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Information linkages across countries around net zero announcements

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ABSTRACT

This study investigates the information linkages around net zero announcements across countries. Relying on rational expectation theory, this study employs the generalized method of moments (GMM) as well as the implied volatility approach to quantify volatility linkages between exchange-traded funds (ETFs) from nine countries and a global ETF (WLD). The GMM analysis reveals that volatility linkages among country ETFs and WLD range from 39.67 % to 71.43 %, while the implied volatility approach indicates that volatility linkages between markets range from 32.31 % to 65.36 %, indicating significant information spillover across countries. A time-varying dynamic analysis further shows that the US Government's net zero announcement increased volatility linkages across markets by 8.7 % to 58.05 %, signaling market approval of the US commitment to net zero targets. Multivariate analysis of the monthly correlation between country ETFs and WLD shows that the US plays a pivotal role. Although net zero announcements by the US, UK, and China individually impacted market correlations, the effect of China's announcement was insignificant when all announcements were considered in the model. Without US participation, efforts by other countries to achieve global net zero goals are unlikely to succeed.

1. Introduction

In the era of climate change, characterized by heated policy discussions on mitigation strategies, more than 140 countries in the world have set targets to achieve net zero by 2050. Countries responsible for 88 % of global emissions have made this commitment, among them major carbon polluters such as the US and UK. The UK was the first country to legislate its net zero target in 2019, while the US announced its net zero commitment on 21 April 2021. These announcements are likely to impact not only domestic markets but also markets internationally.

To verify this assumption, we draw on Tauchen and Pitts' (1983) rational expectation theory, according to which heterogeneous traders in the market react to the arrival of new information, revise their expectations about asset prices, and, as a result, cause a price change. We also draw on the model developed and Kodres and Pritsker (2002) that establishes a relationship between volatility correlations and information linkages.

We select ten exchange-traded funds (ETFs) traded on the US stock market, comprising nine country ETFs and one global ETF (WLD). Based on the availability of options market data, the study's timeframe is 2 January 2014 to 28 February 2023,[1] covering more than nine years and 2305 daily observations.

First, this study applies the generalized method of moments (GMM) approach proposed by Fleming et al. (1998) to estimate the volatility linkages of log information flows between ETF markets. The results indicate that there is a strong volatility linkage, ranging from 39.67 % to 71.43 %, between country ETFs and WLD, all significant at a 5 % level. We also apply the implied volatility approach developed by Wang (2009), in which the implied volatility of at-the-money (ATM) options are calculated as the average of the implied volatilities of the two nearest put and call options with the shortest time to maturity. To ensure that the model does not capture a spurious effect, we set up a Monte-Carlo simulation and estimate the cut-off R^2, which indicates that the model estimation is precise and the volatility linkages between country ETFs and WLD range from 32.31 % to 65.36 %, statistically significant at a 5 % level. Using the log series of daily implied volatilities and running spurious regression simulations between WLD and all other ETFs, we

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[1] 28 February 2023 is the last day that options data was available in Option Metrics. Options data for WLD was available from the start of 2014, hence we chose the start of 2014 for our study's time frame.

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found that the positive correlation captured between each pair of ETFs is statistically significant and is not captured due to the spurious regression. Given this result, we conclude that the co-movement between markets is statistically significant, and that the findings of this study are robust.

Having established a volatility linkage between markets, we next investigate the impact of the net zero announcements by the UK, the US, and China on the volatility linkages between country ETFs and WLD. The increase in the correlation between country ETFs and WLD ranges from 8.7 % to 58.05 %, all positive and statistically significant after the US net zero announcement, indicating that the correlation among markets strengthened after announcement. This positive correlation stems from the role of the US as the world's biggest economy (26.05 % of the global economy), and therefore its impact on the world economy and financial markets. The US is also the biggest per capita carbon emitter in the world and announcing its net zero commitment resulted in eliminating the uncertainty in its climate policy and strengthening the correlation between markets in the post announcement period. However, the correlation between ETF markets declined after the UK's net zero announcement. The decrease in rate of correlation ranges from −33.2 % to −10.39 %, showing that other markets did not anticipate an impact from the UK net zero announcement. The negative correlation can be explained by the small size of the UK economy in relation to the global economy, its limited role in the financial markets compared to the US, and its smaller share of global carbon emissions.

A multivariate analysis of the monthly correlation between country ETFs and WLD indicates that the US plays a pivotal role. Although net zero announcements by the US, UK, and China individually impacted market correlations, the effect of China's announcement was insignificant when all announcements were considered in the model. Without US participation, the efforts of other countries to achieve global net zero goals are unlikely to succeed.

This study contributes to the literature on information linkages by demonstrating that volatility linkages among country ETFs are strong due to information spillovers, and by quantifying the impact of net zero announcements on volatility linkages. Finding from the study confirm the expectation that the decision by the US to commit to net zero resulted in strengthened volatility linkages among ETFs. Additionally, the study addresses a gap in the literature concerning market interconnectedness in the context of achieving net zero and reducing carbon emissions.

By focusing on country ETFs traded on the US market, this study also contributes by estimating the information linkages among country ETFs, which have become popular financial instruments among active investors. The study extends the identification of the positive and strong information linkages among country ETFs by estimating the impact of the net zero announcements on volatility linkages. By quantifying the impact of the net zero announcement on the volatility linkages, the study finds that the decision by the US to commit to net zero strengthened volatility linkages among countries. The finding that the market reacted positively to the net zero announcement by the US, given its status as the world's largest economy and one of the biggest polluters globally, is also important for investors, seeking to manage their risk and diversify their portfolio.

The remainder of this study is organized as follows: a literature review is presented in Section 2, followed by the methodology in Section 3. We describe the data in Section 4 and the empirical results are presented in Section 5. Section 6 concludes.

2. Literature review

The growing need for effective risk management among investors operating across multiple markets has spurred a surge in research focused on understanding market volatility linkages. A seminal study in this area by Fleming et al. (1998) evaluated the volatility linkages between stock, bond, and money markets, employing bivariate GMM to show the presence of volatility linkages in raw returns in these three markets. Subsequently, Hassan and Malik (2007) explored the transmission of shocks and volatility across US sector indexes from 1992 to 2005, finding significant transmission of shocks and volatility among sectors. Their study highlighted the importance of cross-market hedging to gain positive returns.

Wang (2009) advanced this line of inquiry by leveraging the information content of option markets and estimating their volatility linkages by employing options market volatility data, after controlling for spurious correlation effects. To compare the results with the approach developed by Fleming et al. (1998), Wang (2009) examined the volatility linkages between equity, money, and bond markets and showed there was a strong and positive linkage between them. This approach was then further applied to various contexts, for instance, to estimate interest rate volatility and risk management (Markellos and Psychoyios, 2018), to investigate the information linkages among real estate markets in Australia (Wang and Croucher, 2021), to evaluate oil price uncertainty and risk return relations in oil importing and oil exporting countries (He et al., 2022), and finally to quantify volatility linkages between the real estate, equity, bond, and money markets in Australia (Wang et al., 2023).

To provide a broader understanding of how information travels in various markets and its effect in portfolio management, Khalfaoui et al. (2015) emphasized the need to capture multiscale features of mean and volatility spillovers between time series to optimize portfolio allocation. By incorporating both multivariate GARCH models and wavelet analysis, they offered a new approach to examining the volatility spillover between oil and stock market of G-7 countries. In addition to finding a strong correlation between the oil and stock markets, they concluded that West Texas Intermediate (WTI) is the leading oil market in G-7 countries. Amid growing concerns about climate change and the expansion of carbon markets globally, Tan et al. (2020) also examined the directional and dynamic connectedness in the carbon-energy-finance market, finding system-wide spillovers due to macro-economic factors. They highlight that the nature of information spillover changes over time, and that return connectedness is higher than volatility interdependence. Hanif et al. (2023) investigated the volatility spillover between oil price shocks and green stock markets, concluding that the lead-lag relationship between oil and green stocks are time-varying, with the highest effect captured in the mid to long-term analysis.

Focusing on research aimed at assessing the impact of specific events on market volatility variations, Hartmann et al. (2004) used the extremal dependence measure to analyze market linkages between bond, stock, and money markets of G-5 countries during crisis and found that volatility linkages between stocks are more pronounced than those for the bond and money markets. Other studies considered the impact of globalization on markets. Baele (2005), for instance, worked on western European equity markets to quantify the volatility spillovers from the aggregate European and US market to 13 local markets. He applied a regime-switching model and found that both the US and EU shock spillover intensity increased in the 1980s and 1990s due to increased trade integration and equity market development. Looking at Asian data, Dungey and Martin (2007) used a latent factor framework to evaluate market linkages across multiple asset classes across 19 Asian countries during periods of financial crisis. They found that the volatility linkages between markets were significant.

Further, Sadorsky (2014) applied a VARMA-AGARCH and DCC-AGARCH to model volatility spillover on stock prices and three main commodity prices, namely copper, oil, and wheat prices in emerging markets. His study shows that the correlation between markets is significant and that the volatility linkages between markets increased after the global financial crisis in 2008. The COVID-19 pandemic prompted numerous studies aimed at understanding the impact of global turbulence on markets and quantifying the volatility linkages between them. Diaz-Rainey et al. (2021) examined the impact of climate policy on U.S.

listed oil and gas firm returns and volatility and found while the Paris Agreement had a large negative impact on oil and gas sector, Trump's decision to withdraw from this agreement affected the sector negatively. Their study indicates that investors price current policies when examining climate risk.

Maghyereh and Abdoh (2022) looked at the volatility linkages between gold and financial assets during the pandemic, while Choi (2022) focused on Northeast Asia and the US market, finding that volatility linkages strengthened after the outbreak of COVID-19. Umar et al. (2022) primarily investigated impacts on the agricultural market, while Foroutan and Lahmiri (2022) examined the pandemic's impact on volatility linkages in the cryptocurrency market. Both studies indicate that COVID-19 significantly strengthened information linkages between markets. Focusing on energy shocks and financial market turbulence, Boubaker et al. (2023) applied a quantile-VAR model to examine volatility linkages in the US market. Their study showed volatility linkages strengthened after crisis, while Bouteska et al. (2023) showed that there are information linkages between cryptocurrencies and the energy and bond markets.

With the rising number of active investors in ETF markets and the emphasis on the role of ETFs in information flow between markets, there has been an increase in studies focusing on the volatility linkages between ETFs. Wang et al. (2009) found information spillovers in six spot and ETF indices in Taiwan, employing a vector autoregressive (VAR) model. Krause and Tse (2013) examined four US and Canadian industry ETFs and found a positive and significant bi-directional volatility spillover between these two markets, concluding that both markets are linked.

