International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2023, 13(3), 579-585.

Applications of Long-Memory and Structure Breaks for Carbon Indexes

Do Thi Van Trang[1]*, Jo-Hui Chen[2]

[1]Postgraduate Faculty, Banking Academy, Hanoi, Vietnam, [2]Department of Finance, Chung Yuan Christian University, Chung-Li, Taiwan. *Email: trangdtv@hvnh.edu.vn

Received: 28 January 2023 **Accepted:** 04 May 2023 **DOI:**https://doi.org/10.32479/ijeep.14289

ABSTRACT

This paper aims to investigate the long-memory properties of four carbon indexes by utilizing the autoregressive frictionally integrated moving average–fractionally integrated general autoregressive conditional heteroskedasticity models. First, this study discovered a significant long-memory effect for two carbon indexes such as CCX and JOI, whereas others like CER and EUA possess intermediate memory in the returns. Second, the multiple structure breaks in the four carbon indexes were examined using the iterated cumulative sum of squares algorithm. Evidence shows that the sudden shifts are mainly attributed to macroeconomic factors, energy dynamics, and political policies.

Keywords: Carbon Index, ARFIMA-FIGARCH Models, Structure Break, ICSS Algorithm
JEL Classifications: O13, Q53, Q56

1. INTRODUCTION

In response to the threat of global warming, the Kyoto Protocol was signed and implemented at the United Nations Framework Convention on Climate Change in Kyoto, Japan, in December 11, 1997. The Kyoto Protocol was enforced on February 16, 2005, aimed to limit emissions of greenhouse gases (GHG) from developed countries and to continue controlling the global warming phenomenon. The Kyoto Protocol agreement has set binding targets for 37 industrialized countries and the European community for reducing GHG and developing new energy technology. Based on the agreement, countries must meet their targets primarily through national measures. Thus, the Kyoto Protocol offers these countries an additional means of meeting their targets through three market-based mechanisms, namely, emissions trading, known as “the carbon market;” clean development mechanism (CDM); and joint implementation. Meanwhile, emissions trading enable countries that have emission units to spare or to sell this excess capacity to countries that are over their targets. Therefore, a carbon price that was created in the form of emission reductions or removals are now tracked and traded similar to any other commodity. A carbon price is the cost applied to carbon pollution to encourage polluters to reduce the amount of GHG they emit into the atmosphere.

In the international carbon trading market, the carbon commodities are distinguished into two types. The first type includes emission trading systems, such as the European Union, Australia, the Chicago Board of Trade, and the United Kingdom emission trading markets, which facilitate the creation of carbon permits (Allowance). The second type is based on the reduction plan (such as the CDM and joint reductions or other voluntary reduction plans) to reduce credit.

This study first examines whether a long-memory effect in the carbon indexes exist given the aim of sustainability. Long-memory properties are examined in both carbon indexes returns and volatilities. Mabrouk and Aloui (2010) and Tan and Khan (2010) provided empirical proof based on the stock market returns of Tunisia and Malaysia, respectively. Segnon and Gupta (2017) used the fractionally integrated GARCH to foresee the carbon dioxide emission price volatility and realized the performance of the model via the superior predictive ability test. According to Huang et al. (2021), the long memory effect was found with the data from the new carbon price while predicting the carbon price volatility. The forecasting of the current carbon price volatility is useful for carbon market investors to identify and reduce price risk. Ahonen et al. (2022) applied the fractionally integrated general autoregressive conditional heteroskedasticity (FIGARCH) model in order to estimate the dynamic conditional correlations among the determinants that affect the carbon market product. Meng et al. (2023) have looked into the relationship between the carbon finance market and the shipping industry by applying wavelet analysis and spillover index methods. The findings have indicated the dynamic dependence and long-memory effects between the carbon finance market and shipping. The current study utilizes the autoregressive fractional integrated moving average (ARFIMA) processes, in which the difference parameter is allowed to be a non-integer. The FIGARCH model is also employed to verify the long memory and asymmetry in four carbon indexes.

