total number of assets involved.

In the context of the subsequent phase, we will compute the time-varying conditional correlation among index returns by applying the general equation of the DCC estimator, it is as shown below:

$$H_t = D_t R_t D_t \qquad (2)$$

In this case, D_t represents a $k \times k$ matrix containing conditional time-varying standardized residuals (ε_t), and H_t represents the multivariate conditional covariance matrix. In the initial phase, these residuals will be obtained from the univariate GARCH model as follows:

$$D_t = diag(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots, \sqrt{h_{kk,t}}) \qquad (3)$$

The matrix, a symmetric and positively definite matrix, exhibits $\sqrt{h_{ii,t}}$ values along its diagonal for each I $= 1, 2, \ldots,$ k.

Meanwhile, matrix R_t represents the dynamic correlation among elements outside the diagonal.

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \qquad (4)$$

Hereby, $Q_t = (q_{ij,t})$ comes from

$$Q_t = (1 - \emptyset - \gamma)\bar{Q} + \gamma Q_{t-1} + \emptyset \sigma_{i,t-1}\sigma_{j,t-1} \qquad (5)$$

The matrix, a $k \times k$ symmetric positive definite structure, involves Q_t as a conditional (time-varying) covariance matrix of standardized residuals, also being $k \times k$ symmetric positive definite:

$$\sigma_{it} = \frac{\varepsilon_{it}}{\sqrt{h_{it}}} \qquad (6)$$

$\bar{Q}$ represents the unconditional correlations of $\sigma_{i,t}\ \sigma_{j,t}, \emptyset$ while γ stands as non-negative scalar parameters that fulfil $\emptyset + \gamma < 1$. Additionally, matrix Q_t^* is defined as the diagonal matrix comprising the square root of the diagonal elements present in Q_t:

$$Q_t^* = diag(\sqrt{q_{11}}, \sqrt{q_{22}} \ldots, \sqrt{q_{kk}}) \qquad (7)$$

Hence, the computation of the conditional correlation between the X and Y stock indices at time t is achievable through the following method:

$$\rho_{ij,t} = \frac{[(1-\emptyset-\gamma)\bar{q}_{ij} + \emptyset\sigma_{i,t-1}\sigma_{j,t-1} + \gamma q_{ij,t-1}]}{\{[(1-\emptyset-\gamma)\bar{q}_{ii} + \emptyset\sigma_{i,t-1}^2 + \gamma q_{ii,t-1}]^{\frac{1}{2}} \cdot [(1-\emptyset-\gamma)\bar{q}_{jj} + \emptyset\sigma_{j,t-1}^2 + \gamma q_{jj,t-1}]^{\frac{1}{2}}\}} \qquad (8)$$

In accordance with Bollerslev's (1988) model, q_{ij} represents the element found at the ith row and jth column within the matrix Q_t. The conditional log-likelihood of the parameters, under the Gaussian assumption, can be succinctly outlined as per Bollerslev's (1988) model.

$$L = -\frac{1}{2}\sum_{t=1}^{T}[k\ log\ (2\pi) + log|D_t|^{\ 2} + \varepsilon_t' D_t^{-1} D_t^{-1}\varepsilon_t + (log|R_t| + \sigma_t' R_t^{-1}\sigma_t - \sigma_t'\sigma_t)] \qquad (9)$$

Here, k represents the number of equations, while T stands for the total number of observations.

In the initial stage, the focus is solely on maximizing the volatility component (Dt), which involves reducing the log-likelihood to the sum of the log-likelihood derived from the univariate GARCH model. Subsequently, during stage two, the emphasis shifts to maximizing the correlation component (Rt) while conditioned on the estimated Dt. This stage involves utilizing the standardized residuals obtained from the first stage.

The assumption of Gaussian distribution for daily returns has stirred controversy due to its tendency to underestimate portfolio risk. Despite maintaining consistency under the two-stage likelihood estimation approach introduced by Engle & Sheppard (2001), reliance on Gaussianity might lead to inefficiencies, as highlighted by Pesaran & Pesaran (2010).

In essence, DCC modelling facilitates the identification of changes in the interdependence among variables within a time series, offering insight into when and how these changes occur. Consequently, it allows the assessment of potential diversification benefits offered by assets like Bitcoin within a dynamic setting, such as during the global COVID-19 pandemic.

