European Carbon Market Connectedness and Risk Contagion: A Study of Return and Volatility Dynamics Between European Union Allowances (EUAs) and Financial Markets post-Fit for 55 and RePowerEU

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Abstract

This paper uses Diebold-Yilmaz model to analyze the return and volatility connectedness between the European carbon market and the financial markets from the commencement of the 3rd phase of the EU emissions trading system in 2013 to August 2024 in order to ascertain the impact of both exogenous shocks and the recent reforms introduced under the Fit for 55 package and RePowerEU Plan. We examine the static and dynamic characteristics of the connectedness network and find that the return and volatility behavior of the European carbon market are primarily driven by their own fundamental factors, thus largely independent of other financial markets, except for coal and natural gas, and except during periods of financial stress where a relatively short-lived increase in the connectedness with other financial markets is observed.

Keywords: Carbon markets, emissions trading system, connectedness measures, system risk

1. Introduction

In the late 19th century the Swedish scientist Svante Arrhenius discovered[1] the link between increases in carbon dioxide (CO2) concentrations in the atmosphere, fossil fuel burning, and the greenhouse effect (**???**). A century and a quarter later, in 2022, emissions worldwide have been recorded at 57.4 gigatons of carbon dioxide equivalent (GtCO2e), with the energy sector accounting for a little over third of these at 20.9 GtCO2e and industry another quarter at 14.4GtCO2e (**?**).

As one of the top polluters (**?**), the European Union (EU) has established an ambitious climate objective of 55% reduction in greenhouse gas emissions (GHGs) by 2030 from the 1990 levels (**?**, Art 4(1)). To ensure the feasibility of this objective, the European Commission (EC) has adopted a comprehensive suite of legislative changes under Fit for 55 package within a broader sustainable growth strategy under the European Green Deal (**?**).

In parallel to its decarbonization efforts, the EU also launched RePowerEU Plan in 2022, a strategic response to the energy crisis triggered by Russia's invasion of Ukraine in that year (**?**). This plan aims to reduce the EU's dependency on Russian fossil fuels by significantly accelerating the transition to renewable energy sources, enhancing energy efficiency, and diversifying the EU's energy supply chains (**?**, 1-5).

Under Fit for 55, the EC has proposed a set of reforms to the EU emissions trading system (EU ETS) which have duly been adopted by the European Commission in May 2023 (**?**). The EU ETS itself is one of the central instruments of the EU in its decarbonization and energy transition efforts (**??**), and it currently covers about 40% of the EU's GHG emissions[2] (**?**). Under this mechanism a European Emission Allowance (EUA) is a permit granting the right to emit one ton of CO2 which can then be traded (**?**).

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[1]Building on the works of Joseph Fourier and John Tyndall roughly half a century earlier (**?**)

[2]The coverage will likely increase after the reforms are transposed into national laws of member states by 30 June 2024 (**?**)

The EU ETS has evolved over four phases. The first phase, covering the period from 2005 to 2007, has essentially established the market mechanism underpinning the EU ETS (**?**, Art. 11(1)). The second phase, covering the five-year period from 1st of January 2008, has imposed a more stringent cap on the Union-wide total EUAs but the mechanism still ended up with surplus of allowances largely due to the 2008 recession (**??**). With the commencement of the third phase on 1 January 2013, there has been a shift from national allocation plans[3] to an EU-wide cap in the total number of allowances[4] (**?**, Art. 1). The fourth and current phase that started in 2021, and will continue until 2030, has further reduced the EU-wide allowance cap with more stringent rules for free allocation[5] (**?**). In parallel, the Fit for 55 package has, among other initiatives, extended the scope of the ETS to include emissions from shipping and has accelerated the reduction of both the free allocations and the total allowances within Phase IV[6] (**?**).

The effectiveness of the EU ETS in decarbonizing and facilitating the energy transition depends on several factors (**????**). Among these factors, the price of EUAs plays a critical role (**???**). Higher EUA prices have the potential to drive significant transformations across multiple sectors, encouraging firms to innovate and reduce emissions (**??**). Such realization of higher EUA prices can be aided by increased participation of financial institutions which can promote liquidity, price discovery, transparency, and improved market efficiency (**??**). This in turn depends, among other factors, on the price volatility which can raise uncertainty and restrain investment into carbon-reducing technologies (**??**).

