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 (Corfee-Morlot et al., 2007; Hart and Victor, 1993; Weart, 2008). 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 (UNEP, 2023).

As one of the top polluters (UNEP, 2023), the European Union (EU) has established an ambitious climate objective of 55% reduction in greenhouse gas emissions (GHGs) by 2030 from the 1990 levels (Regulation, 2021/1119, 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 (European Commission, 2021).

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 (COM, 2022/230). 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 (COM, 2022/230, 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 (Directive, 2023/959). The EU

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[1] Building on the works of Joseph Fourier and John Tyndall roughly half a century earlier (Corfee-Morlot et al., 2007)

ETS itself is one of the central instruments of the EU in its decarbonization and energy transition efforts (Decision, 2015/1814; Bai and Okullo, 2023), and it currently covers about 40% of the EU's GHG emissions[2] (European Commission, n.d.). 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 (Directive, 2003/87).

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 (Directive, 2003/87, 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 (Ellerman et al., 2014; Bel and Joseph, 2015). 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] (Directive, 2009/29, 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] (Directive, 2018/410). 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] (Directive, 2023/959).

The effectiveness of the EU ETS in decarbonizing and facilitating the energy transition depends on several factors (Backe et al., 2023; De Cara and Jayet, 2011; Marin et al., 2018; Scheelhaase et al., 2021). Among these factors, the price of EUAs plays a critical role (Pietzcker et al., 2021; Quemin, 2022; Lovcha et al., 2022). Higher EUA prices have the potential to drive significant transformations across multiple sectors, encouraging firms to innovate and reduce emissions (Pietzcker et al., 2021; Rečka and Ščasný, 2015). 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 (Bohl et al., 2023; Corgnet et al., 2021). This in turn depends, among other factors, on the price volatility which can raise uncertainty and restrain investment into carbon-reducing technologies (Acworth et al., 2017; Laing et al., 2013).

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 Phases I to 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

[2]The coverage will likely increase after the reforms are transposed into national laws of member states by 30 June 2024 (Directive, 2023/959)

[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. (Directive, 2003/87, 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 (Decision, 2015/1814; Simões, 2022)

[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.

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.

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 (Demiralay et al., 2022; Dai et al., 2022).

Ability to accurately forecast carbon prices are important in enabling decisions on emissions and transition tradeoffs (Wang et al., 2021; Zhang et al., 2024; Chen and Zhao, 2024). To that end, while some have considered the role of attention in carbon pricing (Zheng et al., 2022; Gong et al., 2023; Zhang et al., 2024), some have used VAR (Arouri et al., 2012), ARIMA (García-Martos et al., 2013), GARCH (Byun and Cho, 2013) and its modifications including, among others, stable-Paretian-GARCH (Paolella and Taschini, 2008), Markov switching GARCH (Benz and Trück, 2009), VMD-GARCH(Huang et al., 2021), switching transition regression exponential GARCH (Arouri et al., 2012), and AR-GARCH (Benz and Trück, 2009) to capture volatility, skewness, and excess kurtosis. Yet others have looked at the impact of fuel switching on carbon prices (Bertrand, 2014; Hintermann, 2010; Pettersson et al., 2012), while some others at the impact of policy uncertainties on the volatility of carbon markets (Dai et al., 2022; Dong et al., 2024a), and some have used various decomposition and artificial intelligence techniques to improve the forecasting ability (Qin et al., 2024; Wang et al., 2021; Chen and Zhao, 2024). 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 (Feng et al., 2011; Lutz et al., 2013; Segnon et al., 2017; Chen and Zhao, 2024).

Emissions trading can help in reducing the abatement costs and dampen the negative impact of emission reductions on GDP (Wu et al., 2016; Lin and Jia, 2019), although some of the carbon reduction gains may decline overtime due to macroeconomic carbon rebound effect (Bolat et al., 2023). 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 (Delarue et al., 2007; Kara et al., 2008; Zachmann and Von Hirschhausen, 2008; Kirat and Ahamada, 2011; Bonenti et al., 2013; Hobbie et al., 2019; Hanif et al., 2021; Dai et al., 2022), and, to a lesser extent, on its negligible impact on the aviation, cement, steel, and aluminum sectors (van Asselt and Biermann, 2007; Zhang and Wei, 2010; Oberndorfer and Rennings, 2007; Efthymiou and Papatheodorou, 2019).

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 (Mansanet-Bataller et al., 2007; Alberola et al., 2008; Keppler and Mansanet-Bataller, 2010; Bredin and Muckley, 2011; Chevallier, 2011; Creti et al., 2012; Aatola et al., 2013; Zhang and Sun, 2016; Ji et al., 2018; Falbo et al., 2019; Fiori, 2024). However, with the changes introduced in each of the subsequent phases such impacts became harder to establish (Arouri et al., 2012; Wu et al., 2020). 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 (Tan et al., 2020; Lovcha et al., 2022; Yang, 2022). Moreover, interconnectedness of the carbon with other markets evolves overtime and has increased with financial markets in recent years (Jiménez-Rodríguez, 2019; Tan et al., 2020; Dong et al., 2024b). 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 (Demiralay et al., 2022).

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 Diebold and Yilmaz (2009, 2012, 2014) is a commonly employed method to evaluate the strength of relationships among variables (Zhang and Sun, 2016; Xia et al., 2019; Ji et al., 2019; Tan et al., 2020; Gabauer, 2021; Hanif et al., 2021; Diebold and Yilmaz, 2023; Dong et al., 2024b; Gong and Liao, 2024). 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[7] 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 (Gabauer, 2021).

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) (Diebold and Yilmaz, 2012; Pham et al., 2023).

