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Financial Asset Returns and Volatility Spillovers Across Developed Markets: Evidence From The DCC-GARCH Approach

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Abstract This paper investigates the volatility spillovers between exchange rates and stock returns across three major developed economies: the United States (US), the Euro area (EA), and the United Kingdom (UK). Using daily data from January 1, 2010, to December 31, 2019, this study employs the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) framework to capture time-varying conditional correlations and inter-market volatility spillovers across financial asset classes. The analysis further computes optimal hedge ratios and portfolio weights to support risk-minimising investment strategies across asset return pairs within each market. The results reveal that volatility spillovers are not significant between foreign exchange markets; however, they are evident across stock markets. Moreover, dynamic correlations among stock markets are consistently positive, whereas correlations in foreign exchange markets are negative over time. Dynamic hedge ratio estimates indicate that short positions are only feasible in the currency markets. Lastly, the portfolio optimisation analysis reveals that, for a $1 portfolio of exchange rate (stock) returns, the US (UK) asset should dominate the portfolio. These findings offer valuable insights for both academics and practitioners, particularly international investors seeking to understand cross-market volatility dynamics among key global financial centres.

Keywords Volatility spillovers · time-varying conditional correlations · optimal portfolio weights and hedge ratios · DCC-GARCH

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Financial Asset Returns and Volatility Spillovers Across Developed Markets: Evidence From The DCC-GARCH Approach

Analysing the correlation between financial markets both within and across economies is essential, as those correlations provide valuable insights for portfolio diversification and investment strategies (Warshaw, 2020). Furthermore, the strength and direction of correlations between asset prices help illuminate the degree of financial market synchronisation through volatility spillovers (Kang et al., 2019). Exploring volatility spillover effects across regions also deepens our understanding of global financial interconnectedness (Su, 2021). A growing body of literature investigates spillover effects between developed and emerging markets, or among emerging markets themselves; however, empirical research on the spillover dynamics of asset returns across developed economies remains relatively limited. Moreover, there is a notable gap in the literature concerning the construction of hedge ratios and optimal portfolio weights for these assets using conditional volatility measures. This paper addresses these gaps by analysing volatility spillovers and estimating risk-minimising hedge ratios and portfolio weights across key developed markets using a DCC-GARCH framework. In doing so, the paper presents notable implications regarding the volatility spillovers of asset returns between peer financial markets across major financial centres, offering evidence on which market and economy may play a dominant role in this transmission. Moreover, such analysis provides insight into which developed market assets should serve as portfolio anchors from the perspective of international investors.

Due to the interconnection between financial markets, asset price movements in one market may affect information flow[1] and, hence, the response of the financial market(s) in another economy (Ross, 1989; Engle et al., 1990). Such a mechanism yields volatility spillovers (Zhong and Liu, 2021). Therefore, information asymmetry in international financial markets may determine both the pattern and the magnitude of spillovers (Kodres and Pritsker, 2002). Consequently, news or shocks originating in one economy may be transmitted to others through spillover channels (Hou and Li, 2016). These cross-border spillovers have significant implications for domestic monetary and fiscal policy, as they can affect financial uncertainty, risk perceptions, liquidity conditions, asset allocation, and pricing within the home economy. More specifically, spillovers between financial markets exert a considerable influence on the composition and performance of international investment portfolios (Yadav et al., 2023).

This paper aims to investigate the inter-regional volatility spillover effects of exchange rate and stock market returns separately across three major financial centres: the United States (US), the Euro area (EA), and the United Kingdom (UK). The empirical analysis is significant for at least two reasons. First, analysing volatility spillovers in asset returns offers valuable insights into the evolving international roles of national currencies and equity markets within these key economies. Second, the study facilitates the estimation of optimal portfolio weights and hedge ratios for various asset return pairs in each market, providing practical guidance for international investors aiming to construct well-diversified and risk-sensitive portfolios.

This research addresses the following key questions: How do volatility spillovers in exchange rate and stock market returns within one advanced economy influence asset returns in the peer financial markets

[1] In the global economy, where the integration of financial markets is deepening, it should be kept in mind that what is happening at home may influence abroad and vice versa. Recent significant examples are the 2007-2009 global financial crisis in the US and the European debt crisis, which erupted in the wake of the crisis. Such events significantly influence the information flow, which implies global spillovers. Thus, uncovering spillovers enhances our understanding of information flow across economies.

of other advanced economies? What are the optimal portfolio weights and risk-minimising hedge ratios for portfolios constructed from the exchange rate and stock market returns?

To address these questions, this study employs the DCC-GARCH model as its empirical framework. Specifically, the model is estimated using daily data from January 1, 2010, to December 31, 2019, to analyse volatility spillover effects between the foreign exchange and stock markets across the US, EA, and UK. Although the sample period excludes the global financial crisis and the COVID-19 pandemic, this does not imply the absence of volatility during the selected timeframe. On the contrary, the period still captures substantial market fluctuations, providing a robust basis for assessing volatility transmission and portfolio optimisation.

This study yields four key findings. First, there is no statistically significant evidence of volatility spillovers between the foreign exchange markets. In contrast, stock markets across developed economies exhibit significant volatility spillover effects, indicating stronger interdependence within equity markets. Second, time-varying conditional correlations among foreign exchange markets are generally negative, whereas correlations among stock markets tend to be positive. Third, based on the estimated hedge ratios, long positions are advisable in stock markets, whereas short positions are more appropriate in foreign exchange markets. Fourth, in portfolios composed of exchange rate returns, US assets hold the dominant weight, whereas in portfolios composed of stock returns, UK assets are more prominent. These results underscore the differentiated roles of national financial assets in shaping international portfolio strategies. Overall, the findings highlight the prominent role of the US dollar and UK stock market performance as significant contributors to global financial conditions. This challenge the traditional view that US financial factors are the only drivers, indicating instead a more nuanced landscape in which multiple developed markets exert influence on international financial dynamics.

We assess the inter-regional volatility spillover effects of exchange rate and stock market returns across major financial centres including the US, the EA, and the UK. By examining these two asset classes separately, the analysis sheds light on the evolving international roles of key currencies and equity markets. In addition, the study contributes to the literature by computing time-varying hedge ratios and optimal portfolio weights, offering practical insights for international investors seeking to manage risk and diversify portfolios across developed economies.

The remainder of this study is organised as follows. Section 2 reviews the relevant literature and outlines the research hypothesis. Section 3 describes the estimation methodology. Section 4 presents the data, variables, and sample. Section 5 reports the empirical findings, and Section 6 concludes the paper.

Literature and Hypothesis

The empirical literature provides rich evidence of the volatility spillover effects of asset returns in the foreign exchange and stock markets.[2] Some studies have investigated the existence of spillover effects among different financial markets within a single country (Zhao, 2010; Sikhosana and Aye, 2018; Malik, 2021). In contrast, other studies have focused on the volatility spillovers of asset returns within the same financial market across multiple countries (Moon and Yu, 2010; Hou and Li, 2016; Jain and Sehgal, 2019; Horpestad et al., 2019; Zhong and Liu, 2021; Su, 2021).