This study, therefore, analyzes, via return and volatility connectedness, the degree of integration of EUAs with other asset classes to assess potential diversification benefits EUAs may offer. If present, such diversification benefits can consequently incentivize increased participation by financial institutions and help the EU's efforts in decarbonization and transitioning into renewables. Accordingly, this study contributes to the literature on energy and sustainable finance as well as on risk management in three complementary ways. First, carbon is treated as an independent asset class whereas previous works largely examine the issue within an energy context. To the best of our knowledge, this is the first time it is treated as such while incorporating the changes emerging from the Fit for 55 package and RePowerEU. Within this context, this study considers return and volatility spillovers within a broader range of markets, ranging from fixed income and European and US equities to commodities. Second, while the existing literature largely considers Phase III of EU ETS, this study also incorporates Phase IV providing a more comprehensive analysis of the recent changes. Third, market stress periods – such as Covid-19 and the Russian-Ukrainian War – are uniquely considered in analyzing the changes in EU ETS connectedness and its integration with other asset classes over time.

Three key results emerge from this study. First, we find that EUAs show stronger connection with other financial markets mainly during periods of financial crises. However, aside from connectedness with coal and natural gas markets, these connections tend to be short-lived, and EUAs generally remain independent. Second, our results indicate that the European carbon market tend to be a net receiver of return and volatility spillovers, suggesting that external factors influence this market more than carbon-specific factors influence other markets. Third, it appears that to date the reforms introduced by the Fit for 55 package, RePowerEU, and Phase IV may not have exerted as strong an impact as market stresses, although it seems that their impact may have a longer duration.

The rest of the paper is as follows. The next section provides a literature review of the related studies. Section 3 specifies the methodology and Section 4 describes the data. Section 5 presents the main empirical findings and discussion, and Section 6 provides our concluding remarks and implications.

[3]During the phases I and II of the EU emissions trading system (EU-ETS), each EU country decided on the allocation of their emission allowances. (**?**, Art. 11)

[4]The total number of annual allowances also decrease by a linear factor of 1.74 percent. To address the surplus allowances that have been accumulating since Phase II, a new market stability reserve (MSR) has additionally been introduced that acts as a repository for excess portions of auctionable allowances and replenishes the market if allowances in circulation are fewer than 400 million (**??**)

[5]It also increased the annual reduction factor to 2.2 percent and earmarked a portion of MSR for innovation support.

[6]This was done by increasing the linear reduction factor from 2.2 percent to 4.2 percent starting in 2024.

2. Literature Review

Since the EU ETS has come into force, empirical literature on carbon trading mechanisms has mainly focused on its price dynamics, on its impact on the economy, and its relationship with various markets along with its hedging benefits (??).

Ability to accurately forecast carbon prices are important in enabling decisions on emissions and transition tradeoffs (???). To that end, while some have considered the role of attention in carbon pricing (???), some have used value-at-risk-forecasting, ARIMA, GARCH and its modifications including, among others, Markov switching GARCH, fractionality integrated GARCH, switching transition regression exponential GARCH, and AR-GARCH to capture volatility, skewness, and excess kurtosis (??????). Yet others have looked at the impact of policy uncertainties on the volatility of carbon markets (??), and some have used various decomposition and artificial intelligence techniques to improve the forecasting ability (???). What is evident is that it is a challenge to forecast carbon prices since they are nonstationary and show nonlinearity, and it is likely that the information shocks transmit between different markets (????).

Emissions trading can help in reducing the abatement costs and dampen the negative impact of emission reductions on GDP (??), although some of the carbon reduction gains may decline overtime due to macroeconomic carbon rebound effect (?). Its impact on the economy, though, mainly has a sectoral perspective. Within that perspective, the predominant focus is on its strong impact on the energy industry (????????), and, to a lesser extent, on its negligible impact on the aviation, cement, steel, and aluminum sectors (????).

