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DAY-OF-THE-WEEK-EFFECT AND MONTH-OF-THE-YEAR-EFFECT ON CARBON EMISSIONS CONTRACT TRADING

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ABSTRACT

Objective: This study aims to examine whether there is a potential Day-of-the-Week-Effect and Month-of-the-Year-Effect on carbon emissions trading. **Research Design & Methods:** This research uses secondary data obtained through the Investing.com website. The carbon market data used is daily closing data, then the daily effect test is carried out, and monthly closing data to determine the monthly effect. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (2,1) and (3,1) method used to analyse the data. **Findings:** The correlogram and GARCH (2,1) and GARCH (3,1) test results show that the carbon market does not move randomly, but there are Day-of-the-Week-Effect and Month-of-the-Year-Effect phenomena. From this study, it was also found that on Wednesday in April, there was a significant increase in returns. So, it can also be concluded that the carbon market is not efficient. **Implications and Recommendations:** There are opportunities that can be taken from carbon trading which turns out to have a Day-of-the-Week-Effect and Month-of-the-Year-Effect so that investors who want to join carbon trading can more easily learn about it to get maximum profit in the carbon market. **Contribution & Value Added:** It is hoped that the results of this study can prove whether or not there is an influence on seasonal patterns so that it can be useful for speculators and business people related to carbon trading to design the right strategy in the carbon emissions market.

Keywords: carbon emission; carbon market; day-of-the-week-effect; month-of-the-year-effect; market anomaly.
JEL codes: G10, Q50
Article type: research paper

INTRODUCTION

In modern times, there are many large companies around the world. The high demand in the market encourages business people to create large companies to meet the needs of the market. The emergence of these companies also causes various problems for the environment. In the operational activities carried out by companies, almost all of them use fossil fuels to run their business, this causes high carbon emissions produced by companies which are then released into the atmosphere, causing changes in the climate. Carbon dioxide, which is included in greenhouse gas emissions, is considered the main cause of climate change. Lavietes (2020) states that it is estimated that the consequences of climate change cause losses of USD 8 billion every day for companies. Apart from harming the environment, carbon emissions also have an impact on the company itself, such as the company having to pay a much larger carbon premium under the Emissions Trading Scheme (ETS) and not many customers want to buy products that are considered not environmentally friendly (Miah et al., 2021).

The climate situation around the world is increasingly worrying, so many countries are competing to make real movements to stop the increase in carbon emissions in the atmosphere (Pranasyahputra et al.,

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2020). Climate change is getting worse plus uncontrolled companies releasing carbon emissions into the air. Therefore, it is necessary to supervise the company. This supervision has been agreed upon by the whole world under the name of the Kyoto Protocol. The Kyoto Protocol is an international agreement to reduce carbon dioxide emissions and greenhouse gases in the atmosphere (V. K. M. Putri, 2022). In addition to the Kyoto Protocol, another way to reduce carbon emissions is by trading carbon emissions. By trading carbon emissions, it can increase income for companies that produce little carbon emissions, while for companies that produce carbon emissions exceeding the predetermined limits, they must buy carbon credits sold by companies that produce less carbon, so there is a trade-in carbon emissions or commonly known as carbon trading. The carbon trading scheme can be seen in Figure 1.

