

Exploring Spillover Effects of Carbon-Negative Credits on Global Financial and Energy Markets

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Abstract

This study examines the spillover effects of negative carbon credits (CORC) on global financial and energy markets, an area with limited prior research. Negative carbon credits, distinct from traditional credits, aim to directly remove atmospheric carbon dioxide, playing a pivotal role in achieving net-zero emissions targets. Using monthly data across nine markets—including CORC, European Union Allowance Futures (EUAF), energy, and stock indices—over a 40-month period, this study employs the BEKK-GARCH model to capture dynamic volatility and spillover relationships. Results reveal that the CORC market operates with a high degree of independence, with its volatility predominantly self-driven. However, the European Union carbon market (EUAF) exerts a consistent and significant positive spillover effect, highlighting its critical influence. In contrast, the energy market (SPEN) exhibits negative short-term spillover effects on CORC, while traditional stock markets show negligible interactions. The findings underscore the specialized role of CORC within financial markets and its emerging interconnectivity with carbon trading systems, offering valuable insights for policymakers and investors aiming to enhance carbon market mechanisms and promote global decarbonization efforts.

Key Words:

Carbon-Negative Credits, BEKK-GARCH Model, Volatility Spillover Effect, Carbon Market

JEL Classification:

Q54, G15, C32

1. Introduction

In order to achieve the 1.5-degree target outlined in Paris Agreement, the implementation of carbon removal projects is also an argument mentioned (Smith et al., 2016), (O. Geden et al., 2018), (A. Buylova et al., 2021). In 2024, a carbon removal report compiled by European and American scientific research institutions was released, mainly covering the latest progress in carbon removal (CDR) technology and its role in addressing climate change. It affirms the necessity of carbon removal and emphasizes the importance of the voluntary carbon market. The article mentions that Canada supports natural climate solutions through the "2 Billion Trees Program" and the "Agricultural Climate Solutions Program" in its "Green Climate Solutions Fund". These projects aim to enhance carbon sequestration capacity through afforestation, wetland restoration, etc. China pledged in its Nationally Determined Contribution (NDC) to increase forest stocks by 600 million cubic meters and incorporate "carbon sink trading" into the national carbon emissions trading market. The U.S. Department of Energy also received \$3.5 billion in financing to develop four domestic direct air capture centers. The Danish energy department also purchased 1.1 million tons of carbon removal type carbon credits and established the fund for negative CO₂ emissions (NECCS fund) for three carbon removal projects. These countries are promoting carbon removal projects and negative carbon credits through policies, market mechanisms and technological innovations.

The carbon offset mechanism comes from the Kyoto protocol in 1997. One of its important functions is to develop a carbon trading system. Under this system, there are three different carbon trading mechanisms, the Emissions Trading System (ETS) and Joint Implementation (JI) for developed countries, and the Clean Development Mechanism (CDM) for developing countries. These three carbon trading mechanisms form the prototype of the carbon trading system. Among them, ETS measures a country's total emissions based on its GDP emissions and determines the quota cap. The government of this country will distribute quotas in different forms (such as free allocation, auction, etc.) in the primary market. Enterprises that emit more than the quota need to purchase carbon quotas or carbon credits (from CDM projects in developing countries) equal to the excess amount in the secondary market, while enterprises that emit less than the quota can sell the remaining carbon quotas in the secondary market. CDM carbon credits are generally credits obtained from emission reduction projects implemented in developing countries, which can be bought and sold in the primary and secondary markets to offset carbon emissions (UNFCCC).

Since the launch of the global carbon market, the European Union's Emission Trading System (EU ETS) has been the world's largest carbon trading system. Other mature systems include New Zealand, South Korea, Switzerland, California, Quebec, Canada, and the Regional Greenhouse Gas Initiative in several states in the eastern United States. Mexico's pilot ETS was launched in January 2020 (S.Verde et al., 2021). Since 2013, China's ETS pilot has included eight regions, namely Beijing, Shanghai, Tianjin, Shenzhen, Chongqing, Guangdong, Hubei, Fujian. And launch a national emission trading system in 2021 (B. Shi et al., 2021; X, Long, L. Goulder, 2023). Moreover, carbon trading markets in Colombia and Ukraine are being developed, and carbon trading markets in Brazil, Chile, Indonesia, Pakistan, Thailand, Turkey and Vietnam are under consideration (S.Verde et al., 2021). It can be seen that the global carbon market is constantly developing and becoming increasingly important in addressing climate change.

However, despite the continuous expansion of carbon markets in size and influence, they still face many challenges. For example, the risk of carbon leakage has always been a core issue in carbon markets, especially in industries such as agriculture and transportation. Since these industries are often not prioritized in national climate policies, their carbon leakage risk is even higher than that of energy-intensive industries (F. Freund et al., 2023). The volatility of carbon credit prices is also a major challenge for the carbon market (Z Feng et al., 2011; B. Ibrahim et al., 2016; A. Aslan et al., 2022). This volatility comes from factors such as policy impact and supply and demand relationship. Q. Dong, Y. Zhao et al. (2024) discussed in their study of China's Risk spillover between carbon markets and stock markets that there is a risk correlation and spillover effect between carbon markets and stock markets. The spillover effect between China's carbon market and stock market is significant, but uneven, and very sensitive to extreme events. The carbon market mainly plays the role of a net receiver in information flow, rather than outputting to the stock market.

On the other hand, carbon credits also play an important role in the carbon market. B. Shi, L. Wu et al. (2021) discussed the CDM project and mentioned that it provides huge environmental benefits to developing countries, making consumption and production patterns more environmentally friendly, and developed countries can also meet emission reduction standards at a lower cost. It is crucial for many countries to deploy renewable energy industries, and it promotes the development of energy technology, enabling more countries to widely use energy technology and clean energy. However, the effectiveness and methodology of these carbon credit projects have also been questioned by many parties (A. Costa et al., 2013; A. Michaelowa, 2009).

Carbon-negative credits are directly remove and store carbon dioxide from the atmosphere through artificial and/or technical methods, such as afforestation, carbon capture and storage (CCS), soil carbon storage, etc. Unlike traditional carbon credits, the purpose of carbon-negative credits is to reduce carbon already in the atmosphere. According to the report of the Intergovernmental Panel on Climate Change (IPCC), carbon removal technology is an indispensable part to achieve the 1.5-degree Celsius temperature control target. Carbon absorption type carbon credits provide economic incentives for these technologies and promote the development and application of negative carbon technologies. In addition, many climate scientists point out that relying solely on emission reduction measures is not enough to achieve the net zero target, so carbon absorption type carbon credits are needed to make up for emissions that cannot be eliminated. Common negative carbon technologies currently include A/R forestation, Soil Management, carbon capture and storage (CCS). C. Hepburn, E. Adlen et al. (2019) studied Economically effective projects for utilizing and removing CO₂. The study included 10 different types of negative carbon projects. The authors predicted the carbon storage and utilization potential and different economic benefits of these 10 different negative carbon projects. The results are shown in the following table.

We can see that, except for forest projects and land management projects, other negative carbon projects are rarely used in the carbon market, and these projects have a lot of carbon storage and utilization potential, as well as economic benefits, which also shows that we have not developed enough carbon credits.

Pathway	Removal potential in 2050 (Mt CO ₂ removed per year)	Utilization potential in 2050 (Mt CO ₂ utilized per year)	Breakeven cost of CO ₂ utilization (2015 US\$ per tonne CO ₂ utilized)
Conventional utilization			
Chemicals	Around 10 to 30	300 to 600	-\$80 to \$320
Fuels	0	1,000 to 4,200	\$0 to \$670
Microalgae	0	200 to 900	\$230 to \$920
Concrete building materials	100 to 1,400	100 to 1,400	-\$30 to \$70
Enhanced oil recovery	100 to 1,800	100 to 1,800	-\$60 to -\$45
Non-conventional utilization			
BECCS	500 to 5,000	500 to 5,000	\$60 to \$160
Enhanced weathering	2,000 to 4,000	n.d.	Less than \$200*
Forestry techniques	500 to 3,600	70 to 1,100	-\$40 to \$10
Land management	2,300 to 5,300	900 to 1,900	-\$90 to -\$20
Biochar	300 to 2,000	170 to 1,000	-\$70 to -\$60

Table 17. 10 different carbon-negative projects

Although negative carbon projects have significant carbon storage potential and economic benefits, their application in the global carbon market is still limited. The differences in the acceptance of negative carbon credits in different countries also show the differences in the implementation of carbon credit mechanisms in various places. For example, in China's national carbon trading market, there are only A/R forestation type negative carbon credits, while in Europe and the United States, there are various types of negative carbon credits, but they are also dominated by forest and land management projects, and most of the carbon credits usually come from non-governmental organizations and are traded in the voluntary market. In this diverse carbon market context, the price of carbon credits is often affected by multiple factors, and the fluctuation of energy prices is an important factor.

The attitudes of carbon trading markets in various countries towards negative carbon credits vary. At the same time, the price and volatility of carbon credits in the market are also significantly affected by the energy market, especially in different economic cycles. C. Gavard & D. Kirat (2018) discussed the relationship between carbon credits and energy prices in detail. Although EUA and CER show the same return trend, the price of EUA is mainly affected by demand, such as changes in EU emission targets and energy demand. However, CER prices are more affected by energy prices. In periods of low economic activity and weak demand, EUA prices are negatively elastic to coal and natural gas prices. In economic downturns, fuel prices and EUA prices fluctuate in opposite directions. In normal times, EUA prices are positively elastic to coal and natural gas prices, and as economic activity increases, fuel prices and EUA prices rise together. Understanding the dynamic behaviour of carbon markets has practical significance for investors, policymakers, and participants in carbon credits. When making price forecasts and market strategies, understanding the dynamic risks of the market can enable investors to better manage risks.

Carbon-negative credits are different from traditional carbon credits because they are not just intended to offset existing emissions, but to reduce the amount of carbon in the atmosphere by directly removing carbon dioxide from the atmosphere. This carbon removal process is more aggressive and aims to reverse carbon emissions that have already been produced, rather than just reducing new emissions.

2. Literature Review

A study from the IMF shows that carbon pricing can be achieved through carbon taxes or emissions trading systems (ETS). Carbon taxes are simple and direct, fixing emission prices by levying taxes on each ton of carbon emissions, while ETS determines prices by issuing and trading carbon emission permits. Both methods can effectively encourage companies and individuals to reduce carbon emissions and provide price signals for clean technology investment. Currently, more than 60 countries and regions have implemented carbon taxes or ETS, including China and Germany. However, despite the increase in the number of pricing mechanisms, the global average carbon price is still far below the level required to achieve climate goals.

The price of carbon credits is highly correlated with the price of EUAs (X. Yang, Y. Ye et al., 2023; C. Gavard, D. Kirat, 2020). In the first phase of the EU Emission Trading System, carbon credits can be used to offset carbon emissions and traded on the market, but starting from the second phase, the offset amount of carbon credits cannot exceed 13.4% of the total quota. In many CDM projects of the UNFCCC, the author observed that some carbon credits will be contracted and priced with buyers at the beginning of the CDM project. Or sellers can also set their own prices based on costs and supply and demand. T. Kanamura (2016) explored the impact of carbon swaps and energy prices on the volatility and price correlation between the EU Emission Trading System's emission union allowances (EUA) and the Clean Development Mechanism's emission reduction credits (CERs). When the price of EUA rises, the price correlation between EUA and CER is mainly driven by swaps between the two. In periods of financial instability and falling EUA prices, price correlations are more affected by falling energy prices. The study also found that carbon market volatility is asymmetric under different price volatility conditions.

