Modeling Volatility in the Stock Markets using GARCH Models: *applied to Carbon, Water and Commodity markets*

KALAFATE Nadia [(1)], **KHIARI Imen** [(2)]
[1] Lecturer"B", University of oran2, Mohamed Ben Ahmed, Algeria,
kalafatenadia3@gmail.com
[2] Dr, Abdelhamid Mehri, University , Constantine 2, Algeria,
Imen.khiari@univ-constantine2.dz

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Abstract:
The perceived distribution of the random variables in the future, assessment and measurement of the variance have a significant impact on the future profit or losses of particular portfolio. The main purpose of this study is to examine the nature and the characteristics of stock market volatility of Carbon Emissions Future markets, Water and Commodity markets and its stylized facts using GARCH models. These models can explain volatility of these specifics markets and its stylized facts. The results indicate the evidence of time varying stock return volatility over the sampled period of time. In conclusion it follows that in a financial crisis; the negative returns shocks have higher volatility than positive returns shocks.

Mots clés:
Mot clé.1: Modèles GARCH
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Le résumé : la distribution perçue des variables aléatoires dans le futur, l'évaluation et la mesure de la variance ont un impact significatif sur les bénéfices ou les pertes futures d'un portefeuille particulier. L'objectif principal de cette étude est d'examiner la nature et les caractéristiques de la volatilité boursière des marchés à terme des émissions de carbone, des marchés de l'eau et des matières premières ainsi que les faits stylisés à l'aide de modèles GARCH. Ces derniers expliquent de manière plus satisfaisante, la volatilité des ces marchés spécifiques et leurs faits stylisés. Les résultats démontrent une volatilité du rendement des actions variant dans le temps. En conclusion, il s'ensuit qu'en cas de crise financière; les chocs de rendements négatifs ont une volatilité plus élevée que les chocs de rendements positifs.

Corresponding Author: KALAFATE Nadia, Email: kalafatenadia3@gmail.com

1- The introduction:

Volatility in financial markets refers to the degree of fluctuation in the prices of financial assets over a certain period of time. High volatility can indicate greater uncertainty and risk in the market, while low volatility may suggest stability and confidence.

Mathematical models such as GARCH (Generalized Autoregressive Conditional Heteroskedasti city) have been developed to help understand and predict volatility in financial markets. GARCH models are a type of time-series model that can be used to analyze the volatility of financial assets such as stocks, bonds, and currencies. They are designed to capture the time-varying nature of volatility, which means that they can model how the volatility of an asset changes over time.

GARCH models are based on the assumption that the variance of a financial asset is not constant over time, but rather is a function of past variances and other relevant factors. The model includes two components: an autoregressive component, which captures the persistence of volatility over time, and a moving average component, which captures the impact of past shocks on the current level of volatility. The model also includes a conditional variance term, which reflects the extent to which current volatility is influenced by past volatility.

there are several different types of GARCH models, including the original GARCH model, as well as more complex models such as EGARCH (Exponential GARCH) (Nelson, 1991) and TGARCH (Threshold GARCH), IGARCH(Integrated GARCH) (Engle & Bollerslev, 1986b) . These models allow for different types of asymmetry and nonlinearity in the relationship between volatility and other variables.

Overall, GARCH models and other mathematical models have been widely used in financial research to help understand and predict volatility in financial markets. While these models have limitations and may not capture all aspects of market behavior, they can be a useful tool for investors, analysts, and policymakers in assessing market risk and making informed decisions.

In recent years, the world has experienced many crises in terms of climate change and public health. Human beings have never felt the impact of unsystematic risks on society as clearly as today. Countries around the world and global investors are beginning to pay attention to the risks and losses that climate change will bring to the economy and financial system. In this context, sustainable investment products are gaining favor from global investors. This study focused on dynamic volatility spillovers across a broad range of asset classes, including Carbon Emissions Future markets, Water and Commodity markets.