To illustrate the nature of intra-country financial market spillovers, for example, Zhao (2010) investigated the volatility spillovers between the foreign exchange and stock markets in China using monthly data

[2]The use of GARCH to model volatility spillovers is not limited to foreign exchange rates and stock markets only. Several studies have also investigated the volatility transmission of assets in other financial markets, including cryptocurrency (Yousaf and Ali, 2020), energy (Sadorsky, 2012; Efimova and Serletis, 2014; Chen et al., 2020; Mensi et al., 2021), futures (Hou and Li, 2016; Buyukkara et al., 2022), credit default swap (Wang and Moore, 2012), and bonds (Tsukada et al., 2017).

from January 1991 to June 2009. The author employed the BEKK-GARCH model to examine the dynamic relationship between the RMB exchange rate and the Shanghai Composite Stock Price Index. The findings indicated significant volatility spillovers from the stock market to the foreign exchange market, highlighting the influence of domestic equity market fluctuations on currency movements. Sikhosana and Aye (2018) examined the volatility spillovers between the stock market and the foreign exchange market in South Africa using monthly data from January 1996 to April 2016. They assessed the relationship between the JSE All Share Index and the real Rand/US dollar exchange rate, employing the GARCH models to capture potential asymmetries. The findings revealed bi-variate asymmetric volatility spillovers between the two markets, indicating that shocks in one market can significantly influence the volatility dynamics of the other. Malik (2021) examined the volatility spillovers between exchange rate and stock market returns in the US. The author found a significant volatility spillover effect from the US stock market to the US currency when volatility shifts were ignored.

Regarding the existence of volatility spillovers between peer financial markets across different countries, Moon and Yu (2010) analysed volatility spillover effects between the US and China using daily data from January 5, 1999, to June 12, 2007. Their study focused on the S&P 500 and the SSE Composite Index, following the GARCH framework to capture the dynamics of return volatility. The results revealed both symmetric and asymmetric volatility spillovers from the US to China. However, following December 2, 2005, only symmetric spillover effects were observed from China to the US, showing a shift in the directional nature of volatility transmission between the two markets. Jain and Sehgal (2019) examined volatility spillovers across major developed economies by analysing daily stock index data from January 1, 2003, to June 30, 2014. They employed the stock indices of the G-7 countries along with Australia and applied the Asymmetric Dynamic Conditional Correlation–Exponential GARCH (ADCC-EGARCH) model to capture the time-varying and asymmetric volatility dynamics. They provided mixed evidence regarding the presence and direction of volatility spillovers among these markets, highlighting the complexity and heterogeneity of cross-country financial linkages. Horpestad et al. (2019) investigated volatility dynamics across international equity markets using daily data from January 3, 2000, to June 22, 2018. They covered stock market indices from 18 countries and employed the EGARCH model to account for potential asymmetries in volatility. The results showed that equity markets exhibit asymmetric volatility effects, with these effects being particularly pronounced in the US and European stock indices, underscoring the dominant influence of these markets in global volatility transmission. Zhong and Liu (2021) explored the dynamic volatility relationships between China and five Southeast Asian stock markets using daily data from January 1, 1994, to August 30, 2019. They used stock indices including the FTSE Straits Times Index (SSPI), Thailand SET Index (TSPI), Jakarta Composite Index (ISPI), FTSE Bursa Malaysia Composite Index (MSPI), and the Manila Composite Index (PSPI). Using the BEKK-GARCH model and comparing it with alternative specifications, the authors found that the DCC-GARCH model provided the best fit for the data. Their results showed a consistently positive dynamic conditional correlation between China and the five Southeast Asian markets, highlighting the region's increasing financial integration with China. Su (2021) examined the magnitude and determinants of volatility spillovers in the global foreign exchange (FX) market using tick-level high-frequency data. The sample period covered January 1, 1999, to December 31, 2013, for AUD/USD, GBP/USD, and USD/JPY, and began on January 1, 2000, for EUR/USD. The study used realised volatility measures along with Heterogeneous Autoregressive (HAR) models to assess the dynamics of volatility transmission. The results provided clear evidence of both meteor shower effects (i.e., inter-regional volatility spillovers) and heat wave effects (i.e., intra-regional spillovers). In addition, conditional volatility persistence emerged as the dominant channel through which evolving market conditions influence future volatility and its cross-market transmission.

In examining volatility spillovers, the literature has commonly employed multivariate GARCH models as the standard methodological framework. Several studies have estimated models belonging to the GARCH family to illustrate inter- or intra-volatility spillovers (GJR-GARCH: Moon and Yu, 2010; DCC-GARCH: Celik, 2012; BEKK-, Diagonal-, CCC-, DCC-GARCH: Sadorsky, 2012; BEKK-, DCC-GARCH: Efimova and Serletis, 2014; Asymmetric DCC-GARCH: Hou and Li, 2016; GJR-, E-GARCH: Sikhosana and Aye, 2018; C-GARCH: Morales-Zumaquero and Sosvilla-Rivero, 2018; Asymmetric DCC-, BEKK-GARCH: Jain and Sehgal, 2019; GJR-, E-GARCH: Horpestad et al., 2019; Asymmetric BEKK-, DCC-GARCH: Chen et al., 2020; BEKK-, Diagonal-GARCH: Zhong and Liu, 2021).[3]

Building on the preceding discussion and the brief review of the literature, this paper proposes the following hypothesis: financial markets across developed economies exhibit intra-regional volatility spillover effects. To test this hypothesis, the study adopts the DCC-GARCH approach, incorporating daily asset prices from major financial markets.

Methodology

This study employs a multivariate GARCH framework to estimate time-varying conditional correlations and to examine volatility spillover effects in a disaggregated manner across financial markets. Specifically, it analyzes the spillover dynamics of exchange rate and stock market returns among three major developed economies: the US, the EA, and the UK. In addition, the study computes optimal portfolio weights and risk-minimising hedge ratios for all asset pairs within each financial market, offering practical insights for portfolio allocation and risk management.

DCC-GARCH

This study employs the VARMA specification of the DCC model proposed by Engle (2002) to examine the presence of volatility spillovers and time-varying correlations in daily asset returns across developed economies over the period from January 1, 2010, to December 31, 2019. The DCC-GARCH framework is particularly well-suited for this analysis because it enables the modelling of dynamic conditional correlations that evolve with market volatility. This feature allows for the identification of changing investor behaviour in response to market shocks. Additionally, the model effectively addresses heteroscedasticity in the financial time series and provides more accurate estimates of conditional variances and covariances. The algorithm of the DCC-GARCH model estimation has two main steps. The first step involves estimating the conditional volatility of each return series using the GARCH model. The second step includes generalising the constant correlation estimator by Bollerslev (1990) to achieve dynamic features in the correlations, which are time-varying conditional correlations (Engle, 2002; Capiello et al., 2006; Abdul Aziz et al., 2019; Gabauer, 2020; Zhang et al., 2022).

