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The Comparison of Long Memory and Multiple Structure Breaks for Carbon Indices and Exchange-Traded Fund (ETF)

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A B S T R A C T

The long-memory properties of four types of carbon indices and prices are tested using models of general autoregressive conditional heteroskedasticity with a moving mean and an integrated fraction (ARFIMA-FIGARCH). The study found that three carbon indices, three ETFs, ETN, and futures have a significant long-memory effect. Using the iterated cumulative sum of squares algorithm (ICSS), the multiple structural breaks in the four carbon indexes were examined during the enormous magnitude of oil price and pandemic from 2019/01/01-2023/02/01. The evolution of distinct fundamentals is made possible by the presence of multiple structural changes between eight carbon indexes (prices). Previous literature has been enhanced by evidence that shows that carbon pricing breaks are typically associated with structural changes that are driven by key events. The carbon prices are responsive to energy, macroeconomic factors, and policy issues.

Keywords: Carbon Indices, ETFs, ARFIMA-FIGARCH Models, The Long Memory, Multiple Structural Breaks, Bai and Perron test, ICSS Algorithm
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1. Introduction

As a response to the urgency of global warming, the Kyoto Protocol was signed at the United Nations Framework Convention on Climate Change in Kyoto, Japan, on December 11, 1997. To control climate change and limit greenhouse gas (GHG) emissions from developed countries, the Kyoto Protocol was implemented on February 16, 2005. The Kyoto Agreement contains a binding target for 37 industrialized countries and the European Community through national measures to reduce greenhouse gas emissions while encouraging new energy technologies. Three market-based mechanisms can be used to meet their objectives: carbon market emissions trading, a clean development mechanism (CDM), and joint implementation. Emissions trading permits countries to sell their excess capacity to countries to enhance the environment that anticipates exceeding their targets. Like any other commodity tracked, a carbon price is a levy on carbon pollution to encourage polluters to reduce greenhouse gas emissions in the atmosphere.

Carbon pricing is a significant incentive for reducing greenhouse gas emissions. The carbon market has become more active in recent years. The carbon market's overall turnover rises as the number of countries participating in regulation increases. Understanding the characteristics of carbon allowance price volatility is essential to maintain a stable carbon market development. In the global carbon market, carbon products are classified under two categories. Emissions trading systems, including Australia, the European Union, the Chicago Board of Trade, and the United Kingdom's emissions trading markets, have facilitated the creative activity of carbon licenses (allowances). A reduction plan (like the CDM and joint reductions or other voluntary lessening procedures) was used in the latter to reduce credit. The European Union Allowances (EUA) price break that occurred in April 2006 was investigated by Alberola et al. (2008) based on the report of verified emissions from 2005. EUA spot prices were measured to determine if they influence energy prices and unexpected temperature variations during the cold period. EGARCH and implied volatility models were the main subjects of significant EUA changes, shown by Chevallier (2011) through retrospective and forward-looking tests.

Pesaran and Timmermann (2004) proposed that forecasting models that neglect structural breaks produce inferior results than models with structural breaks. The issue of structural disruptions has many vital uses. According to Guo and Wohar (2006), there are multiple structural breaks in the VIX that the CBOE publishes. According to the study, the means of the lowest market volatility were at their lowest during 1992–2007.

Bai (1997) and Bai and Perron (2006) created a method for detecting multiple structural breaks in time series and analyzing their statistical significance. Gadea et al. (2004) demonstrated that recognizing non-linear dependence based on the conditional mean and variance requires a long memory occurrence, supported by the risk of ignoring structural breaks. Structural breaks and the long memory phenomenon were the focus of their study.

The carbon market is a marketplace for products made from carbon-based policies with financial advantages (Boersen and Scholtens, 2014). Bai and Perron test introduced by Bai and Perron (2003) and Iterated Cumulative Sums of Squares (ICSS) algorithm created by Aggarwal et al. (1999) is generally used for detecting breakpoint information in time series. These models are applied to other papers, such as financial assets (Hwang and Shin, 2017), stock prices (Wang and Moore, 2009; Charfeddine and Ben Khediri, 2016), and tourism demand (Cro and Martins, 2017). The ICSS identified endogenous changes in the volatility of carbon indices.

Moreover, sudden volatility changes could occur in emerging markets like the carbon market. The estimation of continued volatility is expected to drive these changes. However, more work needs to be done on structural breaks in carbon markets. Political change, climate change, and allowance allocation are external factors that affect the price volatility in the carbon market. The empirical results for equity returns in Tunisia and Malaysia were demonstrated by Tan and Khan (2010) and Mabrouk and Aloui (2010) while analyzing ARFIMA-FIGARCH.

This study aims to determine if carbon indices have a long memory effect following the sustainability goal. The carbon index returns and volatilities incorporate long memory properties. The main points of this article are as follows:

(1) This study uses an ARFIMA model, where a whole difference parameter is allowed. Four types of carbon indexes (prices) are tested for long memory and asymmetry using the FIGARCH model. In order to find high persistence in volatility, the GARCH model extensively modeled the time-varying volatility for carbon indexes, including carbon index, carbon futures, Exchange-traded note (ETN), and Exchange-traded fund (ETF).

(2) The Bai and Perron test and the Iterated Cumulative Sums of Squares (ICSS) algorithm are used in this article to explore structural breaks in volatility. The more extensive the test results, the more sufficient they are for identifying structural breakpoints in the carbon price. In addition, this paper explains why these breakpoints occur to aid individuals in understanding the mechanism behind the carbon price.

This paper is organized as follows: Section 2 presents the literature review; Section 3 describes the data and explains the models; Section 4 Empirical results and findings; and Section 5 is the conclusion.

2. Literature Review

The European Union (EU) set mandatory objectives for carbon emissions and implementing renewable energy sources (RES) in 2008. By 2050, the EU will be a climate-neutral economy with no net-zero greenhouse gas (GHG) emissions. The European Emissions Trading System (ETS) supports the reduction of greenhouse gas emissions from the power sector to industry, such as mobility, buildings, agriculture and forestry, and Intra-EU flights in line with European Commission policy. The EU-ETS is the main focus of the current research on carbon market volatility.

The European market was analyzed by Feng et al. (2011) using a random walk model, and they concluded that changes significantly influenced carbon prices in the carbon market. The findings of Fang et al. (2018) support these results. To explore China's Carbon Market, Song et al. (2019), using the Logit model, found that environmental regulations and carbon emission rules have significantly influenced carbon pricing in the near term. Yuan et al. (2020) used the general equilibrium model and found that carbon prices were strongly connected to carbon market prices. The GARCH model was utilized by Byun and Cho (2013) to estimate the volatility of carbon futures prices.