Previous studies have confirmed that EUA prices are related to many financial markets. Among them, some empirical studies show that EUA is correlated with the stock market. R. Jiménez-Rodríguez (2019) explained that increased economic activity will increase energy demand, thereby increasing carbon emissions and pushing up EUA prices. Improved stock market conditions usually indicate a good economy environment, which leads to an increase in EUA prices.

But overall, stock markets in different regions are geographically specific. C. Luo and D. Wu (2016) studied the dynamic correlation between European carbon emission permits, crude oil, and the stock markets of China, the United States and Europe. The results show that the correlation between European carbon spot prices and the US and European stock markets is high and volatile, while the correlation with the Chinese stock market is low. A. Dutta, E. Bouri et al. (2018) showed that EUA price fluctuations have a positive impact on clean energy stock returns, but are generally not statistically significant. At the same time, it was found that there is a significant volatility relationship between EUA and the European Clean Energy Index, while the US market does not show a similar correlation, indicating that volatility shocks are geographically specific.

In addition, previous researchers have also discussed the connection between EUA and clean energy company stock prices. U. Oberndorfer (2009) concluded that changes in the price of EU emission allowances (EUA) have a significant positive correlation with the stock prices of major European power companies, and the correlation is asymmetric. Y. Tian, A. Akimov et al. (2016) studied the impact of (EUA) on the stock returns and volatility of European power companies. It is pointed out that the impact of EAU returns on power company stocks depends on carbon emission intensity, that is, carbon-intensive companies (non-clean energy companies) are negatively correlated with EUA returns, while low-carbon emission companies (clean energy companies) are positively correlated during non-shock periods.

Meanwhile, the price of EUA is closely related to other types of financial markets. M. Gronwald et al. (2011) studied the relationship between the returns of EU emission permit (EUA) futures and the returns of commodities, stocks and energy indices, and the results showed that there was a significant relationship between EUA returns and the returns of other assets. X. Tan, K. Sirichand et al. (2020) analyzed the information connectivity between carbon markets, energy markets and traditional financial markets, and showed that the overall returns of these three markets were highly correlated and volatile, among which oil prices and carbon markets were closely related to stock and non-energy commodity markets, while the correlation with bond markets was weaker. Q. Jiang and X.Ma (2021) showed that the volatility of the fossil energy market would affect the carbon market and then be transmitted to the clean energy market, while the volatility of the clean energy market would also affect the carbon market, and the volatility would be transmitted to the fossil energy market.

Not only that, but EUA has experienced different policy change periods: from 2005 to 2007 was the first phase of EU ETS, mainly used to test and improve the mechanism; From 2008 to 2012, the second stage, EU ETS coverage expanded from power generation and energy-intensive enterprises to the aviation industry; from 2013 to 2020, the third stage, EU ETS covers more industries, with a coverage rate of about 45% of EU greenhouse gas emissions, and the allocation mode of EUA gradually shifted from free allocation to auction, and the emission limit was reduced by 1.74% each year; the fourth stage is from 2021 to 2030, further expanding the auction EUA ratio, and reducing the emission limit by 2.2% each year. In general, the policy tends to tighten. Y. Zhang, Z. Liu et al. (2017) showed that carbon prices were strongly correlated with financial indices in the early stage, but the correlation weakened afterwards. P. Dai, X. Xiong et al. (2022) studied and analyzed the impact of economic policy uncertainty in Europe and the world on the volatility of the European carbon market. The study found that both types of policy uncertainty will lead to greater long-term volatility in the returns of the European carbon spot market. Among them, under the same policy change range, global economic policy uncertainty has a greater impact on the carbon market.

Even though EUA is closely related to various financial markets, it seems that the fluctuations and changes in the carbon market are more dependent on the supply and demand of carbon emission permits rather than the direct impact of macroeconomic conditions. J. Chevallier (2009) found that the yield of US Treasury bonds and the return rate of global commodity markets have little predictive effect on the carbon futures market. This finding shows that the carbon market is mainly affected by its own supply and demand relationship and is not directly affected by macroeconomic variables (such as interest rates and economic cycles) like other commodity markets.

In addition, due to the tightening of policies, the correlation between EUA and financial markets has weakened, and it is not directly affected by macroeconomic conditions. Many scholars have also studied the investment performance of EUA. A. Afonin, D. Bredin et al. (2018) found that EU emission permit futures were less attractive as independent investments in the first, second and third stages. Q. Jiang and X. Ma (2021) proved that the carbon market is a "bridge" for the transmission of fluctuations between the fossil energy market and the clean energy market, and empirically showed that investing in oil is the lowest cost hedging tool. X. Tan, K. Sirichand et al. (2020) proved that EUA is more suitable as a diversified asset for investment portfolios than oil because of its low correlation with financial assets. Y. Zhang, Z. Liu et al. (2017) also pointed out that given the relative independence of carbon assets, the study pointed out that incorporating them into the investment portfolio can help diversify risks.

Previous quantitative research literature mainly focuses on the correlation between carbon market and other markets, spillover effects, hedging strategies and forecasting models, etc. Moreover, a large number of carbon market prices are quantitatively studied using EUA prices or EUA futures prices and their rates of return. Quantitative research on CER is rare in quantitative research on carbon markets, and quantitative research on other carbon credits in voluntary markets has not been seen so far. The author observes that the monthly price of carbon-negative credit of Nasdaq-Puro.earth can be used to study the correlation and spillover between negative carbon credits in the voluntary market and other markets. However, due to the price frequency limitation of this carbon credit index, we do not consider the research on hedging strategies and forecasting, but focus on the correlation and spillover effect between carbon-negative credit and different markets.

The concept of spillover effect was first proposed by SA Ross (1989), who pointed out in his study that the flow of information between markets is the key factor causing volatility changes. The core idea of this effect is that the connection between different markets is not isolated. However, it has a significant mutual influence through information transmission and interaction. For example, when one market fluctuates, other markets may be affected by information transmission, thus showing changes in volatility: price fluctuations in the stock market may affect investor behavior in the bond market. This cross-market information flow reflects the correlation between markets. Therefore, changes in market volatility are not just a phenomenon within the market, but can also reveal the relationship between markets through information flow.

Previous studies have used different quantitative methods to study spillover effects, such as VAR, GARCH, Copula and other methods (S. Zeng, J. Jia et al., 2020). X. Gong, R. Shi et al. (2021) used the TVP-VAR-SV model to study the spillover effects between the carbon market and the fossil energy market, then concluded that there is a significant spillover effect between the carbon market and the fossil energy market, and the intensity and direction are time-varying and asymmetric. Y. Wang and Z. Guo (2018) used the KPPS framework (the generalized VAR model proposed by Koop, Pesaran and Shin) to explore the time-varying spillover effects between the carbon market and the energy market, then drew the following main conclusions: 1. The spillover effects between the carbon market and the energy market are asymmetric in the yield and volatility series. 2. The intensity and direction of the spillover effect vary over time and are significantly affected by policy changes or major events. 3. In the energy market, the WTI crude oil market has the strongest spillover effect on the entire system. 4. The natural gas market also has a significant

spillover effect on the carbon market. Q. Zhang and R. Wei (2024) used the Quantile VAR method to explore the volatility spillover effect between carbon emission reduction attention and financial market pressure. It was concluded that there is a close two-way spillover effect between carbon emission reduction attention and financial market pressure. S. Qiao, Y. Dang et al. (2023) used the TVP-VAR-SV model to explore the dynamic spillover effect between the carbon market, fossil energy market and electricity market. The results showed that there is a significant spillover effect between the carbon market, fossil energy market and electricity market. Moreover, the impact of the carbon market on the electricity market is more significant, especially in promoting the optimization of energy structure and emission reduction targets in the electricity market.

J. Chevallier (2011) studied the dynamic relationship between oil prices, natural gas prices and carbon prices by using the MGARCH model (including BEKK, CCC and DCC - MGARCH). The study found that there are significant self-volatility effects and cross-market volatility spillover effects in the oil, natural gas and carbon markets, and the volatility has strong persistence. M. Balciilar, R. Demirer et al. (2016) used the Markov Regime-Switching DCC-GARCH model to evaluate the risk transmission mechanism of the energy market to the carbon market and analyze the hedging performance of the carbon spot and futures markets. The results show that the spot and futures branches of the carbon market show volatility hedging effectiveness under different market conditions. X. Song, D. Wang et al. (2022) used the BEKK-MGARCH model to study the linkage between China's carbon trading market (represented by Hubei and Shenzhen) and the energy market (represented by the coal market). It is concluded that China's carbon market is easy to regulate, has higher liquidity and less volatility. S. Zeng, J. Jia et al. (2021) used the BEKK-GARCH model to study the dynamic volatility spillover effect between the EUA and CER markets. It was concluded that the volatility spillover effect of the EUA market on the CER market is more significant, and there is an asymmetric volatility spillover effect between the two markets (the volatility of the EUA market is more easily transmitted to the CER market).

B. Zhu, X. Zhou et al. (2020) used the Copula-CoES model to study the risk spillover effects between major carbon trading markets in China, and found significant risk spillover effects between the Guangdong and Shenzhen markets, as well as high-risk characteristics in Chongqing, Tianjin and Shenzhen. N. Yuan and L. Yang (2020) used the GAS-DCS-Copula model to study the risk spillover mechanism between financial market uncertainty (stock market and crude oil market) and the carbon market. The results showed that the transmission of financial market uncertainty to carbon market risk is more intense under extreme market conditions.

In quantitative studies on spillover effects, the BEKK-GARCH model is often used due to its capability to capture the volatility spillover effects between markets. In multivariate scenarios, it is particularly advantageous for modeling asymmetry and complex linkages between markets. Compared to VAR analysis, which typically requires a large sample size to ensure robust parameter estimation, the BEKK-GARCH model has been shown to perform reliably in analyzing volatility and spillover effects even with smaller sample sizes. While Copula models are powerful for modeling static dependence structures, they may face challenges in naturally incorporating dynamic modeling over time and in directly analyzing time-varying linkages between markets, areas where BEKK-GARCH models demonstrate strength. Additionally, although DCC-GARCH models are effective in capturing dynamic correlations, certain studies

(e.g., Y. Huang, W. Su et al., 2010) suggest that BEKK-GARCH models may exhibit superior fitting performance under specific conditions.

3. Methodology and Data

3.1 Data and data processing

1) Data

This article collects data from nine markets. For simplicity, the author uniformly codes different markets, which are: CORC (CORC Biochar Price Index), OMXG (NASDAQ OMX Green Economy Index), MXAP (MSCI AC Asia Pacific Index), MXEU (MSCI Europe Index), MXNA (MSCI North America Index), SPAG (S&P GSCI Agriculture Index), SPEN (S&P GSCI Energy Index), SPPM (S&P GSCI Precious Metals Index), EUAF (EUA futures). The price of CORC is publicly available on Puro.earth and NASDAQ (The CORC price index is the only carbon-negative credit index existing in the market currently). The price of Nature based carbon credit and EUA futures traded in the voluntary market is publicly available on carboncredits.com (After verification, the data of carboncredits.com comes from tradingview.com, and the data from tradingview.com comes from Intercontinental Exchange, ICE). Other data comes from S&P Global. Among them, MXAP, MXEU and MXNA represent the stock indices of Asia Pacific, Europe and North America respectively.

