European Carbon Market Connectedness and Risk Contagion: A Study of Return and Volatility Dynamics Between European Union Allowances (EUAs) and Financial Markets Between 2013 and 2025 and their Potential for Portfolio Diversification

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 the 4th phase until January 2025 in order to ascertain the impact of fixed income, equity, commodities, and energy markets, as well as 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 it is 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. With such characteristics, EUAs can offer diversification benefits, especially for non-energy portfolios.

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

1. Introduction

In the late 19th century the Swedish scientist Svante Arrhenius discovered[1] the link between the grenhouse gas effect, increases in carbon dioxide (CO_2) concentrations in the atmosphere, and fossil fuel burning (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 ($GtCO_2e$), with the energy sector accounting for a little over third of these at 20.9 $GtCO_2e$ while industry accounting for another quarter at 14.4 $GtCO_2e$ (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 (European Council, 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 (European Commission, Communication 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 (European Commission, Communication 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 (European Council, Directive 2023/959). The EU ETS itself is one of the central instruments of the EU in its decarbonization and

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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)

energy transition efforts (European Council, 2015; Bai and Okullo, 2023), and it currently covers about 40% of the EU's GHG emissions[2] (European Commission, 2025). 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 (European Council, 2003).

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 (European Council, 2003, 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] (European Council, 2009, 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] (European Council, 2018). 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] (European Council, 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 (Acworth et al., 2017; Laing et al., 2013), on policy uncertainty, (Raza et al., 2023; Fang et al., 2018; Huiming Zhu, Rui Huang, Ningli Wang and Liya Hau, 2020; Wang et al., 2015), on market stress due to geopolitical and other exogenous shocks such as Covid-19 (Deng et al., 2024; Yang et al., 2022; Tiwari et al., 2022; Babar et al., 2024), and on financial stress (Bakas and Triantafyllou, 2018; Ding et al., 2021) which can raise uncertainty and restrain investment into carbon-reducing technologies.

This study, therefore, analyzes, via return and volatility connectedness of EUAs with other financial markets, the extent to which EU Fit for 55 and RePowerEU as potential policy shocks, and market stress due to Russian-Ukrainian War and Covid-19 impact the degree of integration of EUAs with other asset classes with a broader view 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 examining the impact of the changes emerging from the potential policy shocks of Fit for 55 package and RePowerEU. Within this context, this study uniquely 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

[2]The coverage will likely increase in due course following the incorporation of maritime transport from 2024 and transposition of the reforms into national laws of member states by 30 June 2024 (European Council, 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. (European Council, 2003, 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 (European Council, 2015; 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.

to date, 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 almost exclusively 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 describes the data, and Section 4 specifies the methodology. 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 impact on the economy, its price dynamics, and its relationship with various markets along with its hedging benefits (Demiralay et al., 2022; Dai et al., 2022).

With respect to its impact on the economy, emissions trading can help reduce 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). Nevertheless, its impact on the economy 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).

With respect to price dynamics, 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 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 (Paolella and Taschini, 2008; Benz and Trück, 2009; Arouri et al., 2012; Byun and Cho, 2013; García-Martos et al., 2013; Huang et al., 2021), 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).

Yet others have looked at the impact of policy uncertainties on the volatility of carbon markets. Dong et al. (2024a) have found that market risk spillovers are exacerbated by uncertainty with respect to climate and trade policies leading to increased volatility in energy markets in China. This to an extent confirms the broader causal relationship between climate policy uncertainty and 'traditional' energy markets (Ren et al., 2023) where indexation of climate policy uncertainty (Gavriilidis, 2021) – which itself was based on economic policy uncertainty index developed Baker et al. (2016) - is utilized. Similarly, Dai et al. (2022) uses both European economic policy uncertainty index - also constructed by Baker et al. (2016) - as well as a proxy for a similar global uncertainty index and demonstrate that both uncertainties impact the long-term volatility of European carbon spot return, though the effect is larger for the global policy uncertainty. They argue that this may be due to European companies adjusting their demand for EU ETS based on revised expectations in response to global economic environment. 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 (Chen and Zhao, 2024; Feng et al., 2011; Lutz et al., 2013; Segnon et al., 2017).

In that respect, there 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 (Ji et al., 2018; Zhang and Sun, 2016; 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). However, with the changes introduced in each of the subsequent phases such impacts became harder to establish (Wu et al., 2020; Arouri et al., 2012). 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 (Lovcha et al., 2022; Tan et al., 2020; Yang, 2022). Moreover, interconnectedness of the carbon with other markets evolves overtime and has increased with financial markets in recent years (Dong et al., 2024b; Jiménez-Rodríguez, 2019; Tan et al., 2020). 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 specific markets, this study aims to expand that understanding further by examining the interlinkages with the equity, fixed income, energy, and non-energy commodity markets, and by including the data that captures Phase IV of EU-ETS to date with a view to ascertain 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. The changes introduced under Fit for 55 and RePowerEU as well as the expansion under Phase IV could be viewed as a policy uncertainty, or shock. If so, volatility connectedness of EU-ETS ought to exhibit patterns that are in alignment with the previous findings of the impacts of policy shocks. Similarly, by examining the impacts of Covid-19 and Russia-Ukraine war we can compare the magnitude of the impacts of the policy shocks to exogenous shocks. This understanding could benefit investors with portfolio diversification benefits and better manage their risks and help policy makers recognize the carbon market volatility connectedness in policy formulation. To this end, we utilize the following data.

3. Data

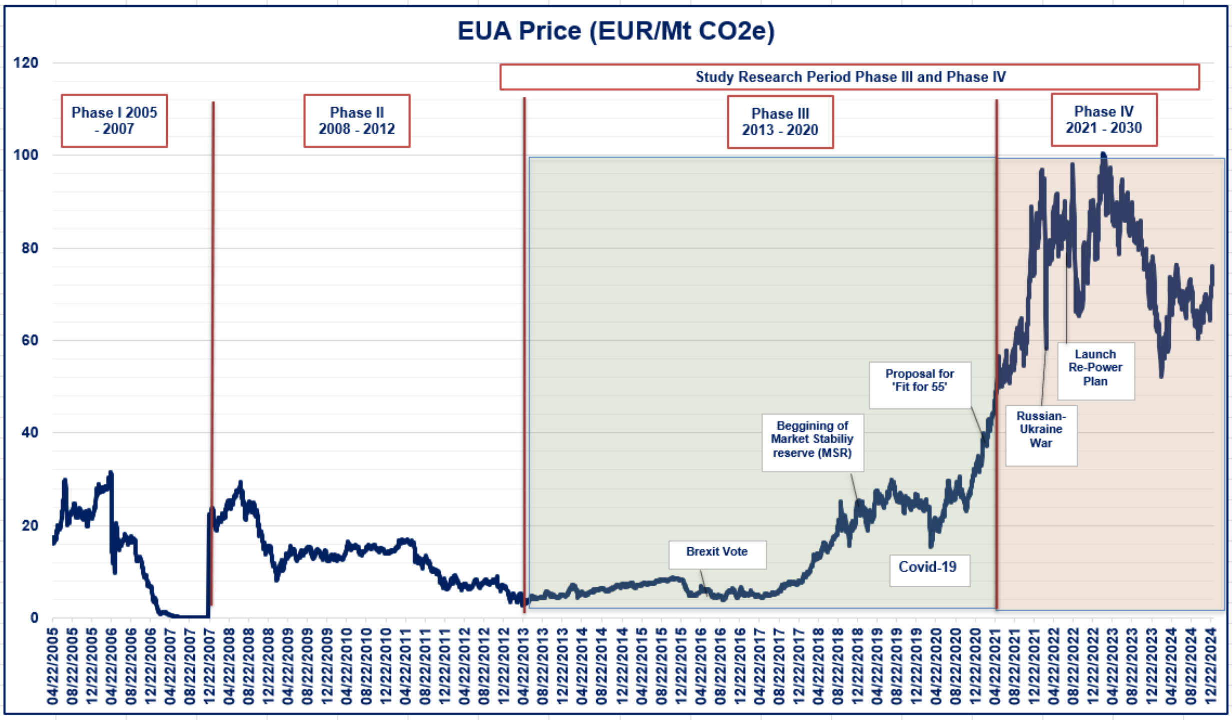
We obtain daily price data for EUAs and other financial markets from Bloomberg LP and Refinitiv, covering the period from January 2, 2013, to January 9, 2025. This time frame, as shown in Figure 1, encompasses Phases III and, to the extent possible, Phase IV of the European Union Emissions Trading System (EU ETS), including the reforms introduced under Fit for 55 package and RePowerEU. This timeframe also captures macroeconomic events such as the 2016 Brexit referendum, the Covid-19 pandemic, and the escalation of the Russian-Ukrainian conflict, ensuring the data reflects diverse market regimes that includes periods of low and high volatility, enhancing the dataset's ability to capture dynamic interrelationships.

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 inclusion of multiple asset classes enables a comprehensive examination of cross-market interdependencies.

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 European oil, coal, and gas markets, respectively.

In total, this data set comprises of 31,320 observations. All prices are converted to EUR at the closing rate of the day to eliminate the impact of currency fluctuations. 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

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



is evident that none of the variables conform to a normal distribution. Therefore, 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.