Examining the volatility linkages between commodity ETFs, Lau et al. (2017) applied an *E*-GARCH model to consider the co-movement between oil, gold, and global equity, finding strong volatility linkages. Chang et al. (2019) used multivariate conditional volatility DBEKK in focusing on the volatility linkages between agriculture and energy ETFs, finding that the co-movement between agriculture and energy ETFs is the result of an increase in biofuel investment. However, Antonakakis et al. (2023) applied a TVP-VAR model with data spanning from 2011 to 2021 to examine the impact of various financial crises on the volatility linkages between crude oil ETF and 13 other assets in the US, finding that volatility linkages ranged from 65 % to 85 %, indicating a high degree of cross-market risk linkage.

In summary, previous studies have mainly focused on market return data to show the presence of information linkages among stock markets, commodity markets, and regional markets. Several studies examine the impact of unusual events, such as the global financial crisis and COVID-19, finding a strong volatility linkage between markets post-crisis due to information linkages. This article aims to address the gap in the literature on market interconnectedness concerning the global challenge of reducing carbon emissions to combat climate change.

3. Methodology

3.1. GMM approach

We use the GMM approach of Fleming et al. (1998), which is framed by Tauchen and Pitts' (1983) rational expectation theory that assumes the economy consists of many active traders with heterogeneous expectations about the real values of assets trading in the market. According to rational expectation theory, trade happens when new information in the market changes traders' expectations about the future values of assets; that is, because the daily number of information arrivals is unpredictable, so too are the daily number of price variations and the trades. Expanding this model, Ross (1989) applied rational expectation theory to propose that the daily information flow is proportional to the variance of daily returns.

Fleming et al.'s (1998) GMM approach (which suggests that market returns fluctuate as new information arrives in the market causing a change in prices and revised expectations of active trades) is shown in Eq. (1):

$$R_{k,t} = \mu_{k,t} + \sum_{i=1}^{I_{k,t}} \varepsilon_{ik,t} \tag{1}$$

where $R_{k,t}$ is the daily return in the market, $\mu_{k,t}$ is the conditional expected value of returns, $I_{k,t}$ is the number of information events that affects market k on day t, and $\varepsilon_{ik,t}$ represents the incremental return generated by event i. Considering that $\varepsilon_{ik,t}$ is iid normal with mean zero and variance $\sigma^2_{\varepsilon,k}$, Eq. (2) can be deducted from Eq. (1).

$$R_{k,t} = \mu_{k,t} + \sigma_{\varepsilon,k}\sqrt{I_{k,t}}z_{k,t} \tag{2}$$

Because $z_{k,t}\rightarrow N(0,1)\ as\ I_{k,t}\rightarrow\infty$, the conditional distribution of $R_{k,t}$ is normal with mean $\mu_{k,t}$ and variance $\sigma^2_{\varepsilon,k}I_{k,t}$. Eq. (3) also indicates that daily information flow is proportional to the variance of daily returns ($\sigma_{k,t} = \sigma_{\varepsilon k,t}\sqrt{I_{k,t}}$) and Fleming et al. (1998) considers the natural logarithm of the daily variance ($ln\left(\sigma^2_{\varepsilon,k}I_{k,t}\right)$) as the daily volatility of information flow ($h_{k,t}$), which is an AR(1) process as indicated in Eq. (3).

$$h_{k,t} = \gamma_{k,t} + \varnothing_{h,k}h_{k,t-1} + \mu_{k,t} \tag{3}$$

where $\mu_{k,t}\rightarrow N(0,1)$ and independent of $z_{k,t}$. Focusing on the unpredicted component of returns ($r_{k,t}$) enables us to explain the dynamic property of returns as shown in Eq. (4).

$$r_{k,t} \equiv exp\left(\frac{1}{2}h_{k,t}\right)z_{k,t} \tag{4}$$

To extract $h_{k,t}$, Eq. (4) can be rewritten as $lnr^2_{k,t} = h_{k,t} + lnz^2_{k,t}$ where the mean and variance of $lnz^2_{k,t}$ are -1.27 and 4.93 respectively due to the normal distribution of $z_{k,t}$ with mean zero and variance one (Abramowitz and Stegun, 1970). The system of equations to estimate the GMM approach and generate the required data for the study can be rewritten as follows:

$$y_{k,t} = h_{k,t} + \delta_{k,t} \tag{5}$$

$$h_{k,t} = \gamma_{h,k} + \varnothing_{h,k}h_{k,t-1} + \mu_{k,t} \tag{6}$$

where $\delta_{k,t} \equiv lnz^2_{k,t} - \mathrm{E}\left[lnz^2_{k,t}\right]$ with mean zero and variance 4.93. As a result, for a single market, namely k, and $\tau > 0$, the following moment restrictions can be considered:

$$E\left[y_{k,t}\right] = E\left[h_{k,t}\right] \tag{7}$$

$$var\left(y_{k,t)}\right) = var\left(h_{k,t}\right) + var\left(\delta_{k,t}\right) \tag{8}$$

$$cov\left(y_{k,t}, y_{k,t+\tau}\right) = \left(\varnothing_{h,k}\right)^{\tau} var\left(h_{k,t}\right) \tag{9}$$

The above analysis shows how the arrival of new information in one market generates volatility in returns. Kodres and Pritsker (2002) expanded this model to suggest a multiple asset model. Aiming to explain market co-movements, they argued that the information arrival in market i not only affects the price expectations in the same market, but also results in a variation in the volume of trading as well as the volatility of returns in market j, because many traders are active in multiple markets, resulting in information spillover between markets.

Since traders rebalance their portfolio when new information arrives in the market, Kodres and Pritsker (2002) argue that the correlation between the two markets is taken into account when traders make their rebalancing decision. Therefore, volatility correlation can provide a picture of the information linkages between markets. Hence, the moment restrictions to assess cross-market linkages between two markets i and j should also include Eq. (10) to (13) as follows:

$$cov\left(y_{i,t}, y_{j,t}\right) = cov(h_{i,t}, h_{j,t}) + cov(\delta_{i,t}, \delta_{j,t}) \tag{10}$$

$$cov\left(y_{i,t}, y_{j,t+\tau}\right) = (\varnothing_{h,j})^{\tau} cov(h_{i,t}, h_{j,t}) \tag{11}$$

$$cov\left(y_{i,t+\tau}, y_{j,t}\right) = (\varnothing_{h,i})^{\tau} cov(h_{i,t}, h_{j,t}) \tag{12}$$

Using the GMM approach developed by Hansen (1982) on the models proposed by Fleming et al. (1998) and Kodres and Pritsker (2002), we can estimate the correlation between the log information flows in different markets. For a bivariate analysis, the moment restrictions are shown in Eq. (14):

$$e_t(\theta) = \left\{ \begin{array}{c} y_{i,t} - \mu_{h,i} \\ \left(y_{i,t} - \mu_{h,i}\right)^2 - \sigma_{h,i}^2 - \sigma_{\delta}^2 \\ \left(y_{i,t} - \mu_{h,i}\right)\left(y_{i,t+\tau} - \mu_{h,i}\right) - \varnothing_{h,i}^{\tau}\left[\left(y_{i,t} - \mu_{h,i}\right)^2 - \sigma_{\delta}^2\right] \\ y_{j,t} - \mu_{h,j} \\ \left(y_{j,t} - \mu_{h,j}\right)^2 - \sigma_{h,j}^2 - \sigma_{\delta}^2 \\ \left(y_{j,t} - \mu_{h,j}\right)\left(y_{j,t+\tau} - \mu_{h,j}\right) - \varnothing_{h,j}^{\tau}\left[\left(y_{j,t} - u_{h,j}\right)^2 - \sigma_{\delta}^2\right] \\ \left(y_{i,t} - \mu_{h,i}\right)\left(y_{j,t} - \mu_{h,j}\right) - \rho_{h,ij}\sigma_{h,i}\sigma_{h,j} - \rho_{\delta,ij}\sigma_{\delta}^2 \\ \left(y_{i,t} - \mu_{h,i}\right)\left(y_{j,t+\tau} - \mu_{h,j}\right) - \varnothing_{h,j}^{\tau}\left[\left(y_{i,t} - \mu_{h,i}\right)\left(y_{j,t} - \mu_{h,j}\right) - \rho_{\delta,ij}\sigma_{\delta}^2\right] \\ \left(y_{i,t+\tau} - \mu_{h,i}\right)\left(y_{j,t} - \mu_{h,j}\right) - \varnothing_{h,i}^{\tau}\left[\left(y_{i,t} - \mu_{h,i}\right)\left(y_{j,t} - \mu_{h,j}\right) - \rho_{\delta,ij}\sigma_{\delta}^2\right] \end{array} \right\} \tag{13}$$

where the vector of eight unknown variable is $\theta \equiv \left[\mu_{h,i}, \sigma_{h,i}, \varnothing_{h,i}, \mu_{h,j}, \sigma_{h,j}, \varnothing_{h,j}, \rho_{h,ij}, \rho_{\delta,ij}\right]$. $\tau = 1, 2, 3\ldots, l$ shows the number of autocorrelation estimations. The variable of interest in this study is $\rho_{h,ij}$. This variable is the correlation between markets from 2 January 2014 to 28 February 2023. It measures the strength of the information linkage.

3.2. 3.2 Implied volatility approach

The second approach to evaluating the volatility linkages between markets is using the options implied volatility data. However, there are concerns that this may capture a spurious effect because the implied volatility series are highly autocorrelated (Ferson et al., 2003). To address this concern, we follow the approach suggested by Wang (2009). First, we calculate the daily implied volatilities of options as the average of the implied volatilities of the two nearest put and call option series, one with the strike price below the underlying price and one with the strike price above the underlying price. Then we estimate the sensitivity between the implied volatilities of different markets by running the following regression:

$$\sigma_{it} = \alpha + \beta\sigma_{jt} + \varepsilon_t \tag{14}$$

where σ_{it} is the natural logarithm implied volatility in market i at time t; σ_{jt} is the natural logarithm implied volatility in market j at time t; ε_t is the error term; α is the constant and β, the slope of this regression, shows the sensitivity of market i to variations in market j. The R^2 of this regression is the root of the correlation coefficient and its sign is determined by the sign of β. A positive sign of β indicates the positive correlation between two markets, while the negative sign of β shows the correlation between markets is negative. To investigate the spurious effect in this regression, the next step is to set up a Monte Carlo simulation and estimate the cut-off R^2. The Monte Carlo procedure begins with generating the same number of observations for the implied volatility series with the same moments and autocorrelation properties as the actual data.