The multivariate GARCH model can be written as follows:

$$\mathbf{r}_t = \boldsymbol{\mu}_t + \varepsilon_t, \varepsilon_t | \ \boldsymbol{\Omega}_{t-1} \sim N(\mathbf{0}, \mathbf{H}_t),$$

where $\mathbf{r}_t$ is an $N \times 1$ dimensional vector of returns of N assets at time t, $\boldsymbol{\mu}_t$ is an $N \times 1$ dimensional vector of the conditional mean, and ε_t is the residuals of the process that follows a conditionally multivariate normal distribution with mean $\mathbf{0}$ and time-varying conditional covariance matrix $\mathbf{H}_t$ given $\boldsymbol{\Omega}_{t-1}$ information set up to $t-1$. $\mathbf{H}_t$ is a positive definite matrix whose dimensions are $N \times N$.

Residuals can be modelled as follows:

$$\varepsilon_t = \mathbf{H}_t^{1/2} \boldsymbol{\xi}_t, \boldsymbol{\xi}_t \sim N(\mathbf{0}, \mathbf{I})$$

[3] Baba-Engle-Kraft-Kroner (BEKK); Glosten-Jagannathan-Runkle (GJR); Dynamic Conditional Correlation (DCC); Exponential GARCH (E-GARCH); Component GARCH (C-GARCH).

where $\mathbf{H}_t^{\frac{1}{2}}$ is the Cholesky factorisation of $\mathbf{H}_t$. ξ_t is an $N \times 1$ dimensional vector of standardised residuals with mean 0 and identity variance matrix, $\mathbf{I}$. In the DCC models, $\mathbf{H}_t$, time-varying conditional covariance matrix, can be decomposed as follows:

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t$$

where $\mathbf{D}_t$ is an $N \times N$ diagonal matrix of the conditional standard deviations for the return series, obtained from estimating a univariate GARCH model with $h_{ii,t}^{\frac{1}{2}}$ on the i^{th} diagonal, $i = 1, 2, 3$.

$$\mathbf{D}_t = diag\left(h_{11,t}^{1/2}, h_{22,t}^{1/2}, h_{33,t}^{1/2}\right)$$

This completes the first step.

$\mathbf{R}_t$ represents a symmetric time-varying conditional correlation matrix whose dimensions are $N \times N$. The matrix $\mathbf{R}_t$ can be decomposed as follows:

$$\boldsymbol{R}_t = \boldsymbol{Q}_t^{*-1} \boldsymbol{Q}_t \boldsymbol{Q}_t^{*-1}$$

$$\mathbf{Q}_t = (1 - \theta_1 - \theta_2)\overline{\mathbf{Q}} + \theta_1 \xi_{t-1} \xi_{t-1}' + \theta_2 \mathbf{Q}_{t-1}$$

where $\mathbf{Q}_t^* = [q_{ii,t}^*] = q_{ii,t}^{\frac{1}{2}}$ is a diagonal matrix with the square root of the i^{th} element of $\mathbf{Q}_t$ on its i^{th} diagonal position, $i = 1, 2, 3$.

$\mathbf{R}_t$ can now be written as follows:

$$\mathbf{R}_t = (diag(\mathbf{Q}_t))^{-1/2} \mathbf{Q}_t (diag(\mathbf{Q}_t))^{-1/2}$$

$$\mathbf{R}_t = (diag(q_{11t}, q_{22t}, q_{33t}))^{-1/2} \mathbf{Q}_t (diag(q_{11t}, q_{22t}, q_{33t}))^{-1/2}$$

$\mathbf{Q_t}$ and $\overline{\mathbf{Q}} = Cov[\xi\xi'] = E[\xi\xi']$ are $N \times N$ dimensional conditional and unconditional covariance matrices of standardised residuals, ξ_t, respectively. Both matrices are positive definite. The parameters θ_1 and θ_2 are non-negative parameters, and $\theta_1 + \theta_2 < 1$ to ensure stationarity and positive definiteness of $\mathbf{Q_t}$.

The conditional correlation estimator at time t is then,

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$$

This completes the second step.

This study estimates the DCC-GARCH model parameters using the Quasi-Maximum Likelihood Estimation (QMLE) with the optimisation algorithm by Broyden-Fletcher-Goldfarb-Shanno (BFGS).

Optimal Hedge Ratios and Portfolio Weights

The presence of volatility in financial markets can have adverse effects on investment performance, underscoring the importance of effective risk management strategies. In this context, estimating risk-minimising optimal hedge ratios for portfolios comprising various asset pairs within each financial market becomes essential. Such estimates provide valuable guidance for investors seeking to protect their portfolios against unexpected market fluctuations (Yousaf and Ali, 2020; Buyukkara et al., 2022).

After estimating the conditional volatility from the DCC model, we can construct the optimal dynamic hedge ratios for different pairs of assets following Kroner and Sultan (1993).

$$\beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}}$$

where $\beta_{ij,t}$ refers to the optimal hedge ratio, implying that a long position in asset i can be hedged with a long position in asset j.

Optimal portfolios can also be calculated through the estimates of the DCC-GARCH model. In line with the relevant literature, this paper also presents optimal portfolio weights for the asset pairs in each financial market. Following Kroner and Ng (1998), the optimal portfolio weights are calculated as follows.

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}$$

$$\begin{cases} 0\, if\ \ w_{ij,t} < 0 \\ w_{ij,t}\, if\, 0 \leq w_{ij,t} \leq 1 \\ 1\, if\, w_{ij,t} > 1 \end{cases}$$

where $w_{ij,t}$ refers to the weight of the asset i in a $1 dollar portfolio of asset i and j at time t. This implies $1 - w_{ij,t}$ is the weight of asset j in the same portfolio. $h_{ij,t}$ is the conditional covariance between asset i and j at time t. $h_{ii,t}$ and $h_{jj,t}$ are the conditional variance of asset i and j, respectively.

Data

This study investigates volatility spillovers in the exchange rate and stock markets of developed economies, focusing on three major financial centres: the US, the EA, and the UK. To proxy for exchange rate dynamics, the analysis employs the daily trade-weighted JP Morgan Real Effective Exchange Rate (hereafter referred to as REER, 2010=100) index. For the stock market component, this study utilizes the daily closing prices of the NASDAQ 100 (US), EUROSTOXX 50 (EA), and FTSE 100 (UK) indices (hereafter referred to as STOCK). All data are sourced from Refinitiv. The sample period spans from January 1, 2010, to December 31, 2019, deliberately excluding the global financial crisis and COVID-19 pandemic periods to ensure that the results are not unduly influenced by extreme market conditions. This research applies logarithmic transformation on each time series to achieve the daily returns of each asset. Calculating continuously compounded daily returns relies on 100*$\ln\left(\frac{P_t}{P_{t-1}}\right)$, where P_t is the price level at day t.