Second, this paper investigates structural breaks in volatility using the iterated cumulative sum of squares (ICSS) algorithm of Inclán and Tiao (1994). Through the GARCH model, the time-varying volatility of carbon indexes was extensively modeled to find high persistence in volatility. The ICSS algorithm that considers endogeneity has been applied in many papers such as Wang and Moore (2009) and Aggarwal et al. (1999) which examined emerging stock markets. Moreover, in emerging markets such as the carbon market, potential sudden shifts in volatility might occur. Therefore, these shifts should be addressed in estimating volatility persistence. The ICSS has endogenously identified changes in the volatility of carbon indexes. Tan and Wang (2017) examined the dependence volatility caused by the structural breaks through the selected period by applying quantile regression. The findings suggest that the carbon investors should address the structure break in different ways to eliminate financial risk. Wang and Cai (2018) studied the relationship between the carbon market and the energy market by employing the analysis of VAR and the Granger causality test, however, there are no causal relationships between the two markets. Based on the research of Wen et al. (2020), the negative long-run and short-run asymmetric relationships between carbon emissions and the whole stock market were significant statistics in China market. The authors used the nonlinear auto-regressive distributed lag model to indicate the asymmetric relation. To the best of our knowledge, this technique has not been explored in the empirical analysis of carbon indexes with structural breaks. Alberola et al. (2008) examined the European Union Allowances (EUA) price break that occurred in April 2006 following the report of 2005 verified emissions to determine whether EUA spot prices react not only to energy prices with forecast errors, but also to unexpected temperature changes during colder events. Chevallier (2011a) has shown evidence of strong shifts in EUA mainly from the EGARCH and implied volatility models using retrospective and forward-looking tests. Thus, the current paper is the first to focus on transition carbon indexes using this technique.

This paper is organized as follows. Section 2 explains the ARFIMA–FIGARCH and ICSS models. Section 3 describes the data and presents the empirical results. Section 4 concludes.

2. METHODOLOGY

2.1. ARFIMA–FIGARCH Model

Granger and Joyeux (1980) and Hosking (1981) applied and developed the long memory property through the ARFIMA (r, d, s) model and the time series is denoted like x_t, t = 1,…,T. Thus, the ARFIMA model can be exhibited as followed:

$$\Psi(L)(1-L)^d(x_t-\mu)=\Theta(L)\varepsilon_t, \quad (1)$$

$$\varepsilon_t = z_t\sigma_t,\ z_t \sim (0,1) \quad (2)$$

Where d identifies a fractional integration of a real number parameter, μ identifies the conditional mean, ε_t identifies the independent and identically distributed (*i.i.d.*) random variables with a variance σ^2, and L denotes the lag operator. Whereas $\Psi(L)=\psi_1L+\psi_2L^2+\ldots+\psi_rL^r$ performs the autoregressive (AR) and $\Theta(L)=\theta_1L+\theta_2L^2+\ldots+\theta_sL^s$ performs moving-average (MA) polynomials outside of the time series.

As mentioned by Hosking (1981) and applied by Tan and Khan (2010), If d > 0, there is appearance of long memory effects in the long run period. Specifically, if d ∈ (0, 0.5) and d ≠ 0, the process is determined by a covariance stationary and mean reversion which there is no appearance of shocks in the long term. If d ∈ (0.5, 1), the time series represents mean reversion. Because the long term influence does not appear on the future time series, the series is not covariance stationary. If d ≥ 1, the process perform non-stationarity and non-mean reversion. In case of d∈ (−0.5, 0), the intermediate memory or antipersistence appears in the time series.

To capture long memory in return volatility, Baillie et al. (1996) proposed the FIGARCH model. This model has many applications in the field of modeling the conditional variance, covering the covariance stationary GARCH for $\bar{d}=0$ and the non-stationary FIGARCH for $\bar{d}=1$. The FIGARCH (p, $\bar{d}$, q) model is shown as:

$$\Phi(L)(1-L)^d\,\varepsilon_t^2=\omega+[1-\beta(L)]v_t \quad (3)$$

where v_t stands for the innovation of conditional variance, and the root of $\Phi(L)$ and $[1-\beta(L)]$ is supposed to lie outside the unit root circle.

2.2. Structure Break

This paper utilized the ICSS algorithm to interpret discrete changes in the variance of carbon index. As an assumption, the data displays a stationary variance over an initial period until a sudden change occurs. That is, a sudden change occurs as a result of a sequence of events causing the variance to revert to stationary until another change in variance occurs. Over time, this process is repeated to create a time series of observations with an unknown number of changes in the variance. This series must be uncorrelated with mean zero and variance σ_t^2.