Stock market volatility is related to the general health of the economy. It can be used to measure the market risk of a single instrument or an entire portfolio of instruments. The volatility in Carbon Emissions Future markets, Water and Commodity markets is similar in various aspects to financial volatility as it relates to the risk and returns associated. Nevertheless, as the characteristics of them may be different from those of financial markets, the results are subject to empirical risk analysis, and need to be investigated. To enrich the different aspects of the subject (empirically), the following question:

- What are the characteristics of return volatility in Carbon Emissions Future markets, Water and Commodity markets?

The understanding of risk and return is important not only in the assessment of the price of a stock, but also for the evaluation of different managerial actions such as managerial investment and financing decisions. Therefore, the hypothesis is formulated as follows:

1- 1- There is a long-term persistenc in the volatility with a statistical significance ($\rho \leq 0.05$) in the three markets under study.
2- There is a statistically significant of leverage effect on volatility ($\rho \leq 0.05$) in the three markets under study.

The layout of the paper is as follows. Section 2 describes the empirical model and methodology. Section 3 presents and discusses the empirical results. Section 4 summarizes our concluding remarks.

2- Methodology:

Volatility is an important concept for finance mostly in portfolio optimization, risk management and asset pricing. Since financial data include leptokurtosis, volatility clustering, long memory, volatility smile and leverage effects, they are insufficient to explain a number of important features common to much financial data by linear models. That is, because the assumption of homoscedasticity is not appropriate when using financial data. In order to model volatility, (Engle) (1982) developed the Autoregressive Conditional Heteroscedastic (ARCH) model which was further extended by (Bollerslev T. 1986) with the Generalized Autoregressive Conditional Heteroscedastic (GARCH) model.

In order to ensure the construction of GARCH models, the data must be stabilized first, and Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are usually used as the main return of stationarity test.

However, the original index prices data are usually not stationary due to the characteristics of high volatility and strong randomness.

The dependent variables are returned in all series. We have plotted the colerogram of the series and found that there is no ACF or PACF value out of the band. Therefore, all variables are regressed on constant terms. Before th**e** ARCH/GARCH model is used, we need to test whether models include ARCH effects (ARCH –LM test and Ljung-Box statistics). This test is very important in time series analysis to ensure that the model ARCH is appropriate for data (that will be the case in the analysis). The test is one of a joint null hypothesis that all q lags of the squared residuals have coefficient values that are not significantly different from zero.

Hence, the data processing is of great significance. Usually, the logarithmic difference method is used to process the original data, and the processed data can be regarded as the rate of return (ROR):

$$R_{i,t} = Ln\left(p_{i,t}\right) - Ln\left(p_{i,t-1}\right)$$

where $R_{i,t}$ represents the ROR of the i^{th} market at time t and p represents the market price. in which t denotes daily closing observations. The return series can be converted with the following conditional mean and variance dynamics equation:

$$r_t = \mu + u_t \;\; ; u_t = v_t \sqrt{h_t}$$

where is the conditional mean, v_t is independent and identically distributed with $N\,(0\,,1\,)$[1], and h_t is the conditional variance, which can be estimated with GARCH type models. h_t can be estimated with different confidence intervals, but a 99% confidence level is more accurate for risk management purposes; therefore, all of the conditional volatility models are estimated with a 99% confidence interval.

2-1- GARCH (p,q) model

The GARCH model is proposed by (Bollerslev T., 1986), extending (Engle) autoregressive conditional heteroskedastic (ARCH) model for time-varying volatility in a time series. This model can be expressed as:

$$h_t = a_0 + \alpha\,(L) + \varepsilon_t^2 + \beta\,(L)\,\sigma_t^2$$

[1] Where expected return is zero and expected standard deviation is one.

in which, a_0 denotes the constant term, $\varepsilon_t \,/\, \psi_{t-1} \sim N(0, \sqrt{h_t})$ as $N(.)$ is a probability density function with mean $(0)$and conditional variance (h_t), and $\sqrt{h_t}$ denotes the conditional volatility of ε_t with the conditions of $\alpha, \beta > 1$ and $a_0 > 1$.

In this model, h_t depends linearly on past squared innovations and past conditional variance. This study uses GARCH (1,1) model and the (1,1) inparenthesis indicates that one length of ARCH lag (α_1) and one length of GARCH lag (β_1) is used.