Figure A 1 (2) depicts the time series of the daily exchange rate (stock) index with their squared daily returns in each developed economy. Time series graphs of squared daily returns of exchange rates and stocks suggest that the foreign exchange and stock markets in each region experienced volatility clustering during bad states of the economy, such as the global financial crisis in the US, the sovereign debt crisis in Europe, and Brexit.

Table 1 presents the descriptive statistics for the daily returns of exchange (Panel A) and stock (Panel B) in the US, the EA, and the UK. Summary statistics provide information about the distribution of each time series.

In terms of the REER, the mean daily returns are positive for both the US and the UK, but negative for the EA. The UK exhibited the highest standard deviation and excess kurtosis, indicating greater volatility and a higher likelihood of extreme return values in its foreign exchange market. In contrast, the REER series for the US and EA display relatively lower kurtosis. The Jarque-Bera test statistics confirm that none of the return series follow a normal distribution. The skewness of the US daily exchange rate returns is positive, implying a long right tail and a higher probability of large positive returns. Conversely, the negatively skewed distributions for the EA and UK show a greater likelihood of extreme negative returns in those markets.

Regarding the descriptive statistics of daily stock returns, the mean returns for all stock markets are higher than that of exchange rate returns. Among all, the stock market in the US has higher returns. Over the sample horizon, the daily returns of the stock market in the EA have the highest volatility. We observe a negatively skewed stock market return distribution for all developed economies. The distribution of daily stock returns in the UK is platykurtic, indicating a flatter shape, whereas the distributions in the US and EA are leptokurtic, showing heavier tails. Among them, the EA exhibits the most pronounced peak.

Table 1

Descriptive Statistics

Statistics	**Panel A.** REER			**Panel B.** STOCK		
	US	**EA**	**UK**	**US**	**EA**	**UK**
Mean	0.0045	−0.0065	0.0001	0.0593	0.0090	0.0127
Std Dev	0.2880	0.3388	0.4437	1.0731	1.2211	0.9156
Kurtosis	3.1177	2.7263	24.0011	3.3082	4.8455	2.7057
Skewness	0.1647	−0.0239	−1.4651	−0.3913	−0.1637	−0.1945
Minimum	−1.9493	−2.1806	−6.9106	−6.3053	−9.0111	−4.7795
Maximum	1.6735	2.2637	2.2328	5.9780	9.8466	5.0322
Jarque-Bera	1067.6***	807.6***	63506.1***	1255.3***	2562.0***	811.67***
Obs	2607	2607	2607	2607	2607	2607

***, **, and * indicate the significance level at 1%, 5%, and 10%, respectively.

Table 2 presents the correlation coefficients and covariances between the daily returns of both assets across economies. Correlations between daily returns of exchange rates (Panel A) are negative, whereas those for daily stock returns (Panel B) are positive. The pairwise correlations of daily exchange rate returns are very weak. The correlation coefficient between daily stock returns between the UK and EA is strong. Table 2 also shows the covariances of daily returns of exchange rates (Panel A) and stock markets (Panel B) between developed economies. According to the values of the covariances, the exchange rate returns in the US and the other two regions vary in opposite directions. However, daily stock market returns in all economies move in the same direction, as shown by the positive covariances.

Table 2

Correlation Coefficients and Covariances

	Panel A. REER			**Panel B.** STOCK		
	US	**EA**	**UK**	**US**	**EA**	**UK**
Correlation coefficients						
US	1			1		
EA	-0.48	1		0.55	1	
UK	-0.05	-0.22	1	0.52	0.85	1
Covariances						
US	0.083			1.151		
EA	-0.046	0.115		0.722	1.490	
UK	-0.006	-0.032	0.197	0.513	0.947	0.838

Empirical Evidence

Table 3 shows the DCC-GARCH estimates belonging to the mean and variance equations of REER (Panel A) and STOCK (Panel B). $m(i, j)$ refers to the mean spillover effects in the mean equation. In the variance equation, $\alpha(i, j)$ refers to the conditional ARCH effects, which measure short-term persistence. $\beta(i, j)$ refers to the conditional GARCH effects, which measure long-term persistence. For both models where this study employs the daily returns of two asset classes, coefficient $\alpha(1, 1)$ refers to the ARCH term in the US equation. Similarly, $\alpha(2, 2)$ refers to the ARCH term in the EA equation, and $\alpha(3, 3)$ refers to the ARCH term in the

UK equation. Similar identification applies to the GARCH terms $\beta(i, j)$. c refers to the constant terms. The variable order is US, EA, UK.

According to the estimates of the mean equation for the REER, $m(1, 1)$ is the only statistically significant coefficient at the 10% level. Past levels of volatility influence returns in the US exchange market. The estimated coefficient of the US REER in the EA REER equation, $m(2, 1)$, is positive and statistically significant. This finding implies a positive relationship between the EA exchange rate returns in the current period and the US exchange rate returns in the last period. In other words, the US REER in the last period affects the EA REER in the current period.

Regarding the estimated coefficients of the mean equation for the STOCK, $m(1, 1)$ and $m(3, 3)$ are found to be statistically significant. Additionally, the estimated coefficients of $m(1, 2)$, $m(2, 1)$, $m(2, 3)$, and $m(3, 1)$ are positive and statistically significant. These results show that the volatility of stock returns in the US has a significant mean spillover effect on the EA ($m(2, 1)$) and the UK ($m(3, 1)$) stock markets. Moreover, the volatility of stock returns in the EA significantly affects the US ($m(1, 2)$) stock market. Lastly, there is also a positive and statistically significant spillover effect from the UK stock market on EA ($m(2, 3)$) stock market.

Parameter estimates in the variance equation indicate volatility clustering for each asset return. For the REER, the estimated coefficients of the own ARCH and GARCH terms, $\alpha(i, i)$ and $\beta(i, i)$, in each exchange rate market are statistically significant, except for the α(3,3), and their sum is very close to one. This result proves the existence of volatility clustering in the exchange market of each developed economy. The estimated coefficients in the variance equation for STOCK reveal that volatility clustering also exists in the stock market of each economy.