Chevallier (2011) found a satisfactory relationship between macroeconomic and EU carbon pricing using Markov's transformative autoregressive model. Carbon pricing has been significantly impacted by the transportation and power generation sectors. Ren et al. (2020) and Chan (2020) used the general equilibrium model to show that carbon pricing had a detrimental effect on economic growth. Wu et al. (2013) investigated the Chinese energy market concerning carbon pricing. The findings showed that coal prices had a significant influence on carbon prices. The price of heating oil and carbon prices were closely connected. Perčić et al. (2020) and Zhu et al. (2020) concluded that power prices also significantly affected carbon prices. The increase in carbon emissions is a sign that carbon prices will increase because higher energy prices have prompted the use of coal.

The European Union carbon market was examined by Creti et al. (2012) using the co-integration method. The findings revealed that government financial subsidies significantly impacted carbon pricing. While renewable subsidies lower carbon levels, Ren and Zhu (2020) thoroughly examined China's carbon market and found that fossil fuel subsidies raise carbon prices. Huang et al. (2021) proved that renewable energy has the potential to reduce CO2 emissions. As a result, industrial companies have reduced their carbon licensing requirements and costs.

Chang et al. (2015) suggested that carbon trade was directly tied to carbon pricing. Wang et al. (2019) used the ARMA-GARCH model and concluded that legitimate trade has an ongoing impact on carbon pricing but that inappropriate trade causes significant volatility in carbon prices. Venmans et al. (2020) examined OECD nations and found that foreign direct investment and imports did not positively impact carbon prices.

This study has gained much knowledge from the available research on carbon pricing. There needs to be more consistency in the current literature. Most of the findings revolve around the assumption that the correlations between carbon pricing and their impact variables are linear. Using linear regression models to examine economic issues has unintended consequences. The relevant estimation known to the researchers used the ordinary least squares (OLS) technique. The average effect of the independent variable on the dependent variable is typically depicted in the results. The carbon market is a complex volatility model, the volatility of carbon price being affected by energy prices and weather, and the development of the carbon market and traders' behavior. As a result, research focused exclusively on the relationship between carbon and energy prices needs to be revised. This work fills in the gaps in previous relevant research and makes necessary enhancements. This study examines the long memory properties of carbon indexes using ARFIMA-FIGARCH from the carbon index data. During the COVID-19 pandemic, the ICSS was utilized to examine the multiple structural breaks in the four types of carbon indexes and prices caused by the enormous magnitude of oil prices.

3. Data and Methodology

The distinct datasets collected from the S&P Dow Jones Indices encompassing indices, futures, ETN, and ETFs, to compute a metric for carbon price volatility from January 1, 2019, to February 1, 2023. A sample of the daily settlement prices for the IHS Markit Global Carbon Index (GLCARB) and IHS Markit Carbon EUA Index (GLCEUA) was collected. The GLCARB is created to assess the performance of the global carbon credit market. Currently, the index encompasses the major cap-and-trade programs in Europe and North America, such as European Union Allowances (EUA), California Carbon Allowances (CCA), and the Regional Greenhouse Gas Initiative (RGGI). The GLCEUA is intended to assess the activity of the European Union Allowance credit market. The GLCEUA only contains carbon credit futures for the current year connected with European Union Allowance December Expiry and vintage years that coincide with the current year of expiration of the futures. Cap-and-trade programs are responsible for carbon credit futures' sustainability and future existence.

The European Union Allowance Yearly Futures (FEUA) daily settlement price sets are collected from the European Energy Exchange (EEX). The Low Carbon 100 Europe (LC100) Index is intended to show the price levels of European companies with the best climate score.

Daily closing prices on an ETN and three ETFs were used in this study. The varying indices' inception dates are the study period's starting point. The data was sourced from Yahoo! Finance websites. The iPath Series B Carbon ETN (GRN) keeps track of the Barclays Global Carbon II TR USD Index. It provides exposure to carbon credit futures from two related mechanisms, mainly the EU Emissions Trading System (ETS). From September 11, 2019 to February 1, 2023, the daily settlement price for GRN is set.

Carbon ETF includes the iShares MSCI ACWI Low Carbon Target ETF (CRBN) and the VanEck Low Carbon Energy ETF (SOMG) daily settlement price, while the KraneShares Global Carbon Strategy ETF (KRBN) daily settlement price is from August 1, 2019 to February 1, 2023.

3.1 ARFIMA

The ARMA model (p, q) was proposed by Box and Pierce (1970) to show stationary, where p describes the autoregressive order and q represents the moving average item. The ARMA model's mean, auto-covariance, and variance are all constants and cannot be influenced by time. The ARIMA model (p, d, q) proposed by Box and Jenkins (1970) uses parameter d to distinguish time series variables and make them stationary. Due to an unsatisfactory parameter d with a value of zero or one, Engle and Granger (1987) indicated an equilibrium error. Controlling a long-term memory effect was limited. Granger and Joyeux (1980) developed the AFIRMA model (p, d, q) that enables the parameter d to be either non-integer or fractional. A long-memory effect occurs in the time series of 0<d<0.5. The mathematical model is described in the following:

$$\phi(L)(1-L)^d(y_t-\mu_t)=\psi(L)\varepsilon_t\,, \tag{1}$$

where d is the real number parameter for the fractional integration, and L and ε_t represent a noise residual with the lag operator, respectively.

The long memory of the time series variable is captured by the ARFIMA model using the d parameter. The variable represents a short memory if d = 0, and ε_t geometrically decays when there is the effect of market shocks. Moreover, the variable is stationary if -0.5 < d <0.5, and ε_t gradually decays near zero (i.e., hyperbolic decay) when the effect of market shocks occurs. A unit root process is present if d = 1 (Styger et al., 2009). In general, empirical results indicate that the ARFIMA model is more accurate in predicting volatility.

3.2 FIGARCH

To illustrate the variance of residual changes over time and a phenomenon called volatility clustering, Engle (1982) proposed the autoregressive conditional heteroscedasticity (ARCH) model. The use of the generalized autoregressive conditional heteroskedasticity (GARCH) model was proposed by Bollerslev (1986) to take into account the time series and the associated prediction error. He asserted that the square of the prior residual is the manipulation of conditional variance, and the prior variance influences it. By modeling the conditional variance, the GARCH model provides more flexibility than the ARCH model.

The incorporation of the fractionally integrated generalized autoregressive conditionally heteroskedastic (FIGARCH) model was proposed by Baillie et al. (1996) to capture the long memory in volatility returns. Hyperbolic decay at an incremental rate of zero. The random external shock of each period can be more delayed if the variables have a long memory. The random external shock can be measured by obtaining a faster geometric decay for stationary variables.