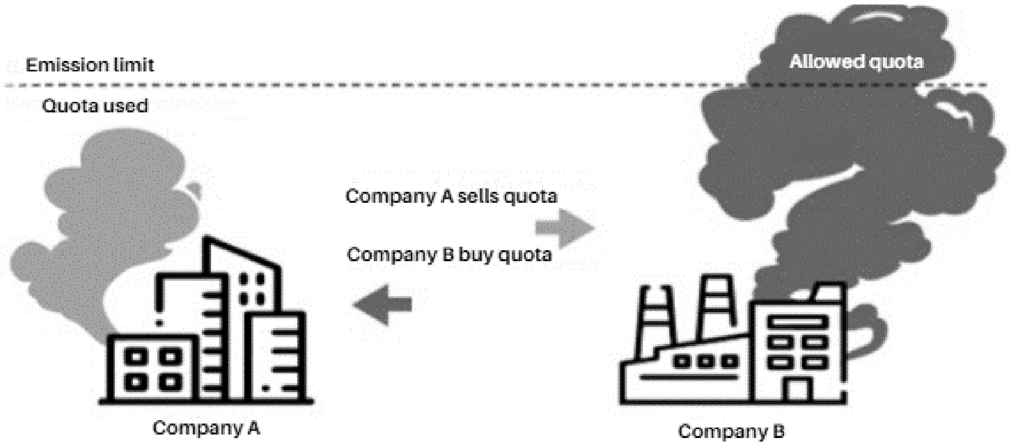

Figure 1. Carbon Trading Scheme

Carbon trading is the buying and selling of carbon certificates where a company produces carbon gas from its industrial process that exceeds the limit set by the world (ICDX Group, 2021). The idea of carbon trading comes from the world's commitment to addressing global warming from the industrial sector. Carbon trading is considered to open up new opportunities for the economies of participating countries (ICDX Group, 2021). Carbon trading is still new in Indonesia, making it easier for companies to enter the carbon market. The carbon market is formed by the trading between companies in buying and selling carbon credits. With carbon trading, it is believed that there are opportunities that stakeholders can see in the carbon market, beyond the project-based Clean Development Mechanism (CDM), alternative schemes such as the allowance market mechanism can be considered for developing countries in the same way as the European Union Emissions Trading Scheme (EU ETS) (Shi et al., 2019).

In its development, carbon trading in the carbon market is considered to have a certain movement pattern that comes from the production cycle. In the production process, companies produce different amounts of carbon emissions every day depending on how much activity is carried out by the company. While in the stock market, there is a pattern that is often seen at the beginning and end of the year, this pattern is affected by the financial statements issued by companies to create the January Effect and Santa Claus Effect.

According to Antari (2020) in financial theory there are four kinds of market anomalies, namely corporate anomalies, seasonal anomalies, accounting anomalies, and event anomalies. The anomalies used in this study are seasonal anomalies consisting of the Day-of-the-Week-Effect and Month-of-the-Year-Effect. This seasonal anomaly is included in a seasonal return pattern in a weakly efficient market. In an efficient market, seasonal return patterns that can be predicted by investors and traders should not occur because it is an aberration for weak-form efficiency markets.

Carbon trading is a relatively new field, so the issues related to carbon trading have yet to be explored. Research that examines potential patterns still needs to be done specifically. While research on the stock market, bond market, and cryptocurrency market has been done to examine the seasonal patterns that can occur in the market. For example, research by Caporale & Plastun (2019) examines the patterns that exist in cryptocurrency, research from Robiyanto (2017) examines the patterns that exist in the bond market and research by Amrullah & Khairunnisa (2019) examines the patterns that exist in the stock market. To be able to see the existence of patterns in carbon trading, the testing method that can be used is using GARCH, which uses daily and monthly closing data on the carbon market. This GARCH method is only used in research with heteroscedasticity problems. The working concept of this method is to predict the value of data that will occur in the future, provided that the value of data in the past is also known. Carbon trading that takes place five days a week is certainly interesting for speculators and business people related to carbon trading. Therefore, this study still needs further investigation on whether there is a seasonal pattern in the carbon emissions market.

This study aims to examine whether there is a potential Day-of-the-Week-Effect and Month-of-the-Year-Effect on carbon emissions trading. It is hoped that the results of this study can prove whether or not there is an influence on seasonal patterns so that it can be useful for speculators and business people related to carbon trading to design the right strategy in the carbon emissions market.

LITERATURE REVIEW

Carbon Emissions, Carbon Markets and Carbon Credits

Carbon emissions are gases produced by burning carbon-containing compounds such as CO2, diesel, coal, and other fuels (Kristina, 2021). The release of carbon emissions into the air causes an increase in temperature on Earth so countries move to curb this by implementing the Kyoto protocol for companies. The Kyoto Protocol is an international agreement between various countries to reduce carbon dioxide (CO2) emissions and the presence of greenhouse gases in the atmosphere. The contents of the Kyoto Protocol contain joint implementation, emissions trading, and clean development mechanisms (V. K. M. Putri, 2022). From the Kyoto protocol, carbon trading began to be traded in the carbon market. In the carbon market, there is a process of buying and selling carbon credits between companies that need certificates to emit carbon emissions above a predetermined limit and companies that have a small number of carbon emissions. Companies that sell carbon credits can use the proceeds as an additional source of revenue for their business.