Then the author determined the time period (01/03/2020-30/01/2024), since March 2020 is the starting point of CORC carbon credits, until January 2024 during the preparation of our paper. The author used linear interpolation to fill the missing values of these daily average data. Since CORC is monthly data, we converted all other data into monthly data (monthly average). The obtained data is statistically descriptive values for each variable as follows:

Variables	Month	Mean	Median	Maximum	Minimum	Sd.	Skewness	Kurtosis
CORC	47	104.3713	111.32	176.55	19.96	35.96162	-0.37291	-0.35386
OMXG	47	2756.036	2775.76	3550.32	1648.36	427.0406	-0.85154	0.65759
MXAP	47	173.7191	165.09	215.12	138.34	21.20434	0.380058	-1.02128
MXEU	47	1816.45	1866.04	2086.41	1360.6	197.9363	-0.64661	-0.45574
MXNA	47	4028.3	4091.73	4767.03	2645.51	518.0816	-0.89664	0.312689
SPAG	47	410.6021	418.6	576.88	260.47	78.15729	-0.24719	-0.13078
SPEN	47	244.3872	252.65	404.73	86.44	76.97363	-0.17534	-0.51741
SPPM	47	2417.292	2421.06	2657.1	2036.11	142.987	-0.41272	-0.25456
EUAF	47	66.24468	77.67	99.44	21.22	26.42604	-0.46564	-1.31032

Table 18. Descriptive Data

The data is visualized, and the moving average and outliers are added as auxiliary lines to obtain the following visualization graph:

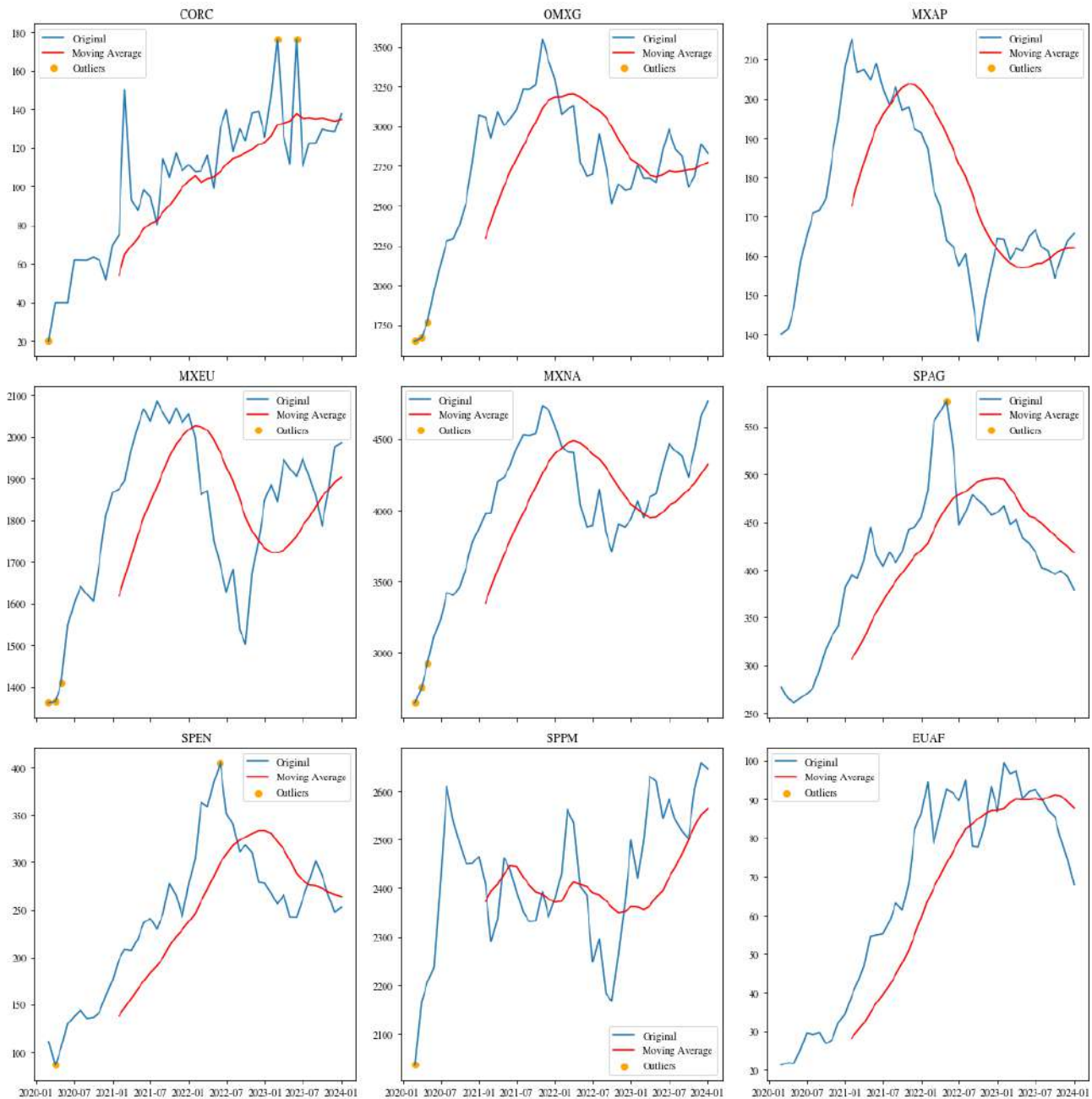


Figure 23: Original price and moving average

Moving averages smooth short-term fluctuations and help to show the long-term trend of the time series. From the data, we can see that CORC and EUAF have long-term and similar trend changes. The stock market in Europe, Asia Pacific and North America shows similar trend changes, but Europe and North America are more stable than Asia Pacific. Agriculture and energy also show similar trend changes.

2) Stationarity test

Stationarity means that the statistical properties of the data (such as mean and variance) remain constant over time. We use the Enhanced Dickey-Fuller (ADF) test to determine whether the time series is stationary. The null hypothesis of the ADF test is that there is a unit root in the data, that is, the data is non-stationary. The stationarity of the data can be determined by calculating the test statistic and comparing it with the critical values of different confidence levels (10%, 5%, 1%). If the test result rejects the null hypothesis, it indicates that the data is stationary, which means that the time series has stable and time-invariant characteristics. We perform stationarity tests on 9 different markets and the results are as follows:

Stationarity Test	ADF Statistic	p-value	1% Critical Value	5% Critical Value	10% Critical Value
CORC	-2.1565	0.2224	-3.5886	-2.9299	-2.6032
OMXG	-2.7953	0.0589	-3.5813	-2.9268	-2.6015
MXAP	-2.7631	0.0637	-3.6104	-2.9391	-2.6081
MXEU	-2.2603	0.1851	-3.5813	-2.9268	-2.6015
MXNA	-2.5053	0.1142	-3.5813	-2.9268	-2.6015
SPAG	-2.1264	0.2340	-3.5848	-2.9283	-2.6023
SPEN	-2.3107	0.1685	-3.5848	-2.9283	-2.6023
SPPM	-2.7541	0.0651	-3.5813	-2.9268	-2.6015
EUAF	-1.7501	0.4055	-3.5813	-2.9268	-2.6015

Table 19. Stationarity Test Results

All p-values are greater than 0.05, which means that at the 5% significance level, we cannot reject the null hypothesis that the series is not stationary, and the ADF statistic is not less than the corresponding critical value at any significance level.

3) First-order differences

Therefore, these series need further difference processing to achieve stationarity. Thus, we apply first-order differences to each column in the dataset and then check stationarity again:

Stationarity Test After Differencing	ADF Statistic	p-value	1% Critical Value	5% Critical Value	10% Critical Value
CORC	-8.7423	2.99E-14	-3.5886	-2.9299	-2.6032
OMXG	-4.8339	4.68E-05	-3.5886	-2.9299	-2.6032
MXAP	-4.4956	0.0002	-3.5848	-2.9283	-2.6023
MXEU	-5.2031	8.66E-06	-3.5848	-2.9283	-2.6023
MXNA	-5.4564	2.58E-06	-3.5848	-2.9283	-2.6023
SPAG	-4.7682	6.25E-05	-3.5848	-2.9283	-2.6023
SPEN	-5.4967	2.12E-06	-3.5848	-2.9283	-2.6023
SPPM	-5.6466	1.01E-06	-3.5848	-2.9283	-2.6023
EUAF	-6.9431	1.01E-09	-3.5848	-2.9283	-2.6023

Table 20. First-Order Differences

All p values are less than 0.05, indicating that at the 5% significance level, we can reject the null hypothesis that the series is stationary.

4) Multicollinearity test

In addition, we also need to perform a multicollinearity test (Variance Inflation Factor, VIF) to assess the degree of correlation between independent variables. Multicollinearity refers to the situation where two or more independent variables are highly correlated, which will lead to unstable regression coefficients in the regression model and reduce the explanatory power of the model (Hoerl, A.E. and Kennard, R.W. , 1970).

Variable	CORC	OMXG	MXAP	MXEU	MXNA	SPAG	SPEN	SPPM	EUAF
VIF Before									
Differencing	35.61595	1571.744	1616.297	2962.975	3070.154	326.4696	196.6809	357.9563	151.2972
VIF After									
Differencing	1.145294	5.610269	3.452025	5.065091	6.704324	1.545159	1.31471	1.546492	1.273128

Table 21. Variance Inflation Factor before and after differencing

In the original data, the VIF values of all variables are very high, especially the VIF values of MXEU and MXNA are close to and exceed 3000 respectively, which indicates that there is a very high interdependence between the variables. After differentiation, the VIF values of all variables are significantly reduced, and all values are less than 10.

3.2 Methodology

1) Vector Autoregression (VAR) model

The Vector Autoregression (VAR) model is an extension of the univariate autoregression (AR) model and is used to analyse the relationship between multiple variables. In the VAR model, all major economic variables are considered endogenous variables. And the lagged values (i.e., the values at previous time points) of all endogenous variables are used to establish the equation. The VAR model was first proposed by Christopher A. Sims in 1980, who suggested that this model could be used for forecasting, evaluating economic models, and assessing the impact of different policies. After years of research and development, the VAR model has become a very important model in time series models. Many researchers have also developed VAR-GARCH models based on the VAR model (Ling and McAleer, 2003). Many researchers have also used VAR-based models to study the carbon market (P. Gargallo, L. Lample et al., 2021; S. Zeng, J. Jia et al., 2021).

