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The Spillover Effect for Carbon Emission ETFs: The Analysis of MGARCH Model

Yan-De Lin[1], Fu-Ying Chen[2] and Jo-Hui Chen[3]

1. *Department of Finance, Chung Yuan Christian University, Taiwan*
2. *Ph.D. Program in Business, Chung Yuan Christian University, Taiwan*
3. *Department of Finance, Chung Yuan Christian University, Taiwan*

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A B S T R A C T

This study utilizes MGARCH models to measure the impact of industry ETFs, carbon emissions ETFs, and the S&P 500 index on return and volatility. The CCC model maintains constant interconnection correlations during the time series, highlighting long-term correlations between variables. The DCC model is in charge of monitoring short-term and long-term impacts. The BEKK model emphasizes the relationships between variables and shows their compatibility by considering dynamic dependencies and conditional correlations among the variables over time. The study explains the connections between industry ETFs, carbon ETFs, and the S&P 500 Index and clarifies investment techniques and risk management. Future work on establishing correlations between volatility and spillover effects will allow us to analyze the impact of low-carbon transitory energy companies.

Keywords: Carbon Emissions ETFs, Industry ETFs, Multivariate GARCH, Spillover effects
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[1] Email : w535793@gmail.c
[2] Email : ares.fy.chen@gmail.com
[3] Email : johui@cycu.edu.tw

1. Introduction

The world's rapid development causes massive greenhouse gas emissions, resulting in extreme climate change. As a result, climate change is becoming an increasingly important issue for people. In 1997, the United Nations Framework Convention on Climate Change (UNFCCC) signed the Kyoto Protocol, the first legislation to restrict greenhouse gases. The objective was to regulate the release of greenhouse gases, including carbon dioxide, and slow down the earth's climate change and greenhouse effect, which was the goal of its enforcement in 2005. In 2015, the UNFCCC approved the Paris Agreement in Paris. The aim was to enhance global response to climate change by keeping global temperature rise this century below 2 degrees Celsius above pre-industrial levels. The UNFCCC is pursuing a goal of lowering the temperature increase to 1.5 degrees Celsius. France is committed to minimizing the average temperature rise of the planet by at least two degrees Celsius.

The Kyoto Protocol has established three mechanisms to reduce greenhouse gas emissions: the Clean Development Mechanism (CDM), Joint Implementation (JI), and International Emissions Trading (IET). These mechanisms serve the goal of reducing greenhouse gas emissions. At present, CDM is the most frequently used mechanism. Its main function is to enable developed nations to plan or provide funds and technologies that promote emission reduction in developing countries and to obtain Certified Emissions Reduction (CERs) to comply with the UNFCCC.

Under the three emission reduction mechanisms, carbon trading methods are divided into two types: (1) Allowance-based transactions refer to the emission rights that can be traded in the trading market under the total volume control, such as the European Union Allowances (EUAs) of the EU emissions trading system. (2) The exchange of emission reduction units produced by emission reduction plans between countries and traded in futures is the primary method for conducting project-based transactions.

There are 25 operational emissions trading systems around the world by 2022. The major trading systems include the European Union Emission Trading Scheme (EU ETS), the Chicago Climate Exchange (CCX), the California Cap-and-Trade Program (California CAT), the New Zealand Emissions Trading Scheme (NZ ETS), the China National Emissions Trading Scheme (ETS) and others. The influence of international carbon markets can significantly affect the efficiency of decreasing global greenhouse gas emissions. Notable participants in the carbon credit trading platform market include Nasdaq, Inc. (USA), CME Group (USA), AirCarbon Exchange (ACX) (Singapore), Carbon Trade Exchange (CTX) (UK), and Xpansiv (USA). The world's leading carbon trading markets include the European Union Emission Trading Scheme (EU ETS), the Chicago Climate Exchange (CCX), the California Cap-and-Trade Program (California CAT), the New Zealand Emissions Trading Scheme (NZ ETS), the European Climate Exchange (ECX) and others. The EU ETS is the trading system of the countries with the most participation. The member states must meet their Kyoto Protocol reduction commitments to achieve an 8% reduction in greenhouse gas emissions between 2008 and 2012 compared to 1990. The system uses the cap-and-trade principle to manage emissions by purchasing and selling emission permits within the total greenhouse gas emissions limit. The trading unit is EUAs, and ECX is the largest exchange, with around 85% of EU ETS being traded.

The United States Environmental Protection Agency (EPA) has recorded greenhouse gas emissions and sinks since 1990. This effort was coordinated by specialists from over a dozen U.S. government agencies, academic institutions, industry associations, consulting firms, and environmental organizations. The analysis in this report concentrates on the total annual greenhouse gas emissions from all artificial sources in the United States. The majority of CO2 emissions in 2020 came from the combustion of fossil fuels, particularly gasoline and diesel, to transport goods and people. In the United States, electricity is a crucial power source for households, businesses, and industries, generating fossil fuels. Electricity is the second largest contributor to CO2 emissions in the US. Many industrial processes generate cement, steel, other metals, and chemicals due to the use of fossil fuels. The third most significant source of emissions in the US is fossil fuel combustion and indirect power generation from various industrial processes, which account for about 16% of the total CO2 emissions. Commercial housing uses significant amounts of cement, steel, etc. The construction process accounts for approximately 13% of its emissions.

The existing literature mainly concentrates on the link between the oil and carbon markets. Reboredo (2014) investigated how volatility is transmitted between the EU and the petroleum market. In China, carbon allowance prices were examined by Zheng, Zhou, and Wen (2021) to evaluate the effects of oil supply shocks, demand, and risk shocks. The connection between carbon and fossil fuel prices was investigated by Zhang and Sun (2016). The risk spillovers between energy and European carbon futures contracts were examined by Balcilar, Demirer, Hammoudeh, and Nguyen (2016). The relationship between carbon futures markets and financial, energy, and commodity futures has been characterized by Li, Ji, Qiao, and Wang (2015). Despite this, the interaction between multiple markets remains to be fully explored. This study is motivated by bridging this research gap and contributing to understanding market interactions. The current study uses the MGARCH model to investigate the spillover impacts of carbon emission ETFs, industrial ETFs, and S&P500 indexes, leading to a better understanding of cross-market dynamics and their implications.

The construction industry has used natural resources and energy, resulting in many greenhouse gas emissions through generation and transportation. The carbon dioxide emissions from energy and non-energy sources in the global construction sector have been examined in a study by Huang, Krigsvoll, Johansen, Liu, and Zhang (2018). Shi, Chen, and Shen (2017) utilized the structural decomposition analysis method to analyze the Chinese construction industry in greater detail and identify the factors that led to changes in carbon emissions. The findings indicate that the total final demand is the primary factor responsible for rising building carbon emissions.

The total carbon emission efficiency of the construction industry was evaluated using a Super Slacks-Based Measure (SBM) Data Envelopment Analysis (DEA) model by Zhou, Liu, Lv, Chen, and Shen (2019). Their research has shown that in addition to internal factors, the efficiency of the construction industry's carbon emissions is also influenced by intersectoral factors in the manufacturing sector. In Turkey, there is a long-term causal relationship between financial development and carbon emissions, as found by Gokmenoglu, Ozatac, and Eren (2015).

1. This article examines three carbon ETF types to explore short-, medium-, and long-term effects and their connection with industrial ETFs. The variables are evaluated using daily data, which is then converted to a stationary sequence by the Unit Root Test. The research's objective is as follows:
2. To investigate the correlation between the returns of carbon ETFs, four industrial ETFs, and the S&P 500 Index on a short-, medium-, and long-term basis.
3. The MGARCH model will be utilized to investigate the spillover effect and changes in return volatility among carbon emission ETFs, the four industrial ETFs, and the S&P500 index.

The purpose of this study is to examine the variations among the Constant Conditional Correlation (CCC), the dynamic conditional correlation coefficient (DCC), and the BEKK models and choose the most appropriate one.

The document is structured as follows: Section 2 presents the literature review. Section 3 provides a summary of the data and theoretical model. Section 4 presents the empirical results, while Section 5 summarizes the conclusions.

2. Literature Review

A growing body of literature has examined relevant factors in the carbon market through empirical analysis. Many scholars claim that several factors influence carbon emissions' price, including crude oil, energy demand, economic factors, and related policies.