Running the regression on simulated strings and repeating this process 1000 times, we recorded the R^2 of each regression and sorted it from lowest to highest. We report the 95th percentile as the cut-off R^2 of the simulated data. We then compare the cut off R^2 to the actual R^2 of this model; the p-value associated with the simulated R^2 is estimated as the number of iterations that the simulated R^2 exceeds the actual R^2. Using the Monte Carlo approach, we aim to understand if the co-movement between markets is captured as a result of spurious regression (null hypothesis) or if the correlation is significant. If the simulated R^2 captured via the Monte Carlo approach is smaller than the actual R^2 and the p-value is less than 0.05, the null hypothesis – the correlation between markets is a spurious effect – is rejected, concluding the actual R^2 is statistically significant and markets are correlated (Chan et al., 2018).

3.3. Time-varying dynamics

We further develop this study by estimating the time-varying dynamics of volatility correlations. We use the implied volatility approach to calculate the average information linkage over time. Then the time-varying dynamic approach is employed to estimate the information linkages between markets around the net zero announcement by the US Government on 21 April 2021 and UK Government on 27 June 2019. It also enhances our understanding about the sensitivity of different markets to this announcement, as based on the rational expectation model developed by Kodres and Pritsker (2002) the degree of cross-market information linkages depends on each market's sensitivity to the shared macroeconomic risk factors.

The net zero announcements in the UK, the US, and China are considered important milestones in the world's transition to a low carbon economy as China and the US are the largest and second-largest carbon emitters in the world, respectively, while the UK is the first developed nation to commit to net zero emissions. To understand if these policy announcements strengthened the co-movement between markets or weakened their information linkage, we consider 27 June 2019 (UK's net zero announcement), 21 April 2021 (US's net zero announcement), and 28 October 2021 (China's net zero announcement) as the event days for our study and to estimate the impact of these announcements on the correlation.

The first step in this process is mitigating the high persistence of implied volatilities between markets. To retain the observations while dealing with the high persistence of implied volatilities, we estimate the monthly correlation of implied volatilities between markets. The next step would be running a regression to evaluate the impact of the net zero announcements in the UK, the US, and China on the correlation between markets as presented by Eq. (19).

$$\rho_{ij} = \alpha + \beta_1 \textit{Post UK Netzero} + \beta_2 \textit{Post US Netzero} + \beta_3 \textit{Post China Netzero} + \varepsilon_t \tag{15}$$

where ρ_{ij} is the monthly correlation between market i and market j; α is the intercept and ε_t is an error term. In this model, "*Post US Netzero*" is a dummy variable that equals 0 prior to the net zero announcement in the US in April 2021 and 1 afterwards, "*Post UK Netzero*" is a dummy that equals zero before the net zero announcement in the UK on 27 June 2019 and 1 afterwards and "*Post China Netzero*" is a dummy variable that equals 1 after China's net zero announcement on 28 October 2021 and zero otherwise. β_1 indicates the impact of the net zero policy announcement in the UK on the correlation between markets while β_2 indicates the effect of the US net zero announcement on the correlation between markets. The impact of China's net zero announcement on the correlation between markets is captured by β_3.

A significant effect will show that the announcement has strengthened the information linkages between the two markets in each model. The UK was the first developed country in the world to commit to meeting net zero targets by 2050 and to enshrine its commitment into law. As such, this announcement is expected to have a significant impact on the correlation between markets. On the other hand, the US, as the world's largest economy and second-largest carbon emitter behind China, plays a significant role in global markets. China, the world's second-largest economy by nominal GDP and the fastest-growing emerging market, is expected to influence other markets through its net-zero announcement, which could potentially affect market correlations.

4. Data description

To investigate the information linkages between markets in different countries, we selected ten ETFs traded on the US stock market. The time frame for our study is from 2 January 2014 to 28 February 2023,[2] covering more than nine years and 2305 daily observations. Both returns data and options market data were used. To estimate the return of each ETF, the closing price of ETFs were drawn from Yahoo Finance and the return is calculated as the percentage change in daily prices. To investigate the information linkages by using the implied volatilities of option markets, the ticker, strike price, expiry date, and implied volatility of all ten ETF options were extracted from OptionMetrics.

We selected country ETFs for India, China, the US, Germany, Switzerland, South Korea, Spain, Australia, and Canada, in addition to an international ETF. The ETFs are representatives of the world's larger economies, and the international ETF is representative of the world market excluding the US. The selected global ETFs provide a holistic sample and allows for an examination of markets beyond the US. An ex-UK version of the global ETF is unnecessary as the UK market has a relatively small allocation weight in the global ETF allocation. Table 1 lists the country of the ETFs used in this study.

4.1. Returns data

This paper uses ETF market data obtained directly from Bloomberg.

Table 1
List of country ETFs used in this study.

Name of the ETF	Country the ETF represents	Abbreviation used in this study
WisdomTree India ETF	India	IND
S&P 500 ETF	United States	USA
iShares China Large-Cap ETF	China	CHI
iShares MSCI South Korea ETF	South Korea	KOR
iShares MSCI Spain ETF	Spain	SPN
iShares MSCI Switzerland ETF	Switzerland	SWZ
iShares MSCI Germany ETF	Germany	GER
iShares MSCI Canada ETF	Canada	CAN
iShares MSCI Australia ETF	Australia	AUS
iShares Core MSCI total International Stock ETF	International stocks excluding the US	WLD

[2] 28 February 2023 is the last day that options data was available in Option Metrics. Options data for WLD was available from the start of 2014, hence we chose the start of 2014 for our study's time frame.

Table 2 presents the descriptive statistics of returns, including two panels. Panel A shows the summary statistics, while the autocorrelation of returns is presented in Panel B. The gross returns, reported as percentages, were calculated as the percentage of change in the daily closing price of ETFs from 2 January 2014 to 28 February 2023. The mean, median, maximum, and minimum presented in Panel A of Table 2 are also reported as percentages while the standard deviation, skewness, and Kurtosis are general numbers.

CHI (China's country ETF) has the smallest returns (0.0008 %) among all ten ETFs, while the largest return (0.0397 %) is captured in USA. Despite this range of variations in the returns, we find that all are insignificantly different from zero. The standard deviation of returns for all ten ETFs is small and almost similar and all have normal distributions. The autocorrelation coefficients of returns are presented in Panel B of Table 2. Panel B shows that all coefficients are insignificantly different from 0, confirming that returns are not related to their lagged values.

Fig. 1 illustrates the cross-market correlations of returns, showing that all ETF returns are positively correlated with each other. The lowest correlations are observed between CHI and all other ETFs, represented by the lighter color on the bottom of the graph. The correlation of CHI returns with other markets ranges from 1 % to 6 %, while in other markets the correlations range from 46 % between IND and USA to 91 % between GER and WLD. Although the return correlations indicate the effectiveness of cross-market hedging (Fleming et al., 1998), the transaction costs should be considered to calculate the degree of information spillovers. As a result, based on rational expectation theory, the correlation of volatilities should be estimated, and absolute returns and squared returns are two proxies for volatilities.

Fig. 2 illustrates the cross-correlation of absolute returns and squared returns, both of which are smaller than the cross-correlation of returns. The upper graph in Fig. 2 shows that the cross-correlation of absolute returns of CHI with other ETFs ranges from 16 % to 23 %, which is higher in comparison to the CHI's cross-correlation of returns with other ETFs. However, the cross-correlation of absolute returns of other ETFs ranges from 50 % between IND and SPN to 86 % between GER and WLD. The lower part of Fig. 2 shows that the cross-correlation of squared returns ranges 62 % between SPN and IND to 94 % between WLD and GER. The cross-correlation of CHI's squared returns with other ETFs ranges from 8 % to 16 %, which is lower than the cross-correlation of absolute returns. The positive cross-correlation of absolute returns and squared returns indicates that there are informational linkages between markets; however, due to the noisiness of these proxies, it is difficult to estimate the degree of market linkages based on these statistics. To overcome this problem and estimate the informational linkages between markets more precisely, we use the implied volatility of options traded on these ETFs and directly estimate the cross-correlation of implied volatilities based on the real option market data.

4.2. Implied volatility data

Following Beckers (1981) and Wang (2009), at-the-money (ATM) options are used to estimate the implied volatility of each ETF option. To calculate the ATM options, two nearest option series with the shortest time to maturity are chosen, one with strike price below the underlying price and one with strike price above the underlying price. The implied volatility of each option for each day is calculated as the average of both put and call options implied volatilities.

There are 2305 observations for the trading days from 2 January 2014 to 28 February 2023. Table 3 shows the summary statistics for both log series and raw series of daily implied volatilities in addition to the first order autocorrelation coefficients. The first-order autocorrelation coefficients for implied volatilities ranges from 60 % for WLD to 90 % for CHI while the first-order autocorrelation coefficients for the log of implied volatilities ranges from 61 % for IND to 86 % for CHI. Considering the magnitude of the AR(1) coefficients, it can be deduced that

Table 2
Descriptive statistics of "Returns".

Panel A: Summary Statistics of Returns							
Raw Series	Mean	Median	Max.	Min.	S.D.	Skewness	Kurtosis
IND	0.0356	0.08703	10.04118	−13.04347	0.01435	−0.7649	11.02411
USA	0.0397	0.05335	9.06033	−10.94237	0.01133	−0.55232	12.7472
CHI	0.0008	0.0000	21.24123	−10.29100	0.01704	0.75646	12.91932
KOR	0.00706	0.0345	12.4454	−15.8053	0.01505	−0.52686	9.75422
SPN	−0.00385	0.04316	8.90624	−16.28665	0.01470	−1.30835	16.28965
SWZ	0.0174	0.05542	7.77186	−10.51598	0.01049	−0.69281	12.77049
GER	0.00299	0.03953	10.75847	−12.6888	0.01378	−0.66604	10.72752
CAN	0.01445	0.06793	12.86119	−13.32195	0.01239	−0.67919	21.46524
AUS	0.00855	0.04488	14.15344	−16.1066	0.01495	−0.66467	19.88461
WLD	0.00801	0.05079	9.11765	−10.79896	0.01098	−0.92768	12.96843
Panel B: Autocorrelation of "Returns"							
Raw Series	AR (1)	AR (2)	AR (3)	AR (4)	AR (5)	AR (6)	AR (7)
IND	−0.116	0.052	−0.005	0.004	0.044	−0.093	0.056
USA	−0.126	0.067	−0.013	−0.065	0.047	−0.114	0.149
CHI	−0.071	0.021	−0.023	−0.009	0.020	−0.061	0.024
KOR	−0.091	0.058	0.009	−0.042	0.048	−0.102	0.093
SPN	−0.090	0.109	−0.012	−0.025	0.043	−0.081	0.055
SWZ	−0.099	0.085	−0.019	−0.019	0.034	−0.108	0.087
GER	−0.055	0.097	0.006	−0.020	0.053	−0.111	0.053
CAN	−0.049	0.038	0.054	0.003	0.013	−0.102	0.120
AUS	−0.194	0.102	0.010	−0.053	0.088	−0.124	0.116
WLD	−0.075	0.084	0.021	−0.040	0.057	−0.110	0.080