Inclán and Tiao (1994) introduced the ICSS test to identify sudden changes in the unconditional volatility of a series.

$$\sigma_t^2 = \left\{ \begin{array}{ll} \sigma_0^2 & 1 < t < k_1 \\ \sigma_1^2 & k_1 < t < k_2 \\ & . \\ & . \\ & . \\ \sigma_{N_T}^2 & k_{N_T} < t < T \end{array} \right\} \quad (4)$$

where $1 < k_1 < \ldots < k_{NT} < T$ are the various points where the changes in variance occur.

Let $\{X_t\}$ indicate a series of independent observations from a normal distribution with zero mean. The variance in each interval is denoted by σ_j^2, j = 0, 1,…, N_T. Notably, N_T is the total number of changes.

Based on the ICSS of the series, the statistic D_k detects the number and time point at which these changes occur.

$$C_k = \sum_{t=1}^{k} X_t^2 \quad (5)$$

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T} \ldots\ldots\ldots\ldots k = 1,\ldots,T; D_0 = D_T = 0 \quad (6)$$

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

If no variance changes over the sample period, then the series D_k oscillates around zero. However, the series drifts up or down from zero when a variance shift occurs. The quality $\left(\left(\frac{T}{2}\right)D_k\right)^{\frac{1}{2}}$ converges in distribution to a standard Brownian motion. The change point of variance over the interval t = 1,…, T is the point k_0 for which $\left(\left(\frac{T}{2}\right)D_k\right)^{\frac{1}{2}}$ reaches its maximum and $\left(\left(\frac{T}{2}\right)D_k\right)^{\frac{1}{2}} > C_{\alpha,}$ *where* C_α is the breaking value. At the 5% level, the breaking value is 1.358.

For anytime t_1 and t_2 with $t_1<t_2$, the notation X $[t_{1:}\ t_2]$ is adopted to indicate the extracted series $X_{t1}, Xt_{1+2},\ldots, X_{t2}$ and D_k (X $[t_1{:}t_2]$), denoted by the value of D_k calculated from $\{X_{t1}, X_{t+2,} \ldots, X_{t2}\}$. First, this paper sets t_1=1.

To compute D_k(X $[t_1{:}T]$), let k (X $[t_1{:}t_2]$) denote the point where $max_k \left|D_k\left(\left[t_1 : T\right]\right)\right|$ is reached. Then set:

$$\mathrm{M}\left(t_1 : T\right) = max_{t_{1 \le k \le T}} \left(\frac{T - t_1 + 1}{2}\right)^{\frac{1}{2}} \left|D_k\left(X\left[t_1 : T\right]\right)\right| \quad (7)$$

If M $(t_1{:}T) > C_{0.05}$, then k* $(X[t_1{:}t_2])$ can be considered as a structure break point. If M $(t_1{:}T) > C_{0.05}$, no variance change in the series occurs.

The D_k function alone is insufficient to highlight the multiple structure breaks change points. Thus, Inclán and Tiao (1994) developed an algorithm that used the D_k function to systematically find the change points at different points of the time series. The algorithm is implemented by evaluating the D_k function over the time periods. These different periods are also determined by break points, which are identified by the D_k plot.

2.3. GARCH Model Estimations with Changes in Variance

Aragó and Fernandez-lzquierdo (2003) modified the GARCH model to consider the changes in unconditional variance. Thus, to identify the change points in variance, the GARCH model is utilized for the case without sudden changes. Using the dummy variables with GARCH allows the representation of various changes in variance. Lamoureux and Lastrapes (1990) and Glosten et al. (1993) proposed the following:

$$\mathrm{h}_\mathrm{t}^2 = \alpha + \sum\nolimits_{i=2}^{p} \mathrm{F_i D_i} + \sum\nolimits_{i=1}^{p} \beta_\mathrm{i} \mathrm{h}_{\mathrm{t-i}}^2 + \sum\nolimits_{i=1}^{q} \delta_\mathrm{i} \varepsilon_{\mathrm{t-i}}^2 \quad (8)$$

$$\mathrm{h}_\mathrm{t}^2 = \alpha + \sum\nolimits_{i=2}^{p} \mathrm{F_i D_i} + \sum\nolimits_{i=1}^{p} \beta_\mathrm{i} \mathrm{h}_{\mathrm{t-i}}^2 + \sum\nolimits_{i=1}^{q} \delta_\mathrm{i} \varepsilon_{\mathrm{t-i}}^2 + \gamma \mathrm{S}_{\mathrm{t-1}}^{-} \varepsilon_{\mathrm{t-1}}^2 \quad (9)$$

where D_i refers to the dummy variables (break) that reflect the changes in variance; the parameters that present these variables (F_i) reflect the differences with respect to α. The estimated value for the first regime of variance is obtained. Moreover, S_{t-1} is equal to the unit as long as ε_{t-1} <0 (innovation in t=1) and zero when ε_{t-1}>0. If the value γ>0, the asymmetrical effect is captured. Lamoureux and Lastrapes (1990) proposed that the GARCH model overestimates the persistence in volatility by ignoring sudden relevant changes in variance.