There also appears to be a positive relationship, albeit in varying degrees, between carbon markets on the one hand and equities, oil, natural gas, coal, and electricity prices on the other (?????????). However, with the changes introduced in each of the subsequent phases such impacts became harder to establish (??). Nevertheless, there is likely a stronger relationship between carbon and energy assets compared to financial assets for the duration of Phase II and most of Phase III, which, for a non-energy portfolio, may provide some diversification benefits (???). Moreover, interconnectedness of the carbon with other markets evolves overtime and has increased with financial markets in recent years (???). Concerning the integration of EUAs into portfolios, it seems to be the case that incorporating a portion of carbon into stock portfolio enhances the risk-adjusted performance of the portfolio (?).

Even though many recent studies have offered some approaches to understanding the linkage of EUAs with energy and other financial markets, this study aims to expand that understanding further by including the data that captures Phase IV of EU-ETS to date with a view to examine the impacts of Fit for 55 reforms and the RePowerEU initiative as well as the exogenous shocks such as COVID-19 and the Russia-Ukraine war to those linkages. To this end, we hypothesize that the reforms of Phase IV would maintain the potential diversification benefits of carbon for a non-energy portfolio. That is, we hypothesize that Phase IV reforms would not strongly alter the previous findings for Phases II and III that carbon is linked more with energy assets than financial assets. We also hypothesize that the impact of Fit for 55 reforms and RePowerEU Plan may strengthen the linkages with energy markets since the former brings shipping emissions within its scope and the latter aims to accelerate energy transition. Thus, we expect the impact of these to be long lasting. On the other hand, we hypothesize that the exogenous shocks would generate, or strengthen, short-lived linkages with financial markets, though, as previous findings indicate, shocks are likely to transmit between markets. We employ the following methodology to test these hypotheses.

3. Methodology

The DY connectedness model proposed by ??? is a commonly employed method to evaluate the strength of relationships among variables (?????????). This approach allows us to assess the extent to which EUAs are linked to other asset classes by examining the connectedness and transmission of return and volatility shocks between markets and by exploring any temporal changes to this relationship.

DY framework incorporates the forecast error variance decomposition (FEVD) technique to measure both the overall and directional spillover effects. It also introduces three primary time-varying spillover measures: Total, Directional, and Pairwise Spillovers. This approach is then further expanded by the Pairwise

Connectedness Index (PCI), that enables the quantification of spillover effects' strength between specific pair of assets (**?**).

Consider a variance stationary n-variable, $VAR(p)$

$$x_t = \sum_{i=1}^{p} \psi_i x_{t-i} + u_t \tag{1}$$

with the error term $u_t \sim N(0, S_t)$ with S_t denoting its variance-covariance matrices, and where x_t is an $n \times 1$ vector of endogenous variables, such as EUA daily returns or volatility, ψ_i represents the autoregressive $n \times n$ matrices of the coefficients, and p is the length of lag with the optimal lag length determined by the Bayesian information criterion (BIC) (**??**).

Here, the moving average is represented using Wold's representation theorem (**?**) which decomposes every covariance stationary process into two uncorrelated component process. If the process is nondeterministic, then

$$x_t = \sum_{j=0}^{\infty} A_j u_{t-j} \tag{2}$$

where $A_j = \psi_1 A_{i-1} + \psi_2 Ai - 2 + \ldots$, with $A_j = 0$ for $j < 0$, and A_0 being an $n \times n$ identity matrix.

To solve the problem of orthogonal innovation, **?** uses the generalized VAR framework proposed by **?** and **?**, hereinafter referred to as KPPS. This framework produces variance decompositions whereby they are invariant to the ordering. We can then define fractions of the H-step-ahead error variances in forecasting x_i into separate parts that are due to various system shocks. Those fractions that are due to shocks to x_i , for $i = 1, 2, \ldots, n$, can be referred to as own variance shares, and those that are due to shocks to x_j, $j = 1, 2, \ldots, n$ and $i \neq j$, can be referred to as cross-variance shares, or spillovers (**????**).