The basic mathematical expression of the var model is as follow:

$$R_t = C + A_1 R_{t-1} + A_2 R_{t-2} + \dots + A_k R_{t-k} + e_t \quad (1)$$

$$e_t | I_{t-1} \sim N(0, H_t) \quad (2)$$

In the formula (1), R_t represents a vector of variables at time t ; C representing the intercept term in the model; from A_1 to A_k are coefficient matrices associated with each lag; from R_{t-1} to R_{t-k} are measuring the influence of the variable's own values from the past k

periods ; e_t is the residual at time t. In the formula (2), the same as the formula (1), e_t is the residual at time t ; I_{t-1} means the market information available at the time t-1.

2) BEKK-GARCH model

Engle and Kroner (1995) proposed the BEKK(p,q)-GARCH model, The BEKK-GARCH (Baba, Engle, Kraft, and Kroner - Generalized Autoregressive Conditional Heteroskedasticity) model is a multivariate extension of the univariate GARCH model. It is specifically designed to capture the dynamic relationships between the variances and covariances of multiple time series. Y. Chen, B. Zheng et al. (2020) emphasized that it can ensure that the variance-covariance matrix is always positive without any restrictions on the parameters, which helps to reduce the number of estimated parameters and makes estimation more convenient.

The basic mathematical expression of the var model is as follow:

$$e_{i,t} = v_{i,t}h_{i,t}, v_{i,t} \sim N(0,1) \quad (1)$$

$$h_{i,t} = c_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{i,t-1} \quad (2)$$

$$H_t = C^T C + A^T e_{t-1} e_{t-1}^T A + B^T H_{t-1} B \quad (3)$$

In the formula (1), $e_{i,t}$ represents the residual of i at time t ; $v_{i,t}$ means a standard normally distributed random variable ; $h_{i,t}$ is the volatility of i at time t. In the formula (2), c_i is a constant term ; α_i represents the coefficient of the previous residual square term ; β_i is the coefficient representing the lagged volatility term. The formula (3) demonstrates the interrelationships between multiple assets, the matrixes for the 9 different markets' inputs of Data is as follow:

$$H_t = \begin{pmatrix} h_{11,t} & h_{12,t} & h_{13,t} & \cdots & h_{19,t} \\ h_{21,t} & h_{22,t} & h_{23,t} & \cdots & h_{29,t} \\ h_{31,t} & h_{32,t} & h_{33,t} & \cdots & h_{39,t} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_{91,t} & h_{92,t} & h_{93,t} & \cdots & h_{99,t} \end{pmatrix}$$

$$C = \begin{pmatrix} c_{11} & 0 & 0 & \cdots & 0 \\ c_{21} & c_{22} & 0 & \cdots & 0 \\ c_{31} & c_{32} & c_{33} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ c_{91} & c_{92} & c_{93} & \cdots & c_{99} \end{pmatrix}$$

$$A = \begin{pmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{19} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{29} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{39} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{91} & a_{92} & a_{93} & \cdots & a_{99} \end{pmatrix}$$

$$B = \begin{pmatrix} b_{11} & b_{12} & b_{13} & \cdots & b_{19} \\ b_{21} & b_{22} & b_{23} & \cdots & b_{29} \\ b_{31} & b_{32} & b_{33} & \cdots & b_{39} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{91} & b_{92} & b_{93} & \cdots & b_{99} \end{pmatrix}$$

The matrix H is a variance-covariance matrix. The diagonal elements represent the conditional variance of each market (i.e., the volatility of the market itself). The off-diagonal elements ($h_{ij(\neq j)}$) represent the conditional covariance between market i and market j, reflecting the volatility transmission effect between markets. The diagonal lines represent the volatility of each of the nine markets. The C matrix is a lower triangular matrix that represents the constant terms of the model. The ARCH coefficient matrix A represents the conditional volatility transmission effect between market i and market j. The diagonal elements represent the ARCH effect of market i (the impact of the market's own volatility on itself); the off-diagonal elements represent the volatility transmission effect between market i and market j. The GARCH coefficient matrix B represents the conditional volatility persistence between market i and market j. The diagonal elements represent the persistence of market i's own volatility (GARCH effect), while the off-diagonal elements represent the spillover effect of market i's volatility on market j.

3) Impulse Response Function (IRF)

The covariance matrix of the random shock term V is Σ , let $E(v_t v_t') = \Sigma_v$, so that the shocks are simultaneously correlated. The core of the formula is to use the covariance matrix to capture the correlation between variables while standardizing to unit shock for easy understanding. This formula is particularly suitable for multivariate time series where shock terms are correlated. The generalized impulse response function of X_i to a unit (one standard deviation) shock in X_j is:

$$\psi_{ij,h} = (\sigma_{ii})^{-1/2} (e_j' \sum_v e_i)$$

where σ_{ii} is the i th diagonal element of Σ_v , e_i is a selection vector with the i th element equal to one and all other elements equal to zero, and h is the horizon (B. Ewing, J. Kruse et al., 2007).

4. Empirical results and analysis

The market correlation matrix reveals the interconnectedness between different markets, with its elements representing the strength of these relationships. Positive values indicate positive correlations, while negative values signify negative correlations. The correlation between the Negative Carbon Credit market (CORC) and OMXG (NASDAQ OMX Green Economy Index), MXAP (Asia-Pacific stock market), MXEU (European stock market), and MXNA (North

American stock market) is negative or close to zero (e.g., -0.222279 and -0.059559). This suggests that the CORC market has a weak or even inverse relationship with these stock markets, indicating that the fluctuations in the CORC market are not directly driven by stock market dynamics but may instead be influenced by other market factors or internal characteristics.

Results for correlation matrix of residuals:

Correlation matrix of residuals									
	CORC	OMXG	MXAP	MXEU	MXNA	SPAG	SPEN	SPPM	EUAF
CORC	1	-0.222279	-0.041991	-0.095959	-0.011344	-0.479072	-0.277366	-0.001769	-0.107398
OMXG	-0.222279	1	0.79594	0.684977	0.839639	0.041817	0.277886	0.512037	0.30631
MXAP	-0.041991	0.79594	1	0.886249	0.824894	-0.210305	0.27446	0.394827	0.574767
MXEU	-0.095959	0.684977	0.886249	1	0.886551	-0.25524	0.145873	0.494696	0.822208
MXNA	-0.011344	0.839639	0.824894	0.886551	1	-0.187227	0.15014	0.517386	0.604785
SPAG	-0.479072	0.041817	-0.210305	-0.25524	-0.187227	1	0.701327	0.369522	-0.115244
SPEN	-0.277366	0.277886	0.27446	0.145873	0.15014	0.701327	1	0.476831	0.051993
SPPM	-0.001769	0.512037	0.394827	0.494696	0.517386	0.369522	0.476831	1	0.401251
EUAF	-0.107398	0.30631	0.574767	0.822208	0.604785	-0.115244	0.051993	0.401251	1

Table 22. Results For Correlation Matrix Of Residuals

The correlation between CORC and the argiculture market (SPAG) is 0.041817, which is relatively low, showing that the energy market has a limited direct impact on CORC. However, indirect influences, such as cost transmission or policy linkages, may exist. The correlation between CORC and the European Union Allowance Futures market (EUAF) is 0.30631, which is positive and the highest among all markets analyzed, indicating a certain level of linkage between the negative carbon credit market and the EU carbon market. This connection may be driven by similar policy mechanisms or pricing structures. Additionally, the correlation between CORC and the agricultural market (SPAG) is -0.479072, indicating a significant negative correlation, suggesting that their relationship is weak and potentially inverse.

An analysis of the Impulse Response Function (IRF) results shows that a shock from the energy market (SPEN) generates a significant negative spillover effect on CORC in the 2nd and 3rd periods following the shock. The response curve deviates negatively from zero and exceeds the confidence interval, indicating that price fluctuations in the energy market suppress the performance of the negative carbon credit market in the short term. Conversely, a shock from the EUAF market on CORC results in a significant positive spillover effect during the initial periods, as evidenced by the response curve positively deviating from zero. Furthermore, the spillover effect from EUAF to CORC is relatively symmetric, with positive and negative shocks exhibiting similar magnitudes and durations, suggesting that the EU carbon market has a stable and balanced impact on CORC. In contrast, most other markets, such as OMXG (Green Economy Index), MXAP, and MXEU, show no significant spillover effects on CORC, possibly indicating weak connections or a lack of effective volatility transmission between these markets and the CORC market.

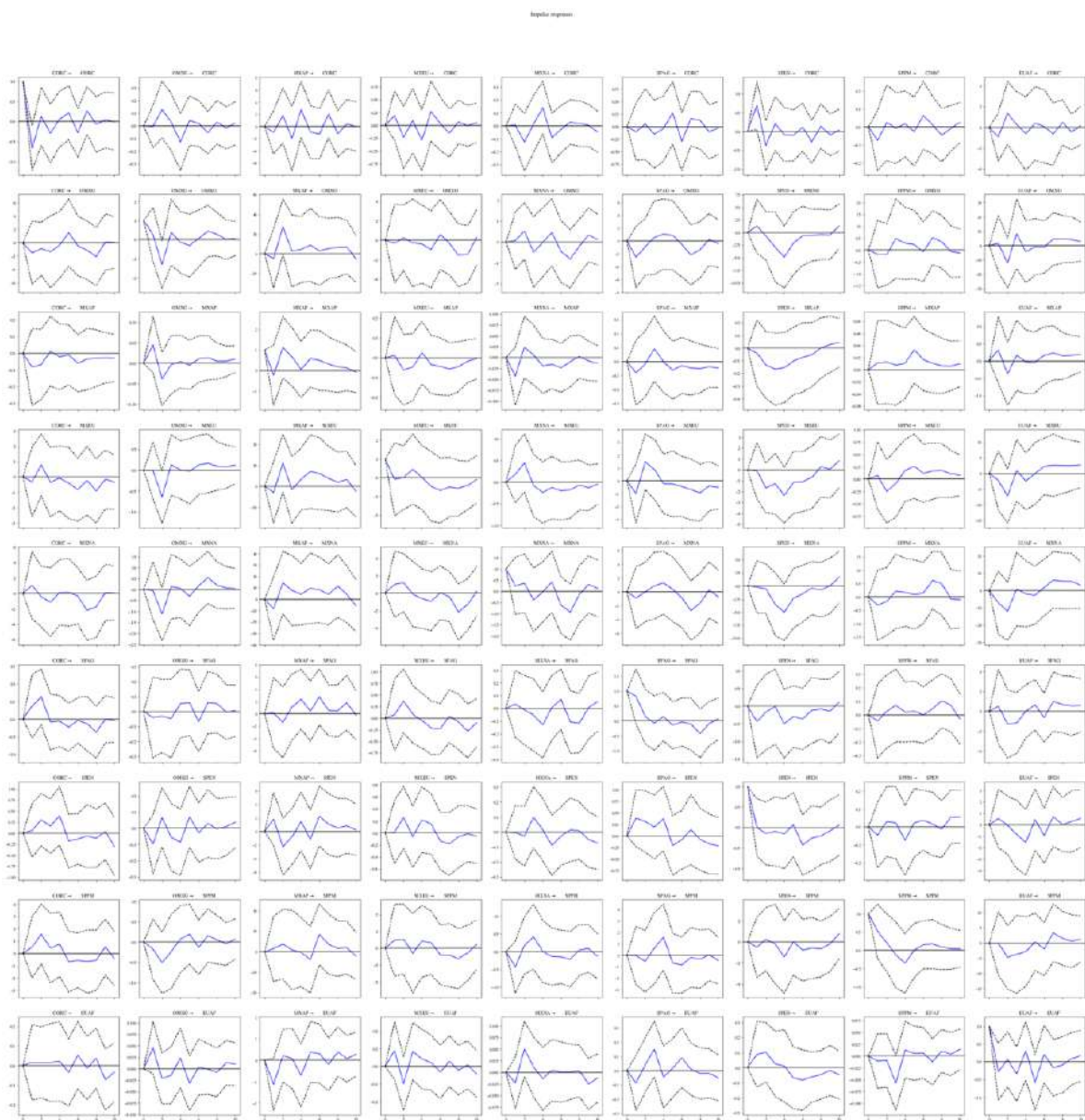


Figure 24: Results of Impulse Response Function (IRF)