Kim and Koo (2010) demonstrated that coal price was the main factor influencing the quantity of carbon quotas traded in the United States market. Nazifi and Milunovich (2010) proved that the carbon futures contract was linked to natural gas, coal, and oil prices. Zhang and Xu (2018) examined the cost of carbon emission permits issued by the Chinese Emissions Exchange (Shenzhen). An increased amplitude of price fluctuations is related to the asymmetric trend caused by the economic downturn and inadequate market information. Yu, Lin, Zhang, Jiang, and Peng (2019) used grey correlation analysis to study the correlation between carbon emissions and other effects of economics, energy, and population. They found that coal and oil consumption correlate most closely with carbon emissions. Using the nonlinear autoregressive distributed lag (NARDL) model, Zheng et al. (2021) found that China's oil supply, demand, and risk shocks have a long-run asymmetric and a short-run symmetric relationship for carbon allowance prices.

Some evidence suggests that carbon allowances are linked to the stock market returns of the electricity company. The EUA price caused a rise in stock returns for the top electricity corporations covered by the EU ETS, as shown by Oberndorfer (2009). Silva, Moreno, and Figueiredo (2016) investigated the impact of EUA price variations on the stock returns of electric power firms using multifactor market models. It was discovered that changes in EUA prices have a long-term impact on stock market returns. Zhu et al. (2020) asserted that power prices also significantly impact carbon prices. The increase in carbon emissions suggests that carbon prices will increase since higher energy costs have motivated the use of coal.

Energy prices, trading volumes, and other factors can impact the price of carbon. Sousa, Pinto, Rosa, Mendes, and Barroso (2005) used the ascending marginal costs (MC) to measure the impact of CO2 emissions trading on the power industry in the Iberian Electricity Market (IBELM). It was discovered that implementing CO2 limits will lead to an increase in electricity prices. The logit model was used by Kanamura (2016) to analyze the volatility structure and dynamic linkage between EUA and certified emission reductions (CER) in order to reveal the beneficial impact of energy prices on EUA prices. Woo, Chen, Olson, Moore, Schlag, Ong, and Ho (2017) used regression analysis to examine California's carbon trading and electricity pricing. It was found that the CO2 premium and the marginal cost of CO2 emissions from natural gas power generation were almost the same. María, Francesco, and María (2015) applied the Autoregressive Moving Average with Exogenous inputs (ARMAX) GARCH, a framework that incorporates GARCH, Exponential-GARCH (EGARCH), Asymmetric Power ARCH (APARCH) and Component GARCH (CGARCH) to analyze the volatility dynamics and futures prices of EUA Phases 2 and 3. The research revealed that the sudden increase in volume had led to increased volatility. Exploring the interaction between South Eastern European Regional Electricity Market (SEE-REM) emissions and hydropower availability via a bottom-up partial equilibrium framework, Višković, Chen, and Siddiqui (2017) found that the emission reductions of the ETS of the SEE-REM mainly depend on the allowance price.

Industrial emissions are commonly associated with CO2 emissions, and numerous studies have indicated that carbon emissions interact with electricity, transportation, buildings, and industry and are based on causal relationships. Bergh, Delarue, and D'Haeseleer (2013) examined the effects of deploying renewable electricity sources (RES-E) in the European power sector on EUA prices and CO2 emissions. Through a partial equilibrium model, they discovered that RES-E was responsible for replacing CO2 emissions from the EU ETS. EUA prices have decreased due to the decrease in demand for EU allowances (EUAs).

Transportation is the primary contributor to CO2 emissions. Singh (2006) utilized a liquidity model to examine the mobility, energy consumption, and CO2 emissions of land passenger transportation in India. The estimated levels and energy demand increase related to CO2 emissions were found to have positive growth slopes. Wang, Chi, Hu, and Zhou (2014) suggested a pricing scheme and demonstrated the benefits of implementing a bi-level programming model in alleviating urban traffic congestion and decreasing CO2 emissions. Wang, Gu, Ma, and Li (2022) created a transition model that utilizes a multiple logistic regression technique to account for the effect of extreme weather on carbon dioxide emissions from daily commutes. The findings show that the gradual decrease in carbon dioxide emissions from daily commutes has been caused by extreme weather. Zhou, Wang, Huang, Bao, Zhou, and Liu (2022) used a bottom-up approach to analyze the CO2 emission characteristics of road traffic in Shenzhen. Their analysis revealed that six factors, including population density, number of workplaces, number of dwellings, arterial road density, subway station accessibility, and bus station accessibility, significantly impact CO2 emissions from road traffic.

The volatility of oil and energy markets has been extensively researched. The analysis of the volatility of the crude oil market compares it to other financial markets and energy ETFs. Lin and Li (2015) assessed the impact of price and volatility spillover on the integrated Vector Error Correction

(VEC)-MGARCH framework. The findings reveal an effect of price spillover in the crude oil and natural gas markets. Chang, McAleer, and Wang (2018) used the Diagonal BEKK multivariate conditional volatility model to identify the Latent Volatility Granger causality and partial volatility spillovers among solar, wind, nuclear, and crude oil ETFs. The findings showed that latent volatility Granger causality had significant positive correlations with these ETFs. The GARCH-MIDAS model was utilized by Lin and Chang (2020) to investigate the spillover effects of volatility from five financial markets to the oil ETF and energy mutual fund. The research showed that volatility was transferred from the stock market's S&P 500 to the oil ETF and energy mutual fund during calm and turbulent times.

Abdullah, Saiti, and Masih (2016) used Maximum Overlap Discrete Wavelet Transformation (MODWT) to investigate the dynamic causal relationship between crude oil prices and Islamic stock indices in Southeast Asian (SEA) countries. The research revealed that Islamic stock indices and certain commodities have a cointegration relationship. The Fractionally Integrated GARCH (FIGARCH) model was utilized by Kashif and Osama (2018) to examine the long-term dependence on the volatility of renewable and unrenewable energy ETFs. Their results showed that all ETFs, both revolving and non-renewable, had a predictable pattern of volatility. The Vector Autoregressive (VAR)-MGARCH framework was utilized by Janda, Kristoufek, and Zhang (2022) to investigate the dynamic connections between oil prices and stock returns of clean energy. It was concluded that a positive conditional correlation exists between the stock prices of clean energy and technology companies.

The following literature uses different GARCH models to analyze the spillover effect of ETF returns between countries and financial markets. Chen and Diaz (2012) applied the Exponential General Autoregressive Conditional Heteroskedasticity-in-Mean-Autoregressive Moving Average (EGARCH-M-ARMA) model to assess the impact of leveraged and inversely leveraged ETFs on stock indices through spillover and leverage effects. According to their analysis, the previous returns of lagged and inverse leveraged ETFs had a significant impact on the stock indices. The use of GARCH-M-ARMA and EGARCH-M-ARMA models by Chen and Malinda (2014) for analyzing financial and non-financial ETFs revealed connections between both kinds of ETFs. Krause, Ehsani, and Lien (2014) utilized variance decompositions to analyze volatility spillovers in three ETFs that concentrate on energy, finance, industry, and their counterparts' stocks. It was found that these securities had a bi-directional impact due to volatility spillovers. Yavas and Dedi (2016) discussed equity returns and volatility using MARMA (Multivariate Autoregressive Moving Average) and GARCH models. The findings indicate that there are significant correlations between the daily returns of the ETFs of the countries. Serletis and Azad (2018) used the Vector Autoregressive (VAR) model to investigate the volatility transmission from emerging economies to the U.S. ETF market. The results indicate that emerging market economies in the United States have significant benefits. The relationship between the Sharia or Islamic index and the composite conventional index in Indonesia and Malaysia was examined using the MGARCH method, focusing on correlation and volatility. The study found that the stock market exhibits a strong correlation during times of crisis.

Some literature suggests that other market prices could affect carbon futures contracts. Asymmetric volatility causes the spillover effects of carbon prices and corporate emissions. The findings of Wang and Zhao (2012) regarding the spillover effect of CCX carbon trading prices were varied. The residual square sequences were used to test causality, and they found that the CCX carbon trade price and the international oil price (WTI) had significant mean and volatility spillover effects.

Changes in the energy market could affect the price of carbon. Boersen and Scholtens (2014) discovered that gas, oil, switching costs, and electricity prices greatly influence EUA carbon futures prices. The volatility risks of carbon emissions prices were analyzed using the ARMA(1,1) - Component GARCH (CGARCH) model. The findings revealed multiple causal connections between the carbon futures market and other futures markets, such as financial, energy, and commodity markets. Balcilar et al. (2016) used a Markov regime-switching (MS-DCC-GARCH) model to analyze the transfer of risks between energy futures prices and carbon futures contracts in Europe. The research showed that the carbon emission markets are linked to modifications in the electricity, natural gas, and coal futures market. Wang, Gu, Liu, Fan, and Guo (2019) utilized AR-EGARCH and ARMA-GARCH models to investigate the relationship between the EU ETS and the trading behavior of emitting companies through a two-way relationship. Their research indicated that carbon prices have an inverse effect on the volatility of the trading behavior of emitting companies. Zeng, Jia, Su, Jiang, and Zeng (2021) found that there were asymmetric volatility spillover effects between the EUA and certified emissions reduction (CER) markets, where only the EUA market had a one-way volatility spillover effect on the CER market after the EU Emissions Trading System (EU ETS) entered its third stage. Liu et al. (2023) analyzed how volatility was connected between European carbon emissions and energy markets using the DCC-MVGARCH model and spillover index approach. Their findings showed that volatility correlations and the overflow index significantly change global economic instability and political events. The volatility connection between coal and carbon markets was significant, but there was a significant increase in volatility spillover from the renewable energy market to the carbon market.