The FIGARCH model, which was highly elastic in modeling conditional variance, was depicted by Bollerslev and Mikkelsen (1996), Beine et al. (2002), and Bentes (2014). The model captured both stationary GARCH for d=0 (Bollerslev, 1986) and non-stationary GARCH. Moreover, IGARCH sets for d=1 (Engle and Bollerslev, 1986). This model is widely used in the field of conditional variance modeling. It contains the covariance stationary GARCH for d=0 and the non-stationary FIGARCH for d=1. The FIGARCH (p, d, q) model was described as follows:

$$\Phi(\mathrm{L})(1-\mathrm{L})^{d}\varepsilon_t^2 = \omega + [1-\beta(L)]v_t, \quad (2)$$

where υ_t represent the innovation of conditional variance, and the root of $\phi(L)$ and $[1-\beta(L)]$ are supposed to locate at the external of the unit root circle. The fractional differencing parameter is $\upsilon \equiv \varepsilon_t^2 - \sigma_t^2$ when $0 \le d \le 1$. The concept of conditional variance is based on the process of υ_t with a zero mean that is serially uncorrelated. The intermediate range of persistence for the FIGARCH model exists when 0 < d < 1. The series is stationary, and the effect of market shocks decays gradually to zero when -0.5 < d < 0.5. The series is short memory, and the effect of market shocks decreases geometrically when d = 0. Furthermore, there is a unit root process when d = 1. According to Beine et al. (2002) and Bentes (2014), the FIGARCH model can predict more accurately than the GARCH and IGARCH models. The discovery of a long-memory process in the Euro exchange rate by Pelinescu and Acatrinei (2014) indicates persistence.

3.3. Structure breaks

Parameter instability and structural change tests were important to the econometric work. The ICSS test was introduced by Inclán and Tiao (1994) to look at sudden variations in unconditional volatility in a time series. The ICSS algorithm is commonly utilized for identifying discrete variance changes and estimating the location and duration of each change. The Quandt-Andrews framework is further extended by Bai and Perron (1998, 2003a) and Bai (1997), who provide theoretical and computational results that allow for multiple unknown breakpoints. The multiple structure breaks model detects sudden changes in the mean of an observed time series.

3.3.1 Structural Break in Mean: The Bai-Perron Method (BP)

The analysis presumes that the financial time series shows a stationary mean during an initial period until a sudden change in variance occurs. Bai and Perron (2003) determine theoretical and computational outcomes that extend the Quandt–Andrews framework by enabling us to test multiple unknown breakpoints. This paper will examine the scenario of a single structural change regression model that involves T periods and m potential breaks. Let us consider that a time series comprising breaks m (regimes m+1) is defined as follows:

$$y_t = x_i'\beta + z_i'\delta_1 + \mu_i, \qquad t = 1,2 \ldots, \mu_i, \quad (3)$$

$$y_t = x_i'\beta + z_i'\delta_2 + \mu_i, \qquad t = T_1+1,\ T_1+2 \ldots, T_2, \quad (4)$$

....

$$y_t = x_i'\beta + z_i'\delta_{m+1} + \mu_i, \qquad t = T_m+1,\ T_m+2 \ldots, T. \quad (5)$$

where y_t stands for the observed dependent variable at time t. x_t and z define covariance vectors with dimensions $(p \times 1)$ and $(q \times 1)$, respectively. The corresponding vectors of coefficients are β and δ_j $(j = 1,2,\ldots,m+1)$, and μ_t refer to the error term at time t. The break dates $(T_1 < T_2 \ldots < T_m < T)$ can be regarded as unknown. Because the parameter vector β does not limit changes, the model is a partial structural shift model and is effectively estimated over the entire sample. The estimation method was built by Bai and Perron (1998, 2003) based on minimizing the sum of squares residuals.

$$\sum_{i=1}^{m+1}\sum_{t=T_{i-1}+1}^{T_i}(y_t - z_t'\delta_i)^2. \quad (6)$$

I. $SupF_T(k)$ test: $SuF_T(k)$ stand for the F statistic.

H_0: no structure.

H_1: a fixed number of breaks k.

II. Double maximum tests (UDmax): the maximum number of breaks is permitted.

H_0: no structure.

H_1: an unknown number of breaks given some upper bound (M).

UD_{max} defines an equal weighted statistic, $UD_{\max} F_T(M,q) = \max_{1 \le m \le M} F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_m; q)$, and $WD_{\max} F_t(M,q) = \max_{1 \le m \le M} F_T(\hat{\lambda}_1, \ldots, \hat{\lambda}_m; q)$ represent the weights are determined by the number of individuals test such that the marginal p-values are equal across values of m.

III. A test of *l* versus *l*+1 breaks: a sequential test $\sup F_T(l+1|l)$.

H_0: no structure.

H_1: a single change.

The estimate of the number of breaks can be taken into account by the Bayesian Information Criterion (BIC), and the modified Schwarz Criterion (LWZ) was proposed by Liu et al. (1997).

3.3.2 Structural Breaks in Variance: The Iterated Cumulative Sums of Squares (ICSS)

The analysis assumes that the time series will have a stationary variance for an initial period until a sudden change in variance occurs. Inclán and Tiao (1994) proposed that there should be a break in the variance specification. The variance is then still for a while until the following sudden change. The process is repeated over time, resulting in a time series of observations with an unknown number of changes in variance.

Let $\{X_t\}$ represent a series of independent observations based on a normal distribution. It is noted that the variance is denoted by σ_j^2, where j = 0, 1, …, NT. A term that describes the total number of changes is NT.

Using the ICSS of the series, the statistic D_k measures the number and time point when variance changes may occur.

$$C_k = \sum_{t=1}^{k} X_t^2, \quad (7)$$

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T}, k = 1, \ldots, T; \; D_0 = D_T = 0, \quad (8)$$

where C_k and C_T stand for the mean centered cumulative sums of squares using k and T observations, respectively.

Without variance changes during the sample period, the series D_k will oscillate around zero. When variations change, the series drifts upwards or downwards from zero. The distribution for the quality $\left(\left(\frac{T}{2}\right) D_k\right)^{\frac{1}{2}}$ will have a convergence linked to a standard Brownian motion. At point k_0, the change point of variance will extend to the interval t = 1,…, T. The quality will reach its maximum when $\left(\left(\frac{T}{2}\right) D_k\right)^{\frac{1}{2}} > C_{\alpha.}$ The breaking value is C_α, which equal to 1.358 at 5% level.

The D_k function alone is insufficient to bring out the multiple points of structural change. Inclán and Tiao (1994) implemented an algorithm examining the D_k function over different periods to seek the different time series change points systematically. The D_k plot can identify the breakpoints.