3. DATA AND EMPIRICAL RESULTS

The current paper uses four different datasets to compute the volatility measures of carbon prices. We collected a sample of CCX daily settlement price ($ per metric ton of CO2) from December 19, 2003 to January 28, 2011. This dataset is collected from the Chicago Climate Exchange. However, for different reasons, the CCX was shut down in 2013, which is why this research has just studied this period. Emission CER and EUA indexes are gathered from the European Union Greenhouse Gas Emission Trading Scheme. CER and EUA indexes (€ per ton of CO_2) are for CCX future contract of maturity for January 2009 (€ per ton of CO_2). The Japan Bank for International Cooperation (Carbon Credit Trading Platform) weekly data are collected from Japan Institute for Overseas Investment (JOI) website from April 21, 2008, to July 30, 2012. The JOI index is no longer in existence, thus, the data is also studied in this phrase.

Table 1 shows the descriptive statistics of four carbon index returns. Over the sample period, the JOI index is the most volatile with the standard deviation at 95.89%, followed by the EUA index at 0.65%, whereas the CER and CCX indexes appeared at 0.65% and 0.086%, respectively. The JOI index had the highest average negative returns posted at −11.2%, whereas the CCX index received the lowest average negative returns at −0.0005%. Most of the samples are negatively skewed. The Jarque-Bera statistic for residual normality illustrates that the four carbon index returns are under a non-normal distribution assumption. To eliminate the serial correlation and heteroskedasticity in the data, this research utilized the augmented Dickey–Fuller test to establish stationarity. The minimum value of the Akaike information criterion identified the optimal models. Based on the results of the lagrange multiplier (LM) test, all carbon index return samples had no serial correlation. The ARCH–LM process was also used to test the ARCH effect, indicating that the GARCH models could be applied in the chosen sample because the null hypothesis was rejected for all the datasets.

According to the ICSS model, Figure 1 shows the return for each series with the points of sudden changes. As depicted by the charts, switching points ranged from three to four shifts for the four carbon indexes. These sudden changes can be clearly seen in Figure 2 and the returns for four carbon indexes and regime shift in volatility. This paper only focuses on the switching points and volatility increases.

3.1. Long-Memory Effect

Table 2 illustrates the results of both the ARFIMA and ARFIMA–FIGARCH models for carbon indexes. The ARFIMA model identified three significant results. With $0 < d < 0.5$, long memory was found in the returns of the CCX and JOI and was significant. This long-term dependence in the observations will in the long run have the characteristic of self-correlation. The implication is that historical return data can be used to predict future return data because the observations are not independent with one another. The coefficient for EUA ($d < 0$) is significant at 5%. However, this coefficient presents intermediate memory in the returns. This finding is consistent with previous research such as the work of Feng et al. (2011). The ARFIMA–FIGARCH models show that the significant results in four carbon index returns have a stationary process but are non-invertible. Investors and traders can exploit this result by having a position on CCX and JOI, but earning extra returns for CER and EUA is difficult because their structures are inherently unstable. Consequently, these results show that the volatilities of CCX and JOI have predictable structures, and with correct modeling and forecasting, investors and traders can benefit from them.

3.2. Structure Break

Table 3 describes the results of structure breaks using the ICSS method to investigate the volatility of carbon indexes. The results indicate switching points range from three to four shifts for carbon indexes.

Four regime shifts for the CCX index occurred, and the initial volatility was 13.43 in March 2006. This value implies that the carbon market was highly influenced by the electric power market because its participants are the main traders on the carbon market. This finding had been shown in the research of Alberola et al.