4. 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

[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)

Table 1: Descriptive statistics of daily return and volatility

(a) Daily returns

	Mean	Median	Max	Min	St.Dev.	Skewness	Kurtosis	Obs.	J-B	p
CARBON	0.0008	0.0003	0.2690	-0.4321	0.0311	-0.8870	17.1200	3132	38659.55	0
EUROSTOXX	0.0002	0.0005	0.0807	-0.1219	0.0099	-1.0461	13.0413	3132	22766.20	0
BRENTOIL	0.0000	0.0008	0.2008	-0.2854	0.0230	-0.7902	17.1398	3132	38663.40	0
COALAPI	0.0001	-0.0002	0.2807	-0.3475	0.0248	-0.2980	30.8349	3132	124124.60	0
NATGAS	0.0002	0.0000	0.4077	-0.3542	0.0391	0.2731	13.6133	3132	24223.52	0
EURSOVER	0.0001	0.0001	0.0198	-0.0173	0.0030	0.0984	4.2839	3132	2399.99	0
EURCORP	0.0001	0.0001	0.0137	-0.0220	0.0019	-0.6403	12.2987	3132	19953.30	0
SPXINDEX	0.0005	0.0005	0.0982	-0.1347	0.0113	-0.7255	15.0566	3132	29859.31	0
COMEXENG	0.0000	0.0000	0.0399	-0.0404	0.0072	-0.1263	2.1173	3132	593.34	0
METALS	0.0001	0.0000	0.0582	-0.1019	0.0101	-0.5316	6.9991	3132	6540.40	0

(b) Volatility

	Mean	Median	Max	Min	St.Dev.	Skewness	Kurtosis	Obs	J-B	p
CARBON	0.4356	0.3862	2.0253	0.1316	0.2300	2.4550	9.5660	3118	15020.48	0
EUROSTOXX	0.1376	0.1216	0.7173	0.0315	0.0753	3.0008	15.2367	3118	34840.52	0
BRENTOIL	0.3157	0.2752	1.6832	0.0771	0.1852	2.8575	11.9073	3118	22663.44	0
COALAPI	0.2999	0.2320	2.4781	0.0440	0.2573	3.9684	25.0456	3118	89678.03	0
NATGAS	0.4810	0.3590	3.0545	0.0506	0.3930	2.2461	7.9864	3118	10907.95	0
EURSOVER	0.0422	0.0359	0.1336	0.0129	0.0219	1.6167	2.7308	3118	2327.09	0
EURCORP	0.0247	0.0193	0.1136	0.0071	0.0151	2.2346	6.3384	3118	7814.34	0
SPXINDEX	0.1545	0.1321	1.0220	0.0574	0.0935	4.7939	35.9813	3118	180139.80	0
COMEXENG	0.1078	0.1013	0.3422	0.0460	0.0368	2.1979	8.2717	3118	11399.38	0
METALS	0.1485	0.1358	0.4857	0.0481	0.0621	1.7763	4.9894	3118	4873.92	0

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) 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 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):

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

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 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:

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

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

5. Empirical Results

We investigate the total connectedness of the carbon with other markets before analyzing its pairwise connectedness to have a better understanding of the bilateral behavior, especially when exogeneous shocks occur. Within these we first consider static connectedness to have a better understanding of the interdependencies, and then consider dynamic connectedness to understand their time-varying character.

5.1. Static Total Connectedness

We begin our investigation with static 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 46.05% for returns and 49.04% for volatility, respectively, indicating a moderate level of connectedness across all markets since this implies that the remainder 53.95% of the market return and 50.96% 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 34.31% to the returns of other markets and 31.83% to their volatility while receiving from other markets 39.94% and 44.34% return and volatility shocks, respectively. Accordingly, the EUAs are net return receiver of 5.63% and volatility spillover receiver of 12.51%. This also means that the remaining 60.06% of the return and 55.6% 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. This low

Table 2: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	DSF (FROM)
CARBON	60.06	**39.94**
DST (TO)	**34.31**	460.50
Inc.Own	96.26	**TCI**
NS (NET)	**-5.63**	**46.05**

(b) Carbon volatility connectedness matrix

	CARBON	DSF (FROM)
CARBON	55.66	**44.34**
DST (TO)	**31.83**	490.40
Inc.Own	87.49	**TCI**
NS (NET)	**-12.51**	**49.04**

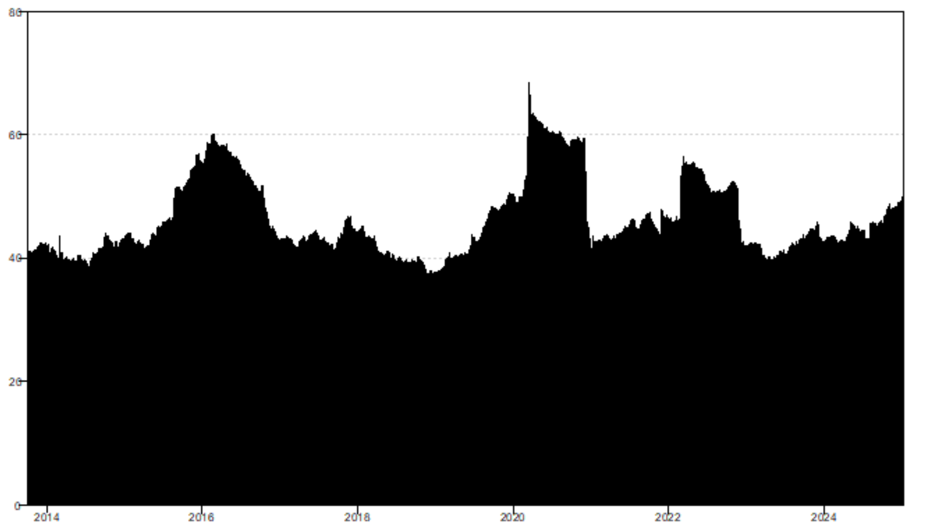
integration may offer diversification benefits for portfolios that include EUAs in their portfolios. Yet, the nature of these influence may not be homogenous across time. To check this, we examine the dynamic total connectedness.

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 the TCI for both return and volatility tends to increase, though tend to drop back within a year or less. For example, consider the system we analyze - i.e. the carbon, European equity, European corporate bond, European sovereign bond, European coal, European gas, European oil, international equity, and non-energy commodity markets. We observe that the total connectedness in both return and volatility within these markets steeply increases to 60% around Brexit in 2016 and coming back down to its 2015 levels a year later almost as steeply. Similarly we see a return connectedness spiking at close to 70% and volatilty connectedness to almost 80% with the Covid-19 shock in 2020 which then again comes back down within a year to around their respective long-term average levels in Table 2 above. We see a similar patter once again during the financial market stress triggered by Russia-Ukraine crisis in 2022. All of these suggest that in periods of stress all the markets we analyze exhibit a stronger connectedness between them with a more pronounced spillover effects, albeit relatively short-lived.

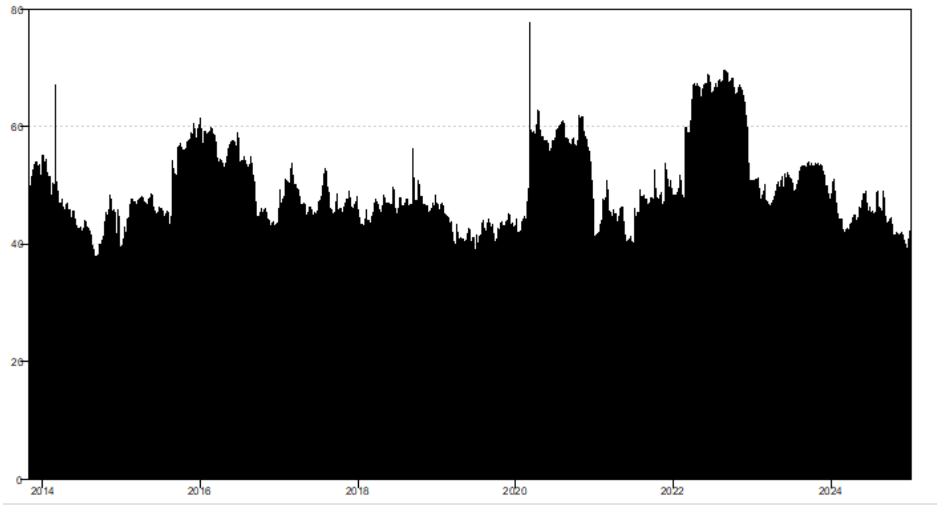
Figure 2: Dynamic Return and Volatility Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return TCI



In contrast, the start of Phase IV in 2021 appears in the first instance to have a lesser impact than these exogenous shocks with return connectedness increasing at a much slower pace, though the effect seems to be

(b) Dynamic volatility TCI

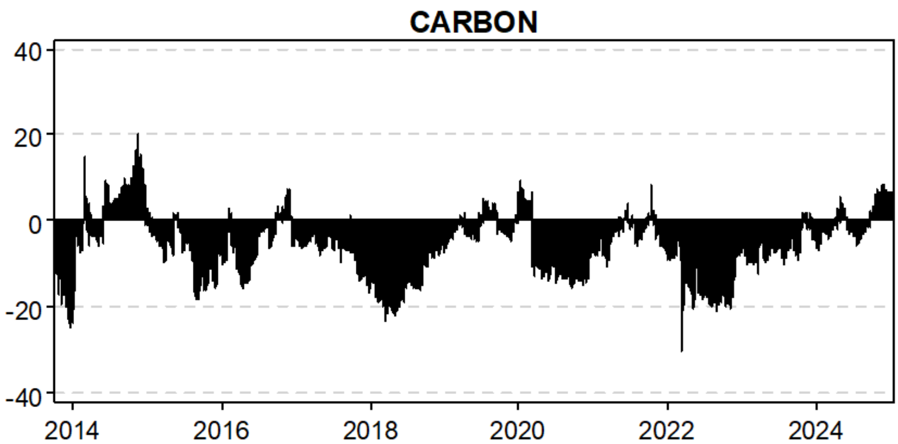


longer lasting as there has not been a persistent reversal to date, if one disregards the Russia-Ukraine shock. The picture is a bit more complicated with respect to volatility connectedness, whereby the magnitude of the initial increase is again lower than the two shocks that bookend the start of Phase IV, which is then followed by a steady decline of this volatility connectedness below its long-run average.