Here, the moving average is represented using Wold's representation theorem(Wold, 1939, 1954) 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, Diebold and Yilmaz (2012) uses the generalized VAR framework proposed by Koop et al. (1996) and Pesaran and Shin (1998), 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

[7] Forecast error variance decompositions from vector autoregressions (VAR) were first discussed by (Sims, 1980). It is a statistical method that dissects the forecast error variance of a multivariate timeseries into individual contributions of variables and their interactions. They show how much of the H-step-ahead forecast error variance of variable i is due to innovations in another variable j. Also see (Diebold and Yilmaz, 2012).

as cross-variance shares, or spillovers (Diebold and Yilmaz, 2012; Yang, 2022; Tan et al., 2020; Susilo and Hendranastiti, 2022).

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

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

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

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

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

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 Diebold and Yilmaz (2012):

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

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

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

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

$$= \frac{1}{n} \sum_{j=1}^{n} DSF_{n,i}(H) = \frac{1}{n} \sum_{i=1}^{n} DST_{n,i}(H). \tag{12}$$

In line with Gabauer (2021), 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:

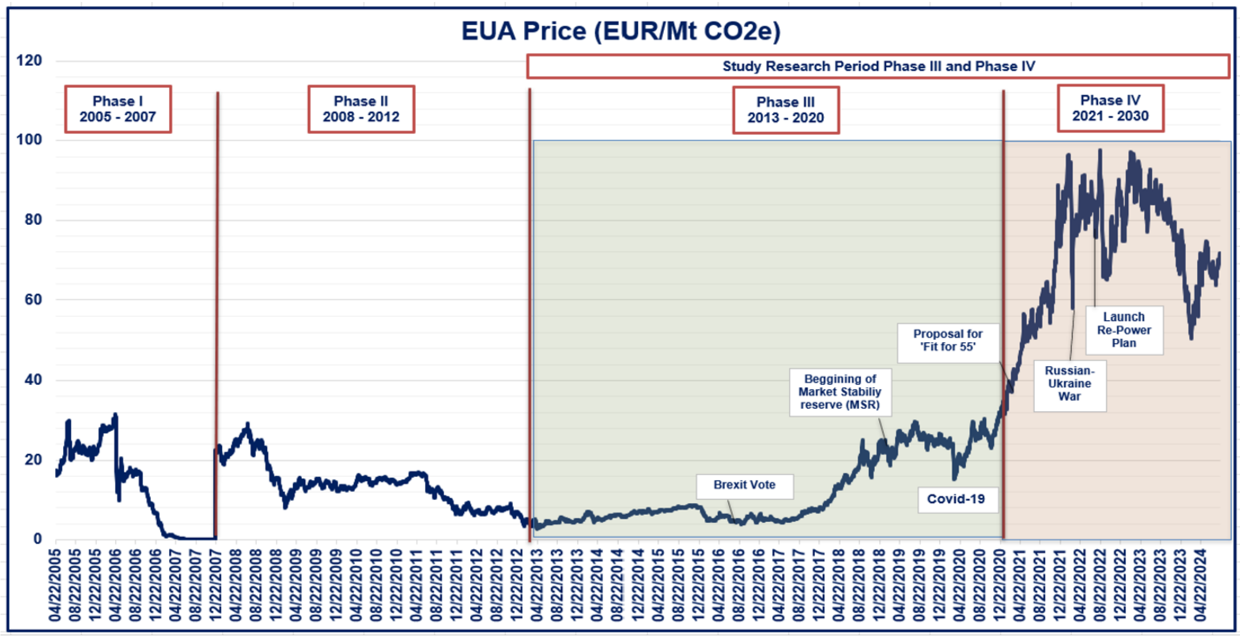
$$PCI_{ij} = 2 \times \frac{\tilde{\theta}_{ij}^{g}(H) + \tilde{\theta}_{ji}^{g}(H)}{\tilde{\theta}_{ij}^{g}(H) + \tilde{\theta}_{ji}^{g}(H) + \tilde{\theta}_{jj}^{g}(H) + \tilde{\theta}_{ii}^{g}(H)} \tag{13}$$

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 1, 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 1 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 (Diebold and Yilmaz, 2012; Reboredo, 2014; Gabauer, 2021) we transform the data with logarithmic returns and 20-day volatility of logarithmic returns.

For connectedness analysis, it is also essential that the time series data are stationary (Diebold and Yilmaz, 2012; Zhang, 2017). To test for stationarity, we employ Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and Phillips-Perron (PP) (Phillips and Perron, 1988) 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.

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

5. Empirical Results

5.1. Static Total Connectedness

We first investigate the total spillover. Table 2 Panel (a) illustrates the static connectedness of returns while panel (b) shows the same for volatility between EUAs and other markets. The full table is in Appendix A. The Total Connected Indices (TCIs) are at 45.19% for returns and 48.62% for volatility, respectively, indicating a moderate level of connectedness across all markets since this implies that the remainder 54.81% of the market return and 51.38% of the volatility variations across the entire system can be attributed to idiosyncratic shocks and market-specific factors, i.e. factors that impact one market but not others.

The static directional spillovers indicate that the EUAs contribute 34.82% to the returns of other markets and 31.25% to their volatility while receiving from other markets 38.56% and 43.2% return and volatility shocks, respectively. Accordingly, the EUAs are net return receiver of 3.74% and volatility spillover receiver of 11.94%. This also means that the remaining 61.44% of the return and 56.8% of the volatility in EUAs are explained by its own specific market factors. Overall, the results seem to suggest a relatively low integration of EUAs with other markets, although they appear to be somewhat influenced by the return and volatility of these other markets.

5.2. Dynamic Total Connectedness

The dynamic connectedness showing the variation over time in return volatility connectedness are plotted in panels (a) and (b) of Figure 2, respectively. This reveals that during period of financial market stress, such as those triggered by Brexit in 2016, Covid-19 in 2020, and Russia-Ukraine crisis in 2022, the TCI for both return and volatility tends to increase, suggesting stronger connectedness in times of crises, albeit short-lived. In contrast, the start of Phase IV in 2021 appears in the first instance to have a lesser impact than these exogenous shocks.