2- 2- GJR (p,q) model

When return volatility tends to respond asymmetrically with respect to negative or positive shocks, the GARCH model might not be appropriate. Two simple volatility models that can cope with an asymmetric effect[2] are the exponential GARCH (or EGARCH) model proposed by (Nelson, 1991) and the so-called GJR model, advocated by (Glosten, Jagannathan, & Runkle, 1993)

(Marcucci, 2005) found that the GJR model has superior forecasting performance than the EGARCH model for longer horizons; therefore, we select the GJR model. This model can be expressed as:

$$h_t = a_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 + \gamma \varepsilon_{t-1}^2 \mathrm{I}_{t-1}$$

where the gamma (γ) is the asymmetric effect parameter, I_{t-1} is a dummy variable and $\mathrm{I}_{t-1} = 1$ if $\varepsilon_{t-1} < 1$, $\mathrm{I}_{t-1} = 0$ otherwise. The Gamma determines the effect of negative return shocks on the conditional variance; therefore, the asymmetric effects in the series are captured by this parameter. In the GJR model, negative lagged shocks have an impact of $\alpha_1 + \gamma$ and positive lagged shocks have an impact of α_1 so that negative lagged shocks have a bigger influence on conditional variance.

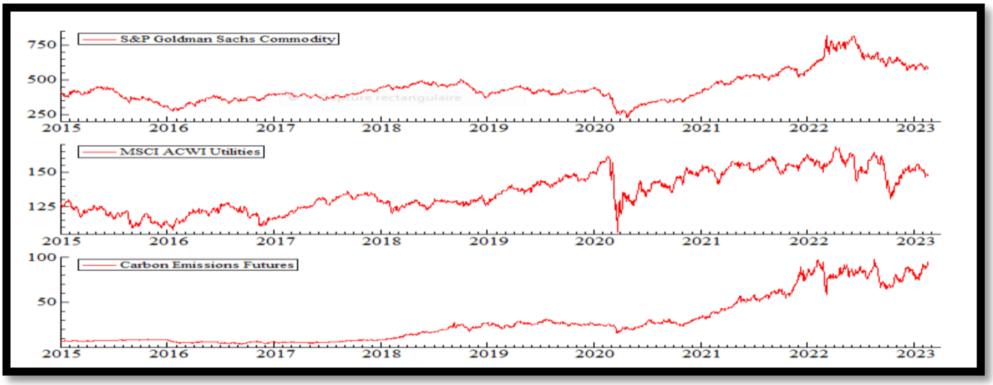
3-DATA DESCRIPTION

the data sources of the variables are as follows: Carbon Emissions Futures index, MSCI ACWI Water Utilities Index (MSCI ACWI), S&P Goldman Sachs Commodity. Each data set is daily from January 2,2015 to February 17,2023 which covers the COVID-19 pandemic, from: investing website

[2] This asymmetric effect is frequently called the “leverage effect”.

database. All the analysis prepared has been developed using OxMetrics 6 and Eviews 9, as discussed later in the paper.

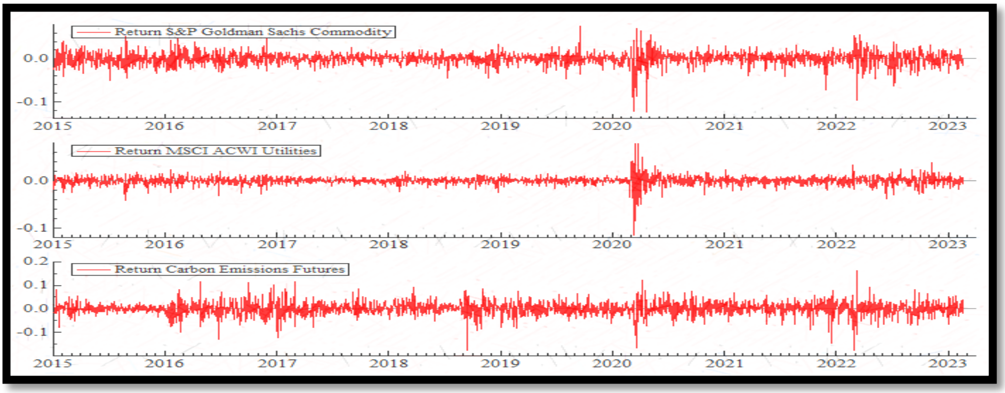
Figure No. 1. The daily prices of the three indices (2015–2023).