Similarly, dynamic *net* directional connectedness of EUAs with other markets are provided in Figure 3 (Appendix B provides the complete set of charts). The charts indicate that during Brexit vote the carbon's net connectedness of returns and volatility has strengthened before reverting back closer to 0 by 2017. We observe a similar pattern for the Covid-19 and Russia-Ukraine shocks. Curiously, we also observe a similar pattern in 2018 for net return connectedness and volatility. Although, there was not a definitive exogeneous shock, these may be attributable to the broader signs of financial stress around this period that witnessed escalating trade disputes, economic downturn, particularly in China, and beginning of a pattern of rises in interest rates with the Federal Reserve raising it four times in that year.

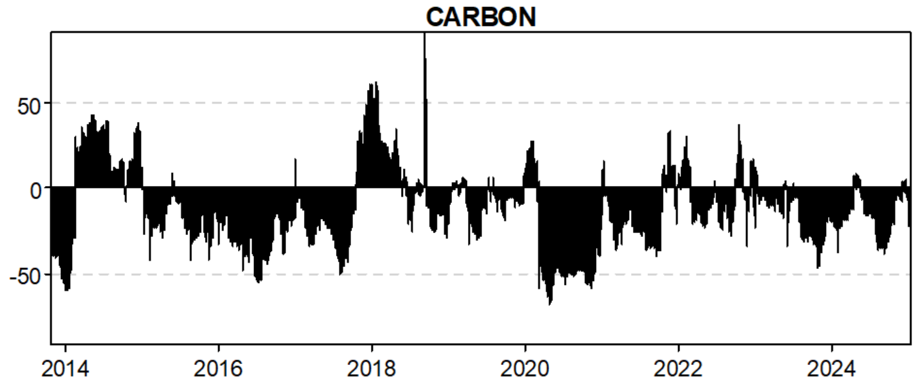
Figure 3: Net Directional Connectedness between EUAs and other markets (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



Overall, these net directional connectedness also suggest that in periods of financial stress the return and

(b) Dynamic volatility net directional connectedness



volatility connectedness between the EUAs and other markets increase. This seem to echo the implications derived from the dynamic TCIs, though the latter looks only at the total connectedness of the markets with each other, whereas here we can ascertain the net connectedness of EUAs with other markets. Importantly, in contrast to the EUAs' net return connectedness in panel (a) that shows, for the mast part, EUAs as a receiver of return shocks from other markets,[8] panel (b) shows that the volatility net connectedness briefly flips to positive in times of financial stress. Despite this increased connectedness during financial stress, the change in the return connectedness in these times is not only relatively small in magnitude but also short lived. Thus it appears that EUAs can provide diversification benefits to the portfolios both in good times and, when shocks occur, albeit at a briefly reduced levels. Of course, not all portfolios are alike. In order to better understand carbon market's behavior with respect to individual markets we subsequently conduct pairwise connectedness analysis.

5.3. Static Pairwise Connectedness

TCI results are informative. However, as Section 4 highlighted, for networks with more than two variables, TCI tends to be less efficient and accurate than PCI. PCI helps us break down the total connectedness by measuring 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.

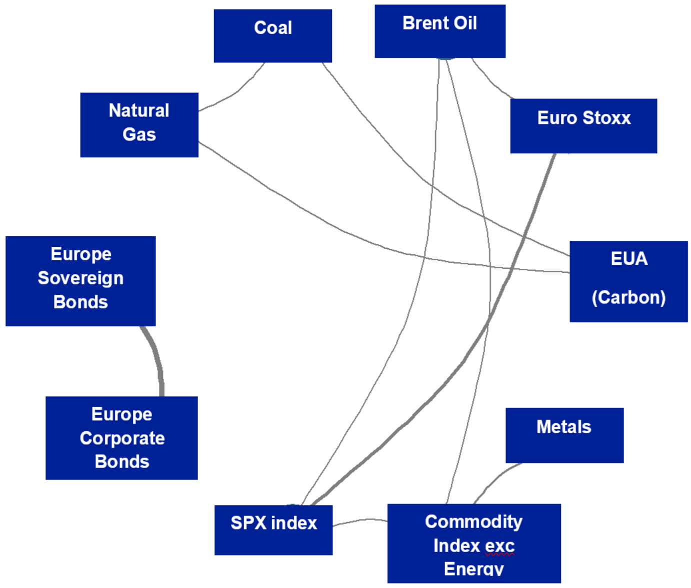
Figure 4 illustrates the network representation of PCI where a line between markets means that a pairwise connectedness exists between them with the thickness of the line indicating the magnitude of such connectedness. For example, in panel (a) a strong pairwise connectedness exists between European 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 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 among coal and natural gas also. 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

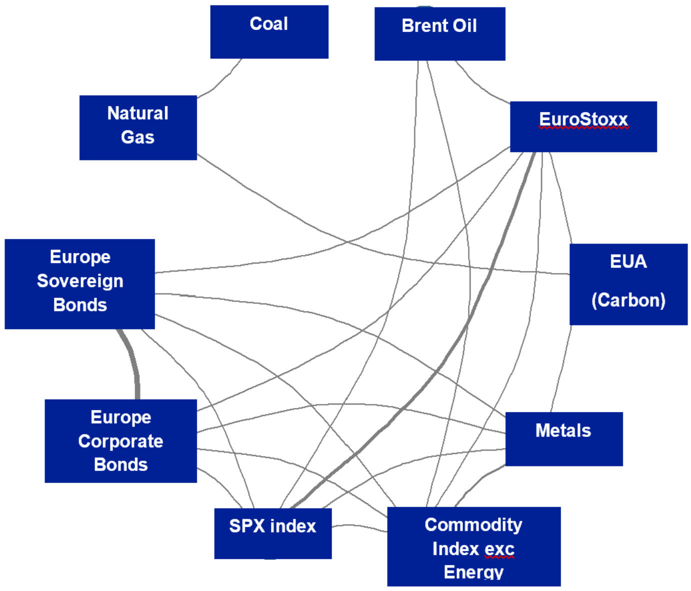
[8]Although, interestingly, we see a recent flip to net positive return connectedness towards the end of 2024

Figure 4: Network representation of Pairwise Connectedness Index (PCI) (Jan 2013 – Jan 2025)

(a) Static return PCI network



(b) Static volatility PCI network



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.

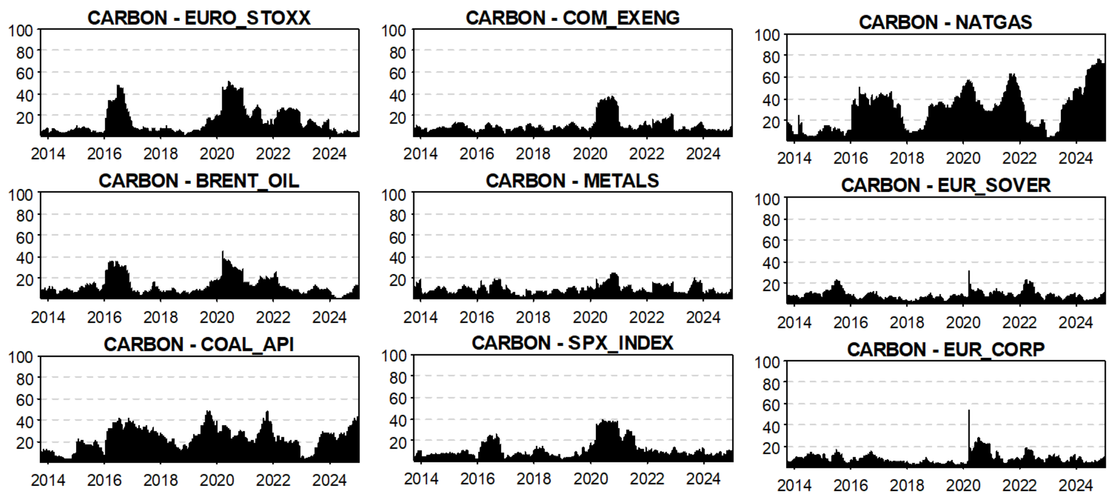
The PCI volatility network in panel (b) reveals similar patterns, though EUAs demonstrate volatility linkages with natural gas, as well as Stoxx 600 Index and Bloomberg Metal Commodity Index, but not with coal. This observation of volatility connectedness not with coal but with natural gas is supported 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. The volatility connectedness with Stoxx 600 and metals, on the other hand, seems to support the observation of stronger total connectedness in times of financial stress. In order to examine the behavior of this over time, we next consider the dynamic pairwise connectedness.

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.

Figure 5: Dynamic Return and Volatility Pairwise Connectedness Index (PCI) (Jan 2013 – Jan 2025)

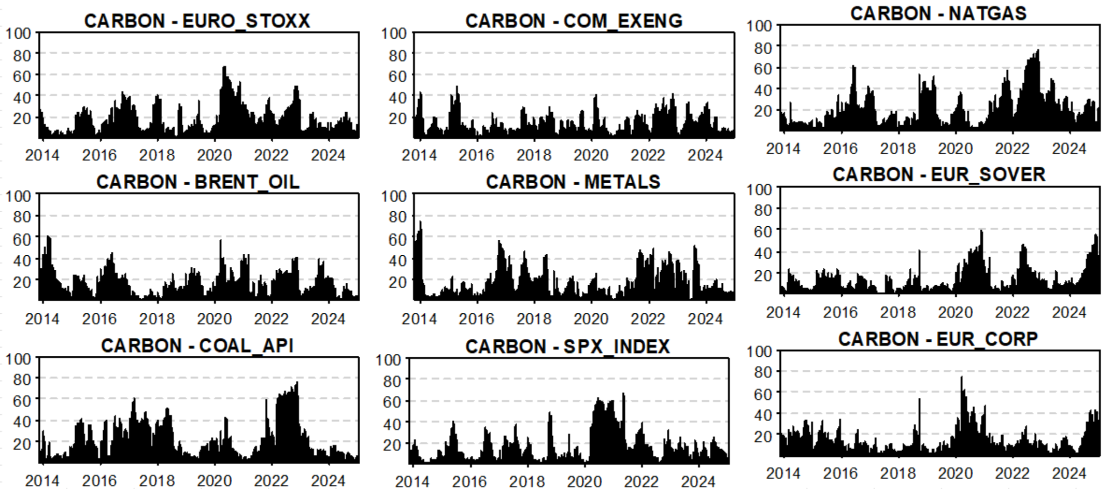
(a) Dynamic return PCI



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 it was observed in the total connectedness most of these are short-lived. From these dynamic PCI charts it also appears that coal and natural gas have stronger return connectedness with the EUAs over time compared to other markets.