For the variance equation of the REER, the estimates of both models demonstrate that the estimated coefficients of their conditional volatility effects were statistically significant. The only exception is $\alpha(3, 3)$ in the DCC-GARCH model, where the model considers the daily returns of the exchange rate. Moreover, own volatility long-term persistence is higher than the short-term. The REER model does not exhibit significant spillover effects; however, the STOCK model reveals notable volatility spillovers. We have evidence of statistically significant short-term volatility spillovers, whereas we do not observe statistically significant long-term spillover effects. The estimation results imply a bidirectional short-term spillover effect of stock returns between the US and the UK. The estimated coefficients ($\alpha(1, 3) = 0.083$ and $\alpha(3, 1) = 0.021$) show higher spillover effect from the UK to the US.

Moreover, we find statistically significant short-term volatility effects from the US to EA ($\alpha(2, 1) = 0.028$) and from the UK to EA ($\alpha(2, 3) = 0.096$). For both asset returns, the time-varying conditional correlations are mean reverting as they are statistically significant and positive, and their sum is less than one. For the REER (STOCK), the sum of the dynamic conditional correlation coefficients is around 0.98 (0.95).

Table 3

Estimates of the DCC-GARCH Models

Parameters	**Panel A.** REER			**Panel B.** STOCK		
	Coeff	**t-stat**	**p-values**	**Coeff**	**t-stat**	**p-values**
Mean Equation						
$m(1, 0)$	0.002	0.454	0.650	0.115	6.305	0.000
$m(1, 1)$	0.037	1.795	0.073	-0.051	-2.623	0.009
$m(1, 2)$	0.007	0.389	0.697	0.050	1.822	0.068
$m(1, 3)$	0.001	0.049	0.961	-0.034	-0.952	0.341
$m(2, 0)$	-0.007	-1.617	0.106	0.052	2.818	0.005

Parameters	Panel A. REER			Panel B. STOCK		
	Coeff	t-stat	p-values	Coeff	t-stat	p-values
$m(2,1)$	0.055	2.401	0.016	0.178	7.367	0.000
$m(2,2)$	0.032	1.345	0.179	-0.029	-0.883	0.377
$m(2,3)$	-0.001	-0.050	0.960	-0.110	-2.545	0.010
$m(3,0)$	0.003	0.467	0.641	0.039	2.690	0.007
$m(3,1)$	-0.028	-1.128	0.259	0.198	9.893	0.000
$m(3,2)$	-0.008	-0.350	0.727	-0.032	-1.298	0.194
$m(3,3)$	-0.019	-0.839	0.402	-0.085	-2.524	0.012
Variance Equation						
$c(1)$	0.000	0.432	0.666	0.077	4.021	0.000
$c(2)$	0.001	2.931	0.003	0.080	2.426	0.015
$c(3)$	0.002	1.146	0.252	0.050	1.956	0.050
$\alpha(1,1)$	0.032	3.678	0.000	0.102	5.880	0.000
$\alpha(1,2)$	0.002	0.456	0.648	0.006	0.399	0.690
$\alpha(1,3)$	-0.001	-0.366	0.714	0.083	2.805	0.005
$\alpha(2,1)$	0.002	0.287	0.774	0.028	2.336	0.019
$\alpha(2,2)$	0.032	4.449	0.000	0.046	2.556	0.011
$\alpha(2,3)$	0.000	0.343	0.732	0.096	2.803	0.005
$\alpha(3,1)$	0.010	0.762	0.446	0.021	2.762	0.006
$\alpha(3,2)$	-0.003	-0.469	0.639	0.012	1.061	0.289
$\alpha(3,3)$	0.051	1.566	0.117	0.070	3.490	0.000
$\beta(1,1)$	0.956	92.874	0.000	0.846	18.421	0.000
$\beta(1,2)$	0.003	0.360	0.719	0.010	0.236	0.813
$\beta(1,3)$	0.002	0.883	0.377	-0.129	-0.897	0.370
$\beta(2,1)$	-0.001	-0.053	0.958	-0.037	-1.032	0.302
$\beta(2,2)$	0.961	105.75	0.000	0.964	18.531	0.000
$\beta(2,3)$	-0.001	-0.963	0.336	-0.195	-1.050	0.294
$\beta(3,1)$	-0.003	-0.131	0.895	-0.024	-1.177	0.239
$\beta(3,2)$	0.001	0.118	0.906	0.005	0.178	0.859
$\beta(3,3)$	0.942	24.886	0.000	0.842	6.582	0.000
θ_1	0.025	3.225	0.001	0.035	3.413	0.001
θ_2	0.957	44.857	0.000	0.920	33.930	0.000

Table 4 reports the results of the Ljung-Box Q test, which tests the null hypothesis of no autocorrelation in the residuals for both asset classes. The Q-statistics, which follow a chi-square distribution with 20 degrees of freedom, are presented alongside their corresponding p-values. As all p-values exceeded the 0.05 significance level, the null hypothesis could not be rejected, indicating the absence of significant autocorrelation in the residuals. This result implies that none of the variables exhibit serial correlation, thereby supporting the appropriateness of the DCC-GARCH model for the empirical analysis.

Table 4
Diagnostic Tests for Standardised Residuals

Q Statistics	Panel A. REER			Panel B. STOCK		
	US	EA	UK	US	EA	UK
Q(20)r	13.41	8.54	16.36	23.84	22.6	15.51
p-values	0.85	0.98	0.69	0.24	0.3	0.74
$Q(20)r^2$	11.3	5.57	22.42	16.2	13.05	16.9
p-values	0.93	0.99	0.31	0.7	0.87	0.65

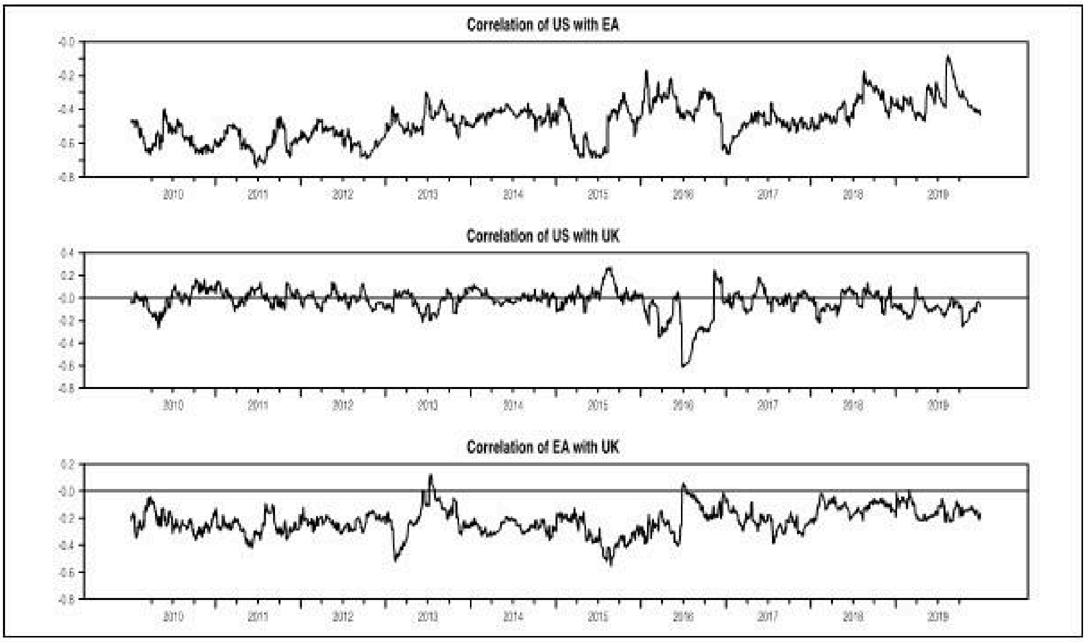
Time-varying Conditional Correlations from the DCC-GARCH Model