Table 1: Descriptive statistics

Index	Obs.	Mean	SD	Skewness	Excess Kutosis	J-Bera	Q (10)	Q^2 (10)
CCX	1800	−0.0005	0.0864	−1.1080	29.132***	64017***	96.8674**	164.079**
CER	1017	−0.0119	0.2186	−0.0451	4.2187***	754.52***	38.3219**	221.131**
EUA	1724	−0.0091	0.6520	−0.6132	16.657***	20039***	1355.60**	461.829**
JOI	217	−11.2010	95.8980	−0.8636	8.6361***	701.32***	15.0132	21.0379*

*, ** and *** are significance at 10, 5 and 1% levels, respectively

Figure 1: Carbon indexes volatility

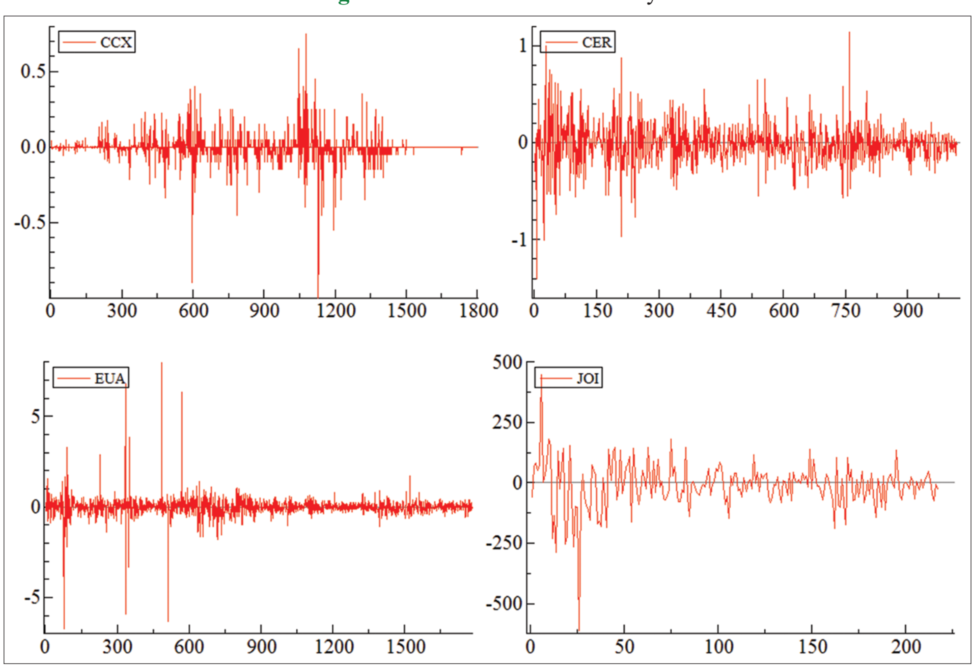
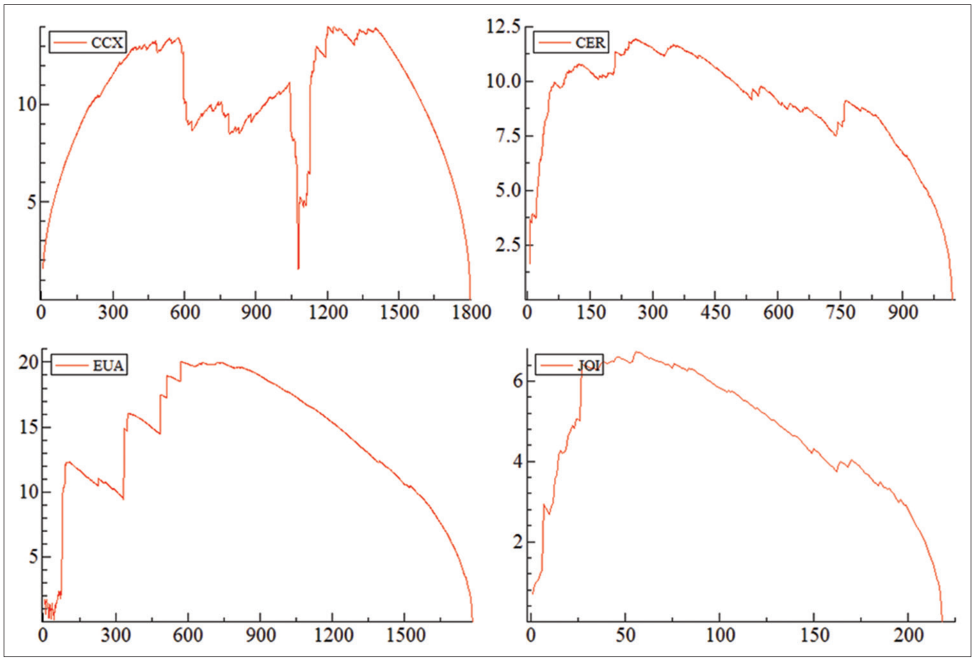