There also seems to be a long-run incline in the return connectedness between EUAs and natural gas, and a higher average connection with coal. These changes may be attributable to various market, regulatory, and policy factors. Especially from 2021 onwards, the introduction of Phase IV and impacts of Fit for 55 and RePowerEU, which is accelerating the deployment of renewable energy across Europe and helping the EU advance its climate goals and reduce greenhouse gas emissions while also diminishing reliance on Russian energy imports (European Commission, 2024), may be contributing to this return connectedness behavior. 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

(b) Dynamic volatility PCI network



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 gradual decrease in coal usage. These may explain why EUA prices' link with coal are lower in strength than that of natural gas.

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 Figure 5 that such connectedness with Stoxx 600 Index and S&P 500 Index seems to have gained prominence around 2020. A similar pattern can also be observed for EUAs connectedness with commodities and metals along with a brief spike in bonds. Yet, it appears that among all pairwise connectedness that gained prominence around 2020, only the return connectedness with coal and natural gas is not short-lived, suggesting that broad exogeneous shocks such as Covid-19 can briefly strengthen the comnnectedness of carbon with other asset-classes.

The trend of strengthened connectedness with the equity markets may also be due to the relatively recent introduction of financial products like Exchange Traded Funds (ETFs) and other investment vehicles focusing on carbon markets, including EUAs. 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 which would be a significant finding for institutional investors looking to integrate EUAs into their portfolios. However, the biggest seven ETFs have about EUR 430m assets under management (AUM) in total,[9] so the magnitude of the impact of this would inevitably be small. Nevertheless the results of this study reveal that the overall interconnectedness of EUAs with markets other than coal and natural gas remains relatively low, reinforcing the potential diversification benefits of including EUAs in investment portfolios, especially for portfolios that exclude coal and natural gas. Such diversification benefits, in turn, ought to incentivize financial institutions to increase participation in the EU ETS and help further the EU's efforts

[9]As of 31 January 2025, the largest seven ETFs on EUAs have a total AUM of EUR 428,695,211 with 5,154,000 total EUA holdings. These are, in descending order, SparkChange Physical Carbon EUA with AUM of EUR 148,604,300 and EUA holdings of 1,817,000; KRBN with AUM of EUR 129,364,862 and EUA holdings of 1,533,000; WisdomTree with AUM of EUR 83,862,474 and EUA holdings of 999,000; XEAL with AUM of EUR 29,878,322 and EUA holdings of 365,000; GRN with AUM of EUR 24,577,978 and EUA holdings of 293,000; KEUA with AUM of EUR 9,597,703 and EUA holdings of 114,000; and Horizons with AUM of EUR 2,809,572 and EUA holdings of 33,000.

in decarbonization and transitioning into renewables.

5.5. Robustness Testing of Connectedness (VAR) Model Parameters

We additionally test the robustness of the connectedness model parameters following the methodology proposed by Wang et al. (2023) by analyzing the sensitivity of the vector autoregression (VAR) model's outcomes to changes in rolling window size and forecast horizon. While the primary estimation utilized a rolling window of 200 observations and a forecast horizon of 10 periods, alternative configurations, including rolling window sizes of 180 and 220 observations and forecast horizons of 8 and 12 periods, were tested. The results, detailed in Appendix D, provide compelling evidence supporting the reliability of the model.

The findings indicate that the total spillover index remains largely stable across the alternative specifications, affirming the robustness of the estimated spillover dynamics. Similarly, the pairwise connectedness index (PCI) network structure exhibits minimal variation, particularly emphasizing the return linkages between EUA carbon markets with gas and coal markets. For volatility spillovers, a notable trend is observed: as the forecast horizon of the VAR model is shortened, the spillovers from EUA carbon markets to other markets decline, indicating reduced volatility interdependence over shorter time frames.

These results are consistent across all tested rolling window sizes and forecast horizons, confirming that the observed outcomes are not sensitive to parameter variations. Consequently, the analysis validates the study's conclusions regarding spillover effects among EUA carbon markets and related markets. The stability of the metrics and network structures further underscores the robustness and effectiveness of the connectedness analysis in capturing intermarket relationships.

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-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 asssist the EU's climate goal by being a market for diversification. Our findings show that in times of financial stress returns and volatility of EUAs are briefly connected with equity markets such as Stoxx 600 and S&P 500, with European sovereign and corporate bond markets, and with metals and non-energy commodity markets, but become become less connected or altogether unconnected again relatively quickly.

On the other hand, we see a stronger connection with the coal and natural gas markets that is more pronounced during exogeneous shocks, though again, short-lived. Nevertheless, it appears that there is a stronger long-term connectedness with these markets - particularly from 2021 onwards - that are lower in magnitude compared to the impacts of exogeneous shocks but longer in duration. These are likely due to various market, regulatory, and policy factors that accelerate the deployment of renewable energy and phasing out of coal. With the introduction of Phase IV, Fit for 55 package, and RePowerEU Plan, there is a drive to change the energy mix which would influence the demand for, and price of, EUAs, which in turn would increase their connectedness. A natural connection with these energy markets exists due to significant participation of power generation in the EU-ETS. Yet the relationship is complex due to fluctuations in natural gas prices that at times makes fuel-switch to coal an attractive proposition, which, in turn, would again impact the demand for, and price of, EUAs. Such multilayered demand dynamics will inevitably 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.

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. These diversification benefits would likely to be more acute for non-energy portfolios. By incorporating EUAs, investors would not only increase their likelihood of generating higher returns for a unit of volatility but also by increasing the demand for EUAs, they would accelerate the decarbonization efforts of the EU. 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.

Appendix A. Static Return and Volatility Connectedness Matrix

Table A.3: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENT OIL	COAL API	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	DSF (FROM)
CARBON	60.06	4.00	3.80	7.85	10.21	2.48	2.26	3.47	2.76	3.11	**39.94**
EUROSTOXX	3.28	49.76	5.70	3.33	3.12	3.05	3.67	19.87	5.20	3.03	50.24
BRENTOIL	3.49	6.00	57.40	5.44	3.61	2.68	2.34	7.27	8.29	3.49	42.60
COALAPI	6.34	3.77	5.80	56.02	13.78	1.85	2.04	3.84	3.96	2.62	43.98
NATGAS	9.93	3.03	3.88	13.58	58.73	1.80	1.76	2.48	2.56	2.24	41.27
EURSOVER	2.03	2.98	2.68	1.67	1.68	48.35	31.93	2.28	2.05	4.36	51.65
EURCORP	1.97	5.05	2.71	1.75	1.81	30.37	45.49	3.97	2.54	4.35	54.51
SPXINDEX	2.42	17.95	6.82	3.35	2.03	2.30	2.73	53.51	6.40	2.50	46.49
COMEXENG	2.48	5.08	7.44	3.49	2.40	2.16	2.37	6.59	53.07	14.91	46.93
METALS	2.37	3.15	3.10	2.28	2.47	4.83	5.59	2.96	16.14	57.11	42.89
DST (TO)	**34.31**	51.01	41.93	42.73	41.10	51.52	54.69	52.73	49.89	40.60	460.50
Inc.Own	94.37	100.77	99.33	98.75	99.83	99.87	100.18	106.24	102.96	97.70	**TCI**
NS (NET)	**-5.63**	0.77	-0.67	-1.25	-0.17	-0.13	0.18	6.24	2.96	-2.30	**46.05**