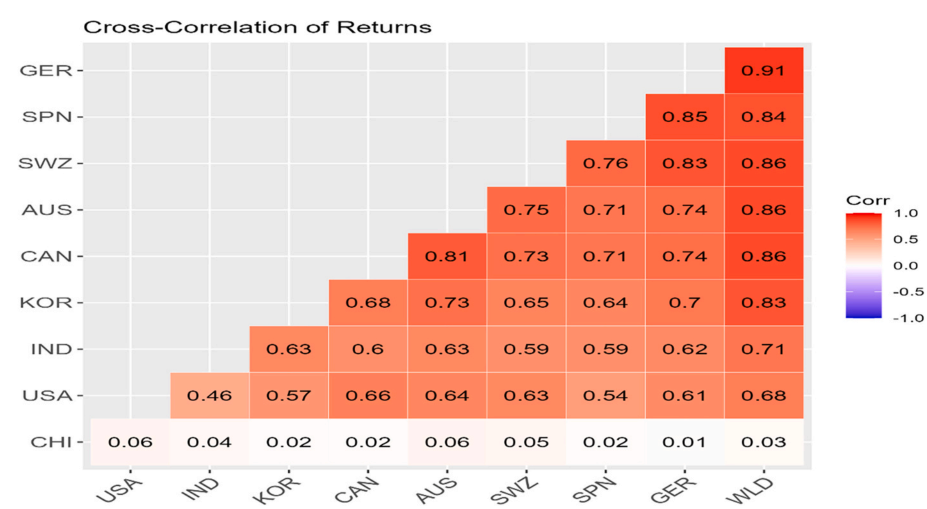

Fig. 1. Cross-market correlations of returns.

implied volatilities in all ten markets are highly persistent, raising concerns about capturing a spurious effect in a correlation study between these series.

Fig. 3 pictures the cross-market correlations between implied volatilities. The orange color in Fig. 3 shows that all the series are correlated and the darker the color, the higher the cross-correlation between markets. The highest cross-correlation between markets is 82 %, which is between the implied volatilities of USA and KOR, and the lowest cross-correlation is captured between IND and WLD which is 21 %.

Looking at the cross-correlation between the log implied volatilities series, the co-movement of series is deduced. This figure shows that the highest cross-correlation between log series is captured between USA and CHI, which is 77 %, and the cross-correlation between IND and WLD is 32 %, which is the lowest among all the series. Fig. 3 implies that there is a high-level of co-movement between series, however, the preliminary examinations and the highly persistent implied volatility series raise concerns about the possibility of a spurious effect. To address this concern, we follow the approach suggested by Wang (2009), use the log series of daily implied volatilities and run spurious regression simulations between WLD and all other ET. This test shows if the correlation between markets is captured due to the spurious effects or they are highly correlated.

5. Empirical results

5.1. GMM approach

To generate the required data for this analysis, we start by estimating the daily returns and removing the seasonal patterns in returns. We regress the raw returns on a set of six dummy variables, including one dummy for each weekday and one for the days after a market holiday to remove seasonality. Obtaining the residuals of this regression, we follow Fleming et al. (1998) to estimate the natural logarithm of the squared residuals, which is a variable to show the volatility of returns in the data, and regress it on two dummy variables, one for Mondays and one for days following public holidays. Estimating the sum of the intercept of this regression and its residual, followed by subtracting −1.27 or

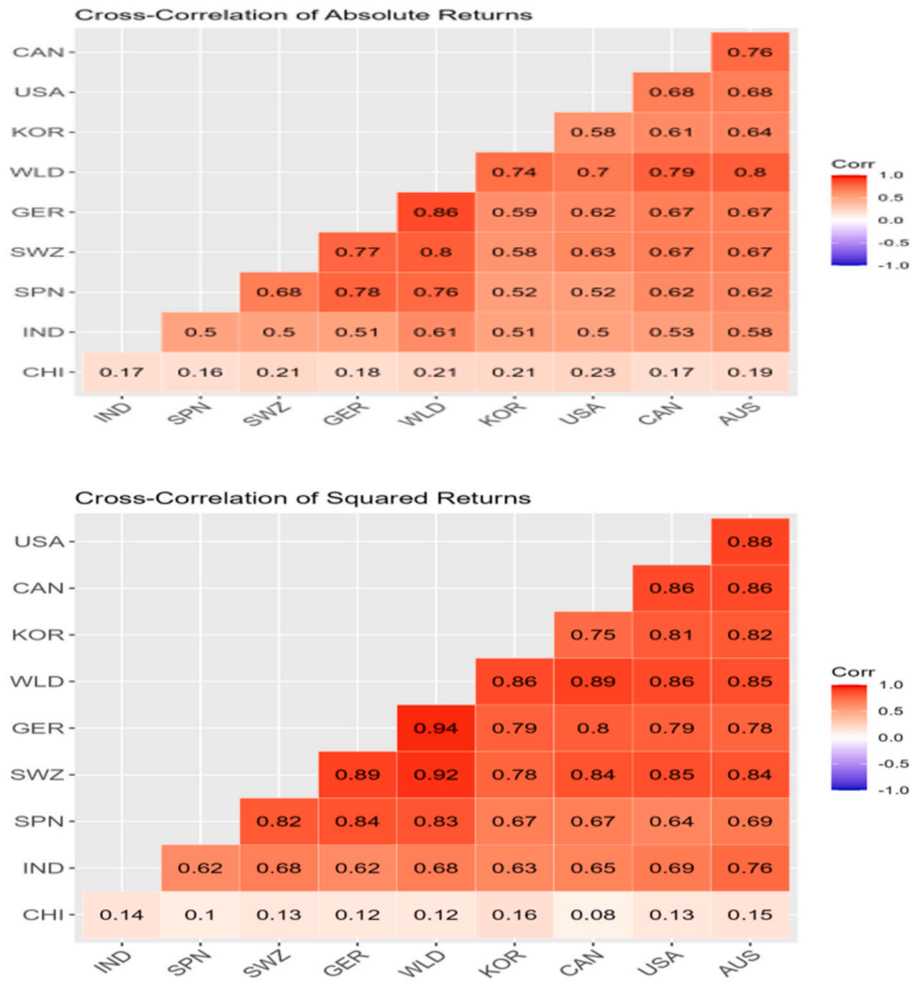

Fig. 2. Cross-market correlations of absolute returns and squared returns.

Table 3
Descriptive statistics of implied volatility series.

Options	Mean	Median	Max.	Min.	S.D.	Skewness	Kurtosis	AR (1)
Raw Series of Daily Implied Volatilities (2305 observations)								
IND	0.2770	0.2423	1.5155	0.0919	0.1383	3.6082	22.4063	0.636
USA	0.1669	0.1369	1.5310	0.0349	0.1122	3.9871	32.7215	0.831
CHI	0.2829	0.2590	1.8451	0.1102	0.11310	2.8833	24.9278	0.897
KOR	0.2433	0.2195	1.3428	0.1207	0.09890	3.6530	27.8968	0.836
SPN	0.2448	0.2237	1.5392	0.1154	0.09635	3.7512	32.8049	0.777
EW	0.1924	0.1706	1.2739	0.0814	0.08871	4.2876	37.8769	0.660
GER	0.2333	0.2093	1.25670	0.08083	0.09952	2.9772	21.2913	0.817
CAN	0.2023	0.1768	1.3925	0.0771	0.09430	4.4747	40.6739	0.748
AUS	0.2324	0.2079	1.6622	0.1056	0.10235	4.8265	46.5120	0.649
WLD	0.1871	0.1567	0.9579	0.0677	0.08525	2.5147	14.0006	0.605
Log Series of Daily Implied Volatilities (2305 observations)								
IND	−0.5920	−0.5936	0.1806	−1.0362	0.16105	1.0047	5.5361	0.610
USA	−0.8419	−0.8617	0.1850	−1.4572	0.22569	0.4815	3.5030	0.800
CHI	−0.5755	−0.5848	0.2660	−0.9577	0.14831	0.5460	3.7156	0.859
KOR	−0.6387	−0.6555	0.1280	−0.9181	0.13876	0.9608	5.0653	0.854
SPN	−0.6351	−0.6341	0.1873	−0.9379	0.1369	0.8317	4.9762	0.780
SWZ	−0.7461	−0.7246	0.1051	−1.0895	0.1529	0.8368	5.1941	0.705
GER	−0.6620	−0.6573	0.09923	−1.0924	0.1558	0.4851	4.1335	0.755
CAN	−0.7249	−0.6944	0.1438	−1.1128	0.15510	0.7246	5.2716	0.752
AUS	−0.6603	−0.6415	0.2207	−0.9762	0.1416	1.0484	6.1015	0.742
WLD	−0.76172	−0.75197	−0.01869	−1.16953	0.16415	0.6657	3.8202	0.726

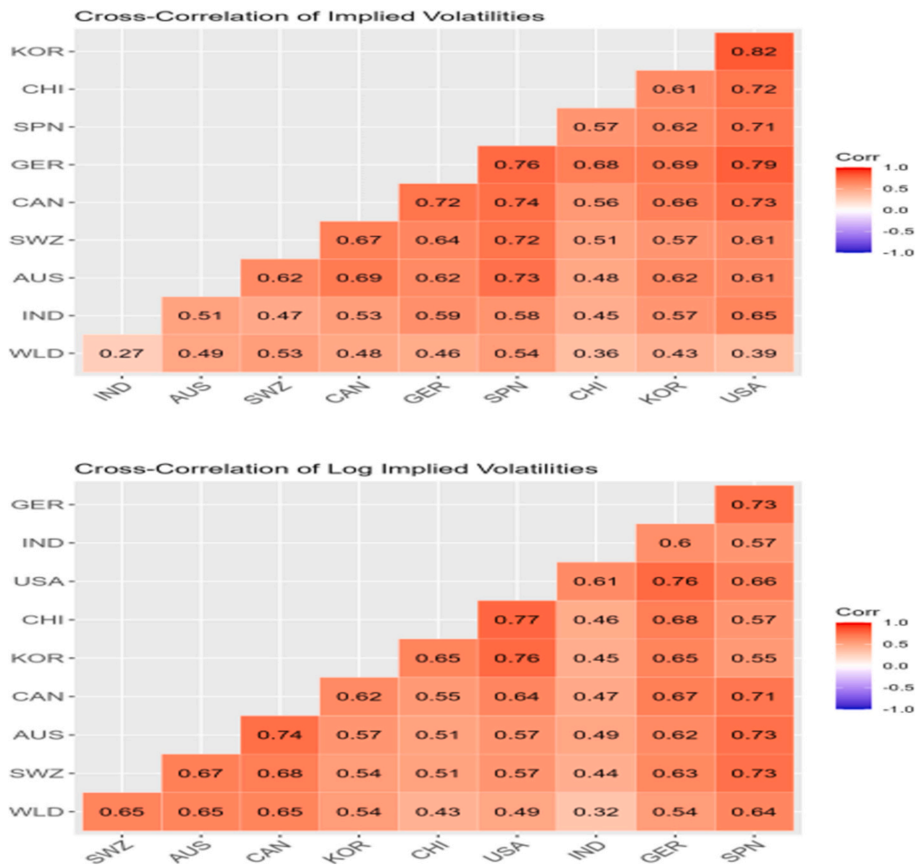

Fig. 3. Cross-market correlations of "Implied Volatilities" and "Log of Implied Volatilities".