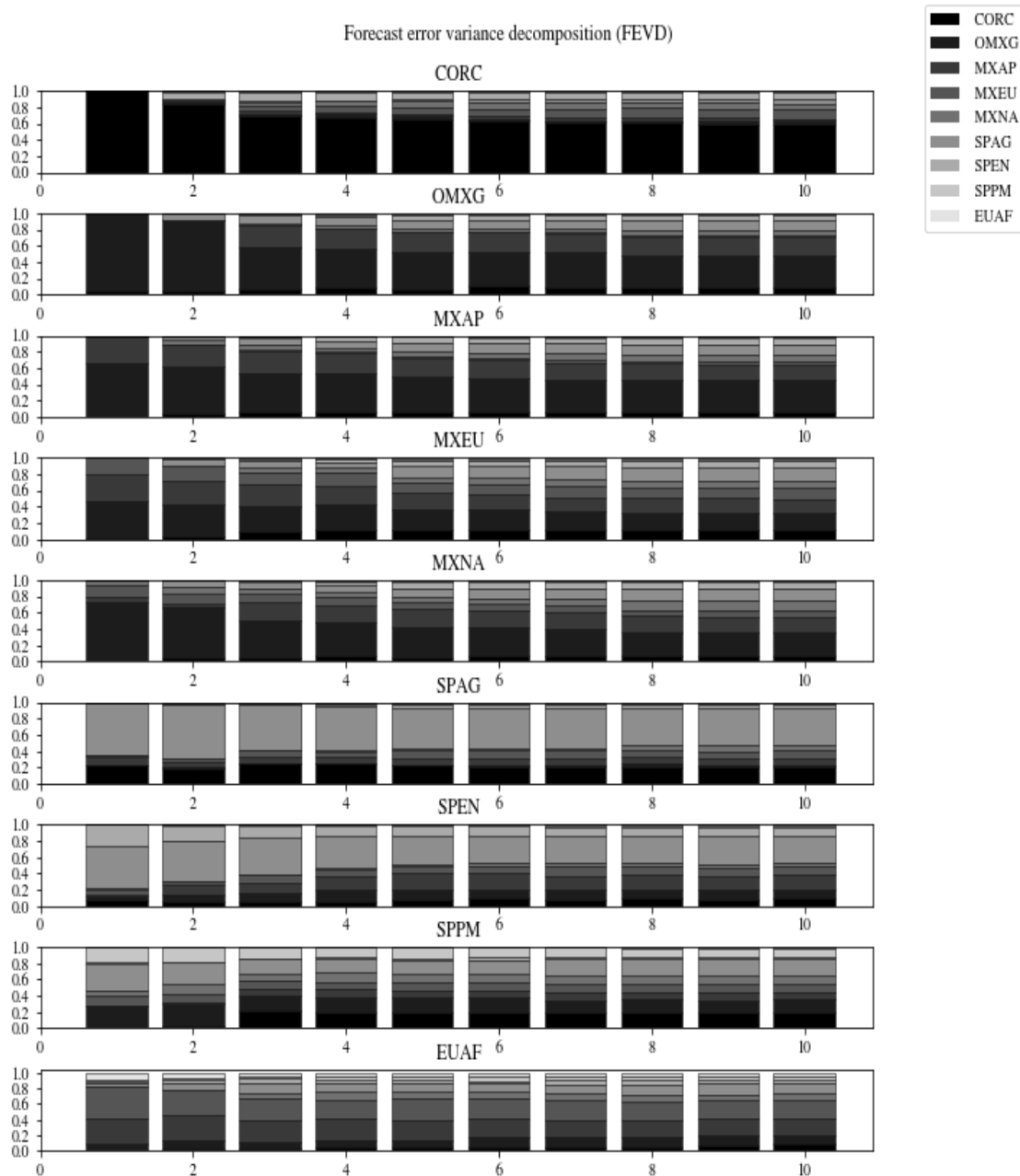


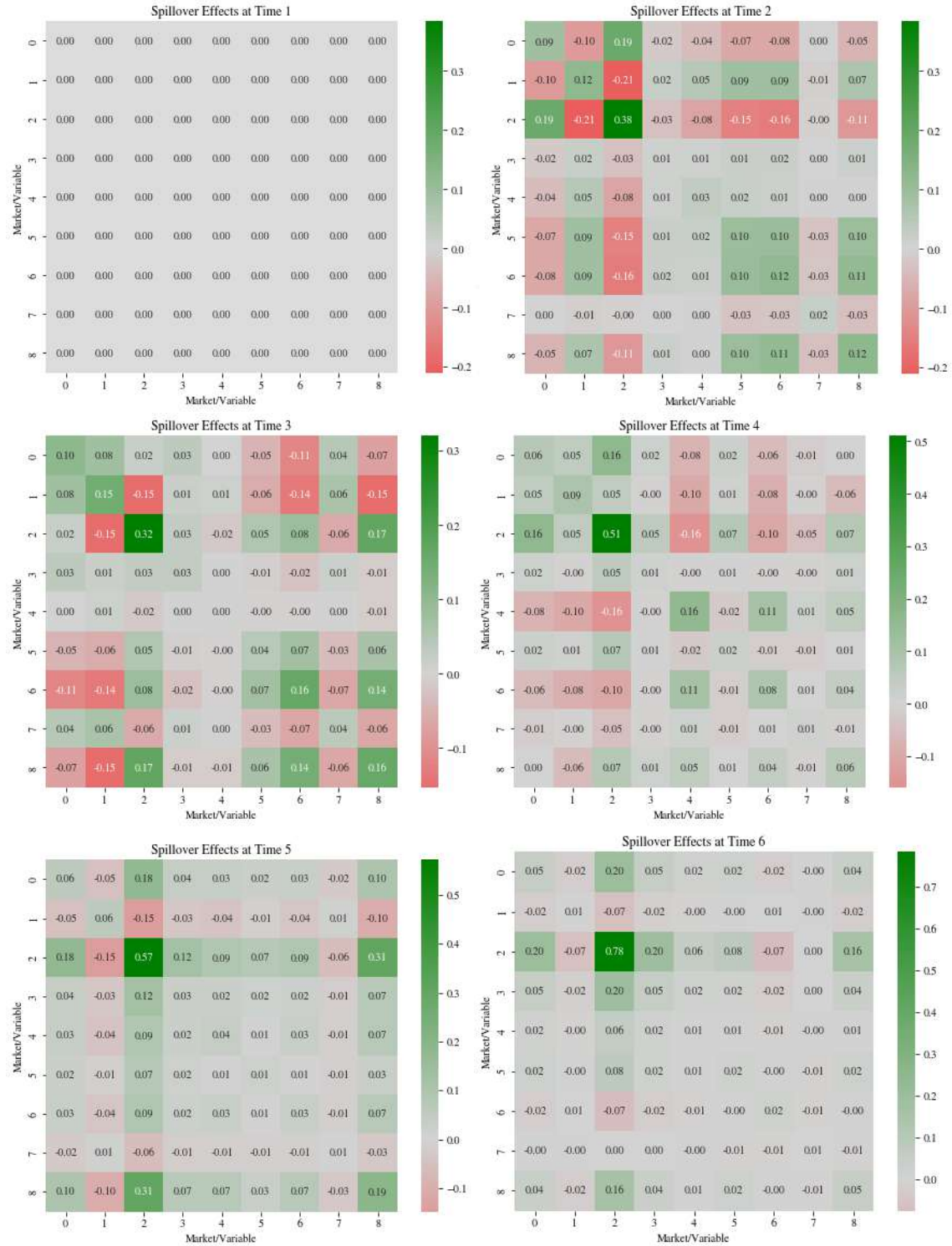
Figure 25: Results of FEVD

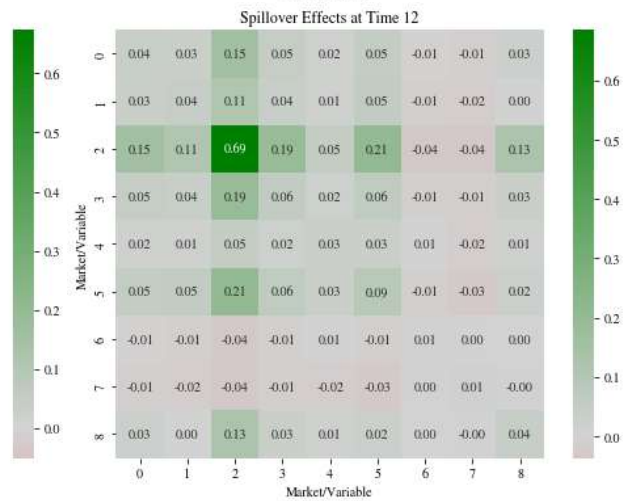
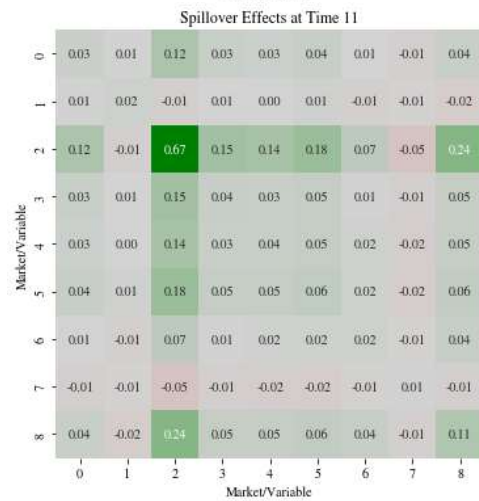
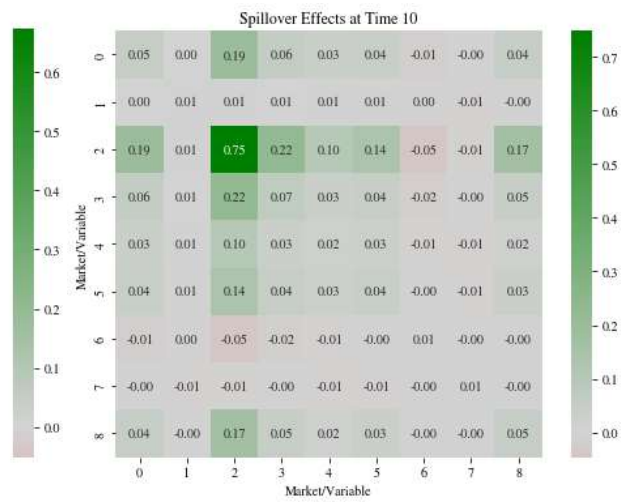
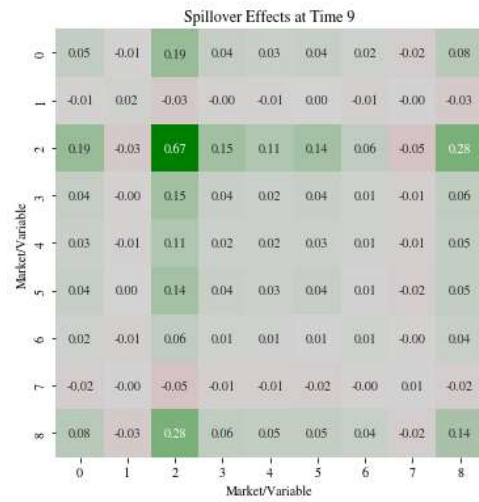
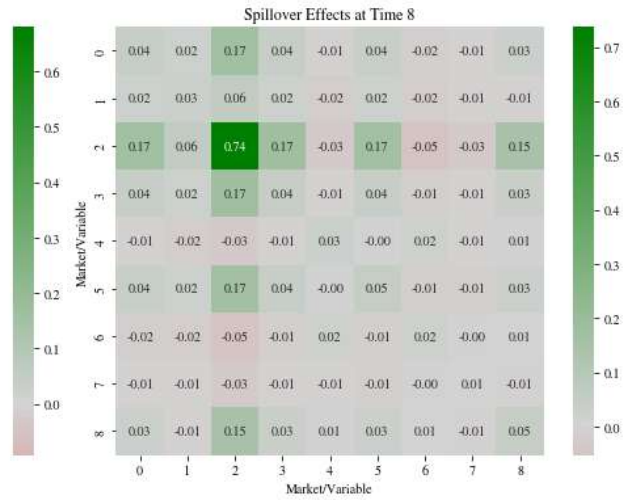
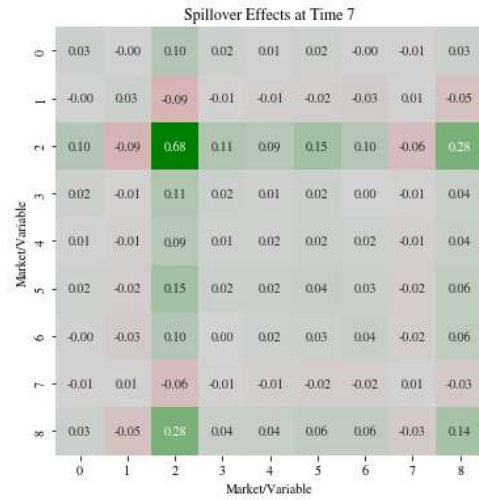
The FEVD results highlight the unique dynamics of the Negative Carbon Credit market (CORC) in relation to other markets. CORC's volatility is predominantly self-driven, with approximately 85%-90% of its forecast error variance being attributed to its own movements even over longer forecast horizons. This suggests that CORC operates with a high degree of independence, with limited direct influence from external markets. However, a notable exception is its relationship with the European Union Allowance Futures market (EUAF). Over time, EUAF contributes up to 10% to the variance in CORC, reflecting an emerging linkage likely driven