The MGARCH-DCC model stands as a dependable tool for estimating portfolios and has been employed by researchers like Fantazzini (2009), Chevallier (2012), and Aas and Berg (2013) to explore concepts such as Value at Risk, time-varying correlations, and multivariate dependence structures.

2.2 Wavelet

The wavelet method offers a distinctive ability to uncover complex interactions in the stock market, often surpassing other modern econometric models in this aspect. This superiority is primarily due to the varied trading behaviours seen across different time frames within financial markets, where perspectives like daily, monthly, and weekly intervals prevail. Using wavelet techniques brings several notable advantages. Firstly, it helps in addressing challenges arising from the non-uniform nature of time series signals. Secondly, wavelet analysis proves valuable in examining financial relationships, particularly when distinguishing between short-term and long-term connections. Wavelets stand out for their ability to localize both in time and scale, allowing for the breakdown of observed variables into different frequency bands. This enables a detailed study of co-movements across various temporal horizons while retaining all pertinent information. The key strength of cross-wavelet coherence-phase analysis lies in its proficiency in examining momentary dynamics that underlie the relationship between two time series.

2.2.1 Continuous Wavelet Transform (CWT)

In this investigation, the approach to wavelet decomposition aligns with Grinsted et al.'s (2004) study, employing wavelet coherency through continuous wavelet transform (CWT) on the return series. This application aims to capture the co-movement of data within both time and frequency domains. The continuous wavelet transforms of a time series x_t, concerning ψ, manifests as a function of two variables, expressed through the convolution equation as follows:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t)\bar{\psi}_{\tau,s}(t)dt = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\bar{\psi}\left(\frac{t-\tau}{s}\right)dt, \qquad (10)$$

2.2.2 Maximum Overlap Discrete Wavelet Transform (MODWT)

The Maximum Overlap Discrete Wavelet Transform (MODWT) is employed due to its advantageous flexibility regarding data length, eliminating the need for an integral power of 2. Additionally, it possesses a time-invariant property. The wavelet family symlet 8 is selected specifically for its minimal asymmetry property, making it particularly suitable for financial series. The transformed return series, denoted as $r(t)$, is expressed as a composite of wavelet functions in the following manner:

$$r(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \ldots + \sum_k d_{1,k}\psi_{1,k}(t), \qquad (11)$$

where:

j is the number of scale crystals (intervals or frequencies);

k is the number of coefficients in the specified component;

$\phi_{j,k(t)}$ and $\psi_{j,k(t)}$ are the father and mother orthogonal wavelet pair that are given respectively by:

$$\phi_{J,k}(t) = 2^{-J/2}\phi\left(t - \frac{2^J k}{2^J}\right)$$

$$\psi_{J,k}(t) = 2^{-j/2}\psi\left(t - \frac{2^j k}{2^j}\right) \qquad (12)$$

Father wavelets correspond to the smoother, low-frequency components of the series, while mother wavelets correspond to the more detailed, high-frequency components of the series. The wavelet coefficients, denoted as $s_{j,k}$ and $d_{j,k}$, are estimated through the following integrals:

$$\int \phi_{J,k}(t)f(t)dt \approx s_{J,k}$$

$$\int \psi_{J,k}(t)f(t)dt \approx d_{J,k} \qquad (13)$$

The coefficients $s_{j,k}$ are termed as the 'smooth' coefficients, characterizing the inherent smoothness of the series, whereas $d_{j,k}$ are referred to as the 'detail' coefficients, capturing deviations in scale from this smooth behavior. These coefficients signify the influence of their respective wavelet functions on the overall series. Following the decomposition of the return series into *j* crystals, the crystals dj are aggregated back into the time domain. The complete excess return series is reconstructed within a multi-resolution decomposition framework as outlined below:

$$\hat{r}^J = D_1 + \cdots + D_J + S_J \qquad (14)$$

Dj represents the reconstructed series in the time domain derived from the crystal dj, while Sj is the reconstitution of the residual. The reconstructed return series $\hat{}r^J$ contains distinct components of the original series at each frequency *j*. *Dj* illustrates the impact of frequency *j* on the initial series. Upon obtaining the reconstructed series for each frequency, the study emulates the approach of Ramsey and Lampart (1998) to estimate beta across different time scales. The coefficient $\beta^j{}_i$, pivotal to the study's examination, varies according to the time scale *j*. The study evaluates wavelet covariance $\tilde{\gamma}_{XY}(\lambda j)$, wavelet variance $\tilde{\sigma}_X(\lambda j)$, and $\tilde{\sigma}_Y(\lambda j)$. To measure correlation, the wavelet correlation coefficient, $\rho_{XY}(\lambda j)$, offers a standardized assessment of the relationship between the two time-series across various time scales. The unbiased estimator of the wavelet correlation at timescale *j* is defined as:

$$\tilde{\rho}_{XY}(\lambda_j) = \frac{\tilde{\gamma}_{XY}(\lambda_j)}{\tilde{\sigma}_X(\lambda_j)\tilde{\sigma}_Y(\lambda_j)} \qquad (15)$$

Whereas $\tilde{\sigma}_X(\lambda j)$ and $\tilde{\sigma}_Y(\lambda j)$ stand for unbiased estimations of wavelet variances, and $\tilde{\gamma}_{XY}(\lambda j)$ denotes the unbiased estimation of wavelet covariance. The study adopts Gençay et al.'s (2002) simple wavelet-based method for testing significant differences. Specifically, it aims to evaluate if wavelet correlation coefficients, analyzed on a scale-by-scale basis between

US REITs index returns and various Asian stock index pairs, exhibit noteworthy disparities. Identification of significant changes relies on examining approximate confidence intervals between US REITs index returns and Asian stock index pairs. The null hypothesis, suggesting no statistically significant difference, could be rejected if the 95% approximate confidence intervals do not overlap.

Table 1: Selected indices for research

Symbol	**Definition**
USREIT	United States REIT index
CHN	China stock index
PLI	Philippines stock index
KOR	Korea stock index
JAP	Japan stock index

3.0 Findings and Results

3.1. Multivariate GARCH – Dynamic Conditional Correlation (MGARCH-DCC)

Our analysis, utilizing the multivariate GARCH model with a t-Distribution, provided insightful findings regarding the conditional volatility dynamics between US REITs and different Asian stock markets over the specified period, from January 11, 2019 to October 27, 2023.

The maximized log-likelihood value achieved by the multivariate t-GARCH model (14686.4) surpassed that of the Gaussian model (14331.3), signaling a more accurate fit for capturing the intricacies of returns in both the US REITs and Asian stock markets. Furthermore, the estimated degrees of freedom for the t-distribution model (5.9769) suggested a robust fit, indicative of its capacity to address the fat-tailed nature inherent in these market returns.

The multivariate t-GARCH model was shown to be the best suitable for evaluating the link between US REITs and Asian equities throughout the given period, after being tested using various statistical metrics and goodness-of-fit tests. This model is a better tool for risk assessment and portfolio analysis since it captured the time-varying volatility and conditional correlations between different asset types.

When considering the Lambda1 estimates from table 2, which represent the persistence parameter for volatility, we noted that the values for US REITs differed imperceptibly from those of Asian stock markets. For instance, the Lambda1 estimate for US REITs stood at 0.85787, while for the Asian stock markets (China, Philippines, Korea, and Japan), the Lambda1 estimates ranged between 0.85669 and 0.93299. While there is a range of Lambda1 estimates across the Asian stock markets, the Lambda1 estimate for US REITs falls within this range, indicating a similarity rather than a notable difference in the persistence of volatility. Consequently, it suggests that US REITs do not display significantly higher or lower persistence in volatility when contrasted with the range observed in the Asian stock indices based solely on the Lambda1 estimates.

Table 2: Results of multivariate GARCH with underlying t-Distribution on the stock index return series.

Parameter	Estimate	Standard Error	T-Ratio [Prob]
lambda1_CHN	0.89136	0.02834	31.4544 [.000]
lambda1_PLI	0.85669	0.05365	15.9695 [.000]
lambda1_KOR	0.93299	0.03806	24.5129 [.000]
lambda1_JAP	0.86255	0.04199	20.5401 [.000]
lambda1_US	0.85787	0.02902	29.5573 [.000]
lambda2_CHN	0.06823	0.01528	4.4669 [.000]
lambda2_PLI	0.08553	0.02857	2.9935 [.003]

lambda2_KOR	0.03962	0.01612	2.4579 [.014]
lambda2_JAP	0.07669	0.01992	3.8493 [.000]
lambda2_US	0.11405	0.02115	5.3924 [.000]
delta1	0.97540	0.00958	101.8043 [.000]
delta2	0.01050	0.00292	3.5967 [.000]
df	5.97690	0.42513	14.0588 [.000]
Maximized Log-Likelihood =	14686.4		

Note: df is the degrees of freedom of the multivariate t distribution.