$E\left[lnz_{k,t}^2\right]$, we obtain $y_{k,t}$. The system of equations used to generate data for the GMM analysis is shown as follows:

$$R_{k,t} = \alpha_0 + \sum_{i=1}^{6} \alpha_i D_i + r_{k,t} \tag{16}$$

$$lnr_{k,t}^2 = \beta_0 + \beta_1 D_7 + \beta_2 D_8 + \varepsilon_{k,t} \tag{17}$$

$$y_{k,t} = \beta_0 + \varepsilon_{k,t} + 1.27 \tag{18}$$

where D_i consists of six dummy variables for each weekday and one dummy for the days after market holidays to remove seasonality from the market raw return. D7 and D8 in Eq. (10) are two dummy variables for Mondays and days after market holidays to remove the seasonality of market volatility and lead us to estimate $y_{k,t}$. Table 4 summarizes the GMM univariate estimation results for $l = 10$. Estimating the model with longer lags (20, 30, and 40 lags) shows that the mean of $h_{k,t}$ does not change significantly. This indicates that the parameters are insensitive to lag length. Also maintaining a smaller number of moment conditions minimizes the possibility of obtaining an ill-conditioned weighting matrix. As a result, the model is estimated by considering 10 lags.

Table 4 shows that all the standard errors are less than 5 %, indicating that the mean, variance, and autocorrelation parameters are statistically significant, and the J-statistics reported in Table 4 confirm that the models are not mis specified and that the chosen instruments are valid. The parameter of interest is $\rho_{h,ij}$, the correlation of log information flow of different ETFs with WLD that shows the strength of cross-market information linkages. Results show the correlation between IND and the global ETF is 40.20 %, while the correlation between USA and WLD is 39.67 %. The estimated correlations between KOR, SPN, SWZ, and AUS with the global ETF (WLD) ranges from 56.44 % to 58.09 %, yet the correlations of CAN and GER with WLD is 50.20 % and 71.43 % respectively. Table 4 reports that, except for China, all correlation coefficients are positive, indicating that country ETFs are positively correlated with WLD. Looking at the magnitude of the standard errors, we can see that all of them are smaller than 0.025, indicating the parameter is statistically significant at 5 %. We conclude that the information linkages between country ETFs and WLD are strong and mainly positive, meaning that when new information enters the market the returns of country ETFs change in the same direction as the return of WLD.

The table reports the GMM parameter estimates and overidentifying test statistics (J-statistics) for the bivariate model of the log information flow $(h_{k,t})$ in each ETF market. The estimation procedure uses the moment conditions implied by the model for seasonally adjusted, log squared returns $(y_{k,t})$ to estimate the mean $(\mu_{h,k})$, variance $(\sigma_{h,k}^2)$, and the AR (1) parameter $(\varphi_{h,k})$ of the log information processes. It also provides estimates of the correlations between the information flows $(\rho_{h,ij})$, and between the disturbance terms $(\rho_{\varepsilon,ij})$ in markets I and j. In this table j is WLD and ten lags are considered for this study $(l = 10)$.

The GMM approach shows that there is a strong volatility linkage between the log of information flows of WLD and country ETFs, indicating their co-movement in the world market and the presence of information linkages.

5.2. *Spurious regression analysis using daily implied volatilities*

We also take Wang's (2009) volatility approach to quantify volatility linkages while simultaneously controlling for spurious effects. To estimate the spurious regression simulations, we use the log series of daily implied volatilities. Table 5 presents the spurious regression simulation results of WLD with all other ETFs, including the actual R^2, the 95 % cut-

Table 4
GMM model estimation results.

Panel A

ETFs Parameters	Coefficient (Standard Error) IND	Coefficient (Standard Error) USA	Coefficient (Standard Error) CHI	Coefficient (Standard Error) KOR	Coefficient (Standard Error) SPN
$\mu_{h,i}$	−10.6402	−11.2168	−10.2125	−7.0529	−10.6355
	(0.0041)	(0.05210)	(0.0444)	(0.03372)	(0.03982)
$\sigma^2{}_{h,i}$	3.3602	3.8329	3.5770	3.1965	3.2094
	(0.0054)	(0.05073)	(0.04862)	(0.0600)	(0.0560)
$\varphi_{h,i}$	−0.1089	−0.1527	−0.1271	−0.1443	−0.1436
	(0.0123)	(0.01251)	(0.01063)	(0.0102)	(0.0101)
$\mu_{h,j}$	−11.099	−7.878	−7.7350	−11.1659	−7.8547
	(0.0443)	(0.0364)	(0.04036)	(0.0427)	(0.0422)
$\sigma^2{}_{h,j}$	2.7862	2.9104	3.4018	3.002	2.9918
	(0.0578)	(0.0631)	(0.05942)	(0.05724)	(0.0626)
$\varphi_{h,j}$	−0.1400	−0.1508	−0.08991	−0.1353	−0.1359
	(0.0011)	(0.0114)	(0.0102)	(0.0100)	(0.0102)
$\rho_{h,ij}$	0.4020	0.3967	−0.0258	0.5771	0.5768
	(0.0287)	(0.03257)	(0.02979)	(0.0318)	(0.0321)
$\rho_{\varepsilon,ij}$	0.6223	−0.2896	−0.5050	−0.4776	−0.4776
	(0.0054)	(0.0088))	(0.01138)	(0.0094)	(0.0093)
$J-stat$	12,694.08	66,635.53	34,632.1682	75,440.91	72,776.2
$p-value$	0	0	0	0	0

Panel B

ETFs Parameters	Coefficient (Standard Error) SWZ	Coefficient (Standard Error) GER	Coefficient (Standard Error) CAN	Coefficient (Standard Error) AUS
$\mu_{h,i}$	−11.28306	−7.4923	−7.7701	−7.3101
	(0.0043)	(0.0039)	(0.0441)	(0.03603)
$\sigma^2{}_{h,i}$	3.5392	3.7330	3.5456	3.7484
	(0.0051)	(0.0553)	(0.0560)	(0.05570)
$\varphi_{h,i}$	−0.1255	−0.1240	−0.1028	−0.09942
	(0.0051)	(0.0092)	(0.01155)	(0.01080)
$\mu_{h,j}$	−7.7757	−11.2417	−7.8167	−7.8341
	(0.0395)	(0.03967)	(0.03671)	(0.0379)
$\sigma^2{}_{h,j}$	3.2594	3.2598	3.1187	3.0600
	(0.0593)	(0.0512)	(0.00575)	(0.0060)
$\varphi_{h,j}$	−0.1143	−0.1168	−0.1014	−0.09969
	(0.0098)	(0.0093)	(0.0010)	(0.001)
$\rho_{h,ij}$	0.5644	0.7143	0.5020	0.58095
	(0.0100)	(0.02598)	(0.0025)	(0.0024)
$\rho_{\varepsilon,ij}$	−0.4730	−0.47013	0.7108	0.71025
	(0.00276)	(0.0088)	(0.00040)	(0.00038)
$J-stat$	5649.071	86,386.71	9401.639	10,127.98
	(0.0090)			
$p-value$	0	0	0	0

Table 5
Spurious regression effect diagnostics of WLD.

ETFs	R^2	95 % cut-off R^2	p-value	$\rho_{i,j}$
WLD & USA	0.2398	0.0015	0.000	0.4896
WLD & IND	0.1044	0.0071	0.000	0.3231
WLD & CHI	0.1812	0.0025	0.000	0.4256
WLD & KOR	0.2940	0.0017	0.000	0.5422
WLD & SPN	0.4096	0.0036	0.000	0.6400
WLD & SWZ	0.4272	0.0021	0.000	0.6536
WLD & GER	0.2918	0.0017	0.000	0.5401
WLD & CAN	0.4181	0.0022	0.000	0.6468
WLD & AUS	0.4277	0.0046	0.000	0.6539

off R^2, the empirical p-values, and the correlation statistics estimated as the square root of the actual R^2. Comparing the R^2 of each pair of ETFs, Table 4 shows that the actual R^2 is larger than the 95 % cut-off R^2, and the p-values are 0, confirming that the actual R^2 and the positive correlation captured between each pair of ETFs are statistically significant and that this positive correlation was not captured due to the spurious regression.

Finding that the correlation between these markets is not spurious, Table 4 shows that the correlation between the WLD and the nine other markets ranges from 32.31 % between WLD and IND to 65.36 % between WLD and SWZ. Confirming the positive and strong volatility linkages between country ETFs and WLD, the finding of the implied volatility approach is in line with the finding of the GMM approach, indicating that the result is robust, and markets are co-related, with a volatility linkage between them.

Looking at the volatility linkages between USA and eight other country ETFs by employing the implied volatility approach enhances understanding of the co-movement between markets. Just like WLD, the US country ETF (USA) has a positive and strong volatility linkage with

Table 6
Spurious regression effect diagnostics of USA.

ETFs	R^2	95 % cut-off R^2	p-value	$\rho_{i,j}$
USA & IND	0.3683	0.0059	0.000	0.6077
USA & CHI	0.5873	0.0021	0.000	0.7664
USA & KOR	0.5833	0.0016	0.000	0.7636
USA & SPN	0.4347	0.0019	0.000	0.6595
USA & SWZ	0.3246	0.0025	0.000	0.5700
USA & GER	0.5750	0.0017	0.000	0.7583
USA & CAN	0.4091	0.0024	0.000	0.6398
USA & AUS	0.3290	0.0017	0.000	0.5738

other ETFs, showing that new information entering one market impacts the volatility of other markets in the same direction as the first market.