by shared regulatory frameworks and pricing mechanisms in carbon markets. This relationship indicates that policy changes or price shocks in the EU carbon market may increasingly shape the dynamics of the

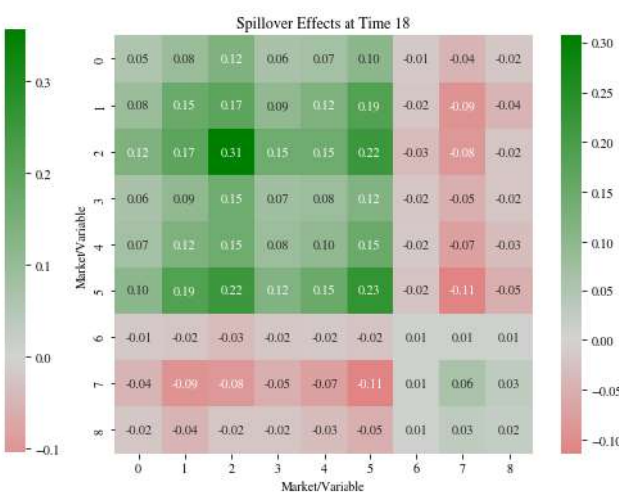
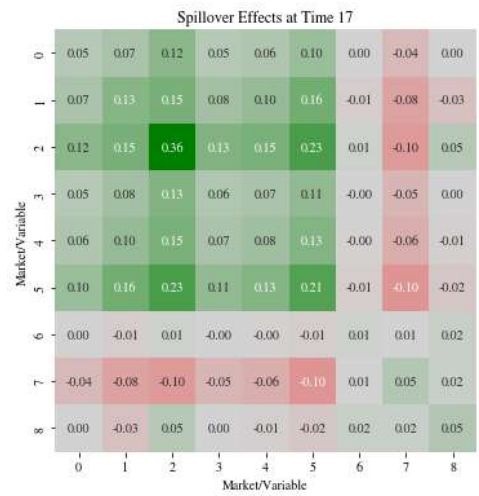
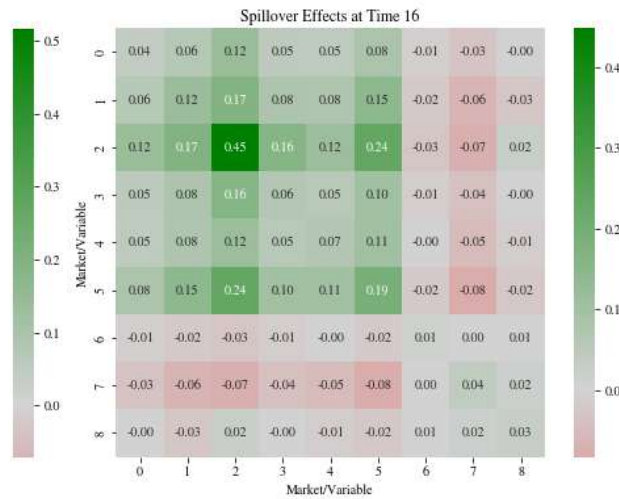
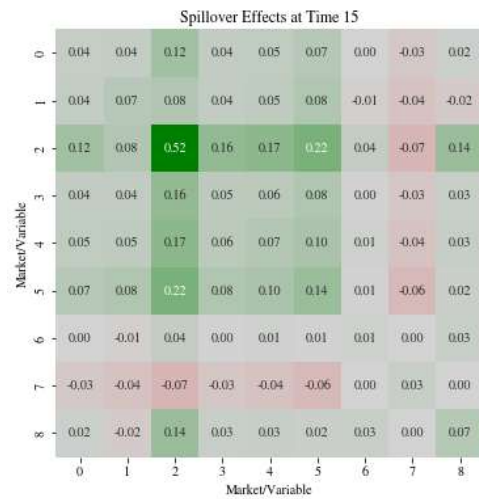
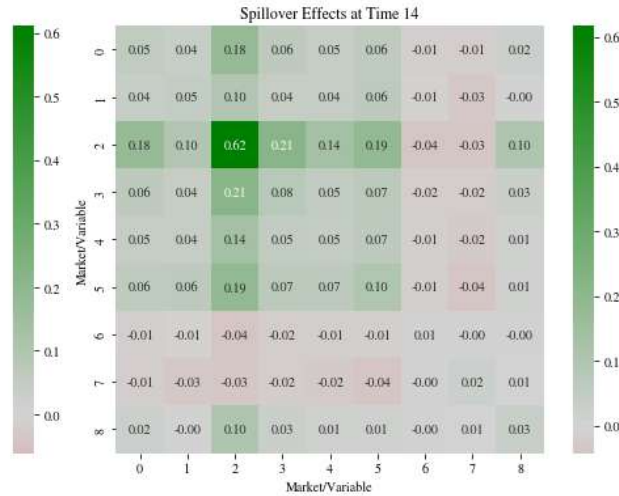
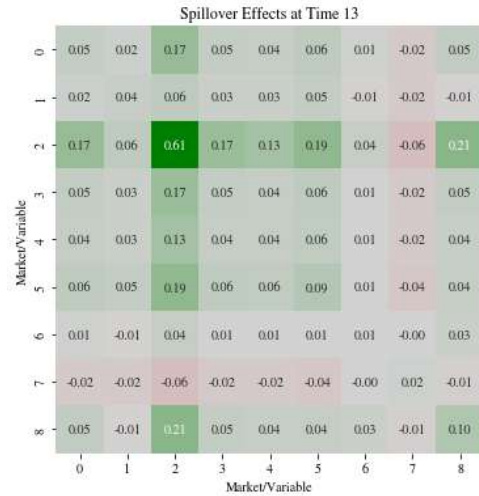
CORC market. Conversely, CORC exhibits a limited response to other markets, such as the energy market (SPEN) and stock markets (OMXG, MXAP, MXEU, MXNA). The influence of SPEN on CORC remains minimal, with negligible contributions even in longer time horizons, suggesting that energy price volatility does not directly spill over into the CORC market. Similarly, traditional stock markets show no significant explanatory power for CORC's variance, indicating a lack of integration between carbon credits and general equity market movements.