Carbon credits are the right for companies to be able to emit a certain amount of carbon/greenhouse gas emissions in their industrial processes (Katadata Insight Center (KIC), 2022). In Indonesia itself, carbon trading can be used as an opportunity for economic growth because Indonesia can absorb around 113.18 gigatons of carbon sourced from tropical rainforests, mangrove forests, and peatlands to be able to absorb carbon (MPR, 2022). Umah (2021) states that not only Indonesia, but several countries also participate in carbon emission trading such as the European Union, Switzerland, New Zealand, Kazakhstan, Korea, Australia, Canada, China, Mexico, and many others countries. This shows that carbon trading has been widely practiced in the world, so it can be used as a new opportunity for investors and traders to jump into the carbon market. In the carbon market, seasonal anomalies or seasonal deviations can occur that cause a decrease or increase in returns received, these patterns are commonly known as the Day-of-the-Week-Effect (daily pattern) and Month-of-the-Year-Effect (monthly pattern).

Day-of-the-Week-Effect

Day-of-the-Week-Effect is a daily pattern that occurs in the carbon market every week, where the returns that will be obtained are very different compared to other days (Caporale & Plastun, 2019; Zhang et al., 2017). Day-of-the-Week-Effect is a phenomenon formed from anomalies inefficient capital market theory so that the average daily return obtained is not the same on trading days (Hendrawaty & Huzaimah, 2019). In the Day-of-the-Week Effect, there are differences in the returns obtained every day in one trading week. The lowest return tendency occurs on Monday and will increase the next day in several capital markets (Chiah & Zhong, 2019; Zhang et al., 2017). The decline in returns on Monday is thought to be the result of pessimistic investors at the beginning of the week because the information obtained was inaccurate. After all, it is because they missed the weekend that investors feel pessimistic.

Month-of-the-Year-Effect

Similar to the definition of the Day-of-the-Week-Effect, the Month-of-the-Year-Effect is a seasonal pattern that exists in the carbon market that occurs every month, so that it will produce returns that are lower or higher than other months during a trading year. The existing pattern in the Month-of-the-Year-Effect is the January Effect where the return generated in January is usually higher than in other months because investors will reorganize their portfolio positions and will buy stocks at the beginning of the month (Robiyanto, 2017). Another pattern that often appears is the Santa Claus Effect or the phenomenon of increasing market value in stocks during the last week of December and entering the first two trading days of the new year due to an increase in month-end spending and optimism to welcome the new year (Adieb, 2020). According to research conducted by Mouselli & Samman (2016) the bond market shows results that in May the resulting returns tend to be positive because the usual dividends will be distributed in May, making investors more interested in investing.

Day-of-the-Week-Effect on Carbon Trading

Carbon trading occurs for five days a week, and this causes frequent increases and decreases in the returns generated due to the daily patterns in trading that occur. For example, only on Monday of the week, the highest return is generated while on the other four days, the return generated does not increase when compared to Monday. Research by Baur et al. (2019) conducted on the cryptocurrency market saw greater volume being traded outside of business hours because investor's ability to process information and decisions is limited during their workday. Research by Zhang et al. (2017) used samples from several countries to analyse Day-of-the-Week anomalies in the cryptocurrency market. The predictable variation in cross-sectional returns depends on the Day-of-the-week trading (Birru, 2018). The Day-of-the-Week-Effect influences the buying and selling activities carried out in the carbon market. The rate of return received by investors is affected by the trading day effect. After all, the information received on Monday is said to be less valid because the information should have been received on the weekend (N. M. Y. Putri, 2020). Then the first hypothesis can be formulated as follows:

H1: There is a Day-of-the-Week-Effect in the carbon emissions market

Month-of-the-Year-Effect on Carbon Trading

The Month-of-the-Year-Effect is a seasonal pattern in the stock market that occurs if the returns obtained in a certain period are significantly different from other months, either getting higher or lower results (Robiyanto, 2017). The monthly pattern that is often seen is the deviation in January and December caused by various influencing factors such as the enthusiasm of investors to welcome the beginning of the year to make investments and the thoughts of investors towards the end of the year which will usually provide high returns because it is approaching the end of the year. Research by Caporale & Plastun (2019) found that the market evolves towards anomalies so that over time the presence of anomalies in the market will fade. The carbon market represents a particularly interesting case, as it is relatively new and unexplored. At the same time, it is highly susceptible to anomalies, given its high volatility relative to forex, stock, and commodity markets (Aalborg et al., 2019). The carbon market is a new type of market in credit trading and this leads to high statistical changes in price changes, coupled with the Month-of-the-Year-Effect that occurs at the beginning and end of the year, making the returns obtained by investors can be different as well as in other financial markets. So the second hypothesis that can be formulated is:

H2: There is a Month-of-the-Year-Effect in the carbon emissions market

METHODS

This research uses secondary data obtained through the Investing.com website. The carbon market data used is daily closing data, then the daily effect test is carried out, and monthly closing data to determine the monthly effect. This study uses time series data from 2005 to 2023 obtained through Carbon Emissions Futures on the website www.investing.com.

This study uses carbon market return as the dependent variable. The return used is the monthly return and will be calculated with Equation 1.

$$RC_t = \frac{P_t - P_{t-1}}{P_t} \quad \text{Equation 1}$$

where:

RC_t	=	Change in carbon price in a period t
P_t	=	Carbon price in a period t
P_{t-1}	=	Carbon price in a period t-1

The data used in this study is time series data. With the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) (2,1) and (3,1) method. This GARCH model was created to avoid levels that are too high in the ARCH model based on the principle of parsimony or to choose a much simpler model to get a more positive variance. GARCH is used to predict future returns and is believed to be able to predict whether there is an increase or decrease in the resulting return due to daily and monthly patterns in the carbon market. This GARCH method is appropriate for time series data that potentially contains heteroscedasticity. Heteroscedasticity itself means the occurrence of inequality of error variance for all observations of each independent variable in the regression model.

Trading in the carbon market takes place on five days and is used as a variable in this study, namely: Monday, Tuesday, Wednesday, Thursday, and Friday (see Equation 2).

$$RC_t = \beta_1 Monday + \beta_2 Tuesday + \beta_3 Wednesday + \beta_4 \text{Thursday} + \beta_5 \text{Friday} + \varepsilon_t \quad \text{Equation 2}$$

with,

$$\varepsilon_t = \phi_t \varepsilon_{t-1} + \cdots + \phi_t \varepsilon_t + \eta_t$$
$$\eta_t = \sigma_t \varepsilon_t$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \eta_{t-1}^2 + \cdots + \alpha_p \eta_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \beta_p \sigma_{t-q}^2$$

where, εt is identically distributed N (0,1) and independent of the previous t-p state; RC = Return carbon trading in a period t; Monday, Tuesday, Wednesday, Thursday, Friday = dummy variable on trading day and 1 if it refers to the month and 0 otherwise.

Carbon market trading occurs every month and in one year it is traded 12 times, these months are: January, February, March, April, May, June, July, August, September, October, November, and December (see Equation 3).

$$RC_t = \beta_1 \text{January} + \beta_2 \text{February} + \beta_3 \text{March} + \beta_4 \text{April} + \beta_5 \text{May} + \beta_6 \text{June} + \beta_7 \text{July} + \beta_8 \text{August} + \beta_9 \text{September} + \beta_{10} \text{October} + \beta_{11} \text{November} + \beta_{12} \text{December} + \varepsilon_t \quad \text{Equation 3}$$

with,

$$\varepsilon_t = \phi_t \varepsilon_{t-1} + \cdots + \phi_t \varepsilon_t + \eta_t$$
$$\eta_t = \sigma_t \varepsilon_t$$
$$\sigma_t^2 = \alpha_0 + \alpha_1 \eta_{t-1}^2 + \cdots + \alpha_p \eta_{t-p}^2 + \beta_1 \sigma_{t-1}^2 + \beta_p \sigma_{t-q}^2$$

where, εt is identically distributed N (0,1) and independent of the previous t-p state; RC = Return carbon trading in a period t; Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec = dummy variable on the trading month and 1 if refers to the month and 0 otherwise.