Table 2: Static Return and Volatility Connectedness Matrix (Jan 2013 - Aug 2024)

(a) Carbon returns connectedness matrix

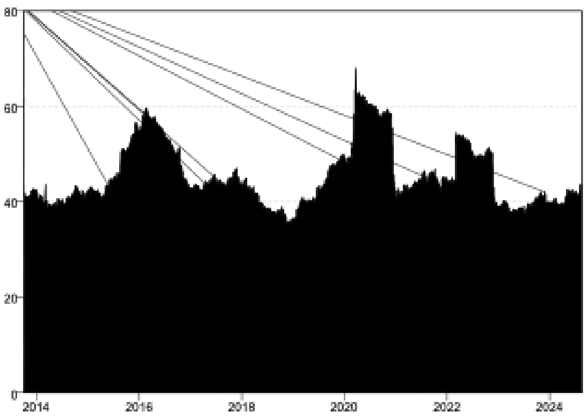
	CARBON	DSF (FROM)
CARBON	61.44	**38.56**
DST (TO)	**34.82**	451.90
Inc.Own	96.26	**TCI**
NS (NET)	**-3.74**	**45.19**

(b) Carbon volatility connectedness matrix

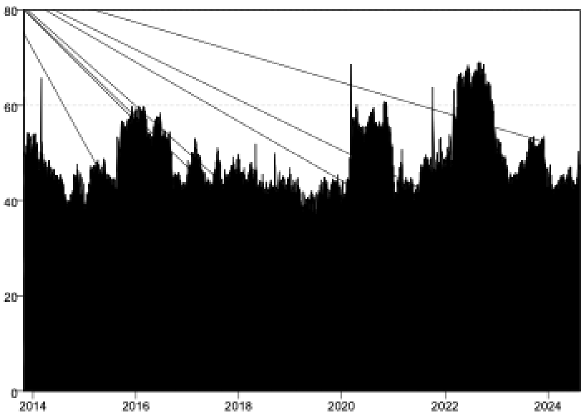
	CARBON	DSF (FROM)
CARBON	56.80	**43.20**
DST (TO)	**31.25**	486.15
Inc.Own	88.06	**TCI**
NS (NET)	**-11.94**	**48.62**

Figure 2: Dynamic Return and Volatility Connectedness (Jan 2013 – Aug 2024)

(a) Dynamic return TCI



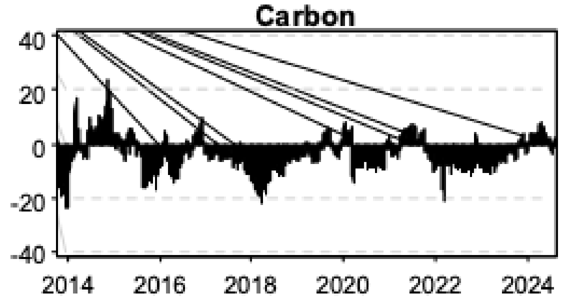
(b) Dynamic volatility TCI



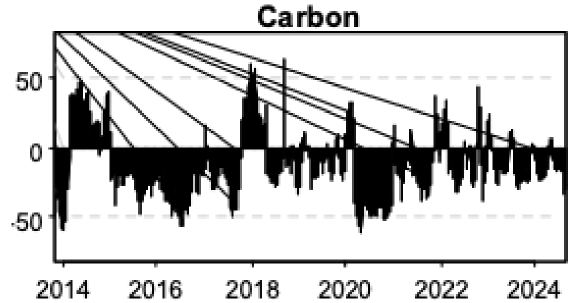
Similarly, dynamic net directional connectedness of EUAs with other markets are provided in Figure 3 (Appendix B provides the complete set of charts). These also suggest that in periods of financial stress the return and volatility connectedness between the EUAs and other markets increase, supporting the implications derived from the dynamic TCIs. Importantly, in contrast to the EUAs net return connectedness in panel (a) that shows EUAs as a receiver of return shocks from other markets, panel (b) shows that the volatility net connectedness briefly flips to positive in times of financial stress.

Figure 3: Net Directional Connectedness between EUAs and other markets

(a) Dynamic return net directional connectedness



(b) Dynamic volatility net directional connectedness



5.3. Static Pairwise Connectedness

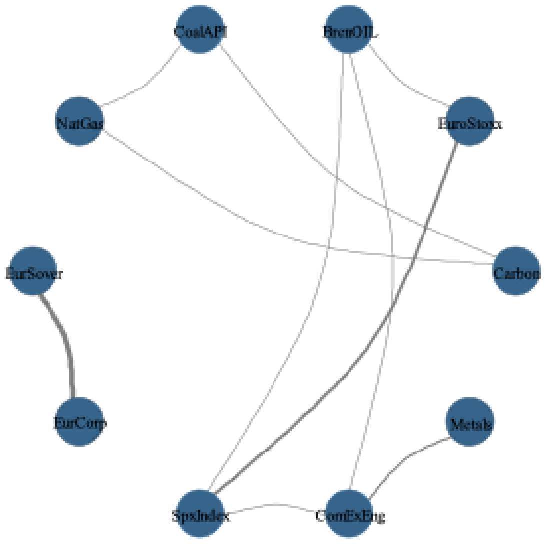
TCI results are informative. However, as Section 3 highlighted, for networks with more than two variables, TCI tends to be less efficient and accurate than PCI. PCI measures the level of connectedness between two specific markets and quantifies how much the return or volatility variation in one market is impacting, or being impacted by, the other market. Figure 4 illustrates the network representation of PCI where a line between markets means that a pairwise connectedness exists between them. The thickness of the lines indicates the magnitude of such connectedness. For example, in panel (a) a strong pairwise connectedness exists between European sovereign and corporate bond returns, whereas such a pairwise connectedness between coal and natural gas returns is weaker, and between either of the European bonds and coal returns is inexistent. Panel (b) displays a similar interpretation for volatility connectedness.