Source : Prepared by researchers based on ox Metrix 6 software outcomes

Figure No.1 depicts the time series of daily prices for carbon futures. The graphical illustration shows that carbon prices are stable from 2015 to mid-2017 and show a strong upward trajectory since mid-2017 due to positive developments in the carbon markets, such as more effective carbon tax policy reforms and the introduction of the Market Stability Reserve (MSR). The global carbon market experiences a fall during March 2020 after the The World Health Organization declared COVID-19 a pandemic, however it appears that it quickly recovered and entered a new period of price growth. It even hits a record high level in mid-2021 with increased financial investment in the carbon allowance markets. We also argue that the increased carbon prices can be attributed to governments actions; market participants have clear signals from governments that they will continue to decarbonize the economy and the supply of carbon allowances will be reduced more rapidly in the years ahead in line with 2030 climate target plan and 2050 net zero strategy, which boosts long-term prospects for higher carbon prices. It is also noted that each of the water and commodity markets take almost the same previous pattern of changes, with greater fluctuations per year 2022.

Figure No. 2. The daily returns of the three indices (2015–2023).



Source : Prepared by researchers based on ox Metrix 6 software outcomes

in Figure 2, there are periods of high and low volatility. Once again, the year 2020 records higher fluctuations. the distribution of the series is far from normal. probably due to the fact that these carbon and water futures markets are quite recent.

Table 1. coverage of the study variables

Segment	Index	Coverage
Carbon	Carbon Emissions Futures index	Carbon emissions trading are emissions trading specifically for carbon dioxide (calculated in tonnes of carbon dioxide equivalent or tCO2 e) and currently make up the bulk of emissions trading. It is one of the ways countries can meet their obligations under the Kyoto protocol to reduce carbon emissions and thereby mitigate global warming. Trading exchanges have been established to provide a spot market in permits, as well as futures and options market to help discover a market price and maintain liquidity. Carbon prices are normally quoted in Euros per ton of carbon dioxide or its equivalent. However, in this study, we choose to use futures market due to trading together quite a lot. Currently there are exchanges trading in carbon credits: the European Climate Exchange (ECX), NASDAQ OMX Commodities Europe, PowerNext, Commodity Exchange Bratislava and the European Energy Exchange. Many companies now engage in emissions abatement, offsetting, and sequestration programs to generate credits that can be sold on one of the exchanges. But the market we are interested in that is ECX because trading volume in large quantities. The ECX manages the product development and marketing for ECX Carbon Financial Instruments (ECX), listed and admitted for trading on the intercontinental exchange (ICE) Futures Europe electronic platform. It listed on the London Stock Exchange. ECX futures is the most liquid, pan-European platform for carbon emissions trading, with its futures contract based on the underlying EU allowances (EUAs) and Certified Emissions Allowances (CERs) attracting over 80% of the exchange-traded volume in the European market. ECX contracts (EUA and CER futures, options and spot contracts) are standardized exchange-traded products and all trades are cleared by ICE Clear Europe.
Water	MSCI ACWI Water Utilities Index	The MSCI ACWI Water Utilities Index includes large and mid cap securities across 23 Developed Markets (DM) countries and25 Emerging Markets (EM) countries. All securities in the index are classified in the Water Utilities as per the Global Industry Classification Standard (GICS®).
Commodity	S&P Goldman Sachs Commodity Index	The S&P GSCI, launched by Goldman Sachs in 1991, is the first major investable commodity index and serves as a benchmark for investment in commodity markets. The index comprises 24 commodities from all sectors (energy, metals, grains, softs, and livestock) .S&P GSCI commodities as Energy (Crude Oil, Brent Crude Oil, Heating Oil, and Natural Gas), Agriculture (Wheat, Corn, Soybeans, Cotton, Sugar, Coffee, and Cocoa), Precious Metals (Gold and Silver), and Livestock (Live, Cattle, Feeder Cattle, and Lean Hogs).