Before the GARCH (2,1) and (3,1) analysis, a classic assumption test will be carried out in the form of a unit root test which is used to prove that the data is fixed or unchanged, namely the Augmented Dickey-Fuller (ADF) method. ADF regression includes a zero mean stationary value in the independent variable of the constant variant (Hartono, 2022). This method is appropriate for time series data that potentially have heteroscedasticity.

FINDINGS

Descriptive Statistics

Table 1 presents descriptive statistics on each carbon trading day calculated using daily returns from carbon trading proceeds.

Table 1. Descriptive Statistics of Carbon Daily Returns

	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	-0.002805	0.000264	0.000956	-0.000496	-0.000783
Maximum	0.607100	0.223500	0.428600	0.155600	0.571400
Minimum	-0.666700	-0.352600	-0.266800	-0.333300	-0.750000
Std. Dev	0.049458	0.036894	0.041504	0.036489	0.046401
N	899	915	920	921	903

Source: Investing.com, data processed.

Based on Table 1, it can be seen that on trading days, the highest average daily return value is found on Wednesday with a value of (0.000956), while the lowest return value is seen on Monday with a value of (-0.002805). The greatest risk can be measured by standard deviation and it is found that on Monday (0.049458) and the lowest on Thursday (0.036489).

Figure 2 presents the rate of return earned by the carbon market from 2005 to early 2023. Each carbon trading is the subject of this study.

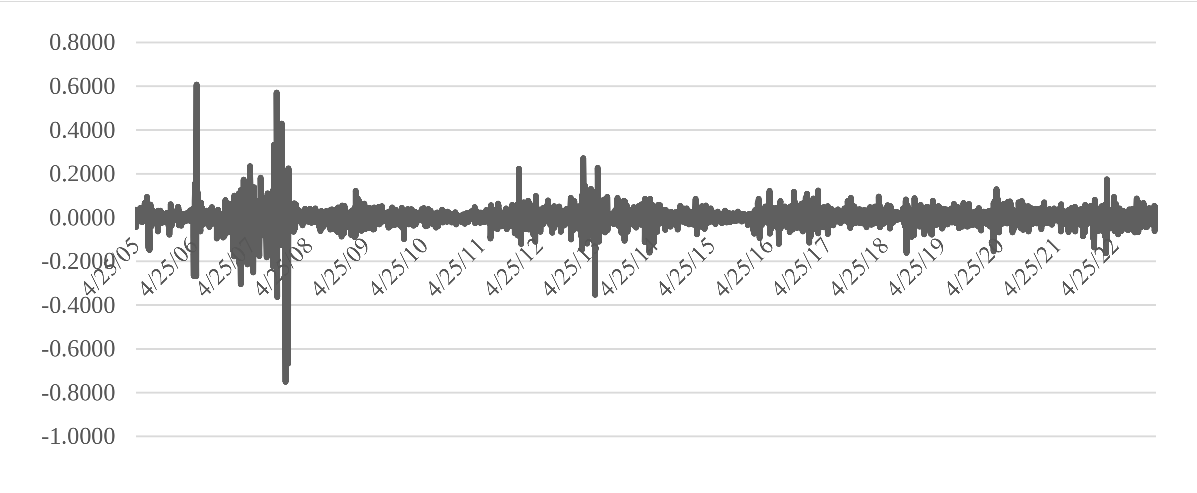

Figure 2. Daily Returns in 2005-2023
Source: Investing.com, data processed.