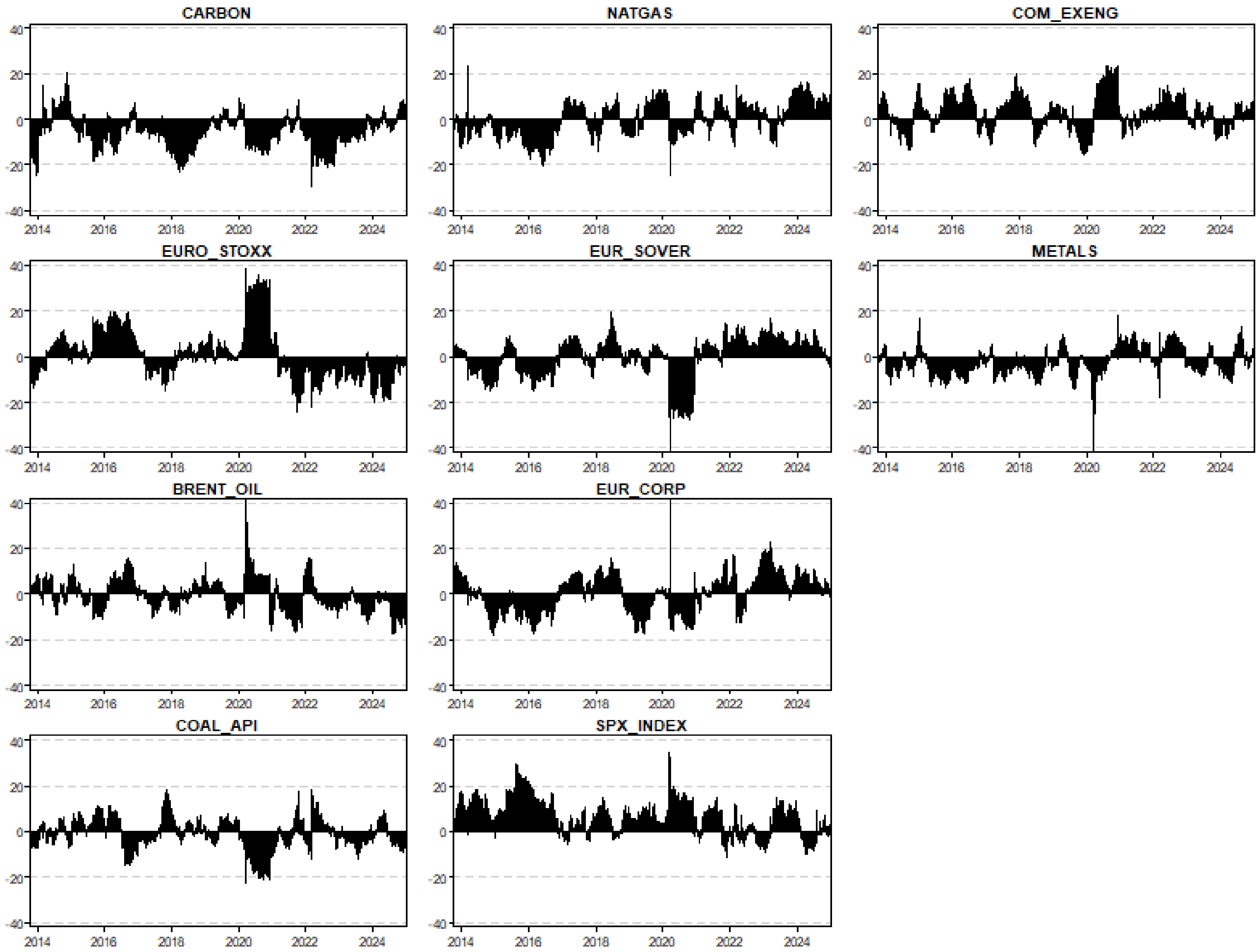
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	DSF (FROM)
CARBON	55.66	4.60	4.29	7.25	7.13	3.77	3.61	5.06	3.83	4.79	**44.34**
EUROSTOXX	3.63	47.09	5.17	3.59	3.45	5.12	4.14	16.60	5.25	5.95	52.91
BRENTOIL	4.20	6.54	52.55	4.93	3.59	3.85	4.54	6.49	7.10	6.20	47.45
COALAPI	4.67	5.83	4.19	57.95	7.85	3.80	2.71	4.59	3.14	5.26	42.05
NATGAS	4.51	4.64	3.43	8.36	59.40	3.52	3.79	4.82	3.56	3.96	40.60
EURSOVER	2.17	6.27	3.30	2.43	1.86	44.69	25.39	5.60	3.86	4.44	55.31
EURCORP	2.81	5.70	2.52	2.34	2.40	28.32	41.90	5.97	4.70	3.33	58.10
SPXINDEX	3.29	15.44	5.03	3.08	1.71	4.71	3.98	53.15	4.44	5.17	46.85
COMEXENG	2.62	7.96	4.69	3.94	4.00	5.32	5.39	6.71	49.30	10.07	50.70
METALS	3.91	8.31	4.44	3.90	3.85	5.08	6.31	6.26	10.05	47.90	52.10
DST (TO)	**31.83**	65.30	37.07	39.82	35.85	63.47	59.86	62.11	45.92	49.18	490.40
Inc.Own	87.49	112.39	89.62	97.77	95.25	108.16	101.76	115.27	95.22	97.08	**TCI**
NS (NET)	**-12.51**	12.39	-10.38	-2.23	-4.75	8.16	1.76	15.27	-4.78	-2.92	**49.04**

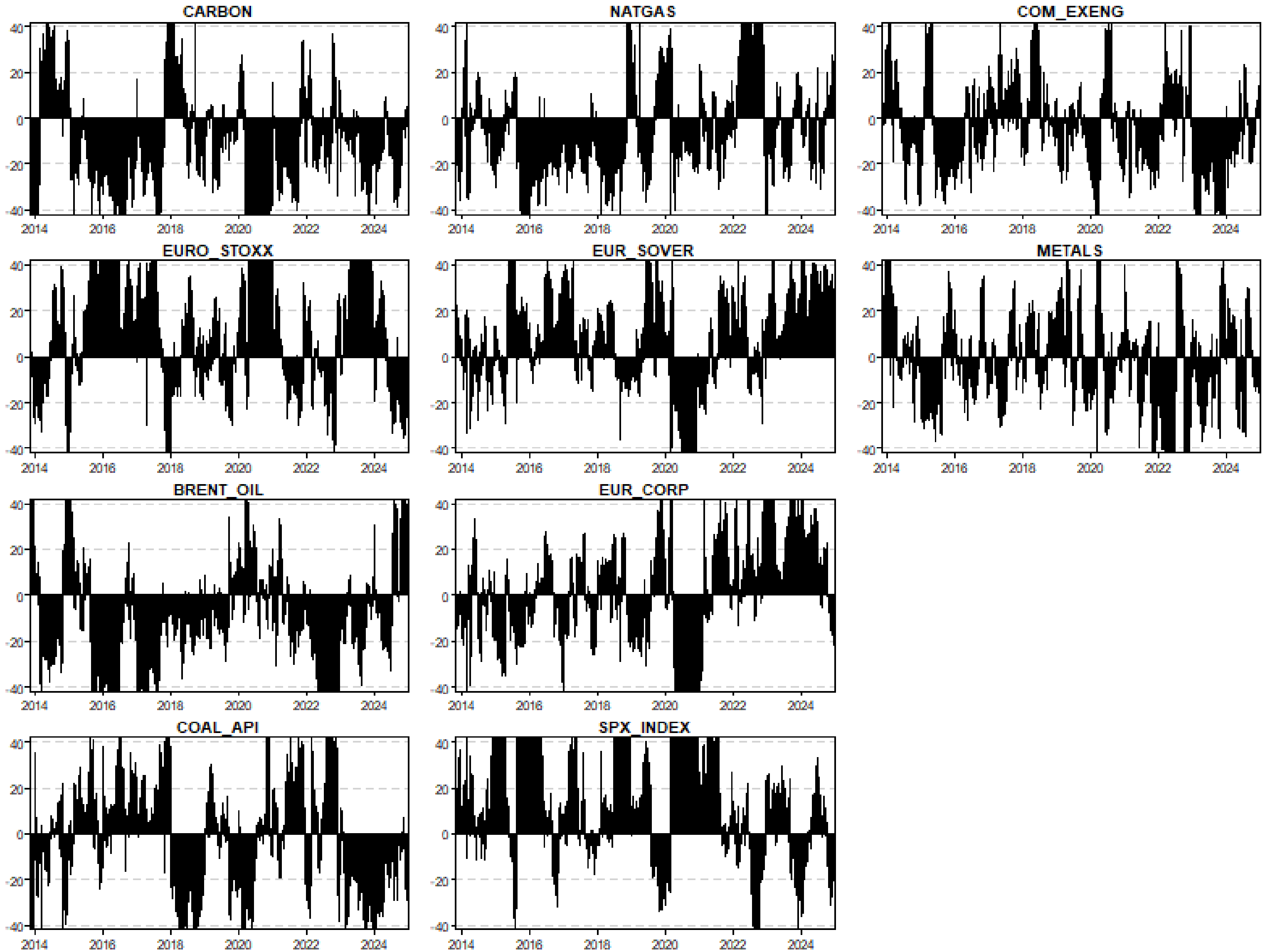
Appendix B. Dynamic Return and Volatility Net Directional Connectedness

Figure B.6: Dynamic Net Directional Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



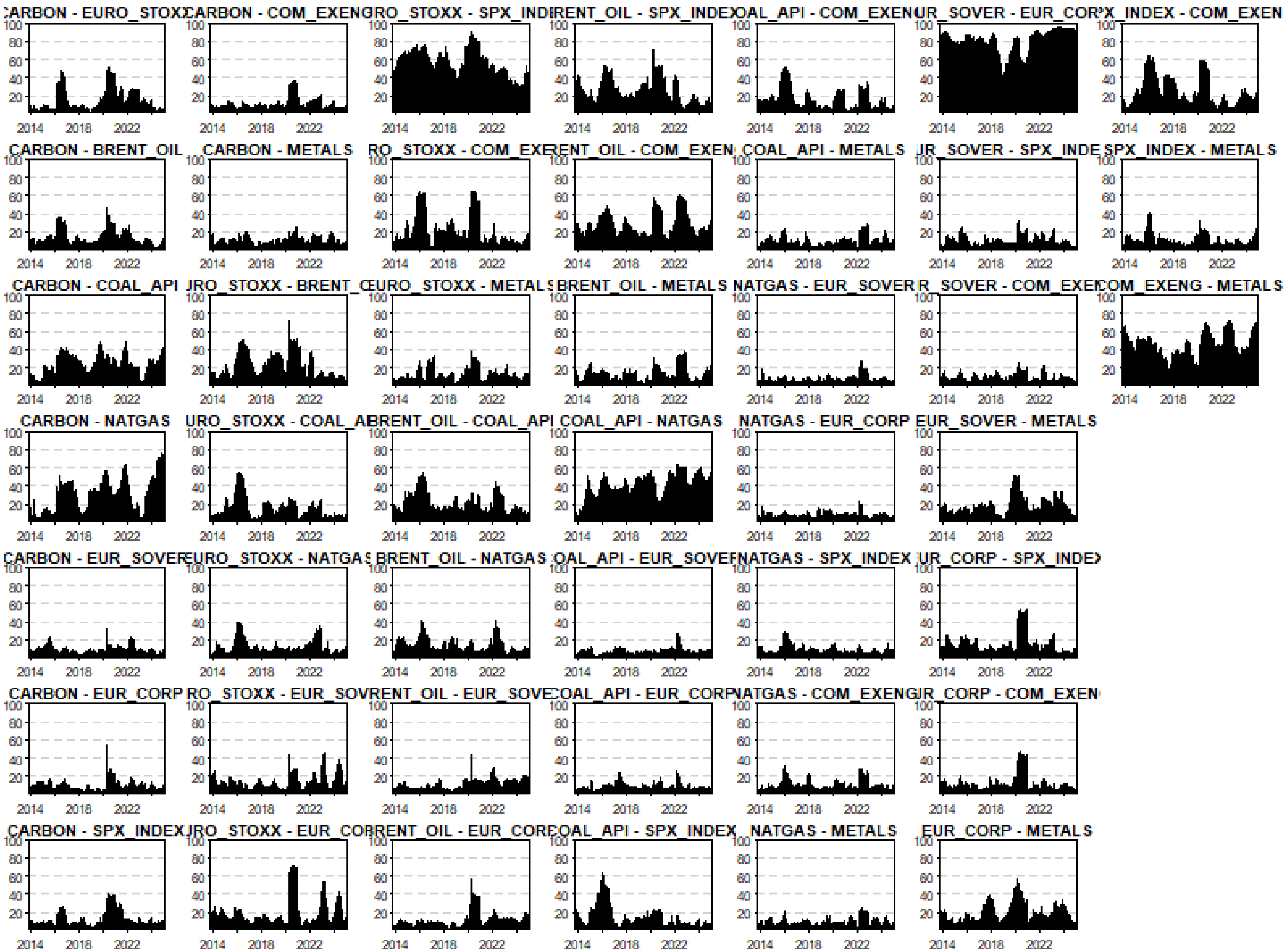
(b) Dynamic volatility net directional connectedness