Note. This table lists the variables used in the research.

Table 2, 3, 4 and 5 demonstrates the description of carbon, water and commodity markets returns. It demonstrates that the returns of the three markets have the typical financial characteristics of peak and fat tail, not normally distributed, and all have passed the Phillips-Perron (PP) and

Kwiatkowski-Phillips-Schmidt-Shin(kpss) (Kwiatkowski, Phillips, Schmidt, & Shin, 1992) unit root test for unit root, the results for the level series with and without a trend. They can reject the null hypothesis at the 1% significant level, suggesting that all series in our study are I (0) processes and **t**hat these variables are not first differenced.

Table 2. Descriptive Statistics

index	Mean	Median	Maximum	Minimum	Std. Dev
Carbon Emissions Futures	0.001237	0.001295	0.161378	-0.177347	0.028610
MSCI ACWI Utilities	7.15E-05	0.000505	0.079334	-0.115751	0.009424
S&P Goldman Sachs Commodity	0.000165	0.000973	0.076829	-0.125228	0.015041

Source : Prepared by researchers based on ox Eviews 9 software outcomes

In addition, the standard deviation of carbon index owns the most observation trading data, and the standard deviation of MSCI water market is the smallest, indicating that its price in the most stable market is the smallest.

Table 3. Normal distribution test Results

index	Skewness	Kurtosis	Jarque-Bera Probability
Carbon Emissions Futures	-0.362743	6.900246	1371.851 [0.000000]
MSCI ACWI Utilities	-0.993920	25.18719	43853.70 [0.000000]
S&P Goldman Sachs Commodity	-0.829120	10.51776	5057.405 [0.000000]

Source : Prepared by researchers based on ox Eviews 9 software outcomes

As shown in Table 2, 3, 4, 5, 6 and 7, the following conclusions can be drawn:

(1) According to the PP and KPSS test results, the rate of return (ROR) for the three markets are all significant at the 1% level. The ROR for each market is stational.

Table 4. PP Test Results

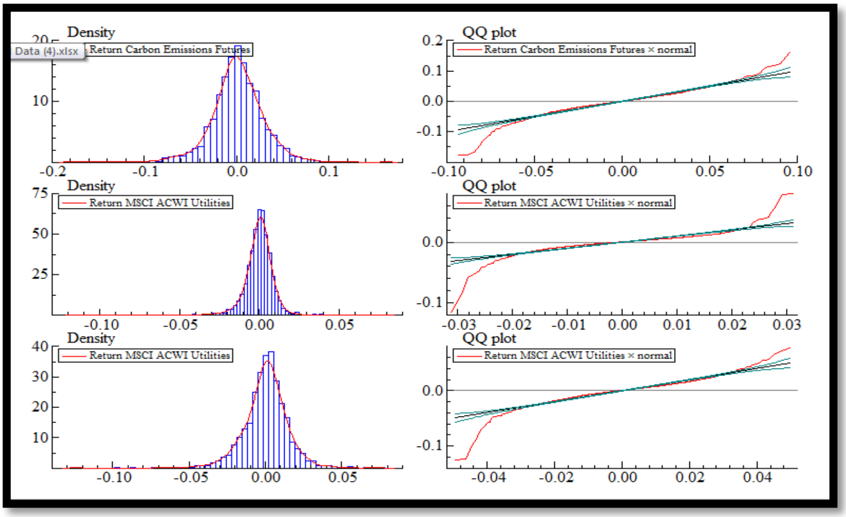
index	Phillips-Perron test		
	None	Constant	Constant, Linear Trend
Carbon Emissions Futures	-48.03956 [0.0001]	-48.11560 [0.0001]	-48.12111 [0.0000]
MSCI ACWI Utilities	-45.50843 [0.0001]	-45.50008 [0.0001]	-45.49024 [0.0000]
S&P Goldman Sachs Commodity	-45.59850 [0.0001]	-45.59377 [0.0001]	-719.7140 [0.0000]

Source : Prepared by researchers based on ox Metrix 6 software outcomes

(2) The daily log returns and the Q–Q plot of the series are shown in Figure No. 2 and 3 There are periods of high and low volatility, and the Q–Q plot shows that the distribution of the series is far from normal.