Research suggests that carbon emissions can predict future volatility. Dai, Xiong, Huynh, and Wang (2022) applied the GARCH-MIDAS model to explore the influence of European Economic Policy Uncertainty (EUEPU) and Global Economic Policy Uncertainty (GEPU) on the volatility of the European carbon spot returns. The results indicate that internal factors with significant predictive power influence the long-term volatility of the carbon spot market. Liu and Chen (2013) investigated the effects of the fractional integrated error correction hyperbolic GARCH model on carbon, oil, gas, and coal markets through the interaction, volatility spillovers, and long-term memory effects. According to the findings, carbon, oil, gas, and coal returns have a long memory effect that can be employed to anticipate future volatility.

Du, Deng, Zhou, Wu, and Pang (2022) used a spatial Markov transition probability matrix to study the impact of carbon emissions on spatial spillovers. The results revealed a substantial spatial spillover effect for provinces regarding carbon emission efficiency. China's carbon emissions trading policies were evaluated by Dai, Qian, He, Wang, and Shi (2022). The results showed that local CET policies significantly decreased the industrial carbon intensity of surrounding areas due to adverse spatial spillover effects. Li (2022) asserted that the volatility spillover effect was directed from the energy market to the carbon market.

Rahman and Kashem (2017) analyzed the correlation, short- and long-term dynamics, and causal relationships between Bangladesh's carbon emissions, energy consumption, and industrial growth using Auto Regressive Distributed Lag (ARDL). They discovered that both industrial production and energy consumption had positive impacts on carbon emissions in the short and long term. Granger causality analysis showed that a one-way link between industrial production and energy consumption causes carbon emissions.

3. Data and Methodology

3.1 Data

This paper obtains daily closing prices for stock indices from both the Investing.com financial website and Yahoo Finance.com website. The timeframe for this study spans from the inception of the various ETFs until November 30, 2022. The information includes three ETFs for carbon emissions, four for industry, and one market index, along with ETFs listed on the New York Stock Exchange. This study categorizes carbon emission ETFs into short-term (KRBN), medium-term (CRBN), and long-term (SMOG) based on their listing periods and compares them to industries and the stock market. Table 1 exhibits the sample information.

Table 1 Research variables

Category	Code	Name	Date	Obs.
Stock Market Index	SPX	S&P 500 Index	2007/05/10	3919
Carbon market	KRBN	KraneShares Global Carbon Strategy ETF	2020/07/31	589
	CRBN	iShares MSCI ACWI Low Carbon Target ETF	2014/12/10	2008
	SMOG	VanEck Low Carbon Energy ETF	2007/05/10	3919
Electricity market	XLU	Utilities Select Sector SPDR Fund	2007/05/10	3919
Transportation market	IYT	iShares U.S. Transportation ETF	2007/05/10	3919
Architecture market	XHB	SPDR S&P Homebuilders ETF	2007/05/10	3919
Industry market	XLI	Industrial Select Sector SPDR Fund	2007/05/10	3919

Examining the daily rate of return through price changes can help examine the contagion effect of volatility between the carbon emission index and the marketplace. The formula for calculating the daily rate of return for the ETF and the stock index is as follows.

$$R_t^e = \ln\left(\frac{P_t^e}{P_{t-1}^e}\right) * 100, \tag{1}$$

$$R_t^m = \ln\left(\frac{P_t^m}{P_{t-1}^m}\right) * 100, \tag{2}$$

where R_t^e and R_t^m represent the returns of the ETF and the stock index at time *t*, and P_t^e and P_t^m are the price of the ETF and the stock index, respectively. The empirical study began with calculating summary statistics for each industry's daily ETF returns. In order to verify the possibility of a Unit Root in the price return, an Augmented Dickey-Fuller (ADF) was carried out.

3.2 Methodology

The generalized Autoregressive Conditional Variance (GARCH) was first proposed by Engle (1982). This model has been widely used in finance. The primary purpose is to analyze the volatility and spillover effects of multiple markets, and it can also measure the size of the shock. The Multivariate GARCH (MGARCH) model, proposed by Bollerslev, Engle, and Wooldridge (1988), can represent dynamic changes in conditional variance and covariance. The model is classified as follows:

$$\sigma_t^2 = \psi + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \ , \quad \psi > 0,\ 0 < \beta \leq 1,\ 0 < \alpha \leq 1,\ \alpha + \beta \leq 1\,, \tag{3}$$

where α is a coefficient measuring volatility shock for the next period. $\alpha + \beta$ represents a measure of the persistence of a volatility shock, which examines how quickly this effect disappears over time.

In order to test the carbon emission ETF, the four industry ETFs, and the S&P500 index, this study uses a multivariate model, CCC-GARCH, BEKK-GARCH, and a nonlinear combination of univariate model DCC-GARCH, to observe the dynamic spillover effect, which can be referenced as follows:

(1) Constant Conditional Correlation (CCC)-GARCH

Bollerslev (1990) proposed a model that posits that only the past and the residual term were responsible for the conditional covariates. The model is as follows:

$$\sigma_{i,t}^2 = \omega_i + \sum_{p=1}^{P} \alpha_{ip}\alpha_{i,t-p}^2 \ + \sum_{q=1}^{Q} \beta_{iq}\sigma_{i,t-q}^2\,, \tag{4}$$

where α is the ARCH effect, which indicates the degree of impact of news on the variable's volatility correlation, indicating a short-term persistent impact on return; β reveals the GARCH effect, which indicates the degree of persistent inter-variable volatility correlation, representing a long-term persistent impact on return. The model must satisfy the condition α+β<1.

(2) Dynamic Conditional Correlation (DCC-GARCH)

This model was presented by Engle (2002) and Tse and Tsui (2002). The DCC model assumes that the correlation coefficient will change over time. The following describes it:

$$H_t = G_t R_t G_t, \tag{5}$$

where G_t stands for the conditional standard deviation calculated by univariate GARCH, the $K \times K$ diagonal matrix formed by the diagonal is taken. H_t is the number of conditional variants estimated by univariate GARCH. R_t represent a matrix of dynamic conditional correlation coefficients.

$$R_t = (diagQ_t)^{-1/2} Q_t (diagQ_t)^{-1/2} \ , \tag{6}$$

$$Q_t = (1 - \alpha_1 - \beta_1)\bar{Q} + \alpha_1(\epsilon_{t-1}\acute{\epsilon}_{t-1}) + \beta_1 Q_{t-1}, \tag{7}$$

$$\begin{bmatrix} 1 & \rho_{12} & \cdots & \rho_{1K} \\ \rho_{21} & 1 & \cdots & \rho_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{K1} & \rho_{K2} & \cdots & \rho_{KK} \end{bmatrix}, \quad Q_t^* = \begin{bmatrix} \sqrt{q_{11}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22}} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sqrt{q_{KK}} \end{bmatrix}, \tag{8}$$

$$\rho_{12} = q_{12}/\sqrt{q_{11}q_{22}} \ , \tag{9}$$

$$\epsilon_{it} = \varepsilon_{it}/\sqrt{h_{ii,t}} \ , \tag{10}$$

where ρ_{12} is the conditional correlation between market 1 and market 2. $\varepsilon_{it} \sim$ niid and the conditional variance, $h_{ii,t}$ can be specified to follow the GARCH (1,1). α_1 and β_1 are non-negative vectors following the criteria $\alpha_1 + \beta_1 < 1$.

(3) Baba, Engle, Kraft and Kroner (BEKK-GARCH)

Baba, Engle, Kraft, and Kroner (1990) proposed the BEKK model, which is characterized by a conditional covariance matrix that is guaranteed to be positive. The model is as follows:

$$Y_t = \mu + \varepsilon_t \ , \tag{11}$$

$$\varepsilon_t|\Omega_{t-1} \sim Multivariate \ \ Normal(0, H_t) \ , \tag{12}$$

$$H_t = DD' + \sum_{i=1}^{Q}\sum_{k=1}^{K} A'\varepsilon_{t-i}\varepsilon'_{t-i}A_{ki} + \sum_{j=1}^{P}\sum_{k=1}^{K} B'_{kj}H_{t-j}B_{kj} \ , \tag{13}$$

where A_{ki}, B_{kj}, and D are all $N \times N$ matrices, and D is the lower triangular matrix. The intercept term is divided into two lower triangle matrices and multiplied to ensure H_t's positive determinism.