The PCI return connectedness network in panel (a) suggests that EUAs (Carbon) seem to operate as an independent market, exhibiting pair connectedness only with coal and natural gas, where there is also an equally weak pairwise connection between coal and natural gas. These could be attributed to fuel switching in the power sector. Coal-to-gas switching in the European energy market is a function of relative carbon and fuel costs, driven by the EU ETS and fluctuating commodity prices. As EUA prices rise the marginal cost of CO2 emissions increases, impacting coal particularly due to its higher carbon intensity. This cost differential incentivizes a shift towards gas-fired generation, which emits roughly half the CO2 per unit of energy, creating a link between these markets. However, the elasticity of this switch is contingent on natural gas prices. When gas prices escalate the cost advantage of switching diminishes, potentially leading utilities to revert to coal despite the higher carbon costs, thereby increasing EUA demand and exerting upwards pressure on EUA prices. Therefore, fluctuations in natural gas or coal prices can alter the economic attractiveness of this fuel switch, further reinforcing the connectedness. This would support the findings of Bertrand (2014), Hintermann (2010), Creti et al. (2012), and Pettersson et al. (2012) among others.

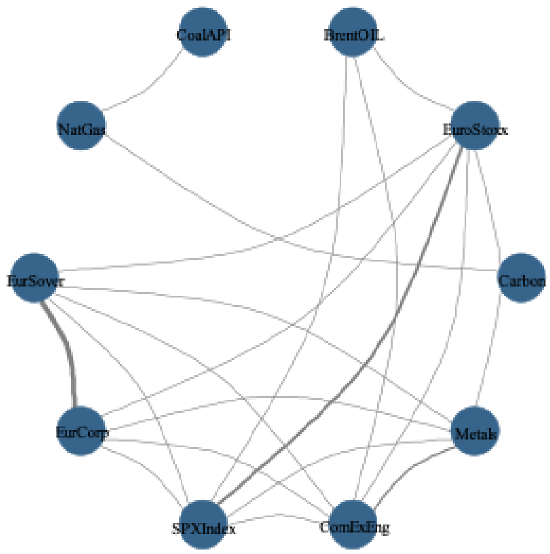
The PCI volatility network in panel (b) reveals similar patterns, though EUAs demonstrate volatility linkages with natural gas exclusively, and not with coal. This observation is supported by the findings of Falbo et al. (2019) and Bertrand (2014), who argue that various EU initiatives and policies aimed at increasing the share of renewables in the power grid have led to EUAs being more closely linked with natural gas rather than coal. This connection appears to persist despite a brief shift back to coal during 2022, driven by the energy crisis caused by the Russia-Ukraine war. This persistence in connections overlaps with RePowerEU Plan which reinforces and accelerates the increase in share of renewables.

Figure 4: Network representation of Pairwise Connectedness Index (PCI) (Jan 2013 – August 2024)

(a) Static return PCI network



(b) Static volatility PCI network



5.4. Dynamic Pairwise Connectedness

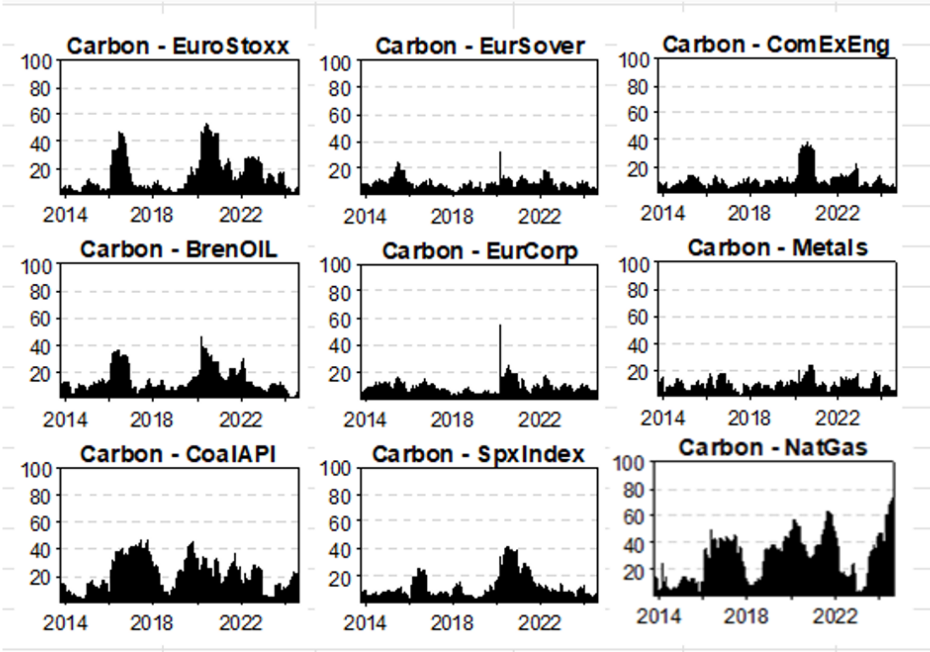
When we examine the return and volatility PCI dynamically over time (Appendix C provides the full set of dynamic PCI charts), we see in panel (a) of Figure 5 considerable fluctuations in EUAs' pairwise return connectedness in times of crises. This appears to especially be the case with EuroStoxx, S&P 500, brent, coal, and natural gas which all spike to varying degrees around the times of exogenous shocks such as the Brexit vote in 2016, Covid-19 crisis in 2020, and Russia-Ukraine war in 2022. A similar behavior is observed, albeit to a lesser extent, with sovereign and corporate bonds, metals and other commodities during these shocks. As we have hypothesized, most of these are short-lived and it appears that coal and natural gas have some return connectedness with the EUAs over time.