(3) The skewness of ROR for the three index is less than zero. Hence, the ROR distributions of the three markets are all asymmetric. Of which, the ROR distributions are left-skewed. Besides, the kurtosis of ROR for all the three markets is greater than three and the J-B statistic are all significant at the 1% level.

Figure No. 3Quantile-Quantile (Q-Q) plot for index (2015–2023)



Source : Prepared by researchers based on ox Metrix 6 software outcomes

The result shows that the ROR of all the markets are significantly different from the normal distribution. All markets show the distribution characteristics of leptokurtic, which reflects the positive correlation characteristics of market fluctuations. Thus, the carbon, water and commodity markets all have the feedback effect.

Table 5. KPSS Test Results

index	Constant	Constant, Linear Trend
Carbon Emissions Futures	0.144635 [0.739000]	0.072707 [0.216000]
MSCI ACWI Utilities	0.025515 [0.739000]	0.023893 [0.216000]
S&P Goldman Sachs Commodity	0.134005 [0.739000]	0.064775 [0.216000]

Source : Prepared by researchers based on ox Metrix 6 software outcomes

(4) The standard deviation of the ROR for water market is smaller than that of the carbon and Commodity markets, indicating that the volatility and risk of the MSCI ACWI Water Utilities Index is smaller than that of the Carbon Emissions Futures index, and S&P Goldman Sachs Commodity.

Table 6. Ljung-Box statistics Results

Index / lags	5	10	15	20	25	30
Carbon Emissions Futures	186.525 [0.0000]	243.079 [0.0000]	259.508 [0.0000]	279.486 [0.0000]	286.817 [0.0000]	287.445 [0.0000]
MSCI ACWI Utilities	1666.93 [0.0000]	2836.08 [0.0000]	3142.99 [0.0000]	3303.31 [0.0000]	3328.71 [0.0000]	3343.18 [0.0000]
S&P Goldman Sachs Commodity	225.967 [0.0000]	418.444 [0.0000]	488.538 [0.0000]	533.582 [0.0000]	616.232 [0.0000]	776.831 [0.0000]

Source : Prepared by researchers based on ox Metrix 6 software outcomes

(5) Moreover, the significant value of the Ljung-Box statistics for the returns series rejects the null hypothesis of white noise, indicating the presence of autocorrelation. The significant value of Ljung-Box

statistics for the squared returns shows the presence of autocorrelation in the square of variable returns. The final statistic test for ARCH-LM indicates that each of the variable series exhibits the ARCH phenomena. In each case, most of these test statistics are at the 1% level, suggesting that property of return series implies that using GARCH family of models to analysis volatility transmission patterns, applied up to 30 lags.

Table 7. ARCH Test Results

Index / lags	5	10	15	20	25	30
Carbon Emissions Futures	25.944 [0.0000]	13.872 [0.0000]	9.8173 [0.0000]	7.9073 [0.0000]	6.5128 [0.0000]	5.4382 [0.0000]
MSCI ACWI Utilities	242.20 [0.0000]	164.03 [0.0000]	114.34 [0.0000]	91.119 [0.0000]	73.420 [0.0000]	61.467 [0.0000]
S&P Goldman Sachs Commodity	32.902 [0.0000]	23.010 [0.0000]	15.755 [0.0000]	12.524 [0.0000]	11.699 [0.0000]	13.151 [0.0000]

Source: Prepared by researchers based on ox Metrix 6 software outcomes

4 - Discussion of empirical results:

Table 8. Parameter Estimates for GARCH(1,1)

	b	α_0	α_1	β_1
Carbon Emissions Futures	0.001638 (0.00047903) [0.0006]	0.092570 (0.059762) [0.0215]	0.085076 (0.022827) [0.0002]	0.909309 (0.025693) [0.0000]
MSCI ACWI Utilities	0.000465 (0.00013717) [0.0007]	1.935557 (0.70700) [0.0062]	0.099188 (0.021405) [0.0000]	0.872458 (0.028381) [0.0000]
S&P Goldman Sachs Commodity	0.000813 (0.00026106) [0.0019]	0.055583 (0.019470 [0.0043]	0.080228 (0.016133) [0.0000]	0.894451 (0.021073 [0.0000]

Source: Prepared by researchers based on ox Metrix 6 software outcomes

Notes. This table reports parameter estimates from the univariate GARCH model. Values in parentheses [ ] represent standard errors (p-values).