3.4 GARCH model estimations with changes in variance

Arago and Fernandez-lzquierdo (2003) updated the GARCH model to examine changes in unconditional variance. To determine points of change in variance, the GARCH model is employed to remove sudden changes. Lamoureux and Lastrapes (1990) and Glosten et al. (1993) looked at the representation of different changes in variance through the use of dummy variables with GARCH and proposed the following:

$$h_t^2 = \alpha + \sum_{i=2}^{p} F_i D_i + \sum_{i=1}^{p} \beta_i h_{t-i}^2 + \sum_{i=1}^{q} \delta_i \varepsilon_{t-i}^2, \quad (9)$$

$$h_t^2 = \alpha + \sum_{i=2}^{p} F_i D_i + \sum_{i=1}^{p} \beta_i h_{t-i}^2 + \sum_{i=1}^{q} \delta_i \varepsilon_{t-i}^2 + \gamma Z_{t-1}^{-} \varepsilon_{t-1}^2, \quad (10)$$

where D_i are the dummy variables (break) that mirror the variance changes, and the variables F_i stand for the differences for α. Moreover, Z_{t-1}^{-} refer to the unit as long as $\varepsilon_{t-1}<0$ (innovation in t=1) and zero when $\varepsilon_{t-1}>0$. If the value $\gamma>0$, the asymmetrical effect occurs. The GARCH model overestimates the persistence of volatility by ignoring sudden and relevant variance changes, as Lamoureux and Lastrapes (1990) suggested.

4. Empirical Results

Table 1 provides descriptive statistics based on four carbon data. The GRN ETN is the most volatile, related to the standard deviation of 2.7527, followed by the GLCEUA index at 1.3568, whereas the CRBN and LC100 index appeared lowly at 0.57% and 0.4973, respectively. The FEUA had the highest average positive return of 0.055, while the GRN had the lowest average negative return of -0.0174. The results for all samples are skewed negatively. These conditions can explain the high volatility of different datasets in the market. The skewness has a negative value, which signifies that the mean of a distribution with a negative skewness is less than the median, which reveals the asymmetry of the distribution. Kurtosis results can determine the risk. The distribution of kurtosis data is leptokurtic due to the high values. The variance of all samples is low because the returns are usually close to the mean and are associated with a leptokurtic distribution, which suggests a lower variance than a normal distribution. An abnormal distribution is indicated by the Jarque-Bera statistic for residual normality, which shows that most of the data is significant at the 1% level. Therefore, the distribution of all samples is abnormal. The correlation coefficient Q (10) is significant as there is no serial correlation.

4.1 Long memory effect

In addition, the ARFIMA and ARFIMA-FIGARCH models are run in this study. The optimal model is obtained using AIC by examining ARFIMA (0, d, 1) to ARFIMA (3, d, 3) based on the minimum. The d parameter makes it possible to estimate the existence of a long memory.

ARFIMA and ARFIMA-FIGARCH models are represented in Table 2. The d-coefficient in the ARFIMA model indicates that FEUA is $-0.5 < d < 0.5$. At 10% levels, a memory with a long term is significant. As a result, FEUA returns can be expected or estimated on a long-term basis. The ARFIMA model has confirmed the existence of a long memory in other studies (Nouira et al., 2004; Chen and Diaz, 2013; Kang and Yoon, 2007; and Chen and Malinda, 2014). The ARFIMA-FIGARCH model indicated that GLCARB, GLCEUA, and GRN have a long memory for volatility at significant levels, suggesting that they can be predicted accurately. A long memory of price and commodity indices was identified by Baillie (1996) and Arouri et al. (2012). Stationary is the term used to describe the LC100, FEUA, KRBN, CRBN, and SOMG. Hence, the effect of market shocks decays gradually to zero, showing that long memory does not exist in their return. The results indicate that the volatilities have predictable structures, and investors and traders can reap their benefits through proper modeling and forecasting. The ARFIMA-FIGARCH for the return volatility outcome revealed that the d-coefficient for the LC100, FEUA, and CRBN are 0<d<1. These findings show that volatility has a more significant impact on negative shocks than positive shocks, which is significant at 1%.

4.2 Multiple Sudden Changes

The work involves two analyses linked to multiple structural breaks in the carbon indices. The first study examines the structural breaks in the average process of the series. The second analysis examines the structural breaks that occur during the variance process of the series. The return graphs in Figure 1 clearly show a variety of volatility periods. The daily adjust close price series of carbon indices has been restructured using multiple structural breaks.

4.2.1 Bai and Perron Test Results

In order to detect multiple structural breaks, the empirical research applies the following set of tests proposed by Bai and Perron (1998, 2003): the double maximum tests, the $SupF_T(k)$ test, and $SupF_T(l+1|l)$. By employing a trimming percentage of 15%, Bai and Perron (2003) examined the tests allowing for a maximum number of 5 breaks based on the sequential testing. The results are in Tables 3, 3-1, 4, and 5. Firstly, the UD_{max} and WD_{max} tests exhibit the result of structural breaks at a 5% significant level, implying the time series has multiple structural breaks.

In Table 3, the $SupF_T(5)$ tests are significant in all sample series. According to the findings, carbon indices have at least three breaks. The significant results pick up the largest statistically significant breakpoint in Table 3-1. The outputs of UD_{max} and WD_{max} reflected the number of breakpoints which corresponding the unweighted and weighted maximized statistics. The results revealed that a maximum of three breaks for the UD_{Max} and four breaks for the WD_{Max} existed.

The F-statistic is shown in Table 4, along with the F-statistic scaled by the number of varying regressors. The sequential result is generated by running tests from 1 to maximum pauses until we cannot reject the null assumption of no pause. In addition, the work further uses $S\mathrm{up}F_T(l+1|l)$ tests to illustrate the number of structural breaks. This result shows that the $S\mathrm{up}F_T(1|0)$ statistic rejects the zero break null hypothesis and accepts the one break alternative hypothesis in GLCARB and FEUA. However, the $S\mathrm{up}F_T(3|2)$ statistic rejects the two breaks null hypothesis and accepts the three break alternative hypothesis, implying GRN has three structural breaks.

The results of sequential, BIC, and LWZ tests are presented in Table 5. Bai and Perron (2003) suggested that a sequential procedure for selecting the breakpoint is effective when the number of breaks present is similar. Consequently, the BIC results reveal that FEUA has three structural breaks. There are four structural breaks in GLCARB, LC100, GRN, and SMOG, while there are five structural breaks in GLCEUA, KRBN, and CRBN.

The structural break approach estimated the multiple structural shifts at unknown dates and breaks. The structure break dates and means are given for each segment, and for FEUA, there are three structural breaks on 8/24/2020, 4/06/2021, and 11/18/2021.