There also seems to be an increase in the return connectedness between EUAs and natural gas, while a decrease with coal, especially from 2021 onwards. These changes can be attributable to various market, regulatory, and policy factors such as the introduction of Phase IV and impact of RePowerEU which is accelerating the deployment of renewable energy across Europe, helping the EU advance its climate goals and reduce greenhouse gas emissions, while also diminishing reliance on Russian energy imports (European Commission, 2024). Changes in the energy mix, with a shift towards a relatively cleaner energy sources including natural gas under the EU's climate targets and the Fit for 55 package can influence the demand for and price of EUAs, thus increasing their connectedness. Coupling this with the impact of RepowerEU in the acceleration of renewables capacity can strengthen such influence and connectedness. Additionally, fluctuations in natural gas prices, due to factors like supply disruptions or changes in demand, can directly impact the cost-effectiveness of gas-fired power plants versus coal, which would also affect the price and demand for EUAs. Furthermore, as EU member states have been phasing out coal and adopting cleaner energy sources, thereby reducing the influence of coal prices on the EUAs market, there has been a regulatory push towards a reduced dependence on coal, leading to decreased coal usage and a weakened link with EUAs prices.

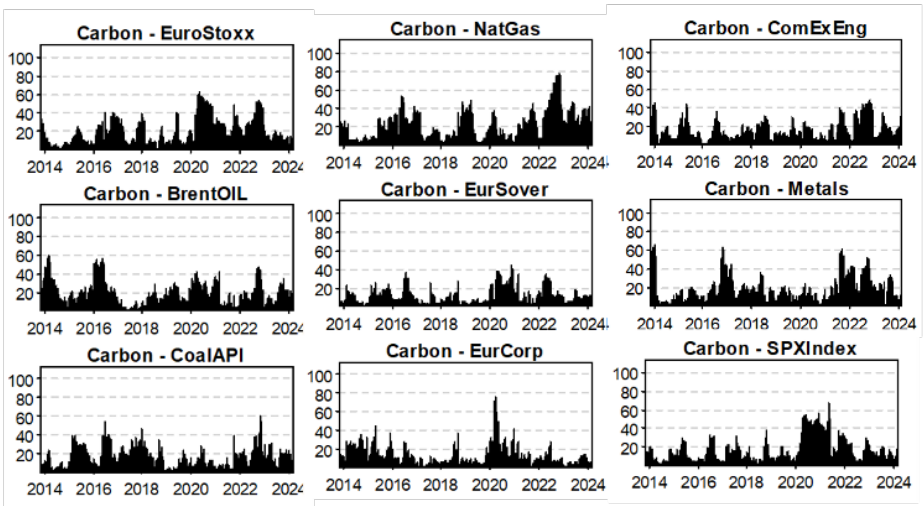
Another important observation emerges on the return and volatility connectedness between carbon and equity markets. While such connectedness seems inexistent on the static return and volatility PCI network in panels (a) and (b) of Figure 3, we can observe in the dynamic return and volatility PCI in panel (a) of Figure 4 that such connectedness seems to have gained prominence since 2020. A similar pattern can also be observed in the same panel for EUAs connectedness with natural gas and metals. Yet, it appears that among all pairwise connectedness that gained prominence since 2020, only the volatility connectedness with natural gas is not in a declining trend in that period.

Figure 5: Dynamic Return and Volatility Pairwise Connectedness Index (PCI) (Jan 2013 – Aug 2024)

(a) Dynamic return PCI



(b) Dynamic volatility PCI network



Relatively recent introduction of financial products like Exchange Traded Funds (ETFs) and other investment vehicles focusing on carbon markets, including EUAs, might be the main contributors to this trend of strengthened connectedness with the equity markets. These new products have broadened the participation of financial investors who may be more responsive to global macroeconomic shifts than specific carbon fundamentals. This could lead to a strengthening of the return and volatility linkage between EUAs and equities - a significant finding for institutional investors looking to integrate EUAs into their portfolios. Despite this increase in connectedness with equity markets, the results of this study reveal that the overall interconnectedness of EUAs with other markets remains relatively low as we hypothesized, reinforcing the potential diversification benefits of including EUAs in investment portfolios.

6. Conclusions

The EU has set an ambitious climate goal for 2030, committing to achieve a 55% reduction in GHG emissions relative to 1990 levels. In order to meet this objective, the EU has adopted the Fit for 55 package, along with the RepowerEU Plan. This aligns with a broader objective to transform the EU into a sustainable economy and establish Europe as a climate-neutral continent by 2050. A pivotal instrument in EU climate policy is the EU Emissions Trading System (EU-ETS), a cornerstone mechanism grounded on a cap-and-trade system that limits and annually reduces emissions covered by the system. The Fit for 55 package introduces reforms to the EU-ETS, targeting a more aggressive reduction in the emission cap for the high-emitting sectors covered by the system.

Various objectives underscore the necessity to tighten the cap, thereby decreasing the supply of European Emission Allowances (EUAs). To that end, this study sought to examine the financial characteristics of EUAs to gain a more comprehensive understanding of this market and explore whether EUAs can be a market for diversification. We hypothesized that with the introduction of Phase IV the carbon market will continue to offer diversification benefits, and that Fit for 55 package and RePowerEU Plan will engender a longer-lasting linkages with energy markets. As a result, carbon markets would offer diversification benefits that would likely to be more pronounced for non-energy portfolios. We also hypothesized that in times of exogenous shocks, carbon may link with other asset classes, though in shorter duration. To test our hypothesis, we have adopted an econometric model of connectedness analysis.