Table 9. Parameter Estimates for GJR - GARCH (1,1)

	b	α_0	α_1	β_1	γ
Carbon Emissions Futures	0.001589 (0.00048432) [0.0010]	0.096386 (0.065549) [0.0416]	0.078189 (0.022794) [0.0006]	0.909110 (0.027240) [0.0000]	0.012700 (0.019482) [0.5146]

MSCI ACWI Utilities	-	0.000454 (0.00015079) [0.0000]	0.062471 (0.019597) [0.0015]	0.926168 (0.013147) [0.0000]	0.037968 (0.017218) [0.0276]
S&P Goldman Sachs Commodity	0.000722 (0.00026220) [0.0059]	0.051099 (0.017370) [0.0033]	0.042878 (0.016900) [0.0113]	0.902270 (0.019989) [0.0000]	0.055717 (0.020194) [0.0058]

Source : Prepared by researchers based on ox Metrix 6 software outcomes

Notes. This table reports parameter estimates from the univariate GJR-GARCH model. Values in parentheses [ ] represent standard errors (p-values).

The parameter's estimates of the both GARCH(1,1) and GJR- GARCH (1,1) model are statistically significant at 1% level. Both constants for the variance equation are approximately equal to zero; this shows that current volatility is heavily premised on squared lagged residuals and previous stock return volatility.

The results also indicate that the persistence in volatility, as measured by the sum of α and β in both models, is slightly closer to one suggesting a stronger presence of ARCH and GARCH effects; Except for the commodity index, which records the least volatility. This implies that current volatility of daily returns can be explained by past volatility that tends to persist over time. The conclusion of persistence volatility is not a strong conclusion for this study because sum of parameters α and β is least than one, indicating that the conditional variance process is not explosive.

The GJR- GARCH (1,1) proved to be more efficient than the GARCH (1,1), as shown by the AIC and BIC criterions [-3.879 &-3.704]. The persistence parameter, β, is very large, implying that the variance moves slowly through time. The coefficient γ = 0.012700 , 0.037968 , 0.055717 measures the presence of asymmetry; it is statistically significant implying the presence of asymmetry and hence the GJR- GARCH model is more efficient than GARCH model. The asymmetry coefficient, γ, is positive, implying that the variance goes further up after positive residuals than after negative residuals. Positive and negative shocks have different effects on the stock market returns series. Bad and good news will increase volatility of stock market returns in different magnitude.

The null hypothesis that there is no remaining ARCH effect in the models is not rejected at 5% significant level based on the the Ljung-Box statistics and ARCH – LM tests. The conformity of the residuals of the estimated model to homoscedasticity is an indication of adequate fit. The probability value of the Q-statistics Appendix No. 1 and 2 for all lags are higher than 0.05, confirming that there is no serial correlation in the standardized residuals of the estimated models at 5% significant level

5. Conclusion:

ARCH and GARCH models have been applied to a wide range of time series analyses but applications in finance have been particularly successful and have been the focus of this introduction. Financial decisions are generally based upon the tradeoff between risk and return; the econometric analysis of risk is therefore an integral part of asset pricing, portfolio optimization, option pricing and risk management. This paper has presented a careful example of risk measurement which could be the input to a variety of economic decisions. The analysis of ARCH and GARCH models and their many extensions provides a statistical stage on which many theories of asset pricing and portfolio analysis can be exhibited and tested.