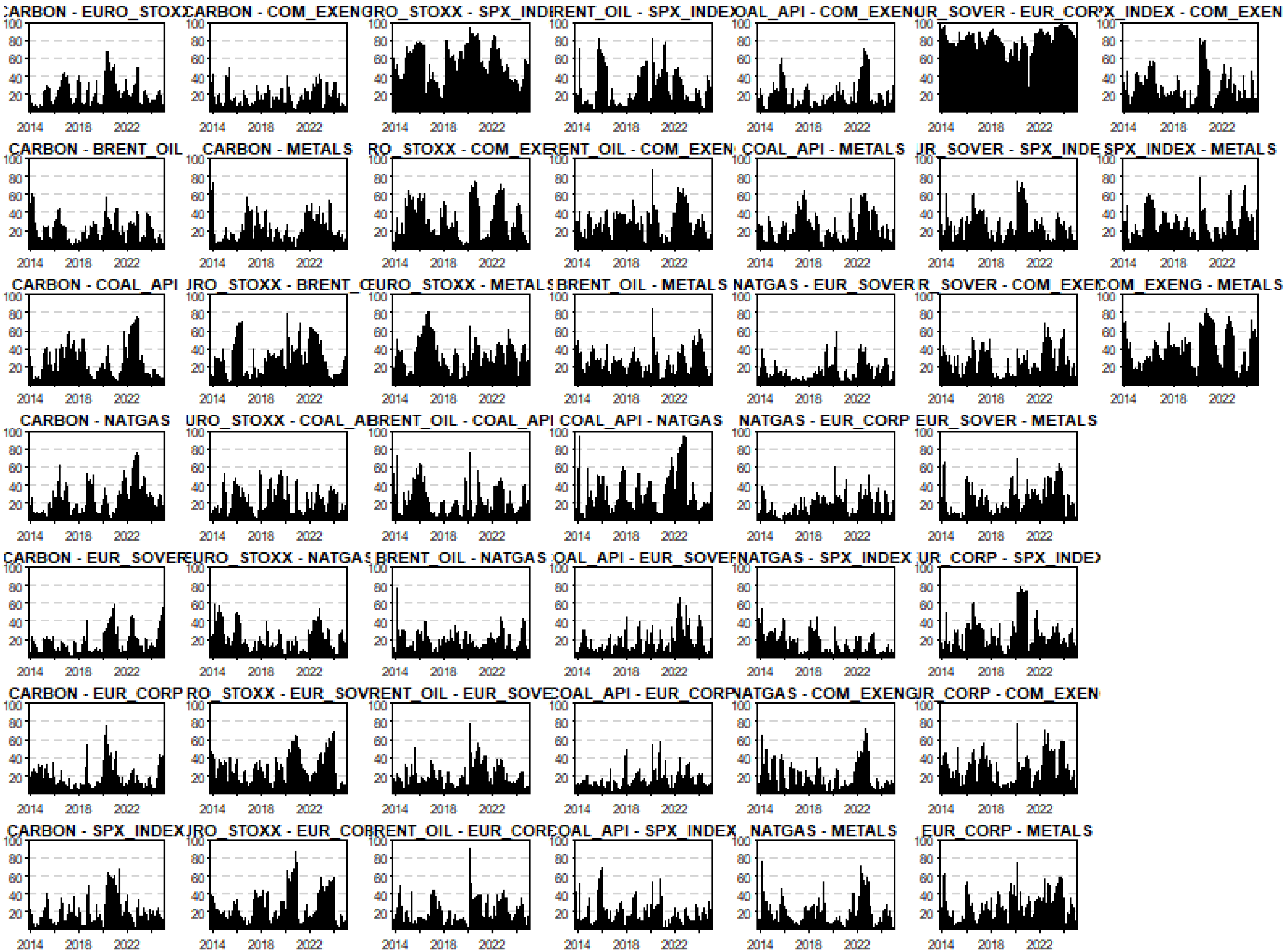
Appendix C. Dynamic Return and Volatility Pairwise Connectedness Index

Figure C.7: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



Appendix D. Robustness Testing of Connectedness Model Parameters

Appendix D.1. 10-period forecast horizon and a rolling window of 180 observations

Appendix D.1.1. Static Return and Volatility Connectedness Matrix

Table D.4: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	58.42	4.13	3.95	7.9	10.32	2.75	2.49	3.71	2.96	3.37	41.58
EUROSTOXX	3.42	48.5	5.77	3.45	3.35	3.4	3.94	19.55	5.3	3.32	51.5
BRENTOIL	3.73	6.14	56.08	5.53	3.75	2.88	2.51	7.34	8.26	3.78	43.92
COALAPI	6.47	3.92	5.88	54.74	13.63	2.07	2.25	4.02	4.11	2.91	45.26
NATGAS	10.05	3.24	4.05	13.36	57.16	2.07	1.99	2.76	2.82	2.49	42.84
EURSOVER	2.25	3.24	2.94	1.89	1.94	47.16	31.34	2.45	2.3	4.48	52.84
EURCORP	2.18	5.15	2.89	1.98	2.05	29.92	44.6	4.04	2.7	4.48	55.4
SPXINDEX	2.62	17.77	6.93	3.49	2.29	2.53	2.92	52.31	6.39	2.75	47.69
COMEXENG	2.68	5.17	7.47	3.64	2.68	2.41	2.56	6.59	51.98	14.82	48.02
METALS	2.58	3.42	3.38	2.51	2.73	4.92	5.67	3.2	15.94	55.65	44.35
DST(TO)	35.98	52.19	43.28	43.75	42.74	52.95	55.68	53.66	50.79	42.39	473.4
Inc. Own	94.41	100.69	99.36	98.49	99.9	100.11	100.28	105.96	102.76	98.04	cTCI/TCI
NS (NET)	-5.59	0.69	-0.64	-1.51	-0.1	0.11	0.28	5.96	2.76	-1.96	52.60/47.34