Table 2: Estimated ARFIMA-FIGARCH model

Index	ARFIMA				ARCH-LM	ARFIMA-FIGARCH			
	Model	d-coeff.	AIC	LM		d-coeff.	Model	d-coeff.	AIC
CCX	(0,2)	0.168 (0.000)***	−2.201	0.531	1.254	0.937 (0.0000)***	(0,3)	0.589 (0.0000)***	−2.987
CER	(3,3)	−0.024 (0.614)	1.362	0.000	0.003	0.023 (0.8635)	(2,2)	0.316 (0.0007)***	−0.510
EUA	(3,3)	−0.173 (0.040)**	3.210	1.238	0.038	0.102 (0.6436)	(1,0)	0.189 (0.0001)***	1.357
JOI	(1,0)	0.124(0.078)*	11.858	0.648	0.161	0.098 (0.1908)	(3,3)	0.934 (0.0000)***	11.682

*, ** and *** are significance at 10, 5 and 1% levels, respectively

Figure 2: Returns for four carbon indexes and regime shifts in volatility (Change points are estimated using ICSS algorithm)



(2008). Another change point was in November 2006 with the maximum value of 10.16. During this period, power generators have to produce more than they forecasted, which increased both allowance demand and CO_2 prices because of the decrease in temperature. This event was called a cooling day (cold event), as mentioned in the study of Alberola et al. (2008). The sudden increase in October 2008 is related to the energy crisis that happened in this year. The rise in crude oil was the highest in history, with a peak of US$143.95/barrel on July 18, 2008.

The EUA index experienced three change points in volatility. The first sudden change was an increase in volatility in June 2006, which can be explained by two main reasons. First, this period exhibited high economic growth and high energy growth, which increased the EUA price. Second, in May 2006, the Czech Republic, France, and Sweden announced that their positions would be longer than expected. Thus, the carbon price fell quickly until the European Commission issued formal certification data on May 15, 2006 that induced the carbon price to increase again. Moreover, the clustering effect and information shock asymmetry resulted in carbon price fluctuation. These findings are also in accordance with the findings on the estimation of chaos effect by Feng et al. (2011).

The second sudden change was an increase in volatility in May 2007. In this period, the carbon price was related to oil price because the price per barrel of crude oil had a rising trend that resulted in supply scarcity in the world market. This influence was improved through the carbon drivers in the Phase I and Phase II[1] equilibrium of Creti et al. (2012). Furthermore, in March 2007, the European Parliament's announcement about a continuing market until 2020 has boosted the price of allowances in the futures market. The final sudden change, which was an increase in volatility in April 2008, also corresponds to the beginning of the energy crisis.

As for the JOI index, a sudden change occurred in September 2008 largely as a consequence of the energy crisis. The sudden shift in May 2009 may also be associated with the 2008 compliance event in the carbon market. Recall that the "trough" date of the National Bureau of Economic Research business cycle dating committee[2] is June 2009. This event is also measured by Chevallier (2011b) in developing a model of carbon pricing by focusing on economic activity and energy prices.

3.3. GARCH Model with Structure Breaks for Asymmetrical Effect

This study also investigates the volatility persistence of the four carbon indexes. Inclán and Tiao (1994) identified the critical

1 The European market was organized in three phases: Phase I in 2005 to 2007, Phase II in 2008 to 2012, and Phase III in 2013 until 2020.
2 See more on the NBER Business Cycle Expansions and Contractions at http://www.nber.org/cycle.html.