Figure 1 illustrates the time-varying conditional correlations between country pairs for each asset class. In the case of REER, the top row reveals that the correlation between US and EA exchange rate returns remains consistently negative throughout the sample period. A notably strong negative correlation, around 0.75, was observed following the US global financial crisis and the European sovereign debt crisis, although this relationship weakened from 2017 onward. The conditional correlation between the US and UK REERs was relatively weak and stable until the end of 2015. A pronounced negative shift is observed thereafter, likely reflecting the impact of the UK's Brexit vote in 2016. The bottom row depicts the correlation between the EA and UK exchange rate returns, which is generally weak and negative, with only brief and minor positive deviations observed around mid-2013 and mid-2016.

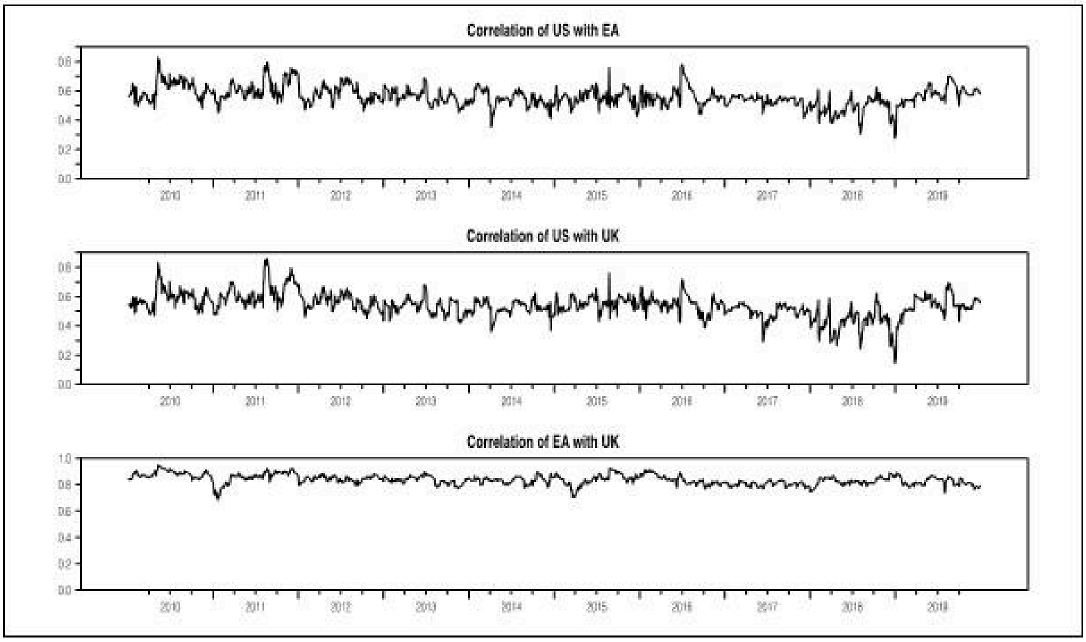
For STOCK, the time-varying conditional correlations across all developed economy pairs are consistently positive. In particular, the correlation between the EA and UK stock returns ranged between 0.8 and 0.9, indicating a strong co-movement. This strong relationship demonstrates that the time-varying correlations between US stock returns and those of the EA and UK follow similar patterns. Among these, the correlation between the US and EA appears stronger than that between the US and UK.

Figure 1

Dynamic Conditional Correlations



Panel A. REER



Panel B. STOCK

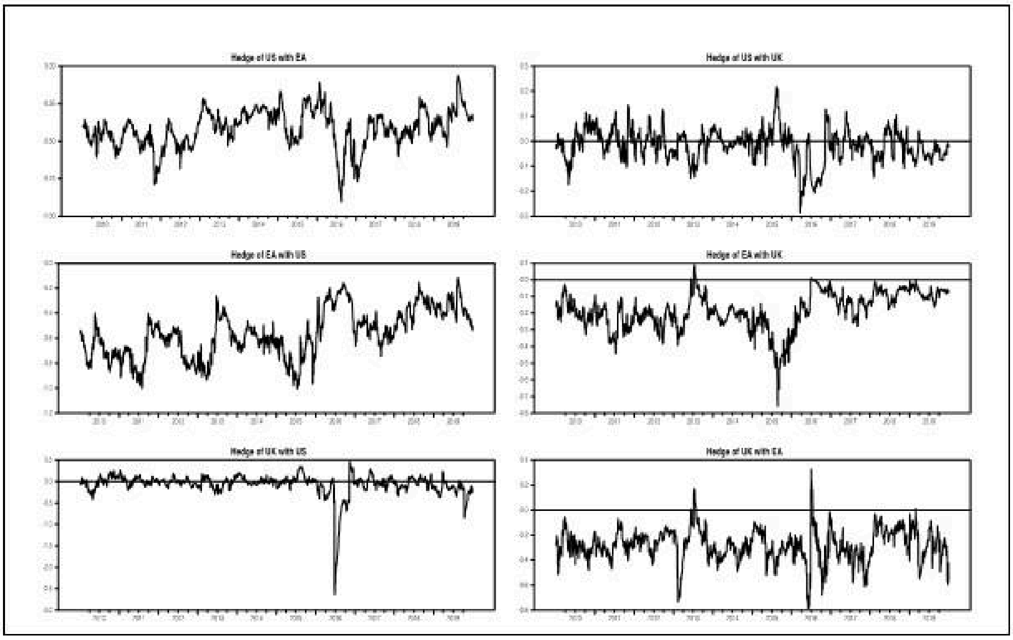
Optimal Hedge Ratios

Panels A and B of Figure 2 display the time-varying hedge ratios derived from the DCC-GARCH model for the REER and STOCK asset pairs, respectively. As the hedge ratios are estimated using a dynamic framework, they exhibit continuous variation over time. Table 5 provides the summary statistics of these hedge ratios for both asset classes. The results indicate that the mean hedge ratios for all REER pairs are negative, while those for the STOCK pairs are positive. This implies that investors aiming to minimise portfolio risk should consider short positions in the foreign exchange market and long positions in equity markets.