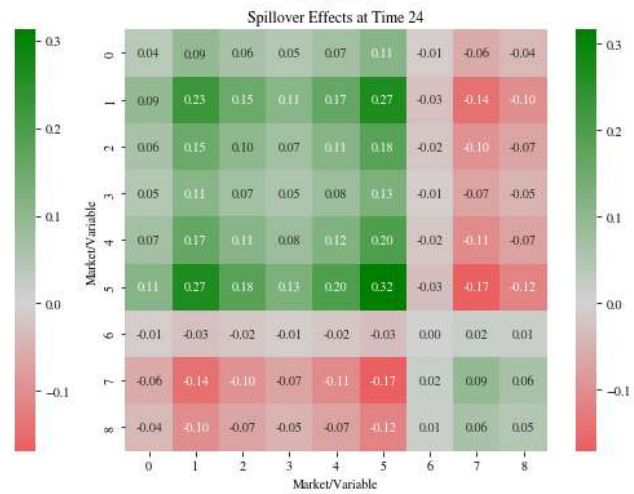
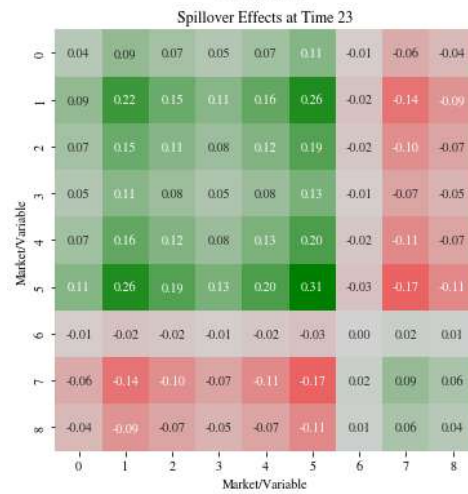
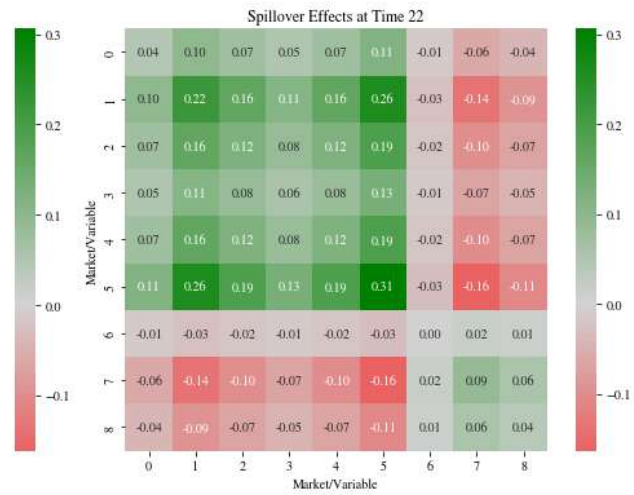
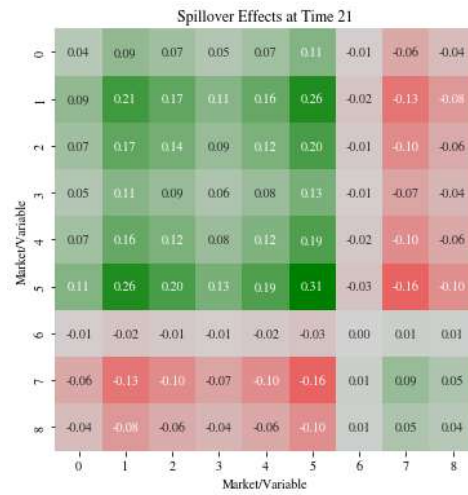
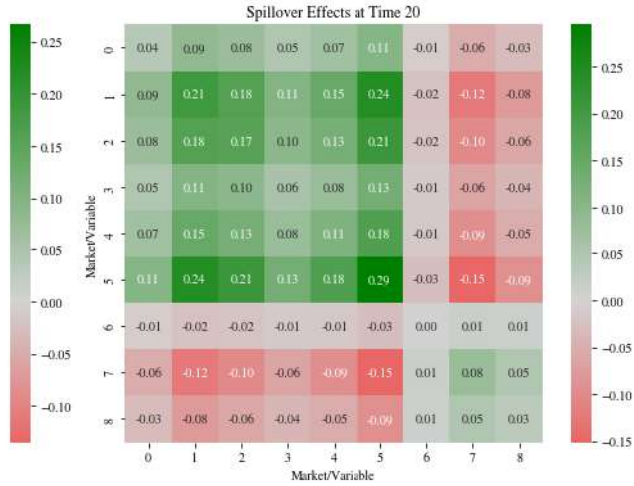
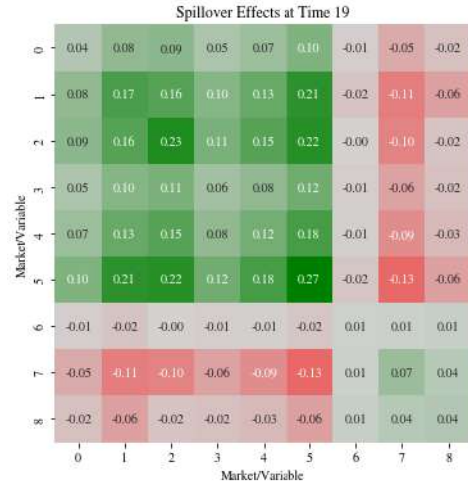
The spillover analysis reveals key dynamics between the Negative Carbon Credit market (CORC) and other markets over time. The results indicate that CORC's volatility is predominantly influenced by the European Union Allowance Futures market (EUAF) and, to a lesser extent, by the energy market (SPEN), while its interaction with other markets, including stock markets, remains negligible. Specifically, EUAF exhibits a consistently significant positive spillover effect on CORC, particularly at Time 2 and Time 4, suggesting that the EU carbon market plays a crucial role in shaping CORC dynamics through shared regulatory mechanisms and aligned price movements. Conversely, SPEN demonstrates a negative spillover effect on CORC, with its influence peaking at Time 4 and Time 5, reflecting the suppressive impact of energy price fluctuations on the negative carbon credit market. On the other hand, CORC also acts as a spillover transmitter, particularly affecting EUAF and OMXG (NASDAQ Green Economy Index). CORC exerts a positive spillover on EUAF during Time 4 and Time 6, indicating a bidirectional relationship between these two carbon markets, possibly driven by investor sentiment and interconnected policy changes. However, CORC's spillover to OMXG is negative at Time 3 and Time 5, highlighting that volatility in the negative carbon credit market may dampen investment dynamics in the green economy index. Across the analyzed time periods, CORC remains relatively insulated from traditional stock markets (MXAP, MXEU, MXNA), further underscoring its specialized and independent nature within the broader market system.

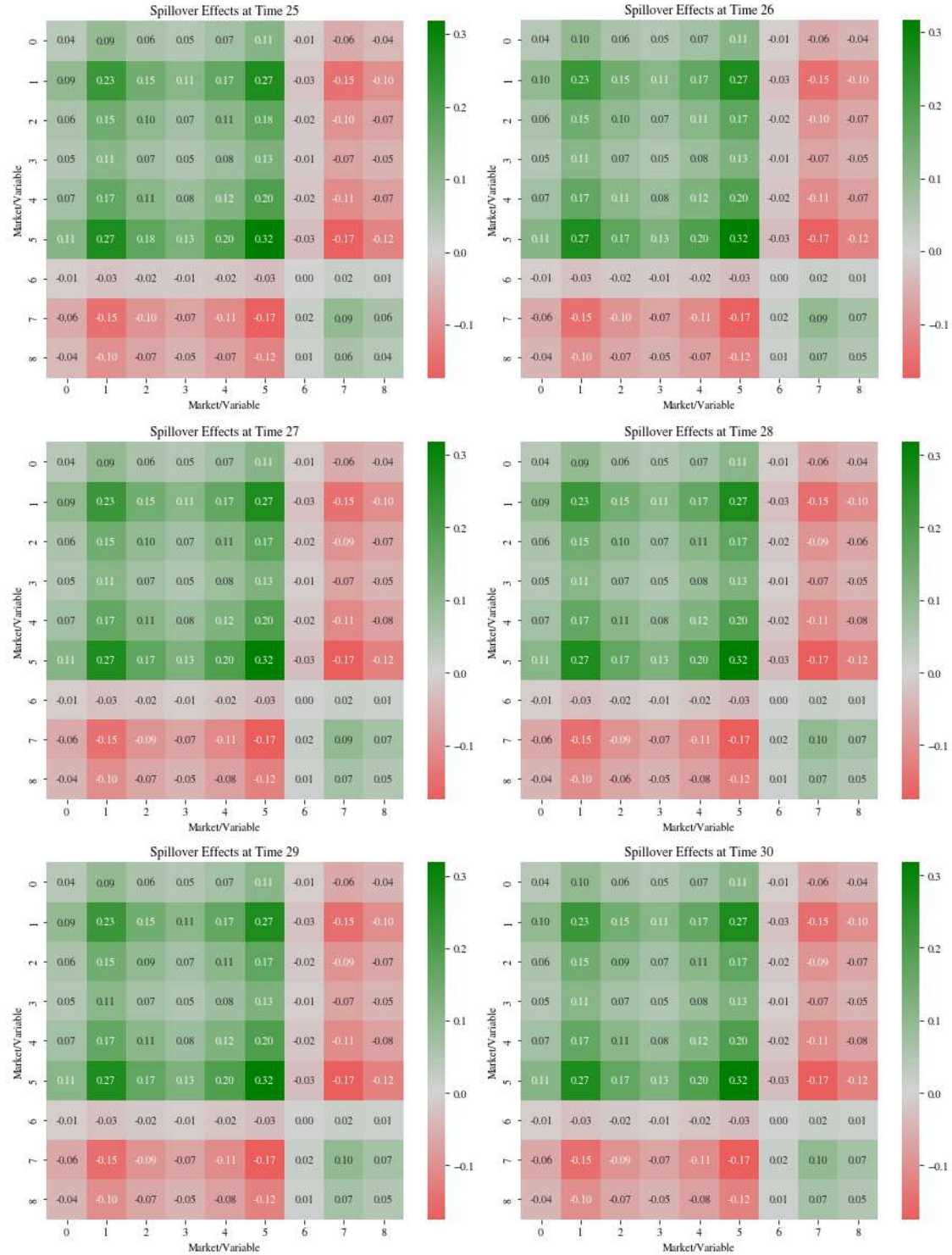
The results show that the CORC market is highly independent, which is in contrast to previous research on the EUA. For example, X. Tan, K. Sirichand et al. (2020) found significant co-movement between the EUA and energy and financial markets. This difference may be due to the stage characteristics of the CORC market as an emerging market. The negative spillover effect of the energy market (SPEN) on CORCs is in stark contrast to the positive correlation between the energy market and the EUA market found in previous studies (e.g. Gronwald et al., 2011). This difference may reflect the structural differences in the CORC market in the face of energy price signals, which may be related to its focus on carbon removal rather than emission quota trading.