Table 3: Sudden changes in volatility

Index	Change point	Interval	max
CCX	24/03/2006	12/12/2003–16/06/2006	13.42817***
	27/11/2006	17/06/2006–02/12/2007	10.16035***
	30/01/2008	28/11/2006–19/03/2008	11.1152**
	23/10/2008	20/03/2008–31/01/2011	13.99675***
CER	07/07/2009	12/01/2009–10/09/2009	10.77112
	18/01/2010	11/09/2009–16/02/2011	11.93532*
	18/03/2011	16/02/2011–13/12/2012	9.76475
EUA	12/06/2006	09/01/2006–27/04/2007	12.30752***
	21/05/2007	28/04/2007–26/11/2007	16.05244***
	01/04/2008	27/11/2007–27/12/2012	20.04813
JOI	16/09/2008	21/04/2008–22/09/2008	4.481773**
	18/05/2009	29/09/2009–16/03/2011	6.549281***
	08/08/2011	20/06/2011–30/07/2012	4.205703***

*, ** and *** are significance at 10, 5 and 1% levels, respectively

Table 4: The effect of structure breaks with dummy variable for four carbon indexes

Index	GARCH	AIC	F & r
CCX	(3,3)	1.734234	F1=−2.2775 (0.0053)***
			F2=−2.0259 (0.0029)***
			F3=−0.8541 (0.0112)**
			F4=−2.3857 (0.0018)***
			r=12.6892 (0.000)***
CER	(1,2)	−0.54288	F1=0.0033 (0.1400)
			F2=0.0034 (0.0956)*
			F3=0.0019 (0.3247)
			r=0.0697 (0.0466)**
EUA	(3,1)	1.065114	F1=0.0492 (0.0000)***
			F2=0.6375 (0.0000)***
			F3=0.0109 (0.2556)
			r=0.0736 (0.0118)**
JOI	(0,2)	11.4469	F1=10452.50 (0.0174)**
			F2=1144.135 (0.0000)***
			F3=958.0093 (0.0000)***
			r=0.0229 (0.0412)**

*, ** and *** are significance at 10, 5 and 1% levels, respectively

value, which is 1.358 at the 5% level and is under the null of independently distributed normal shocks. Thus, the present research has estimated the GARCH model to determine the change points that are statistically significant and how these regime shifts can have a persistence effect on volatility. This process is implemented thrice: without regime shifts and with all of the sudden changes estimated by ICSS in variance. Therefore, the GARCH model is applied using dummy variable (F) based on the value from the ICSS model. If the value is greater than 1.358, F is equal to 1 and is zero for others. Moreover, this study also utilized r to examine the asymmetrical effect. Based on the minimum AIC when selecting the optimal fitting model, if r is positive and significant, the asymmetrical effect exists.

Table 4 describes the results of the effect of structure breaks with dummy variable for the four carbon indexes. The table shows that the estimated coefficients for F_1, F_2, F_3, and F_4 of the CCX index are all negative and significant at the 1% and 5% levels. The value of the unconditional variance decreases when dummies are included. Moreover, in the CER index, F_2 is positive and significant at the 10% level, which is evidence of an increase in the value and stability of the unconditional variance. These results are also the same for the EUA and JOI indexes. However, the EUA and JOI indexes are significant for all sudden changes, except for F_3 in EUA. When all coefficients are positive, unconditional variance increases when the dummy variable is included. Likewise, another parameter considered in testing the asymmetry effect is r. For all carbon indexes, the r parameters are all positive and significant at the 1% level for CCX and at the 5% level for CER, EUA, and JOI. Thus, the asymmetrical effects are captured. These results are in accordance with those of Lamoureux and Lastrapes (1990) in that persistence in volatility is overestimated when applying the GARCH models to a series with sudden changes in variance.

4. CONCLUSION

This paper has focused on two issues: the examination of long memory using the ARFIMA–FIGARCH models and the investigation of the sudden change shifts of volatility and volatility persistence for four carbon indexes utilizing the ICSS algorithm methodology. Based on the results, this study makes the following contributions: First, the results of the ARFIMA–FIGARCH models revealed a significant long-memory process for the CCX and JOI indexes, indicating the possibility that they can be forecasted, making traders and investors gain extra profits by choosing the correct model. However, structures for CER and EUA are inherently unstable because of the intermediate memory in the returns, thus creating difficulty for traders in earning extra returns.

Second, this study has focused on the ICSS model to detect multiple structure breaks instead of testing a single break. The use of the ICSS algorithm revealed that sudden shifts are mainly interpreted by macroeconomic factors, energy dynamics, and political policies. The structure breaks may also be associated with temperature volatility, that is, the reaction to unanticipated temperature changes during the colder events, particularly with the CCX index. Furthermore, the sudden shifts were also derived from the international politics and negotiations, which developed significant volatility in carbon, like what happened to the EUA index.