4. Empirical Analysis

This section will explore the correlation between carbon emission ETFs, industry ETFs, and S&P 500 indexes based on the literature and research methodology discussed previously. The descriptive statistics are shown in Table 2. The Mean value for KRBN is 0.162497, while the Standard Deviation value is 2.297541. The Unit Root test, Granger Causality analysis for each variable, and estimation and validation of the three models are all performed.

Table 2 Descriptive statistic

	KRBN	CRBN	SMOG	SPX	XLU	IYT	XHB	XLI
Mean	0.162497	0.027543	0.023524	0.034305	0.02135	0.036593	0.037674	0.035482
Median	0.233297	0.059175	0.081708	0.067098	0.079572	0.076574	0.049714	0.085848
Standard Deviation	2.297541	1.103926	2.124211	1.310876	1.249874	1.601253	2.104477	1.432351
Variance	5.278696	1.218652	4.51227	1.718397	1.562186	2.56401	4.428824	2.051628
Kurtosis	4.553647	13.31634	9.434596	11.47573	15.24717	5.617667	6.459547	8.31769
Skewness	-0.49357	-0.85191	-0.13912	-0.24583	0.351259	-0.20563	0.056857	-0.1743
Minimum	-13.0816	-11.0196	-14.9522	-11.9841	-11.3577	-11.0675	-18.3859	-11.3441
Maximum	12.19101	8.067974	19.31589	11.58004	12.79343	13.0109	15.45308	12.65122

Note: KRBN, CRBN, and SMOG represent short-term, mid-term, and long-term carbon emission ETFs, respectively. XLU, IYT, XHB, and XLI represent the electricity, transportation, architecture, and industry markets, respectively.

4.1 Unit Root Test

A stationary test is being conducted in this study for carbon emission ETFs (KRBN, CRBN, SMOG), industry ETFs (XLU, IYT, XHB, XLI), and the S&P 500 index. If the variables are not stationary, Spurious Regression will occur (Granger and Newbold, 1974). Therefore, the Augmented Dickey-Fuller (ADF) method proposed by Said and Dickey (1984) is used to evaluate empirical analysis. Table 3 shows that all variables are significant at the 1% level, and the null hypothesis of Unit Root is rejected, meaning there is no Unit Root for each variable. Thus, it remains constant for further empirical research.

The presence of heteroscedasticity or uneven conditional variance indicates that ARCH effects are present in time series data. The ARCH-LM test (Lagrange Multiplier) developed by Engle (1982) evaluates ARCH effects for every variable. All variables reject the null hypothesis at a 5% significance level, which implies that ARCH effects are present in all time series. Consequently, additional fitting can be done using the ARCH and GARCH models.

The Akaike Information Criterion (AIC) value determines the complexity of statistical models and chooses the most appropriate one. In this study, ARMA and GARCH orders are employed that have minimum AIC values for each variable. The lowest AIC values for the CRBN variable were 2.9817 and 2.5576 in the ARMA order (2,2) and GARCH order (2,2), respectively. The indicator shows that the variable has the best-fit performance in the order combination. In addition, the Q statistics results for all variables are not significant, suggesting that the residual terms of each variable model lack series correlation. The ARCH-LM test eliminates the ARCH effects of all variables, which means that all univariate variables do not have ARCH effects.

4.2 Constant Conditional Correlation (CCC)

A correlation coefficient model for conditional correlation was utilized to validate the link between the return volatility of carbon emission ETFs, industry ETFs, and the S&P 500 index, respectively. The results in Tables 4, 5, and 6 show that the short-term carbon emission ETFs (KRBN) in the multivariate ARCH model are insignificant and consistent with Engle and Sheppard (2001), and the results of the Tse (2000) test indicate that all samples, except for XLI (Industrial) in KRBN, are significant. They are suitable for the application of the MGARCH model. As a result, the MGARCH model is applicable. All samples are significant in ARCH(α) and GARCH(β), except for the transportation (IYT) and industry (XLI) sectors in KRBN. It indicates a long-term correlation between medium and long-term carbon ETFs, industry ETFs, and the market index. The linkage affects all of CRBN, SMOG, and industrial ETFs during severe market volatility, with KRBN being more unaffected. However, it is observed that the α and β values among short-term carbon ETFs, industry ETFs, and S&P500 are not significant; Tables 5 and 6 show that the $\alpha+\beta$ values fall in the range of 0.980 to 0.991 for both medium and long-term. Table 4 shows that most of the CCC coefficients are significant. SMOG and CRBN have been established for an extended period, making them more indicative of the performance of the U.S. carbon emissions industry market. The outcomes show that SMOG provides more information than CRBN, and CRBN is more relevant than KRBN. In addition, all the results show $\alpha+\beta<1$, except KRBN, IYT, and XLI. This means that the maximum likelihood estimation condition (Likelihood) is satisfied, and the results tend to be distributed normally.

The empirical results show that the performance of the CCC coefficients of the four major industries is positively significant with carbon ETFs. It has been observed that the Log Likelihood values of XLI with carbon ETFs and the S&P500 index are more significant, which indicates a higher probability of occurrence. Among the four major industries, the industry ETF (XLI) is also more likely to have a return volatility correlation with the S&P500 index. In KRBN, XLU has the highest Log Likelihood value (-2937.237), indicating a strong correlation between short-term carbon ETFs and the electricity industry. This correlation applies to the industrial market, covering different stages of electricity generation, and significantly affects the environmental impact of carbon emissions. Therefore, the impact of fluctuation in return between SMOG, industry ETFs, and S&P500 is more closely related. Krause, Ehsani, and Lien (2014) confirmed that the volatility spillover effects between the industrial and financial markets were bidirectional.

In summary, long-term carbon and industry ETFs have a high volatility correlation with the S&P500 under the model. In contrast, the volatility of returns in the electricity industry is higher than in the short term. Medium- and long-term carbon ETFs interact with the broad market index because they have been listed for extended periods and have a long-term persistent correlation.

Table 3 The results of Unit Root test, ARCH-LM test, and Q-test

	ADF	ARMA	AIC	ARCH-LM	GARCH	AIC	ARCH-LM	Q-test(10)
KRBN	-26.073***	(1,1)	4.4996	F(2,583) = 25.511[0.0000]**	(1,1)	4.3886	F(2,581) = 0.25980[0.7713]	3.6899 [0.8839665]
CRBN	-63.003***	(2,2)	2.9817	F(2,2002) = 323.72[0.0000]**	(2,2)	2.5576	F(2,1998) = 0.18127[0.8342]	11.0216 [0.0877122]
SMOG	-14.383***	(2,2)	4.3450	F(2,3913) = 368.15[0.0000]**	(1,2)	3.8445	F(2,3910) = 0.085368[0.9182]	11.1918 [0.0826278]
SPX	-24.622***	(2,1)	3.3607	F(2,3913) = 597.33[0.0000]**	(1,2)	2.7805	F(2,3910) = 0.40421 [0.6675]	8.9372 [0.2571969]
XLU	-24.528***	(2,2)	3.2734	F(2,3913) = 758.64[0.0000]**	(1,1)	2.8144	F(2,3911) = 9.6112[0.0001]**	2.7315 [0.8417143]
IYT	-13.763***	(1,0)	3.7780	F(2,3913) = 260.34[0.0000]**	(1,2)	3.4366	F(2,3910) = 0.18572 [0.8305]	4.5468 [0.8718907]
XHB	-61.937***	(2,2)	4.3234	F(2,3913) = 323.69[0.0000]**	(2,2)	3.8019	F(2,3909) = 2.0819 [0.1248]	4.1753 [0.6529722]
XLI	-23.666***	(2,2)	3.5492	F(2,3913) = 518.25[0.0000]**	(2,2)	3.1138	F(2,3909) = 0.75731 [0.4690]	9.8286 [0.1320603]

Note: KRBN, CRBN, and SMOG represent short-term, mid-term, and long-term carbon emission ETFs, respectively. XLU, IYT, XHB, and XLI represent the electricity, transportation, architecture, and industry markets, respectively.