The rate of return received on each day of carbon trading can be seen in Figure 2, which shows that the movement of return on each day is always changing, indicating that the carbon market often experiences profits and losses.

Meanwhile, monthly descriptive statistics on carbon trading are presented in Table 2 which is calculated from the monthly return of carbon trading.

Table 2. Descriptive Statistics of Monthly Return of Carbon Trading

Month	Mean	Maximum	Minimum	Std. Dev	N
January	-0.071372	0.246600	-0.643900	0.227638	18
February	0.007582	0.450200	-0.595700	0.214927	17
March	0.013982	0.378900	-0.342800	0.177989	17
April	0.008847	0.246300	-0.595400	0.249606	17
May	0.019444	0.273600	-0.452800	0.161605	18
June	0.016983	0.307800	-0.551700	0.206544	18
July	-0.026339	0.171400	-0.233200	0.101004	18
August	0.058972	0.199600	-0.166700	0.088431	18
September	-0.041183	0.160600	-0.200000	0.108013	18
October	-0.006422	0.198400	-0.249300	0.124394	18
November	-0.071944	0.281800	-0.888900	0.260344	18
December	0.042289	0.427900	-0.195100	0.146210	18

Source: Investing.com, data processed.

It is seen that in Table 2 the highest average monthly return value is found in August (0.058972), while the lowest return value is seen in November (0.071944). Similarly, the level of risk, which can be measured by standard deviation, was found to be highest in November (0.260344) and lowest in August (0.088431).

Figure 3 presents the returns earned by the carbon market from 2005 to early 2023, with each month being the subject of this study.

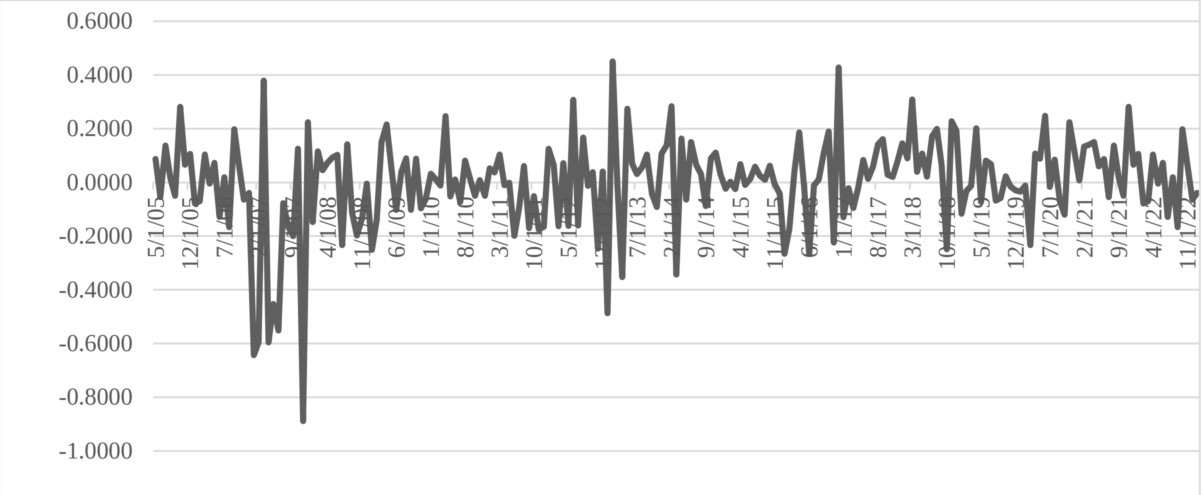

Figure 3. Monthly Returns in 2005-2023
Source: Investing.com, data processed.

The monthly return on carbon trading can be seen in Figure 3, which shows a fluctuating monthly return movement, indicating that the carbon market often experiences profits and losses.

Normality Test

The first step taken to see whether the data obtained is normal or not is to conduct a normality test. The normality test is carried out at 5 percent significance level of which can be seen in Table 3.

Table 3. Normality Test Results

	Probability	Result
Daily Return Data	0.000000	Not Normally Distributed
Monthly Return Data	0.733652	Normally Distributed

Source: Investing.com, data processed.