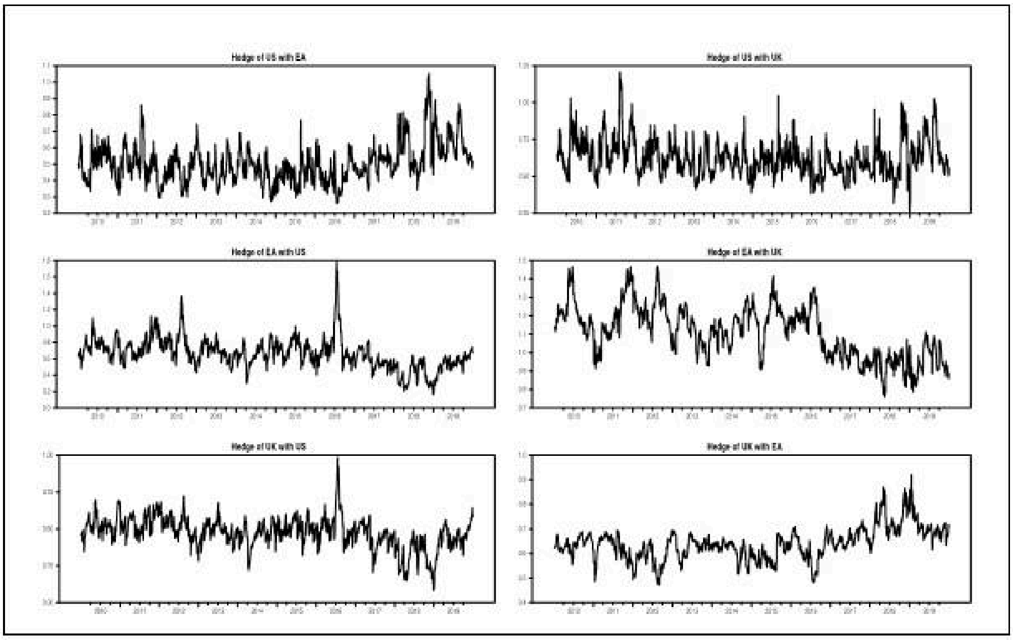
For STOCK, the average hedge ratio is positive across all asset pairs, reflecting strong and consistent co-movement in stock returns among developed markets. Specifically, the mean hedge ratio between US and EA equities is 0.50, while that between US and UK equities is 0.62. These values indicate that a $1 long position in US equities can be effectively hedged with a $0.50 short position in EA equities or a $0.62 short position in UK equities. However, due to the high positive correlation between the EA and UK stock markets, hedging one with the other may be less effective in reducing portfolio risk. Furthermore, the maximum hedge ratios for STOCK are either close to or exceed unity, underscoring the high degree of synchronisation in stock market movements across these major developed economies.

Figure 2

Time-varying Hedge Ratios for Asset Pairs



Panel A. REER



Panel B. STOCK

Table 5

Summary Statistics of Hedge Ratios

Panel A. REER	**Mean**	**St. Dev**	**Min**	**Max**	**Panel B.** STOCK	**Mean**	**St. Dev**	**Min**	**Max**
US/EA	−0.42	0.13	−0.91	−0.06	US/EA	0.5	0.12	0.26	1.05
US/UK	−0.02	0.07	−0.29	0.22	US/UK	0.62	0.12	0.26	1.21
EA/US	−0.57	0.19	−1.01	−0.11	EA/US	0.66	0.19	0.17	1.79
EA/UK	−0.18	0.11	−0.76	0.09	EA/UK	1.11	0.14	0.76	1.47
UK/US	−0.07	0.26	−2.65	0.48	UK/US	0.48	0.11	0.08	0.99
UK/EA	−0.28	0.13	−0.79	0.33	UK/EA	0.64	0.06	0.47	0.92

Optimal Portfolio Weights

Table 6 presents the summary statistics for the portfolio weights derived from the estimated DCC-GARCH model. In the case of REER, the results in Panel A indicate that for a $1 portfolio comprising US and EA assets, $0.55 should be allocated to the US and $0.45 to the EA; similarly, for a US/UK portfolio, $0.69 is allocated to the US and $0.31 to the UK. For the EA/UK pair, the average optimal weight is $0.61 in favour of the EA and $0.39 for the UK. These findings show that the US REER consistently dominates the exchange rate return portfolios. Turning to STOCK, Panel B shows that in a US/EA portfolio, $0.64 is optimally allocated to the US, while $0.36 goes to the EA. In contrast, for a US/UK portfolio, only $0.36 is allocated to the US, with $0.64 invested in the UK. Most notably, for the EA/UK pair, $0.96 of the $1 portfolio is allocated to UK equities. These results clearly indicate that UK stock market assets dominate equity portfolios, highlighting their strong relative performance and co-movement characteristics within developed markets.

Table 6

Summary Statistics of the Portfolio Weights

Panel A. REER	**Mean**	**St. Dev**	**Min**	**Max**	**Panel B.** STOCK	**Mean**	**St. Dev**	**Min**	**Max**
US/EA	0.55	0.08	0.26	0.74	US/EA	0.64	0.22	0.00	1.00
US/UK	0.69	0.10	0.40	0.93	US/UK	0.36	0.15	0.00	0.99
EA/UK	0.61	0.12	0.26	0.98	EA/UK	0.04	0.10	0.00	0.74

Conclusion

This paper individually investigates time-varying conditional correlations and asset return volatility spillovers in the foreign exchange rate and stock markets across developed economies, including the US, the EA, and the UK, using daily data between January 1, 2010, and December 31, 2019. Following the DCC-GARCH model estimation, this study also calculates optimal portfolio weights and risk minimising hedge ratios for the pairs of assets in each financial market between key financial centres.

The empirical investigation generates results in line with the relevant literature. We find evidence of a significant volatility spillover effect between stock market returns, whereas exchange rate returns show no significant spillover effects. This finding that volatility spillovers are not statistically significant between foreign exchange markets, yet are present across stock markets in developed economies, is partially consistent with prior research. Su (2021) identified inter-regional volatility spillovers (i.e., meteor shower effects) in the FX market but emphasized that these effects were conditional on underlying market states and may not persist uniformly across time. In this context, our results, which reveal no significant FX spillovers during the 2010–2019 period (a span that excludes major crisis episodes), align with Su (2021) argument regarding the state-dependent nature of FX volatility transmission. Conversely, the evidence of significant volatility spillovers across stock markets agrees with the findings of Moon and Yu (2010) and Horpestad et al. (2019).