Table 1 The Descriptive Statistics of Variables

Indices	Market	Type	Index	Code	Period	Obs	Mean	SD	Skew	Kurt	J-B	Q(10)
Carbon Indices	NYSE	Index	IHS Markit Global Carbon Index	GLCARB	2019/01/01-2023/02/01	1012	0.041	0.9483	-0.5	4.56	924.83***	23.92
	NYSE	Index	IHS Markit Carbon EUA Index	GLCEUA	2019/01/01-2023/02/01	1012	0.052	1.3568	-0.6	4.41	83.74***	27.43
	AMS	Index	Low Carbon 100 Europe	LC100	2019/01/01-2023/02/01	1050	0.013	0.4973	-1.3	14.2	9101.4***	37.33
Futures	EEX	Futures	European Union Allowance Yearly Futures	FEUA	2019/01/01-2023/02/01	1055	0.055	1.2992	-0.5	4.19	819.40***	23.38
ETN	NYSE	ETN	iPath Series B Carbon ETN	GRN	2019/09/11-2023/02/01	860	-0.017	**2.7527**	-19	489	8.636***	23.38
ETFs	NYSE	ETF	KraneShares Global Carbon Strategy ETF	KRBN	2020/08/01-2023/02/01	641	0.047	1.0487	-1.7	14.1	5618.9***	16.82
	NYSE	ETF	iShares MSCI ACWI Low Carbon Target ETF	CRBN	2019/01/01-2023/02/01	1060	0.015	0.5716	-1.1	13.1	7780.2***	43.65
	NYSE	ETF	VanEck Low Carbon Energy ETF ETF	SMOG	2019/01/01-2023/02/01	1032	0.033	0.945	-0.5	5.86	1520.5***	12.23

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.
Sources: S&P Dow Jones Indices website and European Energy Exchange and Yahoo Finance website.

Table 2 Estimated ARFIMA-FIGARCH model

	Index	ARFIMA				ARFIMA-FIGARCH				
		Model	d-coeff.	AIC	ACH-LM	d-Arfima	Model	d-Figarch	AIC	ARCH-LM
Carbon Indices	GLCARB	(3,3)	-0.0829 (0.1420)	3.555	20.719 (0.0000)***	**-0.1670 (0.0614)***	(2,1)	0.1347 (0.2454)	2.596	1.348 (0.2419)
	GLCEUA	(3,3)	-0.0758 (0.1830)	3.450	15.282 (0.0000)***	**-0.1900 (0.0433)****	(2,1)	0.1296 (0.2818)	3.332	1.366 (0.2348)
	LC100	(3,3)	-0.7452 (0.0000)***	1.436	35.334 (0.0000)***	-0.3460 (0.1660)	(1,2)	0.5431 (0.0001)***	1.073	0.2696 (0.9298)
Futures	FEUA	(1,2)	**-0.1631 (0.0550)***	3.364	15.278 (0.0000)***	-0.0480 (0.4096)	(3,3)	**0.2786 (0.0111)*****	3.332	0.8588 (0.5083)
ETN	GRN	(1,0)	0.0075 (0.8700)	4.872	0.002 (1.0000)	**0.2692 (0.0000)*****	(2,1)	1.2012 (0.0000)***	4.705	0.0044 (1.0000)
ETFs	KRBN	(2,0)	-0.1166 (0.1640)	2.936	2.458 (0.0322)	-0.1160 (0.1441)	(1,2)	**-0.1121 (0.0000)*****	2.812	0.3012 (0.9122)
	CRBN	(2,3)	0.0545 (0.2650)	1.702	104.730 (0.0000)	-0.0510 (0.2387)	(3,3)	**0.655 (0.0002)*****	1.208	0.1396 (0.9830)
	SOMG	(2,2)	-0.0047 (0.8450)	2.730	47.674 (0.0000)	0.0232 (0.3831)	(3,2)	1.0351 (0.0000)***	2.397	0.0910 (0.9937)