Table 3 it can be seen that at a significance level of 5 percent, the daily prob. normality < alpha 0.05. Since the probability of normality is smaller than alpha, the data is not normally distributed. And at a significance level of 5 percent, Prob. Monthly normality > alpha 0.05. Since the probability of normality is greater than alpha, the data is considered normal. After testing the stationary data, the next step is to test the constancy of existing data using the Augmented Dickey-Fuller (ADF) test. January, February, March, April, May, June, July, August, September, October, November, and December.

Unit Root Test

In this study, the data stationarity test was carried out using Augmented Dickey-Fuller (ADF) with a significance level of 5 percent. Unit root testing or commonly called (ADF) is used to see whether the data obtained is stationary or not.

The unit root test results are shown in Table 4.

Table 4. Augmented Dickey-Fuller (ADF) Test Results

	Probability	Result
Daily Return Data	0.0000	Stationer
Monthly Return Data	0.0004	Stationer

Source: Investing.com, data processed.

It can be seen in Table 4 that at the 5 percent level of significance, the prob value. ADF values for both daily and monthly show results < alpha 0.05. Since the results show that the ADF probability is smaller than alpha, the data obtained is considered stationary. After conducting the unit root test, it can proceed to the next test, namely the Correlogram test to see if there is autocorrelation in daily and monthly returns.

Correlogram Test

The correlogram test is used to determine the autocorrelation leg coefficient (p) in GARCH. The first significant autocorrelation leg will be used as the coefficient in determining GARCH.

Based on Appendix 1, it can be seen that autocorrelation for daily returns occurs in the second leg because the second lag shows significant results at 5 percent alpha. And in Appendix 2 also shows that autocorrelation occurs in the third leg which shows significant results against 5 percent level of significance. So, the correlogram analysis results on daily and monthly returns show the presence of autocorrelation which means the carbon market tends to be inefficient.

Table 5. GARCH (2,1) Test Results

Variable	Coefficient	Std.Error	z-Statistic	Prob.
Monday	0.001354	0.000711	1.904089	0.0569
Tuesday	0.001822	0.000657	2.772345	0.0056
Wednesday	0.002731	0.000757	3.607488	0.0003
Thursday	2.93E-05	0.000793	0.036986	0.9705
Friday	0.000516	0.000789	0.653907	0.5132
Variance Equation				
C	1.75E-05	1.65E-06	10.59340	0.0000
RESID(-1)^2	0.219328	0.010856	20.20280	0.0000
RESID(-2)^2	-0.073101	0.011794	-6.198307	0.0000
GARCH(-1)	0.853616	0.005893	144.8610	0.0000

Source: Investing.com, data processed.

Table 6. GARCH (3,1) Test Results

Variable	Coefficient	Std. Error	z-Statistic	Prob.
January	-0.053186	0.022324	-2.382876	0.0172
February	0.016414	0.039919	0.411174	0.6809
March	-0.019330	0.027183	-0.711108	0.4770
April	0.090240	0.038283	2.357213	0.0184
May	0.009921	0.059988	0.165390	0.8686
June	0.035464	0.029581	1.198900	0.2306
Jul	-0.008843	0.039768	-0.222370	0.8240
August	0.054728	0.048168	1.136195	0.2559
September	-0.031679	0.036966	-0.856967	0.3915
October	0.008712	0.032700	0.266438	0.7899
November	0.045698	0.023065	1.981285	0.0476
December	0.027062	0.037563	0720431	0.4713
Variance Equation				
C	0.001832	0.000963	1.903019	0.0570
RESID(-1)^2	0.152668	0.084453	1.512209	0.1305
RESID(-2)^2	0.140888	0.143105	0.0984512	0.3249
RESID(-3)^2	0.030693	0.097056	0.316241	0.7518
GARCH(-1)	0.649024	0.105719	6.139133	0.0000

Source: Investing.com, data processed.

GARCH Analysis Results

After conducting normality test, unit root test and correlogram test, the next test is GARCH test, GARCH test is conducted to see the seasonal pattern in carbon trading. GARCH performed in this study is GARCH (2,1) on daily data and GARCH (3,1) on monthly data performed on daily and monthly carbon returns.