Table 4 The results of the CCC model: KRBN, industry ETFs, and S&P 500

	Model	AIC	Multivariate ARCH test		alpha		beta		a+b	CCC	Log likelihood
			Tse (2000)	E&S (2001)							
1. KRBN					α	0.156*** (0.009)	β	0.657*** (0.000)	0.813	ρ21 0.299*** (0.000)	
2. S&P500	(1,1)	10.065	9.260** (0.026)	4.619 (0.593)	α	0.145* (0.084)	β	0.832*** (0.000)	0.977	ρ31 0.135*** (0.000)	-2937.237
3. XLU					α	0.027*** (0.007)	β	0.972*** (0.000)	0.999	ρ32 0.505*** (0.000)	
1. KRBN					α	0.121* (0.100)	β	1.218*** (0.000)	0.893	ρ21 0.303*** (0.000)	
2. S&P500	(2,2)	10.817	18.963*** (0.000)	2.619 (0.855)	α	0.134 (0.244)	β	0.095 (0.732)	0.956	ρ31 0.062 (0.104)	-3149.092
3. IYT					α	- -	β	- -	1.000	ρ32 0.086*** (0.000)	
1. KRBN					α	0.156*** (0.009)	β	0.657*** (0.000)	0.813	ρ21 0.295*** (0.000)	
2. S&P500	(1,1)	11.269	7.766* (0.051)	4.322 (0.633)	α	0.145* (0.084)	β	0.832*** (0.000)	0.977	ρ31 0.038 (0.349)	-3290.959
3. XHB					α	0.039 (0.338)	β	0.948*** (0.000)	0.987	ρ32 0.083** (0.037)	
1. KRBN					α	0.121* (0.100)	β	1.218*** (0.000)	0.893	ρ21 0.301*** (0.000)	
2. S&P500	(1,1)	10.502	5.126 (0.163)	2.623 (0.854)	α	0.134 (0.244)	β	0.095 (0.732)	0.956	ρ31 0.043 (0.275)	-3056.698
3. XLI					α	- -	β	- -	1.000	ρ32 0.096*** (0.000)	

Note: KRBN, XLU, IYT, XHB, and XLI represent short-term carbon emission ETFs, electricity market, transportation market, architecture market, and industry market, respectively. ***, **, and * represent 0.01, 0.05, and 0.1 significant levels for p-value, respectively.

Table 5 The results of the CCC model: CRBN, industry ETFs, and S&P 500

	Model	AIC	Multivariate ARCH test		alpha		beta		a+b	CCC	Log likelihood
			Tse (2000)	E&S (2001)							
1. CRBN					α	0.176*** (0.000)	β	0.801*** (0.000)	0.978	ρ21 0.911*** (0.000)	
2. S&P500	(1,1)	5.914	143.994*** (0.000)	247.800*** (0.000)	α	0.218*** (0.000)	β	0.762*** (0.000)	0.980	ρ31 0.296*** (0.000)	-5915.749
3. XLU					α	0.093*** (0.000)	β	0.884*** (0.000)	0.977	ρ32 0.358*** (0.000)	
1. CRBN					α	0.177*** (0.000)	β	0.801*** (0.000)	0.978	ρ21 0.910*** (0.000)	
2. S&P500	(1,1)	5.626	150.586*** (0.000)	263.555*** (0.000)	α	0.218*** (0.000)	β	0.762*** (0.000)	0.980	ρ31 0.716*** (0.000)	-5626.914
3. IYT					α	0.107*** (0.000)	β	0.852*** (0.000)	0.960	ρ32 0.764*** (0.000)	
1. CRBN					α	0.177*** (0.000)	β	0.801*** (0.000)	0.978	ρ21 0.910*** (0.000)	
2. S&P500	(1,1)	5.932	165.484*** (0.000)	246.552*** (0.000)	α	0.218*** (0.000)	β	0.762*** (0.000)	0.980	ρ31 0.668*** (0.000)	-5933.519
3. XHB					α	0.094*** (0.000)	β	0.894*** (0.000)	0.989	ρ32 0.712*** (0.000)	
1. CRBN					α	0.177*** (0.000)	β	0.801*** (0.000)	0.978	ρ21 0.909*** (0.000)	
2. S&P500	(1,1)	4.896	178.185*** (0.000)	302.550*** (0.000)	α	0.218*** (0.000)	β	0.762*** (0.000)	0.980	ρ31 0.774*** (0.000)	-4893.782
3. XLI					α	0.131*** (0.000)	β	0.833*** (0.000)	0.964	ρ32 0.841*** (0.000)	

Note: CRBN, XLU, IYT, XHB, and XLI represent mid-term carbon emission ETFs, the electricity market, the transportation market, the architecture market, and the industry market, respectively. ***, **, and * represent 0.01, 0.05, and 0.1 significant levels for p-value, respectively.

Table 6 The results of the CCC model: SMOG, industry ETFs, and S&P 500

	Model	AIC	Multivariate ARCH test		alpha		beta		a+b	CCC	Log likelihood
			Tse (2000)	E&S (2001)							
1. SMOG					α	0.096***	β	0.895***	0.991	ρ21 0.735***	
						(0.000)		(0.000)		(0.000)	
2. S&P500	(1,1)	8.226	138.298***	128.434***	α	0.157*	β	0.829***	0.986	ρ31 0.336***	-16096.008
			(0.000)	(0.000)		(0.000)		(0.000)		(0.000)	
3. XLU					α	0.099***	β	0.885***	0.984	ρ32 0.516***	
						(0.000)		(0.000)		(0.000)	
1. SMOG					α	0.096***	β	0.895***	0.991	ρ21 0.735***	
						(0.000)		(0.000)		(0.000)	
2. S&P500	(1,1)	8.076	171.149***	80.818***	α	0.157***	β	0.829***	0.986	ρ31 0.643***	-15800.956
			(0.000)	(0.000)		(0.000)		(0.000)		(0.000)	
3. IYT					α	0.094***	β	0.886***	0.980	ρ32 0.811***	
						(0.000)		(0.000)		(0.000)	
1. SMOG					α	0.096***	β	0.895***	0.991	ρ21 0.737***	
						(0.000)		(0.000)		(0.000)	
2. S&P500	(1,1)	8.720	153.916***	80.1275***	α	0.157***	β	0.830***	0.986	ρ31 0.593***	-17064.427
			(0.000)	(0.000)		(0.000)		(0.000)		(0.000)	
3. XHB					α	0.086***	β	0.908***	0.994	ρ32 0.745***	
						(0.000)		(0.000)		(0.000)	
1. SMOG					α	0.096***	β	0.895***	0.991	ρ21 0.733***	
						(0.000)		(0.000)		(0.000)	
2. S&P500	(1,1)	7.2512	189.535***	111.446***	α	0.157***	β	0.829***	0.986	ρ31 0.687***	-14186.850
			(0.000)	(0.000)		(0.000)		(0.000)		(0.000)	
3. XLI					α	0.114***	β	0.867***	0.981	ρ32 0.890***	
						(0.000)		(0.000)		(0.000)	

Note: SMOG, XLU, IYT, XHB, and XLI represent long-term carbon emission ETFs, the electricity market, the transportation market, the architecture market, and the industry market, respectively. ***, **, and * represent 0.01, 0.05, and 0.1 significant levels for p-value, respectively.

4.3 Dynamic Conditional Correlation Model (DCC)

In contrast to the fixed conditional correlation model, the DCC model stresses that the conditional correlation changes over time. The model requires a two-step assessment process. The GARCH model is adapted to each variable during the initial phase. The second stage uses the standardized residuals from the first stage to estimate the dynamic conditional correlation. The second stage's estimated coefficients that are not statistically significant mean there is no significant dynamic correlation between variables.

From Tables 7 to 9, it can be observed that medium-term to long-term carbon emission ETFs and industry ETFs mostly exhibit multivariate ARCH effects based on the tests of Hosking (1980) and Li and McLeod (1981), while short-term carbon emission ETFs and industry ETFs are not significant. The ARCH (α) and GARCH (β) parameters are mainly significant, further confirming the applicability of the MGARCH model and verifying the presence of long-term persistence in time series.

Regarding the analysis of the impact of short-term shocks in the DCC model, the results of the first stage of DCC_E^1 for carbon emissions ETFs and industry ETFs indicate that XLU is significantly different from other industries in all periods. For example, the highest value in the DCC_E^1 among XLU, CRBN, and the S&P500 index is 0.052, followed by 0.040 among XLU, SMOG, and the S&P500. Other industries have significant values only in a single period, such as the maximum value of 0.066 in the DCC_E^1 among IYT, CRBN, and the S&P500 index. Therefore, it concludes that the DCC_E^1 parameter for XLU in the four industry ETFs is significant, indicating that the power ETF, carbon emissions ETFs, and S&P500 index are mainly subject to short-term persistent shocks. A logit model was used by Kanamura (2016) to
examine the volatility structure and dynamic linkage between EUA and CER, revealing that energy prices positively impact EUA prices. In addition, the results of the DCC_E^2 parameter for industry ETFs are significant, indicating that they have long-term persistent impacts except for XHB. Therefore, carbon emissions ETFs, industry ETFs, and the S&P500 index are prone to long-term and short-term persistent impacts.