Third, based on the GARCH model, the CCX and JOI indexes show a significant F_i, which indicates long-memory effects. Therefore, high volatility is present in the CCX due to several shifts in the early period; however, sudden changes have declined and showed a downward trend in volatility. Nevertheless, the CER, EUA, and JOI indexes exhibited some shifts and an upward trend. The implication is that the carbon market has become gradually stable in transition economies. This condition requires traders and countries to consider the trends and factors that influence the carbon market to meet the second commitment to the Kyoto Protocol until 2020. Therefore, this article is a suggestion for applying ARFIMA–FIGARCH models and algorithm methodology while studying the structure breaks of many other carbon indexes.

REFERENCES

Aggarwal, R., Inclan, C., Leal, R. (1999), Volatility in emerging stock markets. Journal of Financial and Quantitative Analysis, 34, 33-35.
Ahonen, E., Corbet, S., Goodell, J.W., Günay, S., Larkin, C. (2022), Are carbon futures prices stable? New evidence during negative oil.

Finance Research Letters, 47, 102723.
Alberola, E., Chevallier, J., Cheze, B. (2008), Price drivers and structural breaks in European carbon prices 2005-2007. Energy Policy, 36, 787-797.
Aragó, V., Fernández-Izquierdo, Á. (2003), GARCH models with changes in variance: An approximation to risk measurements. Journal of Asset Management, 4, 277-287.
Baillie, R.T., Bollerslev, T., Mikkelsen, H.O. (1996), Fractionally integrated generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 74, 3-30.
Chevallier, J. (2011a), Detecting instability in the volatility of carbon prices. Energy Economics, 33, 99-110.
Chevallier, J. (2011b), A model of carbon price interactions with macroeconomic and energy dynamics. Energy Economics, 33, 1295-1312.
Creti, A., Jouvet, P.A., Mignon, V. (2012), Carbon price drivers: Phase I versus Phase II equilibrium? Energy Economics, 34, 327-334.
Feng, Z.H., Zou, L.L., Wei, Y.M. (2011), Carbon price volatility: Evidence from EU ETS. Applied Energy, 88, 590-598.
Glosten, L.R., Jagannathan, R., Runkle, D.E. (1993), On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48, 1779-1801.
Granger, C.W.J., Joyeux, R. (1980), An introduction to long-memory time series models and fractional differencing. Journal of Time Series Analysis, 1, 15-29.
Hosking, J.R.M. (1981), Fractional differencing. Biometrika, 68, 165-176.
Huang, Y., Dai, X., Wang, Q., Zhou, D. (2021), A hybrid model for carbon price forecasting using GARCH and long short-term memory network. Applied Energy, 285, 116485.
Inclán, C., Tiao, G.C. (1994), Use of cumulative sums of squares for retrospective detection of changes of variance. Journal of the American Statistical Association, 89, 913-923.
Lamoureux, C.G., Lastrapes, W.D. (1990), Persistence in variance, structural change, and the GARCH model. Journal of Business and Economic Statistics, 8, 225-234.
Mabrouk, S., Aloui, C. (2010), One-day-ahead value-at-risk estimations with dual long-memory models: Evidence from the Tunisian stock market. International Journal of Financial Services Management, 4(2), 77-94.
Meng, B., Chen, S., Haralambides, H., Kuang, H., Fan, L. (2023), Information spillovers between carbon emissions trading prices and shipping markets: A time-frequency analysis. Energy Economics, 120, 106604.
Segnon, M., Lux, T., Gupta, R. (2017), Modeling and forecasting the volatility of carbon dioxide emission allowance prices: A review and comparison of modern volatility models. Renewable and Sustainable Energy Reviews, 69, 692-704.
Tan, S.H., Khan, M.T.I. (2010), Long memory features in return and volatility of the Malaysian stock market. Economic Bulletin, 30, 3267-3281.
Tan, X.P., Wang, X.Y. (2017), Dependence changes between the carbon price and its fundamentals: A quantile regression approach. Applied Energy, 190, 306-325.
Wang, P., Moore, T. (2009), Sudden changes in volatility: The case of five central European stock markets. Journal of International Financial Markets, Institutions and Money, 19, 33-46.
Wang, Y., Cai, J. (2018), Structural break, stock prices of clean energy firms and carbon market. IOP Conference Series: Earth and Environmental Science, 120(1), 012018.
Wen, F., Zhao, L., He, S., Yang, G. (2020), Asymmetric relationship between carbon emission trading market and stock market: Evidences from China. Energy Economics, 91, 104850.