To evaluate the behaviour of US REITs and several Asian stock indexes during the research period, the dynamic conditional volatilities of these securities were examined. These estimates are shown in Figure 1, which also highlights some interesting trends in conditional volatilities. Except for US REITs, the conditional volatilities of the stock indexes showed patterns that were comparatively comparable. The China stock index returns showed the least conditional volatility among Asian stock indices, implying that China experienced the smallest average returns for both REITs and stocks prices, whereas US REITs showed the highest volatility behaviour, implying that the U.S. REITs experienced the largest average returns for both REITs and stocks prices. This difference is consistent with the unconditional volatilities results shown in Table 3.

From table 3, looking at the unconditional volatility figures, we observe the following values for each Asian stock index and US REITs: China (CHN) displays an unconditional volatility of 0.011769, the Philippines (PLI) at 0.015123, Korea (KOR) at 0.013912, Japan at 0.013339, and US REITs at 0.017877. These values represent the inherent level of total volatility within each asset without considering external factors. Notably, US REITs exhibit a slightly higher unconditional volatility compared to the individual Asian stock indices, suggesting a comparatively higher level of inherent volatility within US REITs during the specified period.

Moving on to the unconditional correlation figures, we note the correlation values between each Asian stock index and US REITs: China (CHN) has an unconditional correlation of 0.16536, the Philippines (PLI) at 0.25165, Korea (KOR) at 0.32279, Japan at 0.28679, and US REITs displaying a correlation of 0.01788 with itself. These values depict the strength and direction of the relationship between the respective Asian stock indices and US REITs. Notably, US REITs exhibit relatively lower unconditional correlations with the mentioned Asian stock indices, indicating a weaker degree of relationship compared to the correlations observed among the Asian stock indices themselves.

Upon reassessment, it is evident that US REITs display higher unconditional volatility compared to the individual Asian stock indices, and they also tend to have relatively weaker unconditional correlations with these Asian stock indices. This implies that while US REITs exhibit higher inherent volatility, their movements are less strongly correlated with the movements of the individual Asian stock indices, potentially indicating diversification benefits in a portfolio context.

Table 3: Unconditional volatility alongside US REITs and unconditional correlation between Asian stock indices and US REITs.

Stock index & US REIT	Unconditional Volatility	Unconditional Correlation
China (CHN)	0.01177	0.16536
Philippines (PLI)	0.01512	0.25165
Korea (KOR)	0.01391	0.32279
Japan (Japan)	0.01334	0.28679
US REITs	0.01788	-

These findings collectively underscore the potential divergence in volatility behaviour between US REITs and Asian stock markets during the specified period. The observed differences in persistence and adjustment speeds of volatility suggest distinct reactions to market fluctuations, highlighting the importance of considering US REITs as potentially offering different risk characteristics compared to the Asian stock markets in portfolio diversification strategies.

Figure 1 below provides a visual representation of the conditional volatilities of various Asian stock indices alongside US REITs over a specified period. The lines or curves in Figure 1 depict the fluctuations in volatility for each asset or index. Observing the movements within these lines offers insights into how volatility changes over time. For instance, higher peaks indicate periods of increased volatility, while lower points suggest relatively stable or lower volatility.

During March of 2020, the U.S. REITs return volatility reached an all-time high. This surge in US REITs return volatility during March 2020 corresponded to a period of unprecedented market turbulence caused by the global COVID-19 pandemic. The outbreak led to widespread economic uncertainty, government-imposed lockdowns, and disruptions across various sectors, including real estate. The uncertainty surrounding the pandemic's impact on commercial properties, such as office spaces, retail centres, and hospitality venues, significantly contributed to the spike in volatility observed in US REITs. This heightened volatility reflected investors' heightened concerns and fluctuating expectations regarding the prospects and financial performance of real estate investment trusts amid the evolving pandemic landscape. Such an exceptional volatility spike underscores the sensitivity of US REITs to macroeconomic shocks and underscores the need for investors to consider their risk exposure and diversification strategies, particularly during periods of significant market upheavals.