Our findings showed that despite an observed increase in the connectedness of EUAs with other financial markets—particularly during periods of financial stress—EUAs remain largely independent from these markets, except for coal and natural gas. A natural connection with these energy commodities exists due to significant participation of power generation in the EU-ETS. Overall, the results suggest that the return and volatility behavior of EUAs are primarily driven by their own fundamental factors. For investors, it suggests that EUAs could offer potential diversification benefits when included in a portfolio, due to their low linkage and spillover effect with other markets. We recommend, for future research, investigating the behavior of non-energy and broad market portfolios when carbon is incorporated at various densities in order to empirically ascertain the magnitude of potential diversification benefits this asset class offers. For policy makers, the results of the connectedness between EUAs and other markets can provide valuable insights. They can, for example, adopt a systemic view in considering the impacts on various markets when developing energy and climate policies. This would help in ensuring that the response of these markets to such policies are not only supportive but even help in accelerating the realization of these policy objectives. Accordingly, for future research, we recommend investigating the potential behaviors of various markets through connectedness analysis in response to broader sustainability policies the EU or other jurisdictions are considering.

Appendix A. Static Return and Volatility Connectedness Matrix

Table A.3: Static Return and Volatility Connectedness Matrix (Jan 2013 - Aug 2024)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	DSF (FROM)
CARBON	61.44	4.10	3.87	6.63	9.94	2.50	2.21	3.6	2.68	2.96	**38.56**
EUROSTOXX	3.54	49.47	5.83	3.10	3.09	3.09	3.58	19.99	5.27	3.04	50.53
BRENTOIL	3.72	6.17	57.92	4.40	3.74	2.56	2.20	7.39	8.37	3.52	42.08
COALAPI	6.17	3.94	5.33	59.58	10.81	1.84	1.91	3.97	3.84	2.60	40.42
NATGAS	9.91	3.00	4.05	10.23	61.68	1.95	1.86	2.51	2.59	2.21	38.32
EURSOVER	1.96	2.96	2.54	1.51	1.74	48.65	31.77	2.37	1.98	4.52	51.35
EURCORP	2.01	5.17	2.68	1.87	1.87	30.07	45.48	3.98	2.47	4.40	54.52
SPXINDEX	2.49	18.09	7.00	3.26	2.02	2.42	2.71	53.19	6.42	2.40	46.81
COMEXENG	2.63	5.16	7.57	3.32	2.51	2.18	2.37	6.70	53.24	14.31	46.76
METALS	2.38	3.08	3.19	2.24	2.50	4.94	5.65	2.91	15.66	57.45	42.55
DST (TO)	**34.82**	51.76	42.07	36.56	38.21	51.55	54.27	53.42	49.29	39.95	451.90
Inc.Own	96.26	101.23	99.99	96.14	99.89	100.20	99.75	106.61	102.53	97.40	**TCI**
NS (NET)	**-3.74**	1.23	-0.01	-3.86	-0.11	0.20	-0.25	6.61	2.53	-2.60	**45.19**

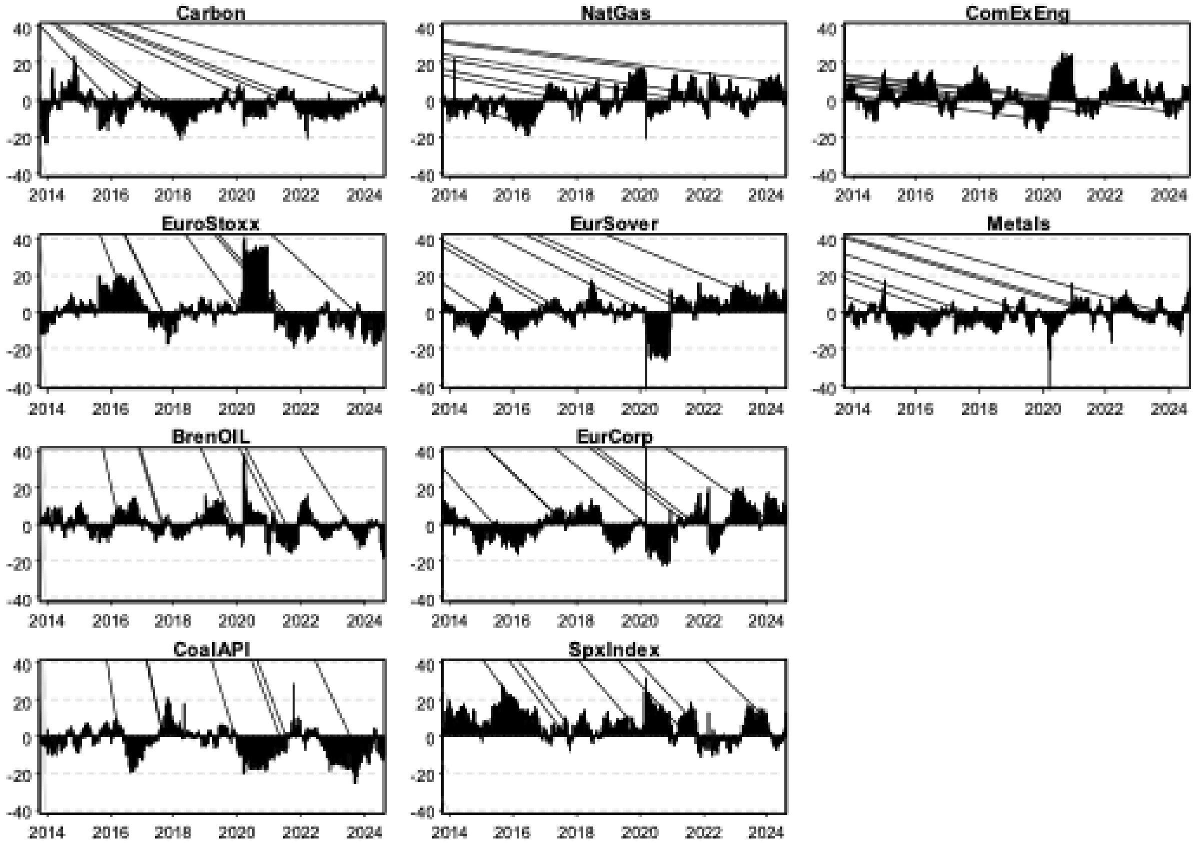
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	DSF (FROM)
CARBON	56.80	4.66	4.45	6.41	7.17	3.41	3.40	4.77	4.19	4.74	**43.20**
EUROSTOXX	3.80	47.26	4.87	3.81	3.69	5.09	4.15	16.18	5.36	5.82	52.74
BRENTOIL	4.35	6.78	51.50	4.50	4.17	3.98	4.67	6.92	7.19	5.94	48.50
COALAPI	4.53	3.91	3.56	61.61	7.36	3.03	2.59	4.79	3.42	5.20	38.39
NATGAS	4.58	4.70	3.61	7.84	58.94	3.87	4.31	4.74	3.76	3.66	41.06
EURSOVER	1.83	6.07	3.51	2.47	2.19	44.66	25.24	5.73	3.73	4.57	55.34
EURCORP	2.52	5.79	2.43	2.56	2.46	27.69	42.37	6.36	4.48	3.34	57.63
SPXINDEX	3.22	15.05	4.92	2.89	1.80	4.78	3.90	53.70	4.55	5.21	46.30
COMEXENG	2.80	7.84	4.64	3.97	4.49	5.51	5.54	6.94	48.77	9.52	51.23
METALS	3.63	8.27	4.06	4.33	4.55	5.17	6.35	6.12	9.28	48.24	51.76
DST (TO)	**31.25**	63.05	36.04	38.77	37.87	62.53	60.15	62.53	45.95	48.00	486.15
Inc.Own	88.06	110.31	87.54	100.39	96.81	107.19	102.52	116.23	94.72	96.24	**TCI**
NS (NET)	**-11.94**	10.31	-12.46	0.39	-3.19	7.19	2.52	16.23	-5.28	-3.76	**48.62**