Table 6 shows the spurious regression analysis of USA with other ETFs chosen in this study. In all the pairs, the 95 % cut-off R^2 is smaller than the actual R^2 and the associated p-values less than 0.05 reject the presence of a spurious effect in the regression. As in all the regressions, the slope parameter β is positive, and the correlation coefficients between USA and other ETFs (estimated as the square root of the actual R^2) are positive. Table 6 indicates that the correlation coefficients range from 76.36 % between USA and KOR to 57.38 % between USA and AUS.

To understand the co-movement between all other ETFs selected for this study, the Monte Carlo simulation is conducted, and the simulation is repeated 1000 times to capture the 95 % cut-off R^2. Table 6 shows that the 95 % cut-off R^2 between all pairs of ETFs is smaller than the actual R^2 and the p-values confirm that there is no spurious effect in the regression. Table 7 reports that the coefficients (except WLD and USA) range from 43.69 % between IND and SWZ to 74.24 % between CAN and AUS. The results show that the co-movements between markets are positive and significant, rejecting the null hypothesis that there is a spurious correlation between ten selected ETF markets due to the small p-values and the higher value of actual R^2 compared to the cut-off R^2. This study finds these markets are strongly correlated and the co-movements between these markets are significant.

5.3. Information linkages after net zero announcement

Having found that the ten selected markets in this study are correlated with significant co-movements, we now seek to establish whether the net zero announcements in the UK, the US, and China have strengthened the correlation between these markets. China and the US are selected for this analysis as the world's largest carbon emitters. The UK was also included as the first developed nation to commit to net zero. To check whether the correlation between markets changed significantly after these announcements, we start by estimating the monthly correlation between ten selected ETFs. After converting the daily data to monthly, we obtain a dataset containing 110 months. This dataset includes 66 months before the net zero announcement in the UK and 44 months after, while the pre-announcement and post-announcement period for the US is 83 months and 27 months respectively. The pre-announcement period for China's net zero announcement is 95 months, while the dataset contains 15 months of China's post-announcement period. We run an OLS regression on the monthly correlation of each pair and three dummy variables including *"Post US Netzero"*, *"Post UK Netzero"*, and *"Post China Netzero"*. This analysis is followed by running a multivariate analysis of monthly correlation of all country ETFs versus WLD first on each of the dummies individually and then on all three dummies. Panel A of Table 8 presents the results of the structural stability test of WLD with all other ETFs and Panel B shows the result of multivariate analysis of the monthly correlation of all the country ETFs versus WLD on dummies.

The first results column presented in Panel A of Table 8 shows that the impact of the UK's net zero announcement on the monthly correlation between WLD and all other ETFs was statistically significant and negative. Table 8 indicates that there was a significant change in the monthly correlation of WLD with all the ETFs after the net zero announcement in the US. This announcement has positively affected the correlation between WLD and other markets and strengthened the information linkage while the impact of China's net zero announcement was not statistically significant except in the correlation between China's ETF and WLD. The announcement of net zero in the UK resulted in a 17.33 % decline in the correlation between WLD and USA, whereas this correlation increased by 22.13 % after the net zero announcement in the US. The greatest change in the correlation between markets after the UK net zero announcement is detected between WLD and KOR, which is equal to 33.20 %, and negative and significant at a 0.1 % level, while the smallest impact is pictured in the correlation between WLD and IND, which is equal to −10.39 %. Reviewing the impact of the US net zero announcement on the markets shows that the highest positive effect is captured in the correlation between WLD and IND, which is equal to 62.51 % and significant at a 0.1 % level while the lowest significant impact is captured in the correlation between WLD and CHI, which is 11.12 % and significant at the 5 % level. The net zero announcement in China only resulted in a positive and significant increase in the correlation between CHI and WLD. Based on the results in Panel A of Table 8, this study finds that the net zero announcements in the US strengthened information linkages between markets, while the UK's net zero announcement weakened them, suggesting that markets did not anticipate any significant changes following the net zero announcement in the UK.

The contrasting effects of the US and UK announcements on the correlation between markets are tied to the relative size of their economies, their role in the global economy, and their contributions to carbon emissions. As the world's largest economy, the US exerts considerable influence on other markets through changes in its growth, fiscal policies as well as uncertainties in financial and economic policies (Kose et al., 2017). In addition, lingering uncertainty around the US economic and climate policy can negatively impact global markets, given the countries role as the largest carbon emitter worldwide with a substantial share in global trade, production and financial activity (Caliendo et al., 2022). Consequently, reducing uncertainty in the US's climate policy and committing the world's largest economy to net zero has a positive effect on market correlations.

On the other hand, UK is a smaller economy with a significantly lower share of carbon emissions and a more limited role in financial markets, global trade and world economy (Adedoyin and Zakari, 2020). According to recent GDP and carbon emissions data from the World Bank,[3] the UK contributed only 3.5 % to global GDP in 2023, while the US accounted for 26.05 %. In terms of carbon emissions, the UK emitted 4.7 tons of carbon per person in 2023, whereas the US's per capita

Table 7
Spurious regression effect diagnostics of other ETFs.

	R^2	95 % cut-off R^2	p-value	$\rho_{i,j}$
IND & CHI	0.2143	0.0021	0.000	0.4633
IND & KOR	0.2021	0.0020	0.000	0.4499
IND & SPN	0.3247	0.0018	0.000	0.5700
IND & SWZ	0.1905	0.0046	0.000	0.4369
IND & GER	0.3648	0.0025	0.000	0.6041
IND & CAN	0.2176	0.0048	0.000	0.4668
IND & AUS	0.2370	0.0057	0.000	0.4871
CHI & KOR	0.4192	0.0018	0.000	0.6476
CHI & SPN	0.3261	0.0024	0.000	0.5718
CHI & SWZ	0.2615	0.0017	0.000	0.5113
CHI & GER	0.4675	0.0035	0.000	0.6839
CHI & CAN	0.3028	0.0022	0.000	0.5505
CHI & AUS	0.2614	0.0043	0.000	0.5115
KOR & SPN	0.3060	0.0042	0.000	0.5534
KOR & SWZ	0.2967	0.0024	0.000	0.5447
KOR & GER	0.4262	0.0017	0.000	0.6530
KOR & CAN	0.3849	0.0022	0.000	0.6206
KOR & AUS	0.3276	0.0019	0.000	0.5725
SPN & SWZ	0.5353	0.0056	0.000	0.7317
SPN & GER	0.5327	0.0033	0.000	0.7299
SPN & CAN	0.5033	0.0017	0.000	0.7096
SPN & AUS	0.5388	0.0019	0.000	0.7341
SWZ & GER	0.3955	0.0021	0.000	0.6291
SWZ & CAN	0.4641	0.0027	0.000	0.6827
SWZ & AUS	0.4545	0.0015	0.000	0.6741
GER & CAN	0.4530	0.0018	0.000	0.6730
GER & AUS	0.3825	0.0028	0.000	0.6184
CAN & AUS	0.5513	0.0040	0.000	0.7424

[3] World bank data accessed August 2024 (World Bank Open Data | Data)

Table 8
The result of structural stability test and Multivariate analysis.

Panel A: The structural stability test				
Pairs of ETFs	*Post UK Netzero* (Standard Error)	*Post US Netzero* (Standard error)	*Post China Netzero* (Standard error)	R^2
WLD & USA	−0.1733 * (0.07377)	0.2213 *** (0.08780)	0.1351 (0.3079)	0.1175
WLD & IND	−0.1039 (sig at 10 %) (0.06177)	0.6251 *** (0.0006)	−0.06290 (0.57044)	0.4339
WLD & CHI	−0.2735 *** (0.07284)	0.1112 * (0.08671)	0.25750* (0.04767)	0.1603
WLD & KOR	−0.3320 *** (0.0006)	0.17431 * (0.09455)	(0.07850) (0.5831)	0.1434
WLD & SPN	−0.22015 ** (0.00255)	0.2640* (0.03531)	−0.07425 (0.56136)	0.0890
WLD & SWZ	−0.20688 ** (0.00197)	0.1383* (0.07737)	−0.07209 (0.5377)	0.0745
WLD & GER	−0.1467 (sig at 10 %) (0.0751)	0.3244** (0.0243)	−0.03924 (0.14609)	0.08163
WLD & CAN	−0.2020 *** (0.0006)	0.2405 * (0.01720)	−0.11849 (0.24923)	0.1155
WLD & AUS	−0.1762 ** (0.0043)	0.1151 * (0.07164)	0.04664 (0.66700)	0.0763

Panel B: Pillai Multivariate Test Result				
Dependent variable	*US Netzero* (*Pvalue*)	*UK Netzero* (*Pvalue*)	*China Netzero* (*Pvalue*)	Number of Dummies
Monthly correlation of country ETFs versus WLD	0.4776 (0.0000) ***			1
		0.4035 (0.0000) ***		1
			0.3484 (0.0000) ***	1
	0.4841 (0.0000) ***	0.2599 (0.0000) ***	0.06815 (0.6204)	3
		0.887 (0.0000) ****		All dummies equal zero

emissions were 14.9 tons, that is, 3.17 times higher than those of the UK. When comparing total carbon emissions, the UK emitted 319 million tons of carbon in 2023, while the US emitted 5125 million tons, approximately 16 times greater. These figures help explain the differing effects of the US and the UK announcements on market correlations. The relatively insignificant impact of China's net zero commitment on markets may be attributed to China's classification as an emerging market, with a much smaller role in the global financial market compared to the US and the UK. Although China is the world's largest carbon emitter due to its large population, its per capita emissions are 7.76 tons, nearly half that of the US. Moreover, China is committed to achieving net zero by 2060, while the UK and the US have committed to reaching net zero by 2050 and must therefore begin their transitions to a low-carbon economy much sooner.

This table presents the structural change test. The dependent variable is the monthly correlation between WLD, and other ETFs and the independent variables are three dummy variables including "Post UK Netzero" which equals 1 from June 2019 onwards and 0 otherwise, "Post US Netzero" that equals 1 from April 2021 till the end of the dataset and 0 otherwise, and "Post China Netzero" that equals 1 from October 2021 till the end of the dataset and zero otherwise. The multivariate analysis of all monthly correlations of country ETFs versus WLD on dummy variables is reported. The reported test is the Pillai test result. Dummy variables for the multivariate analysis are the net zero announcements by the US, the UK and China. *** shows the significance at 0.1 % level, ** shows the significant at 1 %, and * shows the significance at 5 %.

Panel B shows the result of the multivariate analysis. By running a multivariate analysis on each country's net zero announcement, the impact of each individual announcement on the market can be examined.