After determining the most important statistical characteristics of the time series of the returns of the three markets under test, and by making sure that there is an effect of ARCH in the residuals of estimating the return on constant equation for each market, and considering that the Student T distribution is the most appropriate in the process of estimating the coefficients of the selected models. The study, as a first stage, examined the behavior of the return in Carbon Emissions Future markets, Water and Commodity markets, by studying the two characteristics of the continuity of volatility and the effect of financial leverage in them, over the period between 2015 and 2023, and it should be noted that the study was based mainly on analyzing the change in the nature of volatility The return rather than its value, as this allows for a better comparative analysis.

According to the results obtained in this regard, the volatility in commodity index recorded the lowest level with the continuity of lower volatility, compared to the Carbon Emissions Future markets, Water and markets, and therefore this market is considered less risky than the rest of the markets; This supports the acceptance of the first hypothesis.

In addition, the results revealed that there is an effect of financial leverage within the returns of the three markets under study, which supports the acceptance of the second hypothesis. By the effect of financial leverage, we mean that negative shocks increase volatility more than positive shocks. The previous explanation is due to the empirical observation in the capital markets. which indicated that volatility and stock prices are negatively correlated; The argument for this is that the decline in stock prices increases the ratio of debt to equity of listed companies. This, in turn, leads to uncertainty by increasing the risk ratio, which increases the volatility of stock prices.

There is some research that suggests that there could be a relationship between volatility in the carbon market and the water and commodities market. However, the exact nature of this relationship is not yet fully understood and may be complex and multifaceted. One possible way in which volatility in the carbon market could impact the water and commodities market is through the use of carbon credits. Carbon credits are tradable permits that allow companies to emit a certain amount of carbon dioxide or other greenhouse gases. If a company emits less than its allotted amount, it can sell its unused credits to other companies that emit more than their allotted amount. If the price of carbon credits is high, companies may be more likely to invest in technologies and practices that reduce their greenhouse gas emissions, which could have a positive impact on water and commodity markets. For example, companies may invest in more water-efficient technologies to reduce their carbon footprint, which could help to conserve water resources and reduce water-related risks in commodity production. On the other hand, if the price of carbon credits is low or volatile, companies may be less motivated to invest in these types of technologies and practices, which could have a negative impact on water and commodity markets. In addition, if carbon prices are volatile, it could make it difficult for companies to plan and invest for the long-term, which could lead to instability in the water and commodity markets. Overall, the relationship between volatility in the carbon market and the water and commodities market is likely to be complex and multifaceted, and further research is needed to fully understand the nature of this relationship.

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6. Appendices:

Appendix No. 01 Serial Correlation Test Results for GARCH(1,1) model residuals

	Ljung – Box Test			ARCH LM Test		
	10	20	30	10	20	30
Carbon Emissions Futures	14.7070 [0.0650986]	19.3750 [0.3690791]	34.5060 [0.1847062]	1.5228 [0.1249]	1.0369 [0.4135]	1.0515 [0.3903]
MSCI ACWI Utilities	6.82132 [0.5560281]	11.3906 [0.8770547]	22.3044 [0.7670085]	0.66888 [0.7543]	0.56326 [0.9385]	0.75159 [0.8322]
S&P Goldman Sachs Commodity	3.22888 [0.9191834]	9.94082 [0.9338209]	15.3424 [0.9745904]	0.31958 [0.9763]	0.49929 [0.9681]	0.51424 [0.9868]

Appendix No. 02 Serial Correlation Test Results for GJR-GARCH(1,1) model residuals

	Ljung – Box Test			ARCH LM Test		
	10	20	30	10	20	30
Carbon Emissions Futures	13.8589 [0.0855189]	18.4419 [0.4269172]	33.9354 [0.2030081]	1.4382 [0.1572]	0.99018 [0.4708]	1.0327 [0.4175]
MSCI ACWI Utilities	12.6608 [0.1240665]	19.2700 [0.3753776]	29.3488 [0.3950009]	1.1722 [0.3048]	0.87392 [0.6216]	0.93921 [0.5612]
S&P Goldman Sachs Commodity	4.50198 [0.8092354]	11.0595 [0.8918142]	15.2866 [0.9752501]	0.44918 [0.9222]	0.54618 [0.9477]	0.49991 [0.9895]