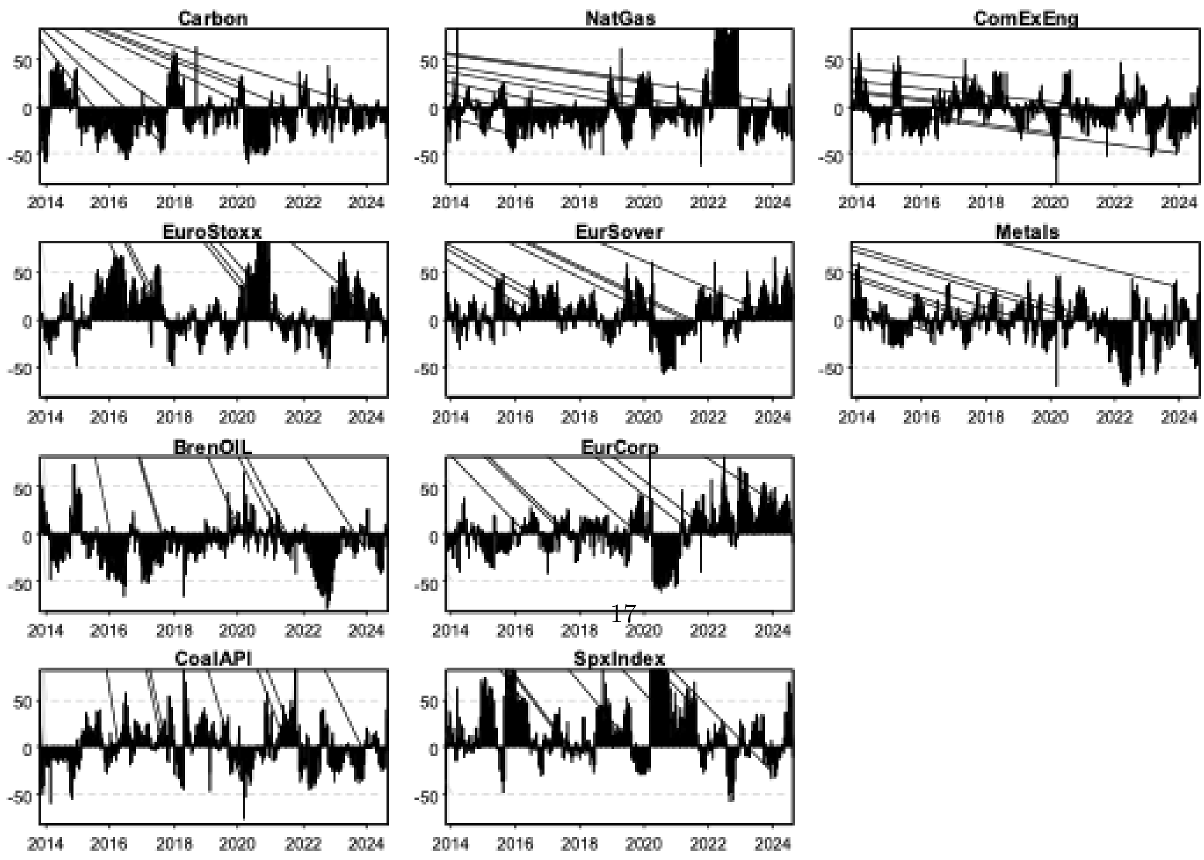
Appendix B. Dynamic Return and Volatility Net Directional Connectedness

Figure B.6: Dynamic Net Directional Connectedness (Jan 2013 – Aug 2024)