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

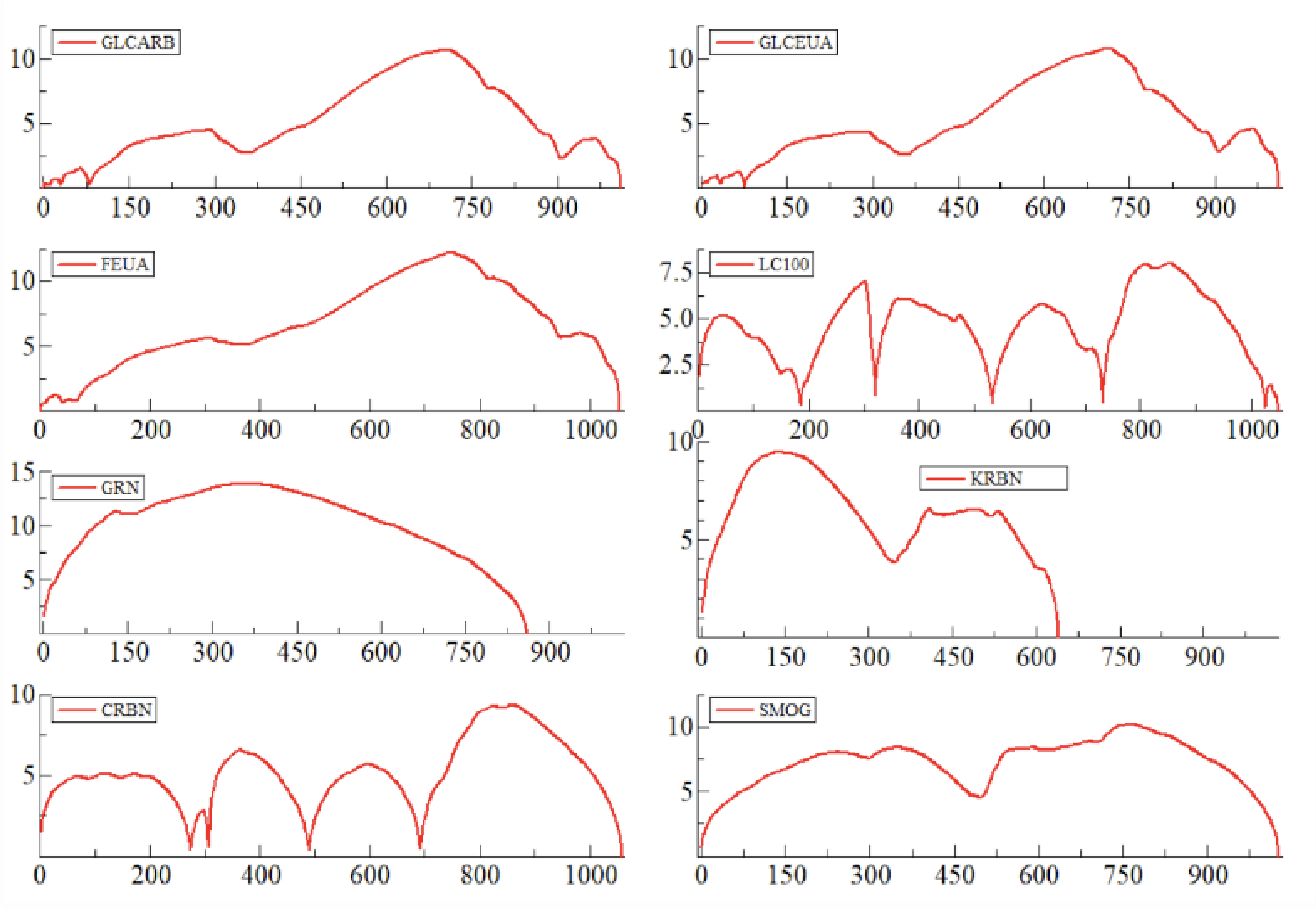

Figure 1 Carbon Indexes (Prices) regime shifts in volatility

Table 3 BP Global L Structural Breaks Point for Carbon Index

Test		VIX-ETFs	H_0	H_1	Determined breaks	F-statistic	Criteria
D_{Max} test	UD_{Max}	GLCARB	m=0	m>0	**3**	49.371**	8.8800
		GLCEUA			5	159.984**	
		LC100			5	38.881**	
		FEUA			3	188.529**	
		GRN			4	1043.149**	
		KRBN			5	108.930**	
		CRBN			5	51.123**	
		SMOG			4	129.710**	
	WD_{Max}	GLCARB	m=0	m>0	5	83.966**	9.91
		GLCEUA			5	351.065**	
		LC100			5	85.319**	
		FEUA			5	400.310**	
		GRN			5	2150.639**	
		KRBN			5	239.033**	
		CRBN			5	112.183**	
		SMOG			4	223.029**	

Note: ** Significant at the 0.05 level, respectively.

Table 3-1 Structural Breaks for in Mean for Carbon index

Test	Indices	H_0	H_1	Scaled F-statistic	Weighted F-statistic	Criteria
SubF	GLCARB	m=0	m=1	9.789**	9.789**	8.58
		m=0	m=2	35.062**	41.690**	7.22
		m=0	m=3	49.372**	71.075**	5.96
		m=0	m=4	45.240**	77.788**	4.99
		m=0	m=5	38.264**	83.966**	3.91
	GLCEUA	m=0	m=1	5.236**	5.236**	8.58
		m=0	m=2	33.620**	39.952**	7.22
		m=0	m=3	114.099**	164.257**	5.96
		m=0	m=4	141.097**	242.609**	4.99
		m=0	m=5	159.984**	351.065**	3.91
	LC100	m=0	m=1	17.858**	17.858**	8.58
		m=0	m=2	20.116**	20.905**	7.22
		m=0	m=3	18.796**	27.058**	5.96
		m=0	m=4	22.697**	39.026**	4.99
		m=0	m=5	38.881**	85.319**	3.91
	FEUA	m=0	m=1	27.581**	27.580**	8.58
		m=0	m=2	54.392**	64.637**	7.22
		m=0	m=3	**188.529****	271.405**	5.96
		m=0	m=4	154.290**	265.291**	4.99
		m=0	m=5	182.426**	**400.310****	3.91
	GRN	m=0	m=1	346.207**	346.207**	8.58
		m=0	m=2	459.818**	546.432**	7.22
		m=0	m=3	898.713**	1293.784**	5.96
		m=0	m=4	**1043.149****	1793.630**	4.99
		m=0	m=5	980.070**	**2150.639****	3.91
	KBRN	m=0	m=1	3.492**	3.492**	8.58
		m=0	m=2	13.566**	16.122**	7.22
		m=0	m=3	13.015**	18.736**	5.96
		m=0	m=4	107.093**	184.140**	4.99
		m=0	m=5	**108.930****	**239.033****	3.91
	CRBN	m=0	m=1	16.858**	16.858**	8.58
		m=0	m=2	29.130**	34.617**	7.22
		m=0	m=3	45.988**	66.204**	5.96
		m=0	m=4	29.570**	50.843**	4.99
		m=0	m=5	**51.123****	**112.183****	3.91
	SMOG	m=0	m=1	1.558**	1.558**	8.58
		m=0	m=2	8.177**	9.717**	7.22
		m=0	m=3	97.027**	139.679**	5.96
		m=0	m=4	**129.710****	**223.029****	4.99
		m=0	m=5	79.373**	174.174**	3.91

Note: ** Significant at the 0.05 level, respectively.

Table 4 BP Structural Breaks Point for Carbon Index

	Indices	H_0	H_1	Seq.	F-statistic	Criteria	Break Dates
$SupF_T(l+1\|l)$	GLCARB	m=(0|0)	m=(1|0)	1	9.789**	8.58	2021/08/26
		m=(1|1)	m=(2|1)		1.676	10.13	
	GLCEUA	m=(0|0)	m=(1|0)	2	48.111**	8.58	2021/04/21
		m=(1|1)	m=(2|1)		20.184**	10.13	2021/11/24
		m=(2|2)	m=(3|2)		4.174	11.14	
	LC100	m=(0|0)	m=(1|0)	1	17.465**	6.58	2021/03/09
		m=(1|1)	m=(2|1)		3.768	10.13	
	FEUA	m=(0|0)	m=(1|0)	2	32.667**	8.58	2021/05/07
		m=(1|1)	m=(2|1)		21.514**	10.13	2021/11/15
		m=(2|2)	m=(3|2)		3.223	11.14	
	GRN	m=(0|0)	m=(1|0)	3	297.632**	8.58	2020/05/08
		m=(1|1)	m=(2|1)		351.967**	10.13	2021/08/27
		m=(2|2)	m=(3|2)		214.561**	11.14	2021/03/03
		m=(3|3)	m=(4|3)		7.123	11.83	
	KBRN	m=(0|0)	m=(1|0)	2	25.485**	8.58	2021/05/07
		m=(1|1)	m=(2|1)		20.243**	10.13	2020/12/15
		m=(2|2)	m=(3|2)		9.782	11.14	
	CRBN	m=(0|0)	m=(1|0)	2	15.905**	8.58	2020/11/09
		m=(1|1)	m=(2|1)		17.588**	10.13	2022/05/05
		m=(2|2)	m=(3|2)		4.796	11.14	
	SMOG	m=(0|0)	m=(1|0)	2	25.914**	8.58	2020/09/30
		m=(1|1)	m=(2|1)		11.664**	10.13	2022/01/24
		m=(2|2)	m=(3|2)		3.394	11.14	

Note: ** Significant at the 0.05 level, respectively.