From the moving average representation, the generalized forecast error variance decomposition (GFEVD) is then expressed as

$$\theta_{ij}^{g}(H) = \frac{1}{\sigma_{jj}} \frac{\sum_{h=0}^{H-1} (e_i^T A_h S_t e_j)^2}{\sum_{h=0}^{H-1} (e_i^T A_h S_t A_h^T e_i)} \tag{3}$$

where σ_{jj} standard deviation of the error term of variable j, e_i is the $n \times 1$ selection vector that takes on a value of one for i^{th} element and zero otherwise. The index of spillover from variable j to variable i is subsequently obtained by normalizing GFEVD by the row sum:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{n} \theta_{ij}^{g}(H)} \tag{4}$$

where $\tilde{\theta}_{ij}^{g}(H)$ is the percent of forecast error in variable i that is explained by variable j,and by construction $\sum_{j=1}^{n} \tilde{\theta}_{ij}^{g}(H) = 1$, and $\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^{g}(H) = n$.

From this normalized GFEVD, we can obtain various connectedness indexes which would in turn help summarize the overall connectedness within a system's variables. Specifically, we can capture from all other markets j within a system the total spillovers to market i with

$$DSF_{n,i}(H) = \frac{\sum\limits_{j=1,i\neq j}^{n} \tilde{\theta}^{g}_{ij}(H)}{\sum\limits_{i,j=1}^{n} \tilde{\theta}^{g}_{ij}(H)} \times 100 \tag{5}$$

$$= \frac{100}{n} \sum_{i=1,i\neq j}^{n} \tilde{\theta}^{g}_{ij}(H) \tag{6}$$

with a high measure indicating that variable i is highly responsive to shocks from other markets. Similarly, the total spillovers from variable i to all other variables, can be captured with

$$DST_{n,i}(H) = \frac{100}{n} \sum_{j=1,i\neq j}^{n} \tilde{\theta}^{g}_{ij}(H). \tag{7}$$

The net directional spillover (NS) from i to j results from the difference between the directional spillovers DST and DSF and represents the net contribution of a specific market to the others. A positive NS indicates that market i is a net shock transmitter. This means, the impact market i has on all other markets j is larger than the impacts of all other markets j has on market i. A negative NS, on the other hand, indicates that market i is a net shock receiver. Thus, the net directional spillover is calculated as

$$NS_{n,i}(H) = DST_{n,i}(H) - DSF_{n,i}(H). \tag{8}$$

Although the NS provides important information on how much of volatility in other markets are attributable to each market in net terms, it is also important to be able to capture the overall degree of connection between two markets. This is then captured by the net pairwise directional spillover (NPDS) index, defined as the difference between the gross shocks transmitted from variable i to variable j **?**:

$$NPDS_{ij}(H) = \frac{100}{n}(\tilde{\theta}^{g}_{ij}(H) - \tilde{\theta}^{g}_{ji}(H)). \tag{9}$$

The volatility spillover or total connectedness index (TCI) and their equivalences are then constructed as

$$TCI(H) = \frac{\sum\limits_{j=1,i\neq j}^{n} \tilde{\theta}^{g}_{ij}(H)}{\sum\limits_{i,j=1}^{n} \tilde{\theta}^{g}_{ij}(H)} \times 100 \tag{10}$$

$$= \frac{100}{n} \sum_{j=1,i\neq j}^{n} \tilde{\theta}^{g}_{ij}(H) = \frac{1}{n}\sum_{j=1}^{n} DSF_{n,i}(H) = \frac{1}{n}\sum_{i=1}^{n} DST_{n,i}(H). \tag{11}$$

In line with **?**, we use the Pair Connectedness Index (PCI) that captures the overall degree of connection between two markets. When considering a network with only two series, the PCI and TCI are equivalent. However, TCI calculation between two series may yield a biased result because by design the approach considers only two series despite each series may be impacted by more series. PCI computation based on a large network, on the other hand, is not only more efficient than calculating the TCI of multiple small networks, but also yields a more accurate result due to the unbiased coefficient estimates of the VAR model. It is calculated as follows:

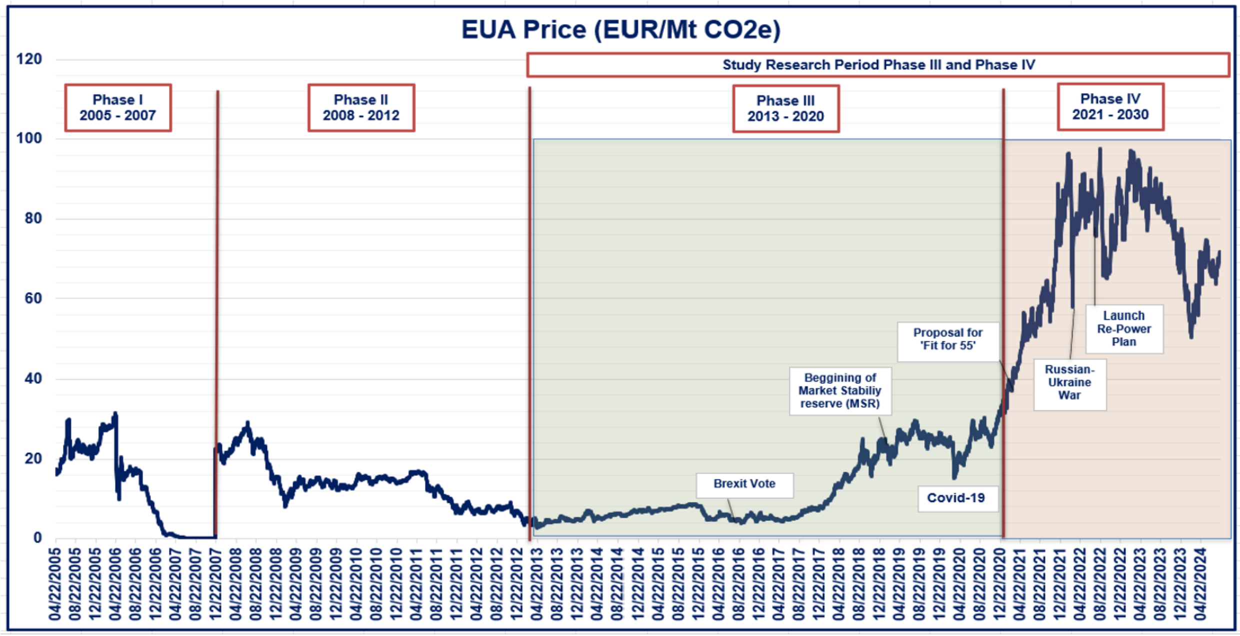
$$PCI_{ij} = 2 \times \frac{\tilde{\theta}^{g}_{ij}(H) + \tilde{\theta}^{g}_{ji}(H)}{\tilde{\theta}^{g}_{ij}(H) + \tilde{\theta}^{g}_{ji}(H) + \tilde{\theta}^{g}_{jj}(H) + \tilde{\theta}^{g}_{ii}(H)} \tag{12}$$

The PCI ranges between 0 and 1 illustrating the overall degree of bilateral interconnectedness across two variables i and j.

4. Data

We obtain daily price data for EUAs and other financial markets from Bloomberg LP and Refinitiv, covering the period from January 2, 2013, to August 16, 2024. This time frame, as shown in Figure ??, encompasses Phases III and, to the extent possible, Phase IV of the European Union Emissions Trading System (EU ETS), including the reforms introduced under Fit for 55 package and RePowerEU. It also includes key economic periods characterized by significant market volatility, such as the 2016 Brexit referendum, the COVID-19 pandemic especially between February and April 2020, and the escalation of the Russian-Ukrainian conflict in March-April 2022.

Figure 1: European Emission Trading System Phases and European Union Allowances (EUA) Prices



For the same period, we also obtain price data for Stoxx 600 Index as a proxy for the European equity market and the S&P 500 Index as a proxy for the International Equity Index. For European sovereign bond markets we utilize iBoxx Eurozone Sovereign Performance Index, and for European corporate bond markets we use iBoxx Eur Corporates Index as proxies. To represent the commodity markets, we additionally obtain the Bloomberg Metal Commodity Index and the Bloomberg Commodity ex Energy Index, as energy market exposure is captured separately.