The p-value of the Pillai multivariate test shows that each announcement had a statistically significant effect at the 0.1 % level, indicating that each of them had a significant effect individually. However, when analyzing the correlation between markets using all three dummy variables (net zero announcements by the US, the UK, and China), the effect of China's announcement becomes insignificant, while the impacts of the US and UK announcements remain statistically significant. This result indicates that while China's announcement individually impacts the markets, the effect of US announcement is much more substantial. After controlling for the US announcement, the impact of China's announcement is no longer significant. This result indicates that, without US participation, efforts by other countries to achieve global net zero goals are unlikely to succeed.

For the pre- and post-net zero announcement, we rely on the implied volatility correlations as there are insufficient time series observations in the two periods before and after each net zero announcement to justify the use of GMM.

5.4. Locally weighted scatterplot smoothing (LOWESS)

To illustrate the structural change after the net zero announcements, we use the Locally Weighted Scatterplot Smoothing (LOWESS) method. Fig. 4 shows the structural change around net zero announcements in the UK, the US and China, confirming that the UK's net zero announcement, pictured by the green dashed line, had a negative impact on the correlation between WLD and USA, while the US announcement, shown by the blue dashed line, had a positive impact.

The orange dashed line shows when China announced its net zero commitment. As evident from Fig. 4, this announcement did not have a significant impact on correlation between WLD and USA.

Figs. 5 and 6 show the structural change around net zero announcements in the UK, the US and China in the monthly correlation of WLD with other ETFs. The green dashed line shows the time that the UK announced its net zero commitment, the blue dashed line points to the

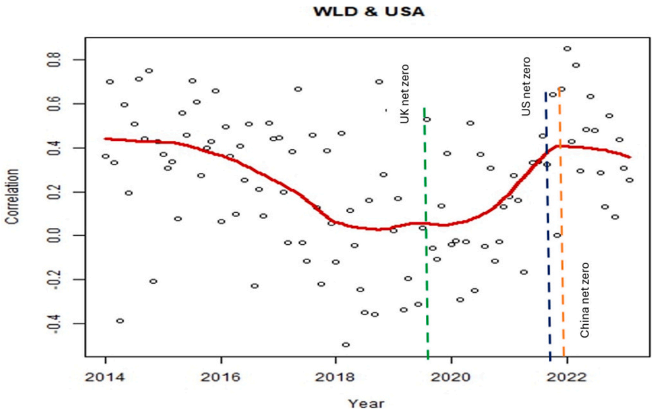

Fig. 4. The structural change in the monthly correlation of WLD and USA.

time that the US made its announcement, and the orange dashed line shows the date that China announced its net zero commitments.

Both figures show structural changes around the UK and US announcements in the monthly correlations, which is supported by the results of the analysis in Table 8, while no star出ctural change is illustrated around China net zero announcement.

The impact of the UK's net zero announcement on the correlation of all nine pairs of ETFs are negative while the net zero announcement in the US had a positive, significant effect on the correlation between WLD and other ETFs. Fig. 5 shows that the structural change around the UK's net zero announcement (pictured by green dashed line) in the correlation of WLD and IND is less significant compared to other pairs. This figure indicates that the structural change around China net zero announcement which is shown by the orange dashed line is insignificant.

Fig. 6 shows the monthly correlation of WLD with four country ETFs, namely SWZ, GER, CAN, and AUS. Less variation in the correlation between WLD and GER around the time of the UK's net zero announcement indicates that there is insignificant structural change associated with this event, while a sharp rise around the net zero announcement in the US is a sign of significant structural change. The structural change between monthly correlation of WLD with SWZ, GER, CAN, and AUS around China net zero announcement is insignificant.

Fig. 6 illustrate that the impact of the US net zero announcement on the correlation between ETFs was more significant than the impact of the UK and China net zero announcements. This is because the US economy plays a more important role in the world economy and has a higher share of total carbon emissions globally. The commitment to net zero emissions by the US Government and the implementation of the policies required to achieve this goal are expected to have a significant impact on global reduction in carbon emissions.

6. Conclusion

This study investigates the volatility linkages between country ETFs, using both the GMM approach suggested by Fleming et al. (1998) and the implied volatility approach developed by Wang (2009).

To analyze the role of information in generating market linkages, we rely on the rational expectations framework developed by Tauchen and Pitts (1983). According to this framework, traders with heterogeneous expectations revise their expectations about current and future asset prices, which generates new rounds of price change and market volatility. To optimally balance their portfolio and reduce their systematic risks, traders who are active in multiple markets consider the

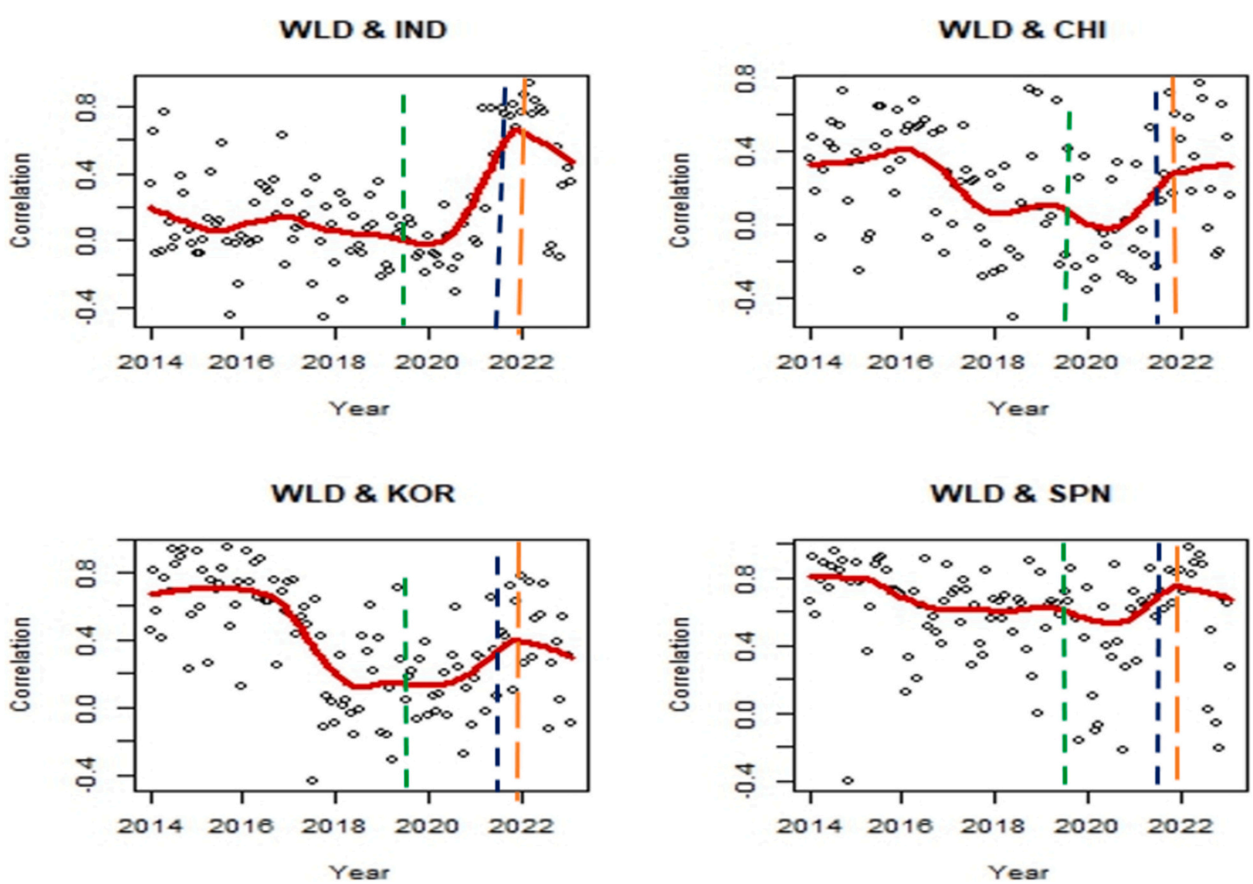

Fig. 5. The structural change in the monthly correlation of WLD with four country ETFs.

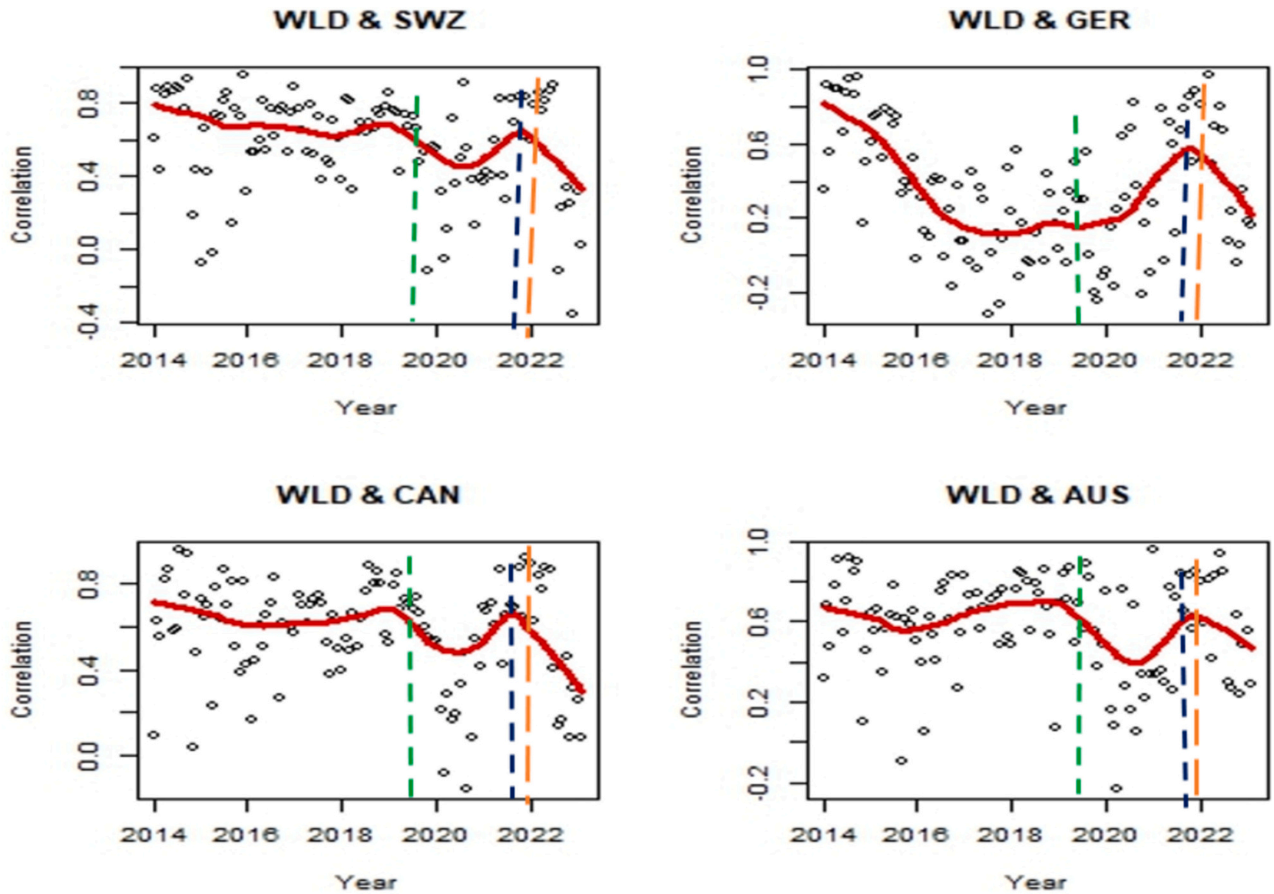

Fig. 6. The structural change in the monthly correlation of WLD with SWZ, GER, CAN, and AUS.

correlations between assets across various markets upon arrival of new information, which generates information spillovers and leads to volatility linkages.