Regarding the coefficient performance in the DCC model, both medium to long-term carbon emissions ETFs and industry ETFs show a high degree of return volatility correlation (ρ31). The carbon emissions from ETFs (CRBN) are greater in the medium term than those from long-term ones. There is significant performance between carbon emissions ETFs and the S&P500 index regarding return volatility correlation in any period (ρ21), indicating a high correlation between carbon emissions and the broad market index. According to the DCC model, carbon emission ETFs, industry ETFs, and the S&P 500 index are vulnerable to both short-term and long-term persistent impacts. Furthermore, industry ETFs for KRBN are not affected as much by short-term persistent impacts.

4.4 BEKK Model

A positive definite covariance matrix is necessary to specify the BEKK model correctly. This model allows us to examine the effect of one variable's rate of return on another variable's rate of return, which helps us assess the effectiveness of the impact of volatility between variables. In the mean equation of the BEKK model, the lower triangular matrix is represented by C, while A and B are N×N matrices. The model's alpha (a) value represents the condition variance only influenced by its lagged effects. Each variable for a^1 and a^2 represents the lagged effect of one and two periods, respectively. Each variable's conditional covariance is affected by its own lagged effects and the lagged cross-product, as represented by the beta (b) value. It indicates that volatility spillover effects are present among variables. Tables 10-12 present empirical results for carbon emission ETFs, industry ETFs, and the S&P 500 index. The test parameters of Hosking (1980) and Li and McLeod (1981) were significant for all except KRBN, consistent with the results of the DCC models, revealing the presence of multivariate ARCH effects.

Table 7 The results of the DCC model: KRBN, industry ETFs, and S&P 500

	Model	AIC	Multivariate ARCH test		alpha		beta		a+b	1.DCC_E^1 2.DCC_E^2	DCC	Log likelihood
			Hosking (1980)	L&M (1981)								
1. KRBN					α	0.156*** (0.009)	β	0.657*** (0.000)	0.813	1. 0.011**	ρ21 0.336*** (0.000)	
2. S&P500	(1,1)	10.060	47.186 (0.305)	47.177 (0.306)	α	0.145* (0.084)	β	0.832*** (0.000)	0.977	(0.017) 2.	ρ31 0.141* (0.062)	-2933.534
3. XLU					α	0.027*** (0.007)	β	0.972*** (0.000)	0.999	0.981*** (0.000)	ρ32 0.520*** (0.000)	
1. KRBN					α	0.157*** (0.009)	β	0.656*** (0.000)	0.813	1. 0.009	ρ21 0.311*** (0.000)	
2. S&P500	(1,1)	10.821	40.442 (0.539)	40.488 (0.537)	α	0.160* (0.067)	β	0.815*** (0.000)	0.976	(0.222) 2.	ρ31 0.068 (0.187)	-3154.286
3. IYT					α	0.048 (0.131)	β	0.936*** (0.000)	0.984	0.965*** (0.000)	ρ32 0.093* (0.075)	
1. KRBN					α	0.156*** (0.009)	β	0.657*** (0.000)	0.813	1. 0.002	ρ21 0.295*** (0.000)	
2. S&P500	(1,1)	11.275	37.102 (0.724)	37.178 (0.721)	α	0.145* (0.084)	β	0.832*** (0.000)	0.977	(0.915) 2.	ρ31 0.038 (0.353)	-3290.954
3. XHB					α	0.039 (0.338)	β	0.948*** (0.000)	0.987	0.000 (1.000)	ρ32 0.084** (0.037)	
1. KRBN					α	0.156*** (0.009)	β	0.657*** (0.000)	0.813	1. 0.008	ρ21 0.310*** (0.000)	
2. S&P500	(1,1)	10.511	49.938 (0.217)	49.962 (0.216)	α	0.145 (0.084)	β	0.832*** (0.000)	0.977	(0.186) 2.	ρ31 0.049 (0.381)	-3066.100
3. XLI					α	0.070 (0.183)	β	0.883*** (0.000)	0.954	0.974*** (0.000)	ρ32 0.103* (0.069)	

Note: KRBN, XLU, IYT, XHB, and XLI represent short-term carbon emission ETFs, the electricity market, the transportation market, the architecture market, and the industry market, respectively. ***, **, and * represent 0.01, 0.05, and 0.1 significant levels for p-value, respectively.

Table 8 The results of the DCC model: CRBN, industry ETFs and S&P 500

	Model	AIC	Multivariate ARCH test Hosking (1980)	Multivariate ARCH test L&M (1981)	alpha		beta		a+b	1.DCC_E^1 2.DCC_E^2	DCC	Log likelihood
1. CRBN	(1,1)	5.691	85.417*** (0.000)	85.385*** (0.000)	α	0.177*** (0.000)	β	0.801*** (0.000)	0.978	1. 0.052*** (0.000)	ρ21 0.928*** (0.000)	-5689.757
2. S&P500					α	0.218*** (0.000)	β	0.762*** (0.000)	0.980	2. 0.924*** (0.000)	ρ31 0.226*** (0.000)	
3. XLU					α	0.093*** (0.000)	β	0.884*** (0.000)	0.977		ρ32 0.289*** (0.000)	
1. CRBN	(1,1)	5.388	83.709*** (0.000)	83.687*** (0.000)	α	0.177*** (0.000)	β	0.801*** (0.000)	0.978	1. 0.066*** (0.000)	ρ21 0.928*** (0.000)	-5385.872
2. S&P500					α	0.218*** (0.000)	β	0.762*** (0.000)	0.980	2. 0.902*** (0.000)	ρ31 0.713*** (0.000)	
3. IYT					α	0.107*** (0.000)	β	0.852*** (0.000)	0.960		ρ32 0.739*** (0.000)	
1. CRBN	(1,1)	5.701	93.144*** (0.000)	93.087*** (0.000)	α	0.177*** (0.000)	β	0.801*** (0.000)	0.978	1. 0.002 (0.915)	ρ21 0.929*** (0.000)	-5699.543
2. S&P500					α	0.218*** (0.000)	β	0.762*** (0.000)	0.980	2. 0.000 (1.000)	ρ31 0.660*** (0.000)	
3. XHB					α	0.094*** (0.000)	β	0.894*** (0.000)	0.989		ρ32 0.684*** (0.000)	
1. CRBN	(1,1)	4.602	93.677*** (0.000)	93.654*** (0.000)	α	0.177*** (0.000)	β	0.801*** (0.000)	0.978	1. 0.008 (0.186)	ρ21 0.921*** (0.000)	-4597.102
2. S&P500					α	0.218*** (0.000)	β	0.762*** (0.000)	0.980	2. 0.974*** (0.000)	ρ31 0.785*** (0.000)	
3. XLI					α	0.131*** (0.000)	β	0.832*** (0.000)	0.964		ρ32 0.839*** (0.000)	

Note: CRBN, XLU, IYT, XHB, and XLI represent mid-term carbon emission ETFs, the electricity market, the transportation market, the architecture market, and the industry market, respectively. ***, **, and * represent 0.01, 0.05, and 0.1 significant levels for p-value, respectively.