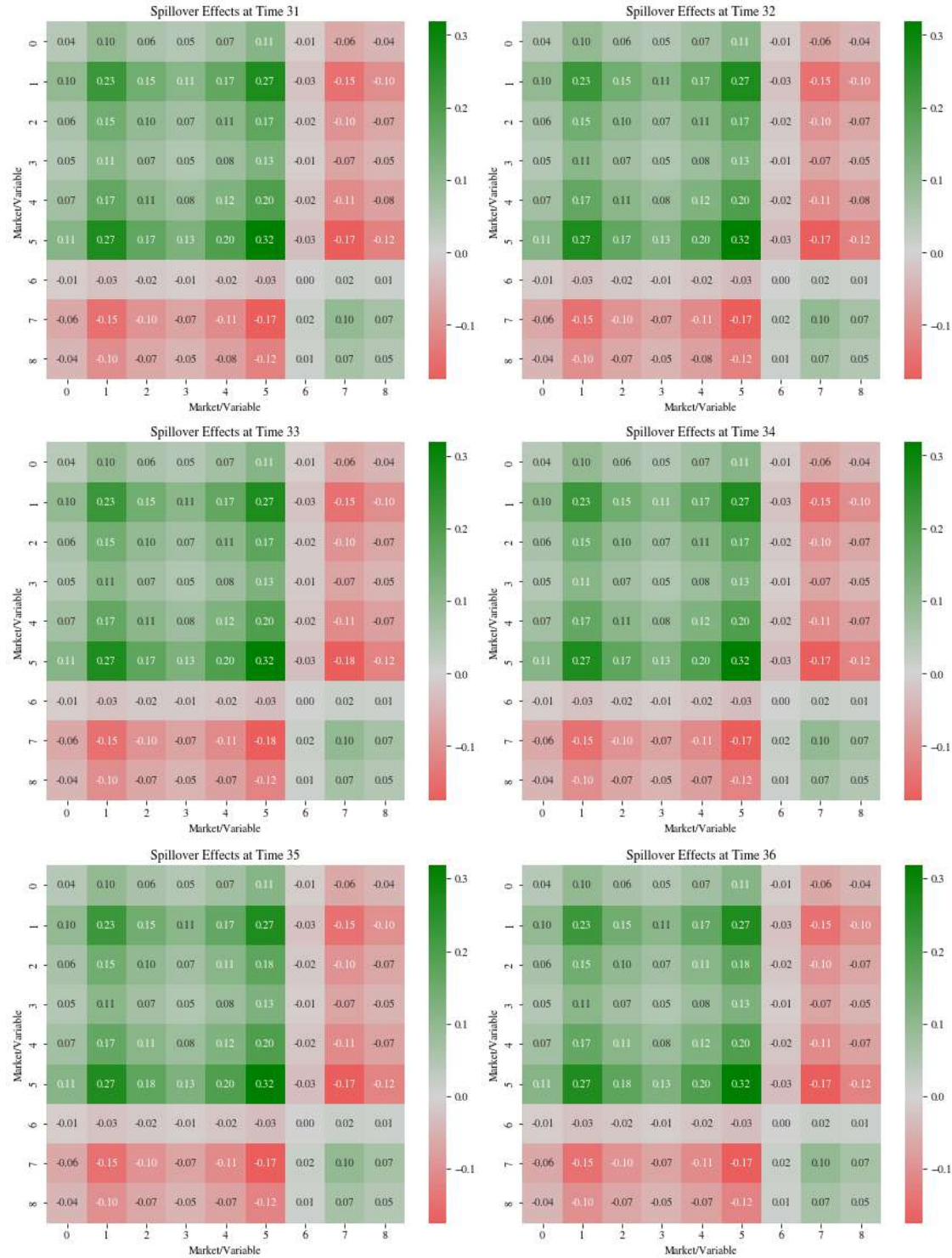


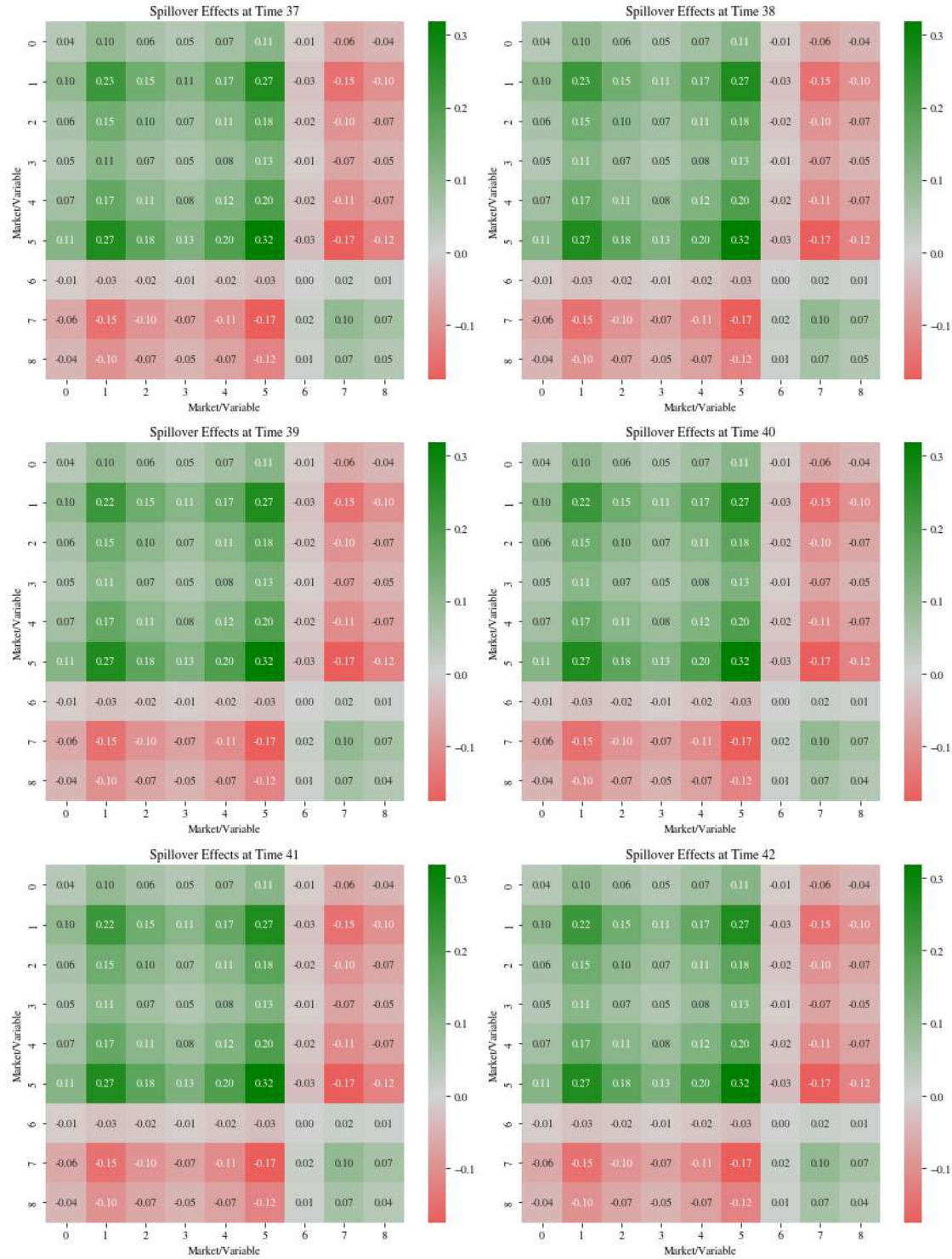












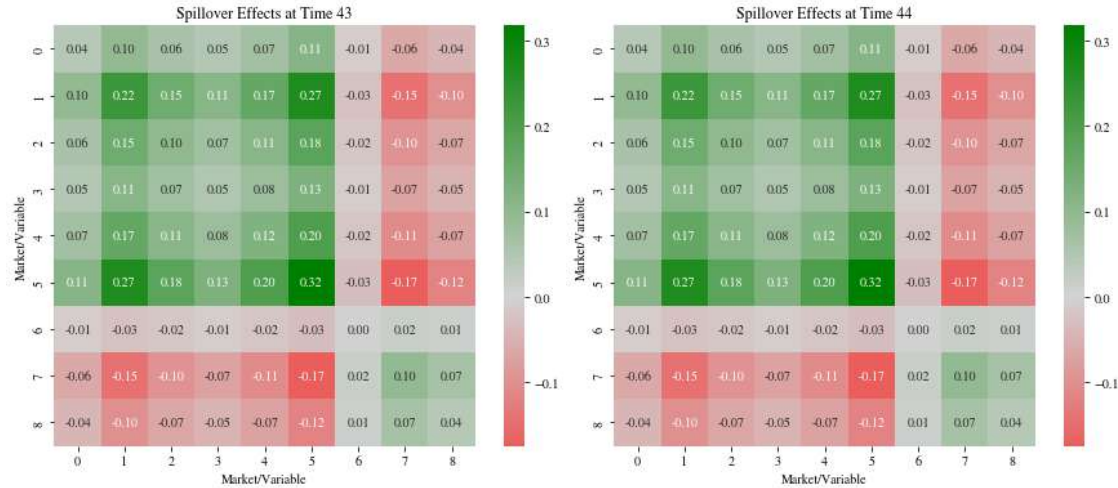


Figure 26: Results of BEKK-GARCH

CORC has the most significant positive spillover effect on the Asia-Pacific stock market (MXAP). In Time 2–6 and Time 8–9, its spillover values are as high as 0.18–0.20, the highest among all markets, but the overall trend has slightly decreased over time. This shows that there is a strong linkage between the volatility of carbon-negative credit prices and the capital markets in the Asia-Pacific region, which may be driven by the rapid development of green policies in the region or investors' increasing attention to ESG tools, such as China's "carbon peak and carbon neutrality" policy goals. In contrast, the spillover effect of European stock markets (MXEU) and North American stock markets (MXNA) with CORC is relatively weak, with average values of 0.045 and 0.050, respectively, and a maximum value of no more than 0.07.

In the commodity market, the coupling between agricultural products (SPAG) and carbon-negative credits is the most obvious, with an average spillover effect of 0.079, a maximum value of 0.11, and an upward trend, indicating that the relationship between land use, carbon sink value and agricultural product fluctuations is becoming increasingly close. The energy market (SPEN) experienced a strong negative shock (-0.11) at some time points (such as Time 3), but the overall trend was not significant, and the system linkage with the energy market was still unstable. The precious metals market (SPPM) has the weakest linkage with CORC among all markets, with an average spillover value of -0.040, which is on a downward trend. This reflects the essential differences between the two in terms of financial structure and market participant composition.

The spillover relationship between CORC and the EU carbon market (EUAF) shows structural fluctuations and a downward trend. Although there is a significant positive spillover (maximum value 0.10) in the medium term (Time 5–9). This shows that the interaction between the two carbon markets is moving towards decoupling, which may reflect the fundamental differences in policy logic, participating entities and credit types between voluntary markets (such as CORC) and compliant markets (such as EU ETS).

In terms of the green finance sector, the spillover effect of CORC on OMXG (Green Economy Index) shows a change process from negative to positive. It was -0.10 at Time 2, and rose to +0.10 at Time 10, showing an upward trend. This shows that as green industry investment tools become

increasingly diversified, carbon negative credit price fluctuations are gradually accepted by the market and internalized as the risk premium of green financial assets.

5. Conclusion

The analysis of the Negative Carbon Credit market (CORC) reveals its distinctive behavior and interactions with other markets. CORC demonstrates a high degree of independence, with its volatility primarily self-driven and minimally influenced by external markets such as energy and stock markets. Notably, its correlation with the European Union Allowance Futures market (EUAF) is the strongest among all analyzed markets, reflecting a growing linkage likely shaped by shared regulatory frameworks and aligned pricing structures. EUAF consistently exhibits a positive spillover effect on CORC, with a stable and symmetric impact, emphasizing the central role of the EU carbon market in shaping CORC dynamics. Conversely, the energy market (SPEN) has a limited direct impact on CORC, although short-term shocks from SPEN exert a suppressive effect on CORC's performance. The agricultural market (SPAG) shows a negative correlation with CORC, indicating a weak and potentially inverse relationship, while traditional stock markets (OMXG, MXAP, MXEU, MXNA) exhibit negligible correlations and spillover effects, underscoring a lack of integration between carbon credits and general equity markets.

Moreover, the spillover analysis reveals bidirectional relationships, particularly between CORC and EUAF, where CORC transmits positive spillovers to EUAF during specific time periods, possibly driven by investor sentiment and interconnected policy changes. CORC also exerts a negative spillover on OMXG, highlighting its potential to dampen investment dynamics within the green economy index. Across all analyzed periods, CORC's interactions with other markets remain limited, further emphasizing its specialized and independent role within the broader financial and environmental market systems. These findings underscore the importance of regulatory and market mechanisms in driving CORC's dynamics and highlight the emerging interconnections within global carbon markets. Unlike traditional carbon markets such as the EUAF, the relative independence of the CORC market suggests that it may serve as an independent carbon management tool. This finding is consistent with the policy goal of promoting carbon reduction through diversified tools proposed by Verde et al. (2021).

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