Table 5 BP Global Information Structural Breaks Point for Carbon Index

Indices	Seq.	BIC		LWZ		Estimated break dates
		Breaks	Value	Breaks	Value	
GLCARB	5	4	4.609	4	4.711	1: 2021/08/26
						2: 2021/01/20 2021/08/26
						3: 2021/02/08 2021/09/15 2022/06/22
						4: 2020/03/15 2021/02/08 2021/09/15 2022/06/22
						5: 2019/09/13 2020/03/26 2021/02/08 2021/09/15 2022/06/22
GLCEUA	5	5	8.542	4	8.644	1: 2021/04/21
						2: 2021/02/05 2021/11/15
						3: 2020/08/02 2021/04/12 2021/11/16
						4: 2020/08/25 2021/04/12 2021/11/18 2022/06/28
						5: 2020/01/10 2020/08/24 2021/04/12 2021/11/18 2022/06/28
LC100	5	4	3.694	4	3.793	1: 2021/03/09
						2: 2021/03/09 2022/05/05
						3: 2020/11/09 2021/06/22 2022/05/04
						4: 2020/03/06 2020/11/09 2021/06/22 2022/05/0
						5: 2019/08/14 2020/03/25 2020/11/09 2021/06/22 2022/05/04
FEUA	5	3	3.385	3	3.462	1: 2021/05/07
						2: 2021/03/09 2021/11/18
						3: 2020/08/24 2021/04/06 2021/11/18
						4: 2020/01/13 2020/08/24 2021/04/06 2021/11/18
						5: 2020/01/13 2020/08/24 2021/04/06 2021/11/12 2022/06/22
GRN	5	4	2.411	3	2.524	1: 2020/05/08
						2: 2020/05/08 2021/08/27
						3: 2020/05/08 2021/03/10 2021/11/16
						4: 2020/05/08 2020/11/16 2021/05/24 2021/11/18
						5: 2020/05/08 2020/11/23 2021/06/01 2021/11/24 2022/07/20
KRBN	5	5	2.114	4	2.252	1: 2021/05/07
						2: 2021/03/09 2021/08/27
						3: 2021/04/21 2021/10/10 2022/08/30
						4: 2020/12/15 2021/05/06 2021/11/10 2022/08/30
						5: 2020/12/15 2021/05/06 2021/11/10 2022/03/30 2020/08/30
CRBN	5	5	3.995	4	4.1	1: 2020/11/09
						2: 2020/11/16 2022/05/05
						3: 2020/07/08 2021/02/03 2022/04/26
						4: 2020/05/28 2020/12/17 2021/08/03 2022/04/26
						5: 2019/09/04 2020/05/28 2020/12/17 2021/08/03 2022/04/26
SMOG	5	4	5.001	3	5.095	1: 2020/09/30
						2: 2020/10/06 2022/01/24
						3: 2020/04/09 2020/11/17 2022/01/24
						4: 2019/09/03 2020/04/14 2020/11/19 2022/01/24
						5: 2019/08/20 2020/03/31 2020/11/06 2021/06/21 2022/01/28

Note: ** Significant at the 0.05 level, respectively.

4.3 Structure break

Figure 1 shows the change point of variance value for each price series with the points of sudden changes separately based on the measurement of the ICSS model for carbon indices in volatility. It is possible to identify any significant changes in the variance of the carbon index among the carbon indexes by examining the switching points range. Significant changes are observed in the variance of LC100 and CRBN carbon index. The subject of this paper is switching points and heightened volatility. The variance of carbon indices showed significant changes in this study.

Table 6 gives an idea of the volatility of carbon indexes by describing the results of structural breaks using the ICSS methodology. The results show that multiple structural breaks affect recognizing sudden changes in the unconditional volatility of a series of endogenous events. A structural break exists when the value is higher than 1.358. The results show that switching points can fluctuate during multiple breaks of carbon indexes.

Three regime shifts for the GLCARB, GLCEUA, and LC100 indexes occurred with an initial volatility spike on March 5 and 6, 2020, where the maximum values were 4.487, 4.339, and 7.009, respectively. In March 2020, rising COVID-19 cases, particularly in the United States and the OPEC–Russia price war, further disrupted crude petroleum markets. The demand for crude oil was substantially decreased by mandatory lockdowns enforced by several European countries and some areas in the United States. Car fuel and lubricant retailers have increased their margins by 24 percent because of the steep drop in demand. The COVID-19 pandemic is dramatically impacting economic activities worldwide in 2020. The lockdown measures included the isolation of infected persons, compulsory closure of offices and educational institutions, shutting down many industries, grounding most passenger flights, and enforced home confinement (Le Quéré et al., 2020) as countries implemented lockdowns and restrictions on economic activities, demand for carbon allowances decreased, which resulted in a surplus of carbon allowances in the market and a drop in carbon prices. The pandemic has directly and immediately impacted emissions, as the decrease in production and traffic volumes significantly reduced emissions. Furthermore, the economic recession has a significant effect on carbon markets. The reduction in allowance prices is caused by the sharp decrease in demand for emission allowances due to the decrease in production. As a result, it encourages investment in cleaner technologies.

The LC100 had a change point on June 10, 2020, with a maximum value of 6.08. The CRBN also had a change point on June 7, 2020, with a maximum value of 6.5494. During this period, the collapse in oil prices in April, 2020 has also affected the carbon market, leading to lower demand for carbon credits. The benchmark for U.S. crude oil dropped to negative territory for the first time because of turbulence. The price of Brent Crude, a reference for Europe and the rest of the world, also dropped significantly. Producers are scrambling to find facilities to store surplus crude oil when faced with an enormous oversupply of demand, with inventories peaking at an all-time high in June, 2020.

The results revealed that GRN, KRBN, and SMOG in the ETN and ETFs samples had a significant change point with the maximum values. During economic uncertainty, the Federal Reserve is still raising interest rates, and the demand for global vehicle production is decreasing. Tesla is part of an extensive portfolio of small carbon ETFs. According to the news report, Tesla stock closes out the worst year ever, with a 65% loss in 2022. The Tesla stock's sell-off outstripped the losses of major indices like the S&P 500 and the tech-heavy Nasdaq, which fell by 20% and 33%, respectively.[2]

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[2] Insider Inc. https://markets.businessinsider.com/news/stocks/tesla-stock-worst-year-ever-700-billion-market-