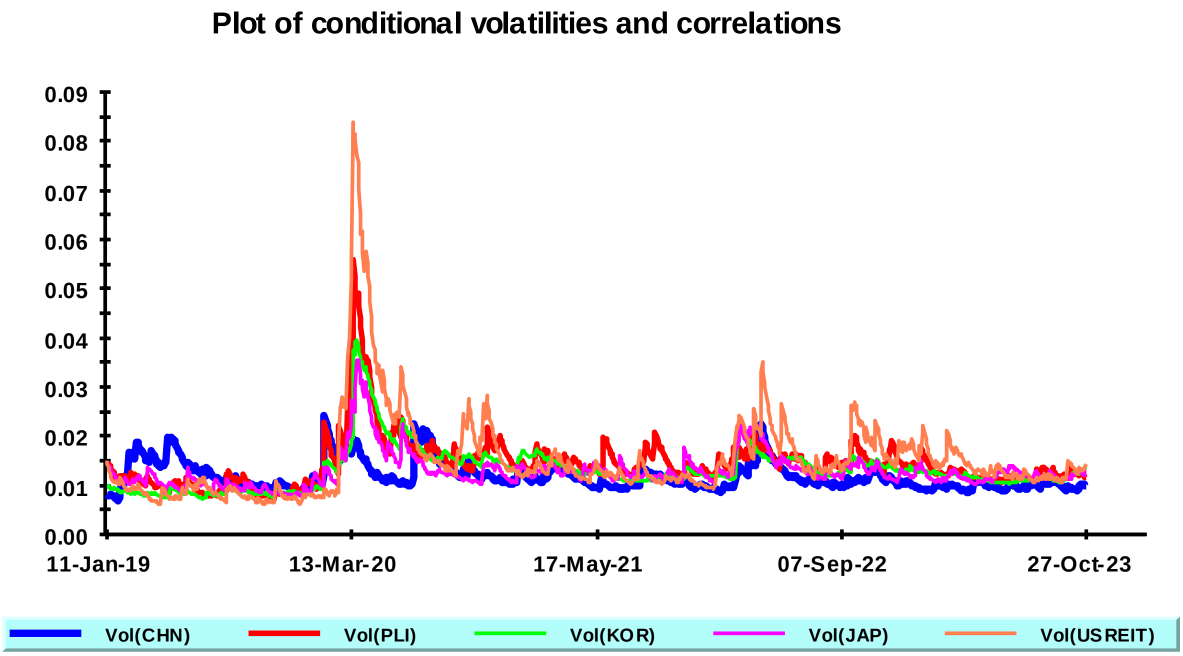

Figure 1: Conditional volatilities of Asian stock indices and US REITs

Moreover, fluctuations in the correlation lines highlight the changing relationships between the Asian stock indices and US REITs over time. The correlation during March period of 2020 has also reached an all-time low, signifying the potential for diversification benefits, as these assets move less closely together. This suggests that US REITs may offer a degree of independence from the movements of the Asian stock indices, presenting opportunities for risk reduction through diversification.

Furthermore, figure 2 confirms the results of the unconditional correlations in Table 2, showing that the US REITs returns are highly correlated with Korea's stock returns as compared to the other stock returns. After the starting of March period, correlations of US REITs and other Asian stocks had remained above 0 at some point. The correlation between US Real Estate Investment Trusts (REITs) and Asian stock indices appears to exhibit varying levels based on our analysis. In comparison to the Asian stock indices, the correlation of US REITs with these indices demonstrates lower correlation, indicating potential diversification opportunities for investors holding Asian stocks.