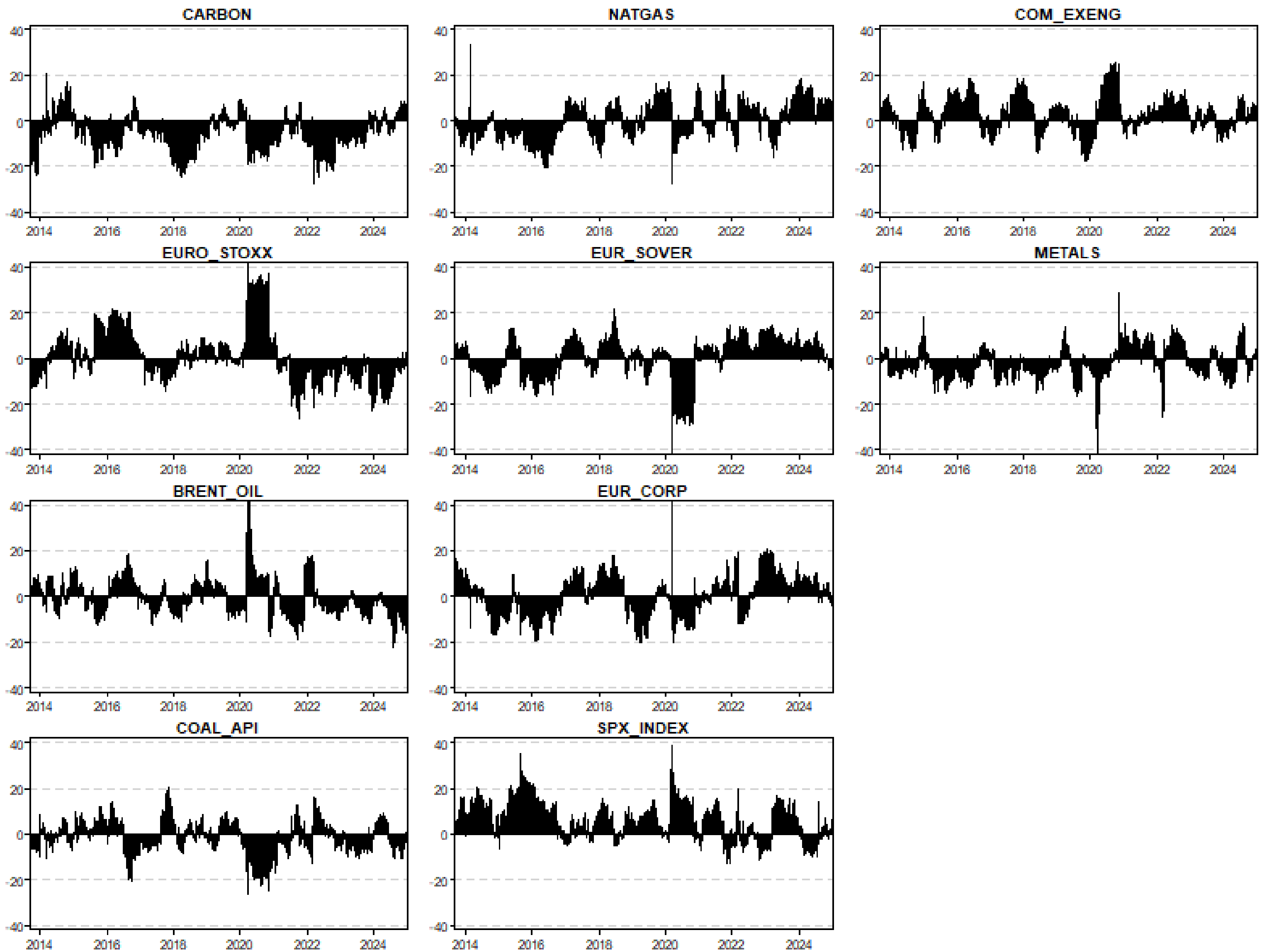
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	52.95	4.7	4.74	7.16	7.63	4.19	3.79	5.42	4.13	5.3	47.05
EUROSTOXX	4.01	45.08	5.34	4.25	3.87	5.52	4.38	15.91	5.33	6.3	54.92
BRENTOIL	4.76	6.68	49.8	5.09	3.85	4.3	4.99	6.78	7.12	6.64	50.2
COALAPI	4.88	6.1	4.69	54.65	8.24	4.24	3.12	5.11	3.45	5.52	45.35
NATGAS	4.74	4.99	3.73	8.42	56.56	3.94	3.96	5.28	4.05	4.33	43.44
EURSOVER	2.49	6.48	3.6	2.86	2.38	42.69	24.76	5.84	4.43	4.47	57.31
EURCORP	3.24	5.76	2.65	2.84	3	27.52	39.98	6.12	5.26	3.63	60.02
SPXINDEX	3.54	15.08	5.4	3.42	2.05	5.22	4.41	50.56	4.69	5.63	49.44
COMEXENG	3.18	7.91	4.75	4.33	4.51	6.08	5.78	7.11	46.34	10	53.66
METALS	4.27	8.4	4.76	4.29	4.33	5.28	6.78	6.91	9.64	45.33	54.67
DST(TO)	35.11	66.11	39.64	42.67	39.87	66.29	61.97	64.48	48.1	51.81	516.05
Inc. Own	88.06	111.19	89.44	97.33	96.43	108.98	101.96	115.04	94.45	97.14	cTCI/TCI
NS (NET)	-11.94	11.19	-10.56	-2.67	-3.57	8.98	1.96	15.04	-5.55	-2.86	57.34/51.60

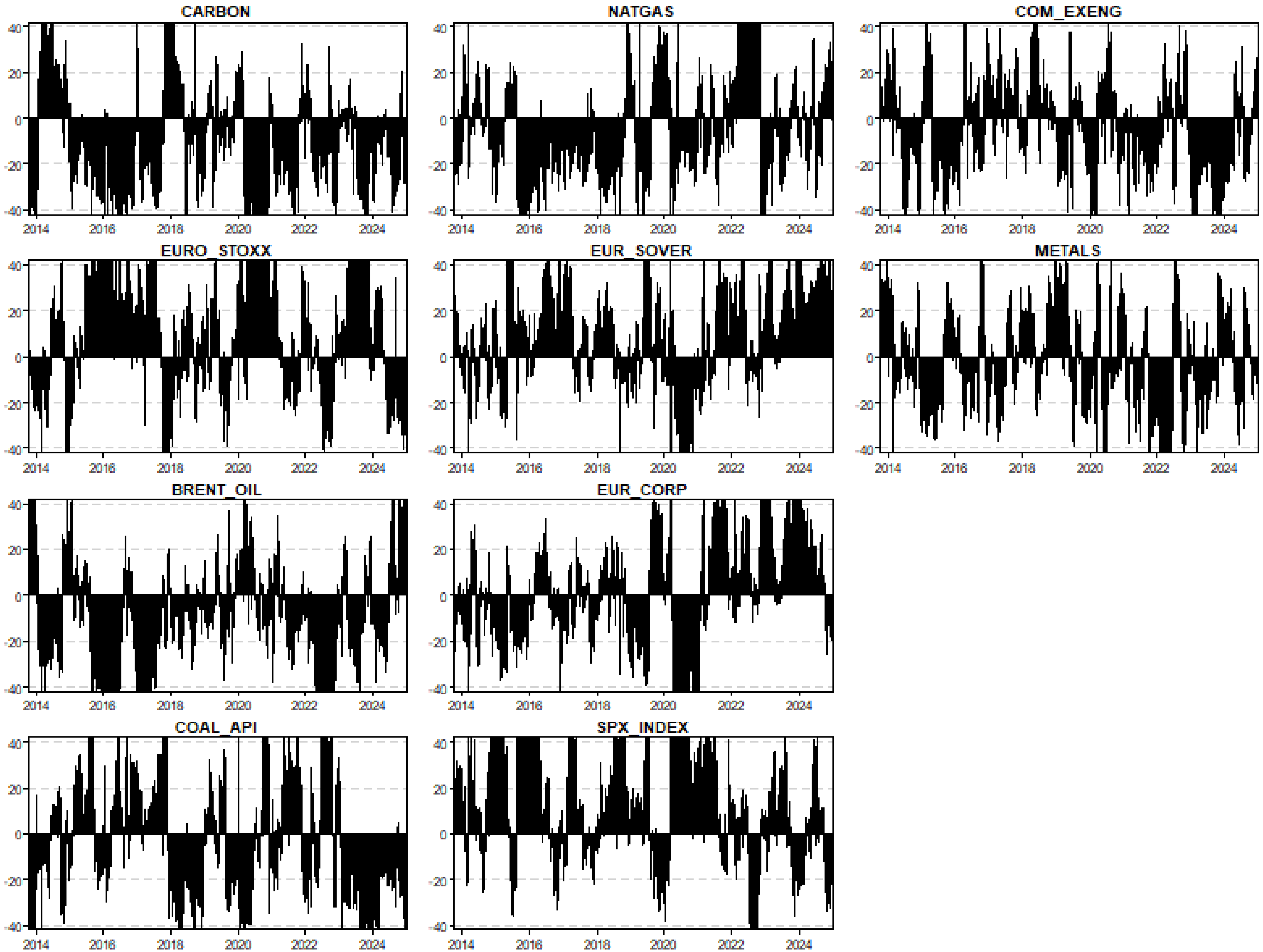
Appendix D.1.2. Dynamic Return and Volatility Net Directional Connectedness

Figure D.8: Dynamic Net Directional Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



(b) Dynamic volatility net directional connectedness

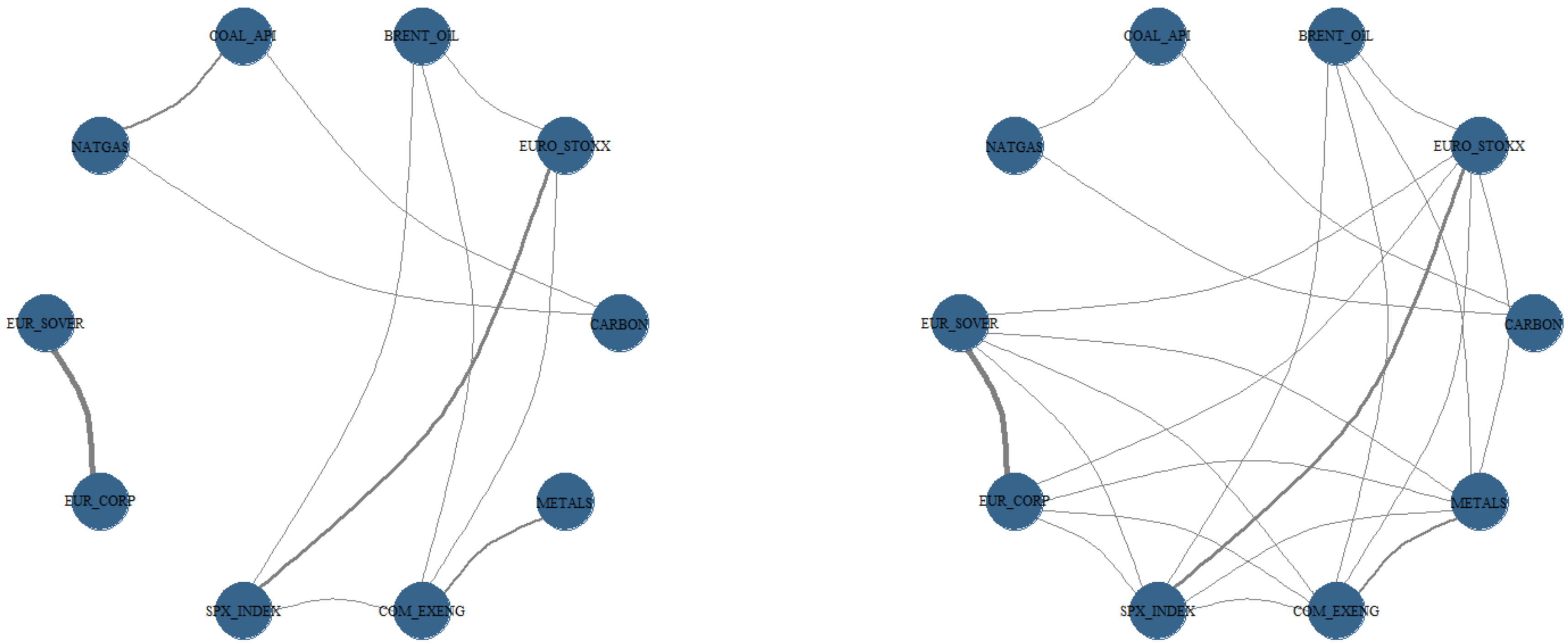


Appendix D.1.3. Static Return and Volatility Pairwise Directional Connectedness

Figure D.9: Network Representation of Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Static Return PCI network