Table 6 Sudden changes in volatility

Index	Change point	Interval	$\boldsymbol{max_k\left(\left(\frac{T}{2}\right)\lfloor D_k \rfloor\right)^{1/2}}$
GLCARB	**03/06/2020**	**04/30/2019-06/17/2020**	**4.4874*** **
	11/05/2021	06/18/2020-09/02/2022	10.7024
	11/22/2022	09/06/2022-02/01/2023	3.8030
GLCEUA	**03/05/2020**	**04/24/2019-06/17/2020**	**4.3485** **
	11/12/2021	06/18/2020-09/01/2022	10.7871
	11/22/2022	09/02/2022-02/01/2023	4.6114
LC100	**03/05/2020**	**09/24/2019 -04/02/2020**	**7.009*** **
	06/02/2020	**04/03/2020 -01/29/2021**	**6.080*** **
	03/08/2022	**01/29/2021 02/01/2023**	**7.980*** **
FEUA	03/10/2020	04/02/2019-06/01/2020	5.6562
	11/18/2021	06/02/2020-02/28/2022	12.1978
	03/07/2022	03/01/2022-02/01/2023	10.2745
GRN	**02/02/2021**	**04/06/2020-02/04/2021**	**13.8655*** **
	02/05/2021	02/05/2021-02/01/2023	13.8647
KRBN	02/18/2021	02/17/2021-05/24/2022	9.4436
	06/07/2022	**05/25/2022-02/01/2023**	**6.5475*** **
CRBN	**05/26/2020**	**08/02/2019-10/30/2020**	**6.5494** **
	03/31/2021	11/02/2020-08/16/2021	5.6971
	04/08/2022	08/17/2021-02/01/2023	9.3323
SMOG	05/14/2020	03/09/2020-12/15/2020	8.3796
	09/16/2021	12/16/2020-09/20/2021	8.8340
	01/05/2022	**09/21/2021-01/31/2023**	**10.213*** **

Note: *, ** and *** are significant at 10, 5 and 1% levels, respectively.

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4.4 Structure breaks of an asymmetrical effect

The current research has calculated the GARCH model to distinguish the statistically significant change points and quantify how regime changes can affect volatility. The critical value of 1.358 at the 5% level was presented by Inclán and Tiao (1994) under the null of independently distributed normal errors. Consequently, the GARCH model uses the dummy variable (Fi) based on the ICSS model value. If the value exceeds 1.358, F will be one and zero for the remainder.

The Fi reveals differences in the variance during the study period. A structural break exists when Fi exceeds the criterion value of 1.358. Furthermore, this research used r to examine the asymmetrical effect. Choosing the optimal fit model is determined by the minimum AIC—the presence of positive and significant r results in an asymmetric effect.

The structural breaks of the dummy variables for the carbon indices are presented in Table 7. The table shows that at the 1% level, the estimated coefficients for F1 and F2 of the GLCARB are negative and significant. Adding dummies decreases the value of the unconditional variance. F1, F2, and F3 for the LC100 index show positive and significant results at the 1% level, which suggests an increase in the unconditional variance's value and stability. Furthermore, the CRBN ETF exhibits a positive and significant r-coefficient at the 1% level, indicating an asymmetric effect.

Table 7 The effect of structure breaks with the dummy variable

Index	GARCH	AIC	F & r	Coefficient	
GLCARB	(3,3)	2.5799	F1	**-0.0383**	**(0.0011)*** **
			F2	**-0.0006**	**(0.0048)*** **
			F3	**0.0307**	**(0.0006)*** **
			r	0.0135	(0.9184)
GLCEUA	(3,3)	3.3316	F1	-0.0193	(0.9151)
			F2	**0.4119**	**(0.0592)** **
			F3	0.0574	(0.8074)
			r	**-0.0281**	**(0.0113)*** **
LC100	(1,2)	3.287	F1	**0.059**	**(0.0011)*** **
			F2	**0.091**	**(0.0048)*** **
			F3	**0.076**	**(0.0006)*** **
			r	-0.020	(0.9184)
FEUA	(1,1)	2.2557	F1	-0.1053	(0.1801)
			F2	-0.0707	(0.3517)
			F3	-0.0455	(0.5558)
			r	-0.0033	(0.8912)
GRN	(1,2)	4.0147	F1	**12.5208**	**(0.0000)*** **
			F2	0.1401	(0.1056)
			r	0.0293	(0.6819)
KRBN	(3,1)	2.8497	F1	0.0348	(0.3843)
			F2	**0.3384**	**(0.0034)*** **
			r	**-0.0804**	**(0.0933)* **
CRBN	(3,3)	1.1813	F1	**-0.0172**	**(0.0508)** **

			F2	-0.0127	(0.1898)
			F3	0.0232	(0.1356)
			r	**0.0095**	**(0.0000)*** **
SMOG	(3,1)	2.4095	F1	0.0269	(0.1344)
			F2	0.0117	(0.1277)
			F3	**0.0304**	**(0.0201)*** **
			r	0.0319	(0.2230)

Note: *, **, and *** are significant at 10, 5 and 1% levels, respectively; p-values are in parentheses.

5. Conclusions

The ARFIMA–FIGARCH models were utilized in this study to address long memory. The Bai-Perron test measured the sudden changes in volatility and its persistence for different types of carbon indices and prices, taking into account multiple structural breaks in mean and variance. The ICSS algorithm methodology is also being utilized. There are several findings in the empirical results. The ARFIMA model shows that the significant findings of the FEUA and the GRN have considerable memory. Investors can observe the investment performance and become aware of changes in market conditions.

GLCARB, GLCEUA, and GRN have a long memory for volatility, as revealed by the ARFIMA-FIGARCH results. Investors and traders can benefit from accurately predicted ones with proper modeling and forecasting. The stationary structures of the LC100, KRBN, and CRBN are hindering traders from gaining excess returns due to the intermediate memory in returns. Consistent with the contributions made by Alberola et al. (2008) and Mansanet-Bataller et al. (2007), they highlighted the apparent long-run dependence on carbon price.

Third, the results of ARFIMA-FIGARCH indicate that the negative shock for the volatility of returns for the LC100, FEUA, KRBN, and CRBN has more impact than the positive shock on volatility.

Fourth, the COVID-19 pandemic has impacted the global economy, including the carbon market. The collapse of oil prices affected the carbon market, leading to decreased demand for carbon credits. Following Malik (2003) and Covarrubias et al. (2006), the present study uses the ICSS method to observe that most variables have structural breaks that are connected with similar changes in different industries. The carbon market can be affected by changes in circumstances, including diseases and economic and political issues, as evidenced by these examples. Lanouar and Dominique (2011) found that the break date coincides with several economic and financial events.

Strong asymmetrical effects cause structural breaks in CRBN, which indicate that all low-carbon ETFs are generally unstable. Investors should be cautious when faced with volatile shocks related to news, political, and economic issues. Investors can gain confidence in predicting the investment by understanding the implications. Carbon emissions can be reduced by companies with measurable carbon emissions industries that reduce dependence on fossil fuels. This research is valued by scholars for enriching their theory, particularly in the financial market. Governments and decision-makers must maintain peaceful political circumstances to achieve a remarkable improvement in the financial market.

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