The GMM approach is used to estimate the correlation between the log of information flows among ten different country ETFs by employing market return data, while the implied volatility approach uses the implied volatility from call and put options trading in the market. The simple log correlation of daily implied volatilities provides the required database to estimate the cross-market correlation of implied volatilities and the magnitude of the volatility linkages between markets.

The result of the GMM approach shows the volatility linkages between country ETFs and WLD range from 39.67 % to 71.43 %, all significant at a 5 % level. Looking at the results of the implied volatility approach after controlling for the spurious effect indicates strong correlation between markets. Using the implied volatility approach, we find that volatility linkages between country ETFs and WLD range from 32.31 % to 65.36 %, all statistically significant at a 5 % level.

The results drawn from both approaches show that the volatility linkages between the global ETF and the country ETFs are strong, indicating that due to the information spillover among markets any information that arrives in one market has an impact on other markets.

Considering the impact of the net zero announcement in the UK, US, and China, this study also uses a time-varying dynamics study based on monthly correlations of implied volatilities. The results show that the US net zero announcement has strengthened the volatility linkages among ETF markets, while the impact of the UK net zero announcement has weakened the correlation among implied volatilities. This study finds that the impact of China's net zero announcement on the correlation between markets was not statistically significant. Looking at the data, after the US net zero announcement, the volatility linkages among country ETFs and WLD increased by 8.7 % to 58.05 %, while the net zero announcement in the UK decreased the volatility linkages by −33.2 % to −10.39 %. The positive and significant effect of the US's net zero announcement can be attributed to its substantial share of global GDP and its influence on financial markets. As the largest carbon emitter, the US's commitment to net zero reduces uncertainty surrounding its climate policy, which leads to a strengthened and significant correlation between markets.

Conversely, given the small size of the UK economy and its low share in total carbon emissions, the net zero announcement in the UK has an opposite effect on markets and results in a significant but negative effect on the correlation between markets. The result of the multivariate analysis indicates that when all net zero announcements are included in the model, the US and UK announcements show significant impacts on markets, whereas the effect of China's announcement is not statistically significant. To illustrate this result, we also used the LOWESS method, which demonstrates that the impact of the policy announcements on the correlations is significant.

Running the multivariate analysis on the monthly correlation between markets for the US, UK and Chinese announcement individually results in capturing significant effects for each. However, the effect of China's announcement was insignificant when all announcements were considered in the model simultaneously. Therefore, and without US participation, the efforts of other countries to achieve global net zero goals are unlikely to succeed.

In summary, empirical analysis shows that there is a strong volatility linkage among ETF markets and this linkage has strengthened after the US Government's net zero announcement. The strengthening of volatility linkages in the market after the net zero announcement can be considered a positive signal that the market welcomes the commitment to net zero and the associated policy changes. Furthermore, this study highlights the information linkages among country ETFs, confirming that traders should consider this in managing their portfolios to gauge market risks.

The results of this study can contribute to a better understanding of the sources of implied risk, enhancing forecasting of option volatility, and improving the estimation of correlations used in optimal portfolio construction. By considering market co-movements as a source of implied risk, this study has demonstrated that market information linkages increases when uncertainty about climate policy decreases, with a more significant rate of change observed when the economy taking decisive climate action has a larger share of the global economy.

Future research can expand upon our findings by further exploring the economic impact of net zero announcements, examining market reactions to other climate policy declarations, or by applying this approach to different economic policy announcements.

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CRediT authorship contribution statement

Mona Mashhadi Rajabi: Writing – original draft, Visualization, Software, Formal analysis, Data curation, Conceptualization. **Martina Linnenluecke:** Writing – review & editing, Funding acquisition, Conceptualization. **Tom Smith:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare no conflicts of interest.

Appendix A. Appendix 1

Table A1 presents the summary statistics for monthly correlations of log implied volatilities obtained by OLS. It shows that all the correlations are almost similar with means close to zero and standard errors that range from 0.2178 to 0.3415. As the coefficients of skewness and kurtosis are small, it can be deduced that the distribution of all pairs of monthly correlations are normal.

Table A1
Summary statistics of monthly correlations.

Pairs of ETFs	Mean	Median	Max.	Min.	S.D.	Skewness	Kurtosis
WLD & USA	0.2451	0.3007	0.8502	−0.4980	0.3083	−0.3207	−0.6836
WLD & IND	0.18064	0.1001	0.9356	−0.4535	0.3225	0.6320	−0.3128
WLD & CHI	0.2086	0.2319	0.7656	−0.5011	0.3079	−0.09364	−0.9787
WLD & KOR	0.3845	0.4093	0.9464	−0.4366	0.3382	−0.20613	−0.9348
WLD & SPN	0.5880	0.6579	0.9767	−0.4008	0.2931	−1.2721	1.3575
WLD & SWZ	0.5798	0.6504	0.9513	−0.3497	0.2699	−1.07378	0.9062
WLD & GER	0.34486	0.3375	0.9647	−0.3112	0.3347	0.0865	−1.0033
WLD & CAN	0.5748	0.6291	0.9520	−0.15021	0.2387	−0.8601	0.2968
WLD & AUS	0.5783	0.6255	0.9559	−0.2302	0.2469	−0.8419	0.3444
USA & IND	0.4238	0.4441	0.8727	−0.3712	0.2359	−0.88283	1.4128
USA & CHI	0.6697	0.7193	0.9352	−0.2504	0.21786	−1.8300	4.1103
USA & KOR	0.6284	0.6892	0.9706	−0.7027	0.2500	−1.9065	6.9613
USA & SPN	0.3713	0.3850	0.8449	−0.5654	0.27061	−0.5350	0.1019
USA & SWZ	0.2841	0.3294	0.8130	−0.5938	0.2822	−0.5554	−0.0017
USA & GER	0.5577	0.6101	0.9231	−0.2763	0.2404	−0.8025	0.4038
USA & CAN	0.3314	0.3879	0.93003	−0.3964	0.3387	−0.4777	−0.7945
USA & AUS	0.2711	0.2894	0.8815	−0.4553	0.2957	−0.4608	−0.2012
IND & CHI	0.4027	0.4241	0.8471	−0.4447	0.2504	−0.6883	0.3863
IND & KOR	0.3614	0.3854	0.8575	−0.5247	0.2604	−0.5156	0.3760
IND & SPN	0.2817	0.2463	0.9372	−0.3232	0.2972	0.1951	−0.6567
IND & SWZ	0.2304	0.1814	0.8775	−0.4017	0.3001	0.3254	−0.6226
IND & GER	0.4281	0.4622	0.9208	−0.3429	0.2732	−0.6838	0.0650
IND & CAN	0.2344	0.2122	0.8207	−0.4022	0.2910	0.1607	−0.7739
IND & AUS	0.2269	0.1977	0.8685	−0.5284	0.3179	0.0294	−0.8276
CHI & KOR	0.6066	0.6652	0.9429	−0.0279	0.2326	−0.9281	0.3993
CHI & SPN	0.2960	0.3247	0.8079	−0.4298	0.2775	−0.3639	−0.3701
CHI & SWZ	0.2489	0.2769	0.7828	−0.3747	0.2602	−0.1369	−0.7474
CHI & GER	0.4860	0.5347	0.9452	−0.3375	0.2595	−0.8026	0.2976
CHI & CAN	0.2653	0.2807	0.8264	−0.3841	0.2922	−0.2215	−0.5657
CHI & AUS	0.2270	0.2558	0.7524	−0.4677	0.2924	−0.1897	−0.8407
KOR & SPN	0.4791	0.5214	0.9292	−0.1289	0.2615	−0.4307	−0.6628
KOR & SWZ	0.3887	0.4422	0.9232	−0.3349	0.3037	−0.5133	−0.5998
KOR & GER	0.5496	0.5671	0.9436	−0.1749	0.2484	−0.54078	−0.21304
KOR & CAN	0.4210	0.4387	0.8721	−0.3974	0.3183	−0.6139	−0.4200
KOR & AUS	0.3546	0.3972	0.9324	−0.4406	0.2982	−0.5472	−0.3559
SPN & SWZ	0.5816	0.6334	0.9575	−0.3673	0.2877	−1.2535	1.3318
SPN & GER	0.4662	0.4671	0.9587	−0.2109	0.3237	−0.2186	−1.0144
SPN & CAN	0.5436	0.5689	0.9267	−0.2048	0.2193	−0.6721	0.5674
SPN & AUS	0.5722	0.6249	0.9256	−0.2591	0.2559	−1.3924	2.1498
SWZ & GER	0.3900	0.3696	0.9687	−0.3663	0.3415	1.4660	0.0421
SWZ & CAN	0.5046	0.5553	0.9561	−0.3396	0.2632	−1.1140	1.4660
SWZ & AUS	0.5296	0.5688	0.9418	−0.2720	0.2534	−0.6854	−0.8959

(continued on next page)

Table A1 (*continued*)

Pairs of ETFs	Mean	Median	Max.	Min.	S.D.	Skewness	Kurtosis
GER & CAN	0.4034	0.4258	0.9446	−0.4261	0.3486	−0.2307	−1.0683
GER & AUS	0.3465	0.3260	0.9481	−0.3476	0.3313	−0.0324	−1.1045
CAN & AUS	0.5833	0.6114	0.9511	−0.2399	0.2295	−0.8837	1.01674

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108062.

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