(a) Dynamic return net directional connectedness



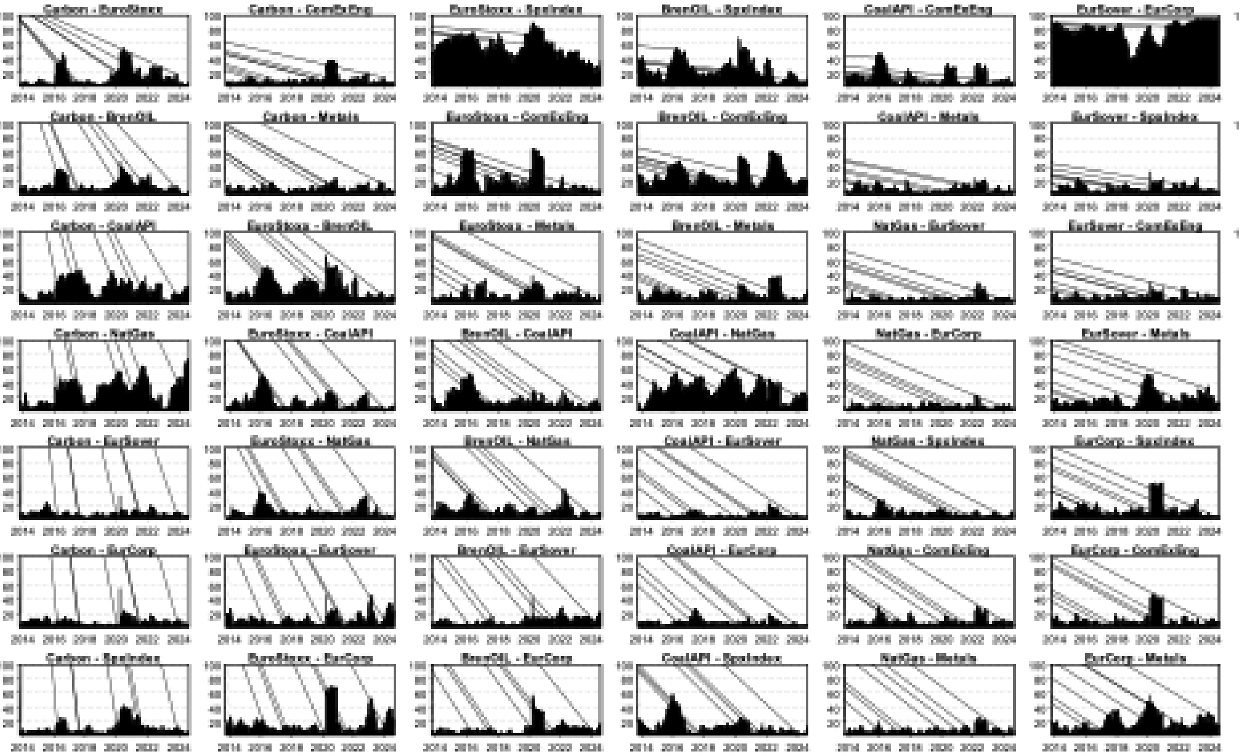
(b) Dynamic volatility net directional connectedness



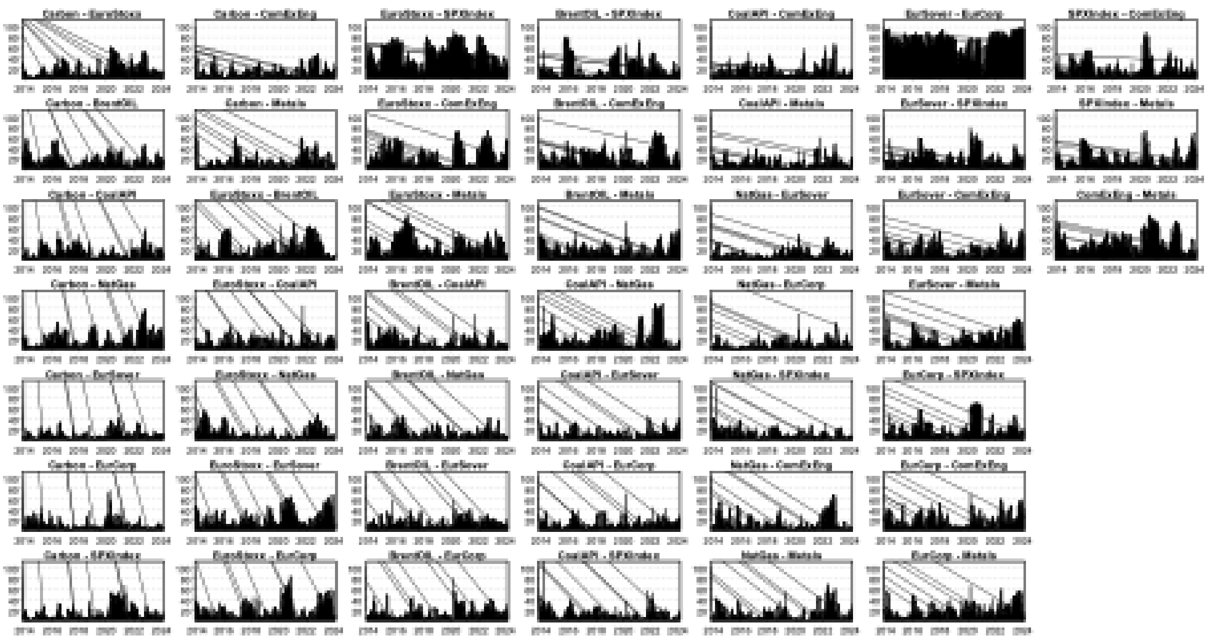
Appendix C. Dynamic Return and Volatility Pairwise Connectedness Index

Figure C.7: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Aug 2024)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



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