Moon and Yu (2010) documented both symmetric and asymmetric spillovers between the US and China, particularly after 2005, while Horpestad et al. (2019) observed pronounced asymmetric volatility effects in global equity markets, especially in the US and European regions. Moreover, our study documents positive time-varying conditional correlations among stock markets and negative correlations within currency markets across developed economies. Regarding the correlations between stock markets, our finding aligns with Zhong and Liu (2021), who reported positive dynamic conditional correlations between China and Southeast Asian stock markets, supporting the broader evidence of positive co-movements in equity returns. By constructing the optimal hedge ratios for pairs of assets in each financial market, our findings show that taking a short position is possible only in the foreign exchange market. The findings suggest that when constructing separate portfolios based on exchange rate and stock market returns, international investors should assign greater weight to US assets in currency portfolios and to UK assets in equity portfolios. These empirical results underscore the dominant role of the US dollar in currency markets and the relative strength of the stock market performance in the UK.

As financial integration deepens in the global economy, interdependence among national markets has become increasingly evident. Asset price movements in one country can generate volatility that transmits financial markets in other economies, prompting renewed interest in how such volatilities propagate across borders. These spillover effects have important implications for both economic policy and financial decision-making. Analysing financial market behaviour across countries offers a useful approach for identifying and understanding these transmissions. In this context, monitoring global economic and financial developments becomes critical not only for making sound investment decisions but also for formulating effective domestic policies aimed at mitigating the adverse effects of external shocks. Given the potentially destabilising nature of financial market volatility, it is essential for investors to implement appropriate hedging strategies to shield their portfolios from negative spillovers.

The empirical investigation in this study aims to contribute to the literature by examining both the direction and magnitude of inter-regional volatility spillovers in asset returns across major developed financial centres. In doing so, the research also sheds light on the distinct roles that financial assets from each key economy play within separate portfolios of exchange rate and stock market returns. This analysis offers practical implications for international investors by informing them of optimal hedge ratio strategies and portfolio weight allocations, thereby enhancing risk management and diversification decisions in a global investment context.

A promising avenue for future research is to examine whether the dominant role of specific financial factors in key developed market economies is generalisable. One approach would be to analyse volatility spillover effects originating from various major developed markets to a common set of emerging market economies. Comparing these spillovers could reveal which developed markets exert a relatively stronger influence on specific emerging markets. A region-based perspective may also offer valuable insights, particularly by assessing the heterogeneity in the spillover intensity across different geographic blocs. Additionally, future studies could investigate how spillovers from developed to emerging markets evolve over different sub-periods—distinguishing between tranquil and crisis episodes. This line of inquiry is especially relevant, as emerging markets tend to exhibit heightened sensitivity to external shocks originating in developed economies. By examining volatility spillovers before and after major global events, researchers can provide more nuanced recommendations for portfolio diversification under varying market conditions. Ultimately, such findings would enable investors in emerging economies to adopt risk-minimising strategies tailored to each financial market and its exposure to global financial dynamics.

Peer Review Externally peer-reviewed.
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Appendix

Figure A 1

Time Series Related to Exchange Rates

Daily Prices of the Exchange Rates	Squared Daily Returns of Exchange Rates

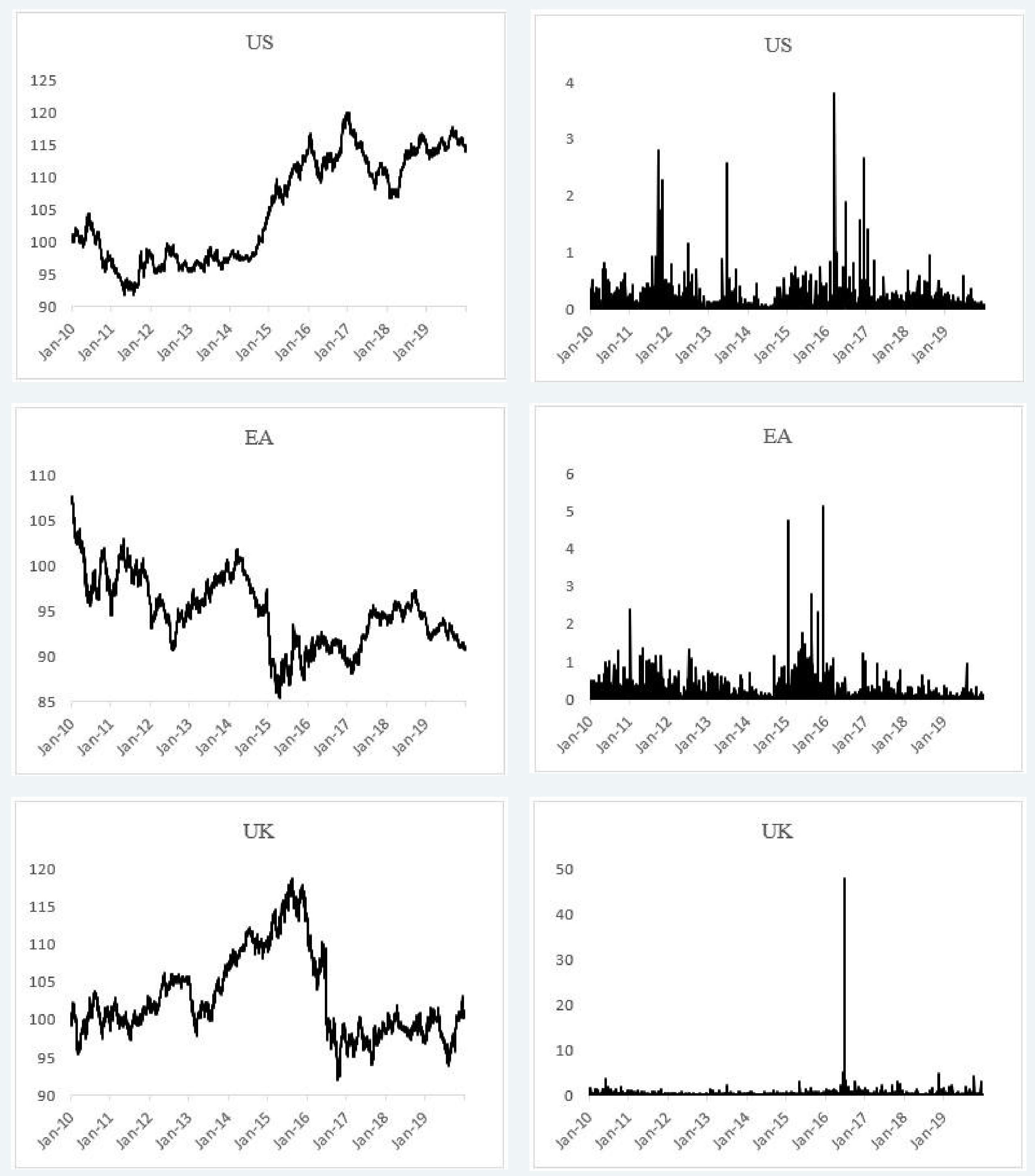

Figure A 2

Time Series Related to Stocks

Daily Prices of Stocks	Squared Daily Returns of Stocks