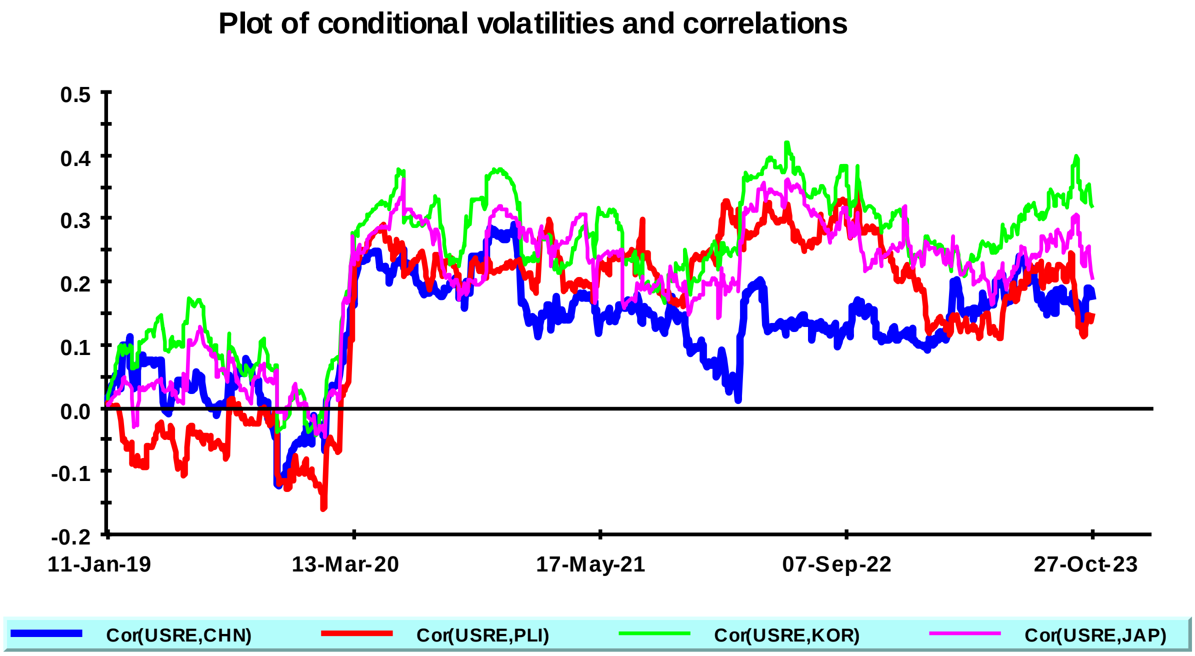

Figure 2: Conditional correlations of Asian stock indices and US REITs

Given the observed lower correlation between US REITs and Asian stock indices, it could be suggested that investors, specifically those with holdings in Asian stocks, might consider integrating US REITs into their portfolios to potentially benefit from diversification advantages. The lower correlation suggests that US REITs could offer a degree of independence from the movements of the Asian stock indices, presenting an opportunity for risk reduction through diversification for investors holding Asian stocks.

3.2 Continuous Wavelet Transform (CWT)

The horizontal axis delineates time in terms of the number of trading days, while the vertical axis signifies the investment horizon. The curved line, indicating the 5% significance level, is derived from Monte Carlo simulations. Observations falling outside this curved line are considered insignificant in this study. The colour gradient, ranging from blue (indicating low coherency, near zero) to red (reflecting high coherency, near one), denotes the power or strength of correlation.

Arrows pointing right suggest in-phase behaviour between indexes, while left-pointing arrows indicate out-of-phase behaviour. Right and upward arrows signify the lagging of the first series (US REITs), whereas right and downward arrows indicate the first series leading. Conversely, left and upward arrows imply lagging for the first series, while left and downward arrows signify that the first series leads.

In general, the wavelet coherence results across all 4 figures predominantly exhibit red coloration during the 200-400-day period, indicating high coherency between MSCI Malaysia and all stock indices. However, there are exceptions, such as with China, which shows fewer red signals during this time frame. To summarize, the significant occurrences of red signals are observed during:

1. The time span between the 200th and 400th day, particularly within holding periods of 16-128 days.
2. The time frame ranging from the 600th to the 800th day, specifically with holding periods of 32-64 days.