The test results using the GARCH (2,1) method are shown in Table 5 with the daily return as the variable to be tested.

Table 5 shows the results of data processing using Eviews and it can be seen that on the trading day the average return gives positive results on carbon trading. Table 5 also shows that Tuesday and Wednesday have a significant influence on carbon emission returns, while on other days there is no significant influence on carbon emission returns.

Furthermore, the test results using the GARCH (3,1) method are shown in Table 6 with the month return as the variable to be tested.

Based on Table 6, the average monthly returns in January, March, July and September show negative results, and other months are positive. Significant average returns only exist in January, April and November, while the other months have no significant influence on carbon emission returns.

It was found that all coefficients on the daily and monthly variance equation have a significant effect. This indicates that the residual variance in the equation follows the GARCH pattern and tends to be influenced by its past volatility.

DISCUSSION

This study aims to determine whether there is a seasonal pattern in the carbon market using the GARCH test. Before the GARCH test is conducted, it is necessary to see whether the data obtained is normal or not, namely, by conducting a normality test. After the normality test is carried out, the stationarity test with Augmented Dickey-Fuller (ADF) can be continued to see whether the data is stationary or not. Then the correlogram test can be done to find out whether the carbon market is efficient or not. After several tests have been carried out to check that the data obtained is normal, stationary and efficient, the GARCH test can be carried out using the returns from the carbon market.

The findings in this study show that the significant z-statistic value is on Wednesday. This shows that H1 which states that there is a Day-of-the-Week-Effect on the carbon market is empirically supported in this study. This finding is similar to the results of Hendrawaty & Huzaimah (2019) who conducted a study on LQ45 stocks on the Indonesia Stock Exchange and studies on the Day-of-the-Week-Effect conducted by Suyanto (2019) in the stock market on the Indonesia Stock Exchange. It was also found in this study that the z-statistic value was also significant in April, which means that H2 which states that there is a Month-of-the-Year-Effect on the carbon market is empirically supported in this study. This finding is also consistent with the results of research conducted by Hawaldar et al. (2017) on the Bahrain stock market and research conducted by Shah & Baser (2022) on the global mutual fund market which also found the existence of the Month-of-the-Year-Effect which is consistent with the results of the research conducted.

From the findings obtained, it can be seen that there are opportunities that can be taken from carbon trading which turns out to have a Day-of-the-Week-Effect and Month-of-the-Year-Effect so that investors who want to join carbon trading can more easily learn about it to get maximum profit in the carbon market. In addition, carbon trading can also increase state revenues, the same results were also found in research conducted by Shi et al. (2019) showed positive results on carbon emissions trading in achieving sustainable economic growth and meeting carbon reduction targets in China.

CONCLUSION

This study aims to determine whether there is a pattern in the carbon market. The correlogram and GARCH (2,1) and GARCH (3,1) test results show that the carbon market does not move randomly, but there are Day-of-the-Week-Effect and Month-of-the-Year-Effect phenomena. From this study, it was also found that on Wednesday in April, there was a significant increase in returns. So, it can also be concluded that the carbon market is not efficient because there is a certain pattern in the movement of returns which results in returns following a certain pattern and not moving randomly due to the large amount of demand and supply in the market. This can certainly be utilized by investors and traders to purchase carbon certificates before the increase in return and can sell them when the return has increased.

This study has several shortcomings and limitations such as when collecting data obtained from the Investing.com website. Some data is not suitable for processing such as data that is too large in return value so that it causes errors when the normality test is carried out, and the daily data is still mixed with days that should not occur trading (Saturday and Sunday) so that some inappropriate data must be deleted. It is expected that future studies can discuss carbon emissions and carbon credits more. Due to the limited number of studies that discuss carbon markets, it is expected that there will be more studies in the future that discuss carbon markets in detail. For example, a study examines the feasibility of carbon trading as a profitable investment tool.

CONFLICT OF INTEREST STATEMENT

There are no known conflicts of interest related to this article.

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