Table 9 The results of the DCC model: SMOG, industry ETFs and S&P 500

	Model	AIC	Multivariate ARCH test		alpha		beta		a+b	1.DCC_E^1 2.DCC_E^2	DCC	Log likelihood
			Hosking (1980)	L&M (1981)								
1. SMOG					α	0.096*** (0.000)	β	0.895*** (0.000)	0.991	1. 0.040*** (0.000)	ρ21 0.733*** (0.000)	
2. S&P500	(1,1)	8.092	55.632 (0.112)	55.633 (0.112)	α	0.157*** (0.000)	β	0.829*** (0.000)	0.986	2. 0.948*** (0.000)	ρ31 0.317*** (0.000)	-15831.257
3. XLU					α	0.099*** (0.000)	β	0.885*** (0.000)	0.984		ρ32 0.525*** (0.000)	
1. SMOG					α	0.096*** (0.000)	β	0.895*** (0.000)	0.991	1. 0.009 (0.222)	ρ21 0.739*** (0.000)	
2. S&P500	(1,1)	7.981	70.661*** (0.007)	70.651*** (0.007)	α	0.157*** (0.000)	β	0.829*** (0.000)	0.986	2. 0.965*** (0.000)	ρ31 0.653*** (0.000)	-15613.725
3. IYT					α	0.094*** (0.000)	β	0.886*** (0.000)	0.980		ρ32 0.809*** (0.000)	
1. SMOG					α	0.096*** (0.000)	β	0.895*** (0.000)	0.991	1. 0.036*** (0.000)	ρ21 0.745*** (0.000)	
2. S&P500	(1,1)	8.643	86.130*** (0.000)	86.117*** (0.000)	α	0.156*** (0.000)	β	0.831*** (0.000)	0.986	2. 0.949*** (0.000)	ρ31 0.599*** (0.000)	-16904.510
3. XHB					α	0.086*** (0.000)	β	0.909*** (0.000)	0.995		ρ32 0.734*** (0.000)	
1. SMOG					α	0.096*** (0.000)	β	0.895*** (0.000)	0.991	1. 0.039*** (0.000)	ρ21 0.731*** (0.000)	
2. S&P500	(1,1)	7.115	62.145** (0.037)	62.142** (0.037)	α	0.157*** (0.000)	β	0.829*** (0.000)	0.986	2. 0.947*** (0.000)	ρ31 0.695*** (0.000)	-13916.515
3. XLI					α	0.114*** (0.000)	β	0.867*** (0.000)	0.981		ρ32 0.895*** (0.000)	

Note: SMOG, XLU, IYT, XHB, and XLI represent long-term carbon emission ETFs, the electricity market, the transportation market, the architecture market, and the industry market, respectively. ***, **, and * represent 0.01, 0.05, and 0.1 significant levels for p-value, respectively.

First, Table 10 shows the volatility correlation among four industry ETFs: the short-term carbon emission ETF (KRBN) and the broad market index. The empirical results indicate that $a^1 33$ of the other industries are significant except for XLU and XLI, indicating a positive effect of the return volatility of IYT and XHB on their own lagged returns. The results of $a^2 33$ for return volatility of XLU and XHB significantly impact their two-period lagged return volatility. In addition, regarding the volatility correlation among KRBN, industry ETFs, and the broad market index, the parameters of the b values are mostly positively significant, indicating a spillover effect among the short-term carbon emission ETF, industry ETFs, and the S&P500 index. Therefore, XLU, IYT, XHB, and XLI exhibit long-term persistence in return volatility.

Furthermore, Tables 11 and 12 show the volatility correlations among medium-term and long-term carbon emission ETFs, four industry ETFs, and the market index. The empirical results indicate that the return volatilities of XLU, IYT, XHB, and XLI have a significant positive impact on their own lagged return volatility $a^1 33$ is significant for all. Additionally, carbon emission ETFs and the S&P 500 index significantly impact their own lagged return volatility in $a^1 22$, implying that the return volatility of medium-term and long-term carbon emission ETFs and the four industry ETFs are positively affected by their own lagged return volatility. The above results infer that the results of a^1 for the four industry ETFs are primarily significant, suggesting that, in addition to being positively influenced by their own lagged value, they also have a short-term impact on return volatility. Table 11 shows that only XLU, IYT, and XLI are positively significant based on the results of a^2. At the same time, XHB has no significant impact, indicating that the volatility of the return of construction ETFs is not affected by their own two lagged periods. Table 12 exhibits that all parameters are positively significant. Regarding the volatility correlation among carbon emission ETFs (KRBN, CRBN, SMOG), four industry ETFs, and the S&P500 index, the results of b values are mostly positively significant, indicating that there is a mutual influence and spillover effect among carbon emission ETFs, industry ETFs, and the S&P500 index, except for SMOG.

In the BEKK model, KRBN, power ETFs (XLU), and the S&P500 index have the highest Log likelihood (-2926.513), which indicates a higher correlation between XLU, KRBN, and the S&P500 index compared to transportation, construction, and industrial sectors. In the medium to long-term carbon emission ETFs, the industrial sector has a higher likelihood of occurrence (-4475.414 and -14488.984), which reveals a stronger correlation between carbon emissions (CRBN and SMOG), industrial ETFs, and the S&P500 index. The cointegration of short- and long-term dynamics was demonstrated, and the causal relationships between carbon emissions, energy consumption, and industrial growth in Bangladesh were analyzed, as Rahman and Kashem (2017) suggested. Their research proved that carbon emissions are positively affected by industrial production and energy consumption, both short and long-term.

In summary, except for the power and industrial industries in KRBN, in all carbon emission periods, the results of the a^1 values in the four industry ETFs are primarily significant, indicating that the volatility of each variable's return is affected by its own lagged value. The results of the a^2 values indicate that the return volatility of most industries is also influenced by its own lagging two periods, except for the transportation and industrial industries in KRBN and the construction industry in CRBN. Furthermore, most variables significantly impact the b values, which suggests that the return volatility of the three variables, carbon emission ETFs, industry ETFs, and the S&P500 index, are interdependent. SMOG and industry ETFs have a long-term and short-term persistent impact on return volatility.

Table 10 The results of the BEKK model: KRBN, industry ETFs, and S&P 500

		1: KRBN 2: SPX 3: XLU	1: KRBN 2: SPX 3: IYT	1: KRBN 2: SPX 3: XHB	1: KRBN 2: SPX 3: XLI
Model		(1,2)	(1,2)	(1,2)	(1,2)
AIC		10.060	10.849	11.387	10.535
Multivariate ARCH test	Hosking (1980)	41.7101 (0.440)	41.233 (0.504)	42.500 (0.493)	54.028 (0.121)
	L&M (1981)	41.724 (0.439)	41.2782 (0.503)	42.549 (0.491)	54.040 (0.121)
C11		1.043*** (0.000)	0.879*** (0.003)	1.458*** (0.007)	0.863*** (0.000)
C12		0.124*** (0.001)	0.076 (0.368)	0.396*** (0.000)	0.069*** (0.001)
C13		0.069*** (0.020)	0.026 (0.414)	0.064 (0.224)	0.015 (0.548)
C22		0.223** (0.018)	0.147 (0.717)	0.034 (0.640)	0.108 (0.349)
C23		0.165** (0.011)	0.059 (0.365)	-0.195** (0.041)	0.099 (0.590)
C33		0.0248*** (0.005)	0.119 (0.145)	0.000 (1.000)	0.240 (0.428)
$a^1 11$		0.273*** (0.008)	0.255* (0.080)	0.396*** (0.009)	0.231* (0.056)
$a^1 22$		-0.010 (0.938)	0.134 (0.456)	0.140 (0.581)	0.180 (0.362)
$a^1 33$		-0.135 (0.169)	0.195*** (0.002)	0.150* (0.051)	0.231 (0.273)
$a^2 11$		0.246** (0.024)	0.199 (0.304)	0.320*** (0.003)	0.234* (0.051)
$a^2 22$		0.313*** (0.000)	0.243 (0.614)	0.453*** (0.000)	0.160 (0.411)
$a^2 33$		0.220*** (0.000)	-0.067 (0.735)	0.118* (0.099)	-0.138 (0.396)
$b^1 11$		0.800*** (0.000)	0.858*** (0.000)	0.567* (0.074)	0.859*** (0.000)
$b^1 22$		0.924*** (0.000)	0.953*** (0.000)	-0.820*** (0.000)	0.966*** (0.000)
$b^1 33$		0.930*** (0.000)	0.975*** (0.000)	-0.974*** (0.000)	0.942*** (0.000)
Log likelihood		-2926.513	-3161.466	-3323.837	-3072.206

Note: KRBN, XLU, IYT, XHB, and XLI represent short-term carbon emission ETFs, the electricity market, the transportation market, the architecture market, and the industry market, respectively. ***, **, and * represent 0.01, 0.05, and 0.1 significant levels for p-value, respectively.