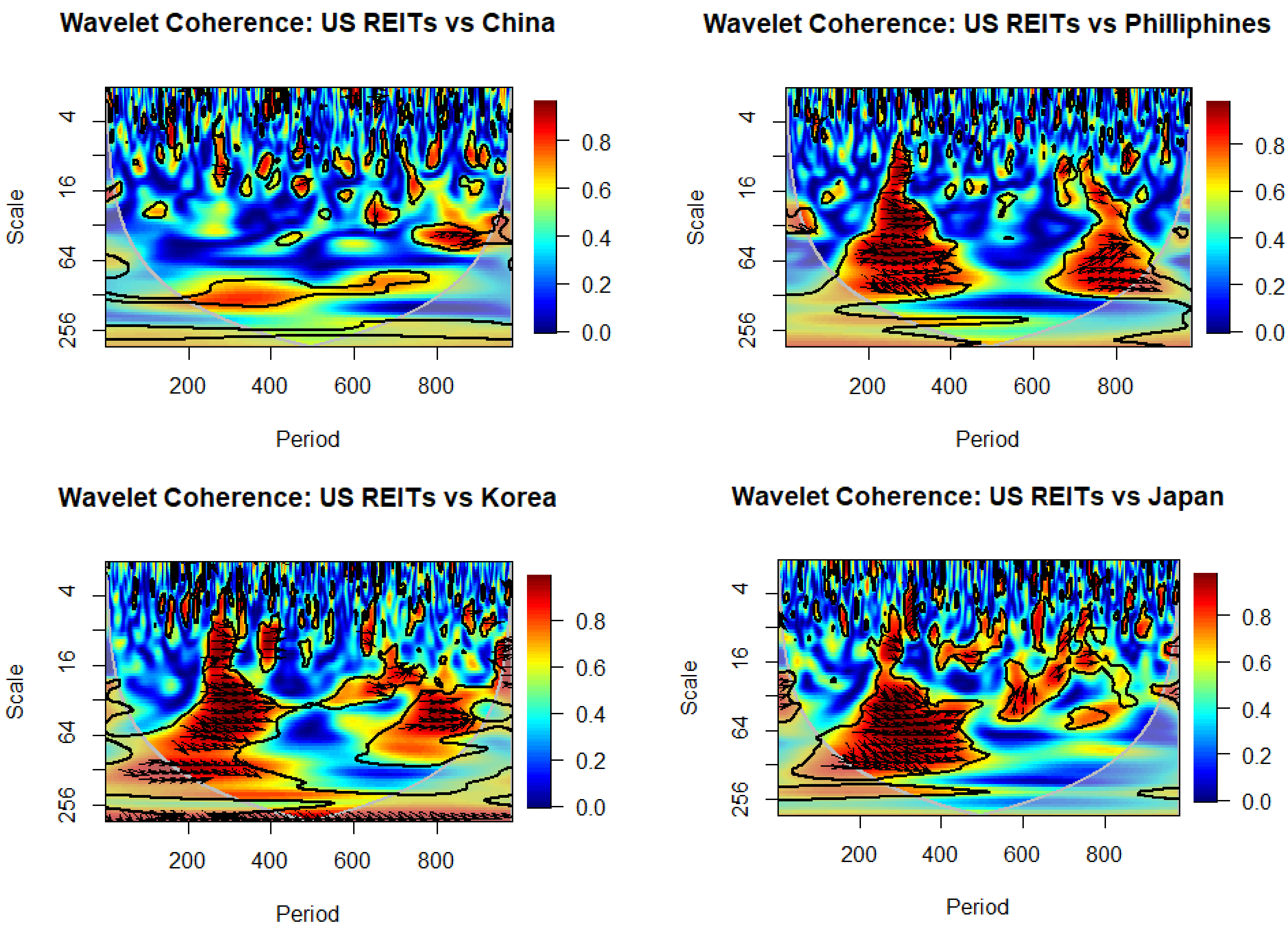

Figure 3: Continuous wavelet transform - US REITs and 4 other Asian stock indices.

During the mentioned time frames and scales, all indices exhibit notably high correlations with US REITs. However, apart from these specific periods indicating similar or distinct correlations with US REIT returns, there are no other instances demonstrating moderate to high correlations with US REITs between the 400th and 800th day at holding periods of 16-128 days. Notably, during this period, China depicts the most prevalent, blue-coloured regions compared to other indices. This suggests that US REITs might offer improved diversification opportunities for China stock holding investors.