The EUA is represented by the continuous contracts of the most actively traded financial futures. Given the carbon markets intrinsic relationship with energy markets, the latter are analyzed independently. Specifically, we use continuous futures contracts for Brent crude oil, API2 Rotterdam coal, and TTF natural gas as proxies for the Europeal oil, coal, and gas markets, respectively. In total, this data set comprises of 30,140 observations. All prices are converted to EUR to eliminate the impact of currency fluctuations. Returns are log-normalized, and volatilities are estimated based on a rolling window of 20-day daily returns.

Table ?? provides the descriptive statistics of daily returns in panel (a) and volatility in panel (b). Both panels show that all variables are skewed and leptokurtic. Together with Jarque-Bera that strongly rejects the null hypothesis of a normal distribution, it is evident that none of the variables conform to a normal distribution.

Following previous studies (???) we transform the data with logarithmic returns and 20-day volatility of logarithmic returns.

Table 1: Descriptive statistics of daily return and volatility

(a) Daily logarithmic return

	Mean	Median	Max	Min	St.Dev.	Skewness	Kurtosis	Obs.	J-B	Prob.
CARBON	0.0013	0.0008	0.2690	-0.3508	0.0311	-0.2896	10.6147	3011	14177.78	0
EUROSTOXX	0.0003	0.0006	0.0840	-0.1148	0.0099	-0.8462	11.3898	3011	16634.71	0
BRENTOIL	0.0002	0.0008	0.2224	-0.2483	0.0230	-0.1878	14.1649	3011	25190.26	0
COALAPI	0.0005	0.0000	0.5935	-0.2571	0.0274	3.2819	98.0915	3011	1212557	0
NATGAS	0.0009	-0.0001	0.5034	-0.2983	0.0401	1.2270	17.3396	3011	38475.98	0
EURSOVER	0.0001	0.0001	0.0200	-0.0171	0.0030	0.1270	4.3384	3011	2369.475	0
EURCORP	0.0001	0.0001	0.0137	-0.0218	0.0019	-0.6075	12.0755	3011	18479.1	0
SPXINDEX	0.0006	0.0006	0.1032	-0.1260	0.0114	-0.4644	13.8660	3011	24229.62	0
COMEXENG	0.0000	0.0000	0.0407	-0.0396	0.0072	-0.0775	2.1079	3011	560.4679	0
METALS	0.0001	0.0000	0.0599	-0.0969	0.0101	-0.3869	6.4988	3011	5373.834	0

(b) Volatility

	Mean	Median	Max	Min	St.Dev.	Skewness	Kurtosis	Obs	J-B	Prob.
CARBON	0.4402	0.3916	1.8455	0.1317	0.2265	2.2435	7.7022	3014	9978.411	0
EUROSTOXX	0.1383	0.1223	0.7035	0.0315	0.0753	2.8685	13.9645	3014	28623.02	0
BRENTOIL	0.3151	0.2732	1.6611	0.0772	0.1852	2.7509	10.9659	3014	18903	0
COALAPI	0.3135	0.2241	2.6857	0.0000	0.2985	3.7413	20.9101	3014	61940.62	0
NATGAS	0.4863	0.3490	3.1750	0.0506	0.4070	2.2835	8.3829	3014	11444.49	0
EURSOVER	0.0422	0.0354	0.1337	0.0129	0.0223	1.5943	2.5774	3014	2111.037	0
EURCORP	0.0248	0.0189	0.1130	0.0071	0.0154	2.1823	5.9139	3014	6784.517	0
SPXINDEX	0.1546	0.1306	1.0152	0.0574	0.0942	4.7283	34.8012	3014	163327.9	0
COMEXENG	0.1080	0.1010	0.3428	0.0460	0.0373	2.1601	7.9794	3014	10339.95	0
METALS	0.1476	0.1343	0.4863	0.0482	0.0624	1.7810	4.8952	3014	4602.693	0

For connectedness analysis, it is also essential that the time series data are stationary (**??**). To test for stationarity, we employ Augmented Dickey-Fuller (ADF) (**?**) and Phillips-Perron (PP) (**?**) tests. Both tests strongly reject the null hypothesis for a presence of a unit root in either returns ($p = 0.000$) or volatility data ($p=0.000$), suggesting that they are both stationary.