Table 11 The results of the BEKK model: CRBN, industry ETFs, and S&P 500

		1: CRBN 2: SPX 3: XLU	1: CRBN 2: SPX 3: IYT	1: CRBN 2: SPX 3: XHB	1: CRBN 2: SPX 3: XLI
Model		(1,2)	(1,2)	(1,2)	(1,2)
AIC		5.602	5.307	5.625	4.491
Multivariate ARCH test	Hosking (1980)	68.620*** (0.004)	71.602*** (0.002)	76.891*** (0.001)	82.435*** (0.000)
	L&M (1981)	68.615*** (0.004)	71.585*** (0.002)	76.874*** (0.001)	82.413*** (0.000)
C11		0.112*** (0.000)	0.129*** (0.000)	0.117*** (0.000)	0.108*** (0.000)
C12		0.105*** (0.001)	0.122*** (0.000)	0.109*** (0.000)	0.099*** (0.001)
C13		0.027* (0.083)	0.153*** (0.000)	0.120*** (0.000)	0.095*** (0.000)
C22		0.043*** (0.000)	0.046*** (0.000)	0.046*** (0.000)	0.042*** (0.000)
C23		0.058*** (0.000)	0.080*** (0.000)	0.062*** (0.000)	0.044*** (0.001)
C33		0.165*** (0.000)	0.149*** (0.000)	0.113*** (0.000)	0.052*** (0.000)
$a^1 11$		0.237*** (0.008)	0.243*** (0.000)	0.248*** (0.000)	0.244*** (0.056)
$a^1 22$		0.255*** (0.000)	0.268*** (0.000)	0.266*** (0.000)	0.257*** (0.000)
$a^1 33$		0.199*** (0.000)	0.224*** (0.000)	0.238*** (0.000)	0.244*** (0.000)
$a^2 11$		0.084 (0.138)	0.112* (0.079)	0.000 (1.000)	0.000 (1.000)
$a^2 22$		0.068 (0.174)	0.089 (0.138)	0.010 (0.863)	-0.004 (0.874)
$a^2 33$		0.150*** (0.000)	0.122** (0.011)	-0.076 (0.166)	0.048** (0.035)
$b^1 11$		0.960*** (0.000)	0.952*** (0.000)	0.959*** (0.000)	0.963*** (0.000)
$b^1 22$		0.956*** (0.000)	0.948*** (0.000)	0.955*** (0.000)	0.960*** (0.000)
$b^1 33$		0.955*** (0.000)	0.951*** (0.000)	0.961*** (0.000)	0.964*** (0.000)
Log likelihood		-5591.045	-5294.746	-5614.030	-4475.414

Table 11 The results of the BEKK model: CRBN, industry ETFs, and S&P 500
Note: CRBN, XLU, IYT, XHB, and XLI represent mid-term carbon emission ETFs, the electricity market, the transportation market, the architecture market, and the industry market, respectively. ***, **, and * represent 0.01, 0.05, and 0.1 significant levels for p-value, respectively.

Table 12 The results of the BEKK model: SMOG, industry ETFs, and S&P 500

		1: SMOG 2: SPX 3: XLU	1: SMOG 2: SPX 3: IYT	1: SMOG 2: SPX 3: XHB	1: SMOG 2: SPX 3: XLI
Model		(1,2)	(1,2)	(1,2)	(1,2)
AIC		8.374	8.236	8.974	7.407
Multivariate ARCH test	Hosking (1980)	42.650 (0.530)	58.296* (0.060)	68.070*** (0.009)	47.271 (0.340)
	L&M (1981)	42.656 (0.529)	58.291* (0.060)	68.058*** (0.009)	47.277 (0.340)
C11		1.427*** (0.000)	1.528*** (0.000)	1.486*** (0.000)	1.526*** (0.000)
C12		0.583*** (0.001)	0.652*** (0.000)	0.574*** (0.000)	0.627*** (0.000)
C13		0.212*** (0.000)	0.819*** (0.000)	0.652*** (0.000)	0.696*** (0.000)
C22		0.000 (1.000)	0.000 (1.000)	0.000 (1.000)	0.000 (1.000)
C23		0.188*** (0.001)	0.414 (0.194)	0.438** (0.021)	0.248** (0.011)
C33		0.150* (0.076)	0.413 (0.174)	0.349*** (0.000)	0.231** (0.015)
$a^1 11$		0.402*** (0.000)	0.384*** (0.000)	0.404*** (0.000)	0.387*** (0.000)
$a^1 22$		0.340*** (0.000)	0.346*** (0.000)	0.383*** (0.000)	0.361*** (0.000)
$a^1 33$		0.248*** (0.000)	0.254*** (0.000)	0.191*** (0.000)	0.268*** (0.000)
$a^2 11$		0.492*** (0.000)	0.422*** (0.000)	0.436*** (0.000)	0.430*** (0.000)
$a^2 22$		0.391*** (0.000)	0.353*** (0.000)	0.332*** (0.000)	0.349*** (0.000)
$a^2 33$		0.215*** (0.000)	0.328*** (0.000)	0.417*** (0.000)	0.384*** (0.000)
$b^1 11$		0.000 (1.000)	0.000 (1.000)	0.000 (1.000)	0.000 (1.000)
$b^1 22$		-0.635*** (0.000)	-0.620*** (0.000)	-0.663*** (0.000)	-0.641*** (0.000)
$b^1 33$		-0.896*** (0.000)	-0.591*** (0.000)	-0.746*** (0.000)	-0.634*** (0.000)
Log likelihood		-16383.501	-16110.229	-17555.293	-14488.984

Note: SMOG, XLU, IYT, XHB, and XLI represent long-term carbon emission ETFs, the electricity market, the transportation market, the architecture market, and the industry market, respectively. ***, **, and * represent 0.01, 0.05, and 0.1 significant levels for p-value, respectively.

5. Conclusion

This study utilized CCC, DCC, and BEKK models to analyze the return spillover effects between carbon emissions ETFs, industry ETFs, and the S&P 500 index. Like Liu and Chen's (2013) research, it also found evidence of long-term memory effects in carbon markets.

After analyzing the empirical data, the following outcomes were achieved.

1. The results from the CCC model indicated a high volatility correlation between long-term carbon emissions and industry ETFs, as well as the S&P 500. Higher volatility contagion was observed in the short term with the electricity industry's return volatility. The impact of carbon emissions ETFs on the broad market index was maintained for a long time because of their longer listing history, which indicates a sustained association.
2. The DCC estimation results show that XLU significantly impacts the first-stage estimation of conditional correlation coefficients, surpassing other industries. These parameters are responsible for capturing the effects of short-term shocks. The dynamic conditional correlation model demonstrated that carbon emissions ETFs, industry ETFs, and the S&P 500 index were susceptible to both long-term and short-term persistency impacts, with industry ETFs being less affected by short-term persistency shocks in KRBN. The findings were based on the CCC model.
3. The results of the BEKK model indicate that, apart from the electricity and industrial sectors in KRBN, most of the four industry ETFs exhibit significant parameter results about their own past periods and values, regardless of the period of carbon emissions. The results of the parameters related to the effect of their own volatility in the past two periods show that the return volatility of most industries is influenced by their own lagged returns, except for the transportation and industrial sectors in KRBN and the construction industry in CRBN. The current volatility is influenced by the past-period variable returns, indicating a significant relationship among the variables and highlighting the interdependence of return volatilities between carbon emission ETFs, sector ETFs, and the S&P 500 index.

The comprehensive empirical analysis showed that the DCC model was more adequate than the CCC and BEKK models. The parameter results showed a close link between mid-term carbon emissions ETFs, industry ETFs, and the S&P 500 index, with both stages of variables indicating long-term and short-term effects. There were substantial spillover effects and connections between ETFs for carbon emissions, industry ETFs, and the S&P 500 index.

Due to severe global warming, people must reevaluate the earth's environment and adopt more effective regulations for high-carbon industries to balance economic growth and environmental preservation. Investors can profit by investing in companies focusing on renewable energy and low-carbon practices. These industries that use carbon are undoubtedly closely linked to carbon emissions indices.

For managers of large financial institutions, this study compares the application results of the MGARCH model in predicting the dynamics between carbon emissions ETFs, industry-specific ETFs, and the S&P 500 index. The optimal model is given, which assists in more precise investment strategies and decreases risks in long-term operational activities.

Investors can use research results to predict prices and trends for carbon ETFs, which helps them make buying and selling decisions with multiple predictive results. Investors can use MGARCH models to optimize their investment portfolios and maximize returns while minimizing price volatility.

The economic impact of this study extends to various stakeholders, such as financial institutions, investors, policymakers, and society. By becoming more acquainted with the connections between carbon emissions ETFs, industry ETFs, and market indices, financial institutions can better protect themselves against volatility and manage their exposure to carbon-intensive industries. Investors can reap the research benefits by utilizing the MGARCH models' predictive capabilities to optimize their investment portfolios, maximizing returns while minimizing the impact of price volatility. The study's insights could also be utilized to guide the development of policies to decrease carbon emissions and mitigate climate-related risks in financial markets.

Compliance with Ethical Standards:

Conflict of Interest: The authors declare that they have no conflict of interest.

Ethical Approval: This article does not contain any studies with human participants or animals performed by any of the authors.

Data Availability Statement: The datasets of current study are availabe in the Yahoo finance and Investing.com.

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