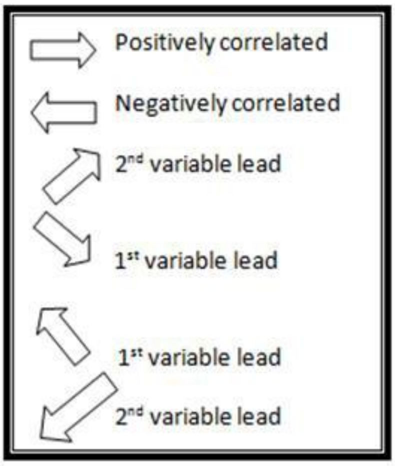

Figure 4: Lead-lag arrow rubric

3.3 Robustness and Validation of Results – MODWT

The findings of Multivariate Generalized Autoregressive Conditional Heteroskedasticity-Dynamic Conditional Correlation (MGARCH-DCC) and Continuous Wavelet Transform (CWT) are validated and robustly presented using the Maximum Overlap Discrete Wavelet Transform (MODWT) technique. The MODWT results will be presented in terms of the time scales for the returns, with seven scales (2-4 days, 4-8 days, 8-16 days, 16-32 days, 32-64 days, 64-128 days, and 128-256 days) extending the scaling into this study. Using the generated MODWT returns series as a robustness test for the results obtained in CWT, the correlations between the US REITs index returns and the four-stock index returns of China, Philippines, Korea, and Japan used in this study are examined. The results are displayed in Table 4 below.

Table 4: Wavelet correlations of US REITs index returns with returns of the 4 indices used in this study-MODWT transformations.

MODWT Scaling	**CHN**	**PLI**	**KOR**	**JAP**
2-4 days	0.13562	0.06078	0.07741	0.07551
4-8 days	0.12313	0.26839	0.43005	0.37327
8-16days	0.23945	0.52096	0.64075	0.58199
16-32 days	0.27620	0.59083	0.65893	0.53217
32-64 days	0.19815	0.74632	0.77757	0.67361
64-128 days	0.29943	0.78250	0.76165	0.70204
128-256 days	0.79785	0.63543	0.79064	0.67218

Throughout various holding periods, it is observed that KOR consistently displays the highest correlations, with the exceptions being the 64-128 days and 128-256 days intervals. In contrast, CHN consistently exhibits the lowest correlations across all holding periods, but exceptionally shows the highest correlation for the 128-256 days period, signifying a noteworthy divergence from its usual pattern. PLI and JAP demonstrate moderate to high correlations across different holding periods, with JAP displaying relatively stable correlation values. Notably, PLI exhibits a substantial increase in correlation from shorter to longer holding periods, displaying a notable upward trend as the time horizon extends. These observations emphasize the varying degrees of correlation between the US REITs index returns and the returns of the other indices, highlighting potential diversification opportunities and underlying changes in interdependencies across different time scales.

4.0 Conclusion

This comprehensive study examined the dynamics between United States Real Estate Investment Trusts (REITs) and Asian stock indices spanning from 2018 to 2023. Leveraging sophisticated econometric tools such as the multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and Wavelet Transform analyses, the research aimed to discern the potential diversification benefits for investors holding Asian stocks by incorporating US REITs into their portfolios.

The findings yielded insightful observations regarding the interconnectedness and diversification potential between US REITs and Asian stock indices. The multivariate GARCH analysis unveiled nuanced volatility dynamics and conditional correlations across different time horizons. Notably, it was observed that US REITs displayed varying volatility persistence akin to several Asian stock indices, suggesting a similarity in their risk characteristics during the specified period.

Furthermore, the Wavelet Transform analyses, including the Continuous Wavelet Transform (CWT) and Maximum Overlap Discrete Wavelet Transform (MODWT), provided deeper insights into the time-varying correlations and frequency domain behaviours between US REITs and Asian stocks. These analyses highlighted significant co-movements during specific time frames, emphasizing instances of high correlations and noteworthy divergence in correlation patterns across various holding periods.

The study's robust methodologies revealed that while US REITs exhibited higher inherent volatility compared to individual Asian stock indices, their movements were relatively less strongly correlated. This indicates potential diversification opportunities for investors holding Asian stocks, as the inclusion of US REITs in portfolios might offer a degree of independence from the movements of Asian stock indices, especially during specific time frames.

The investigation underscored the importance of understanding the intricate relationships and evolving dynamics between US REITs and Asian stock markets. The insights gleaned from this study are instrumental for investors seeking optimized portfolio allocations, risk management strategies, and enhanced diversification in an increasingly interconnected global financial landscape.

In conclusion, the empirical evidence provided valuable implications for market participants, highlighting the potential benefits of integrating US REITs into portfolios containing Asian stocks. The study's findings offer critical guidance for investors aiming to capitalize on diversification advantages and manage risk effectively in dynamic financial markets.

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