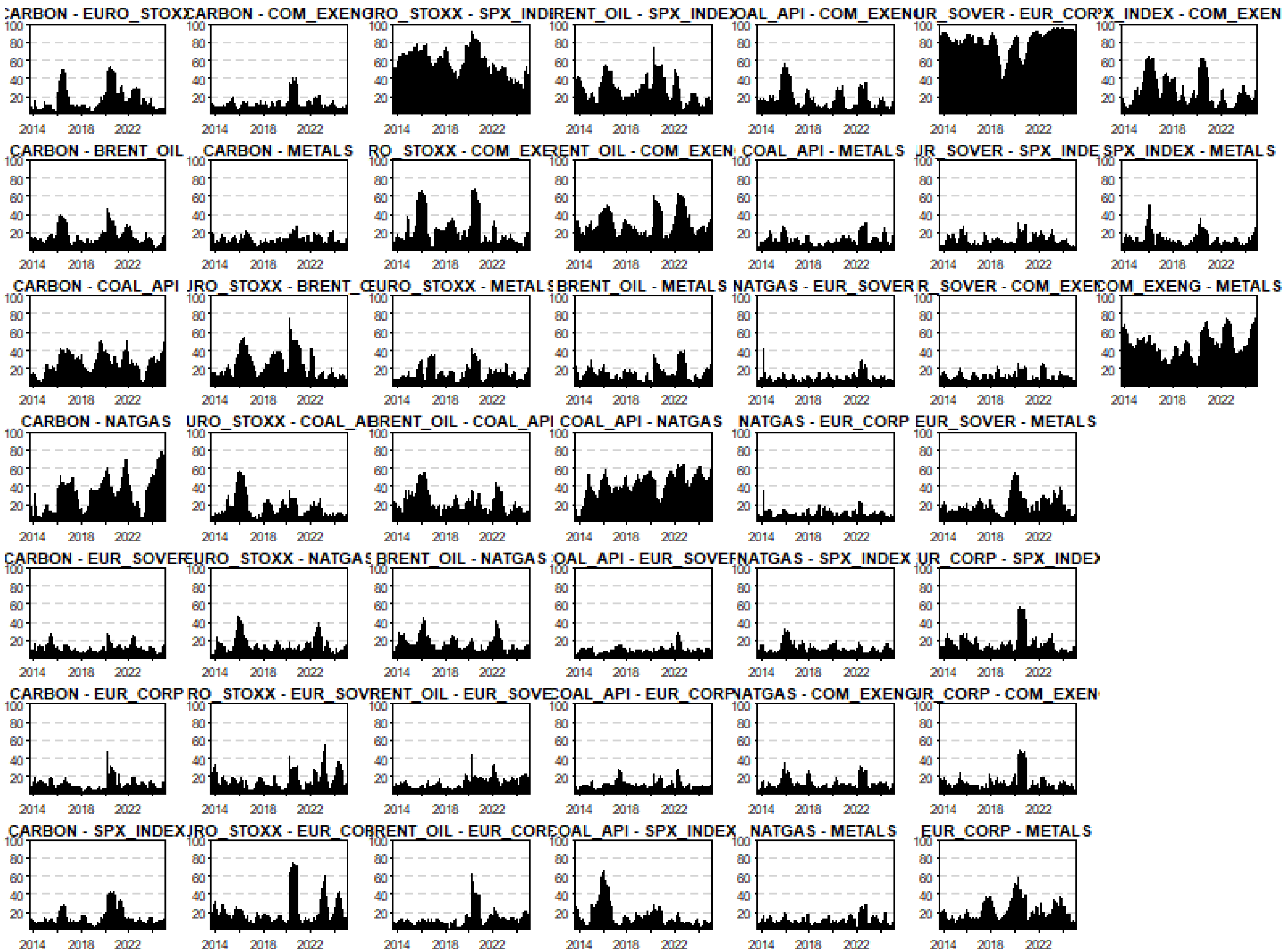
(b) Static Volatility PCI network



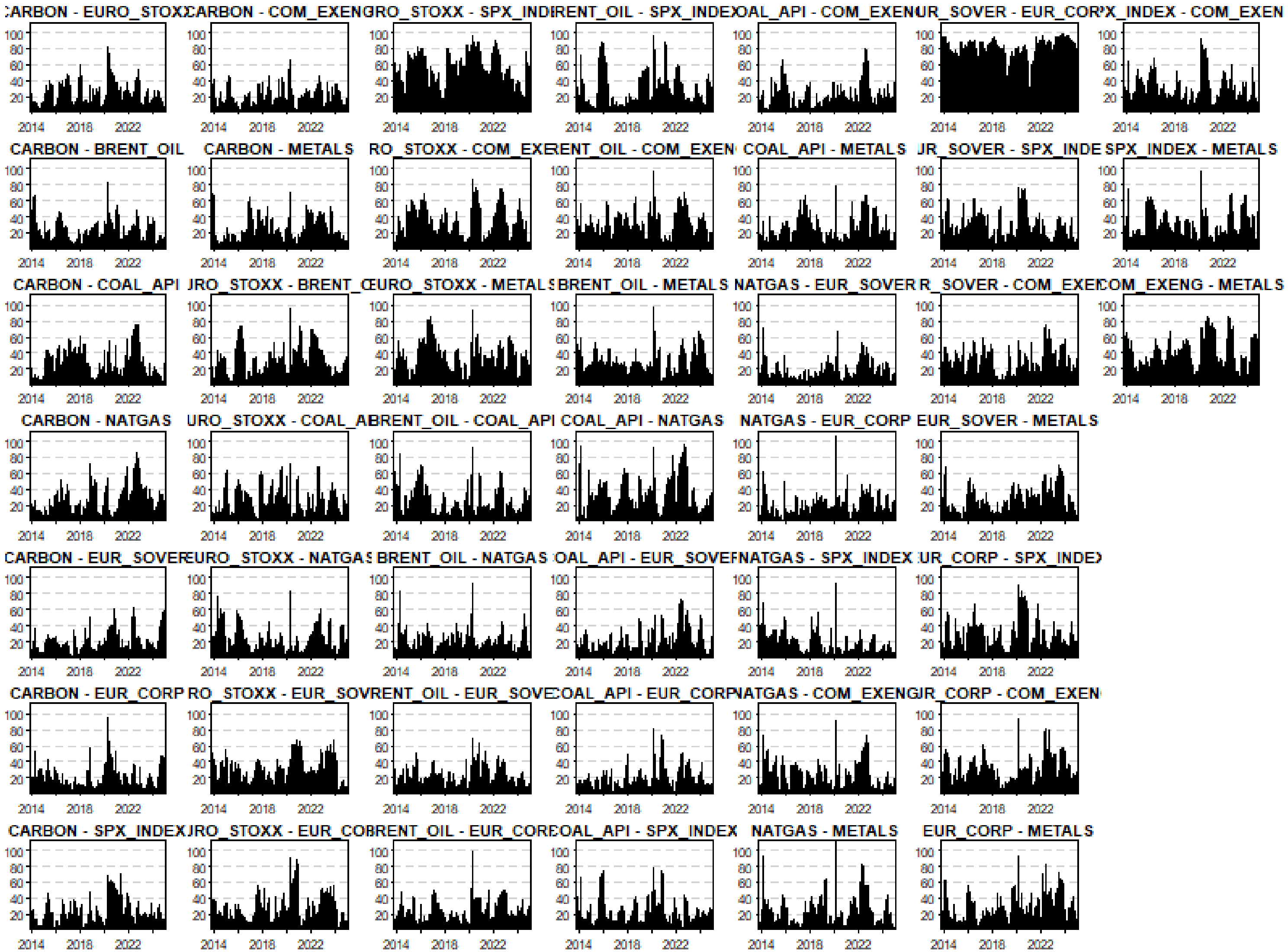
Appendix D.1.4. Dynamic Return and Volatility Pairwise Directional Connectedness

Figure D.10: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



Appendix D.2. 10-period forecast horizon and a rolling window of 220 observations

Appendix D.2.1. Static Return and Volatility Connectedness Matrix

Table D.5: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	61.35	3.93	3.67	7.77	10.07	2.29	2.12	3.28	2.6	2.91	38.65
EUROSTOXX	3.17	50.79	5.67	3.23	2.94	2.75	3.43	20.12	5.14	2.77	49.21
BRENTOIL	3.31	5.91	58.43	5.38	3.49	2.5	2.22	7.19	8.32	3.25	41.57
COALAPI	6.21	3.65	5.74	57.04	13.87	1.71	1.88	3.69	3.82	2.38	42.96
NATGAS	9.8	2.86	3.74	13.76	59.97	1.62	1.6	2.23	2.37	2.05	40.03
EURSOVER	1.86	2.78	2.47	1.5	1.47	49.32	32.36	2.14	1.84	4.25	50.68
EURCORP	1.83	5	2.6	1.56	1.6	30.68	46.15	3.92	2.43	4.22	53.85
SPXINDEX	2.25	18.12	6.71	3.21	1.8	2.12	2.58	54.48	6.44	2.29	45.52
COMEXENG	2.32	5.03	7.42	3.34	2.17	1.96	2.21	6.63	53.93	14.98	46.07
METALS	2.21	2.9	2.88	2.07	2.24	4.77	5.5	2.76	16.3	58.36	41.64
DST(TO)	32.96	50.19	40.89	41.83	39.66	50.41	53.92	51.95	49.25	39.11	450.17
Inc. Own	94.31	100.98	99.31	98.87	99.63	99.74	100.08	106.43	103.18	97.48	cTCI/TCI
NS (NET)	-5.69	0.98	-0.69	-1.13	-0.37	-0.26	0.08	6.43	3.18	-2.52	50.02/45.02

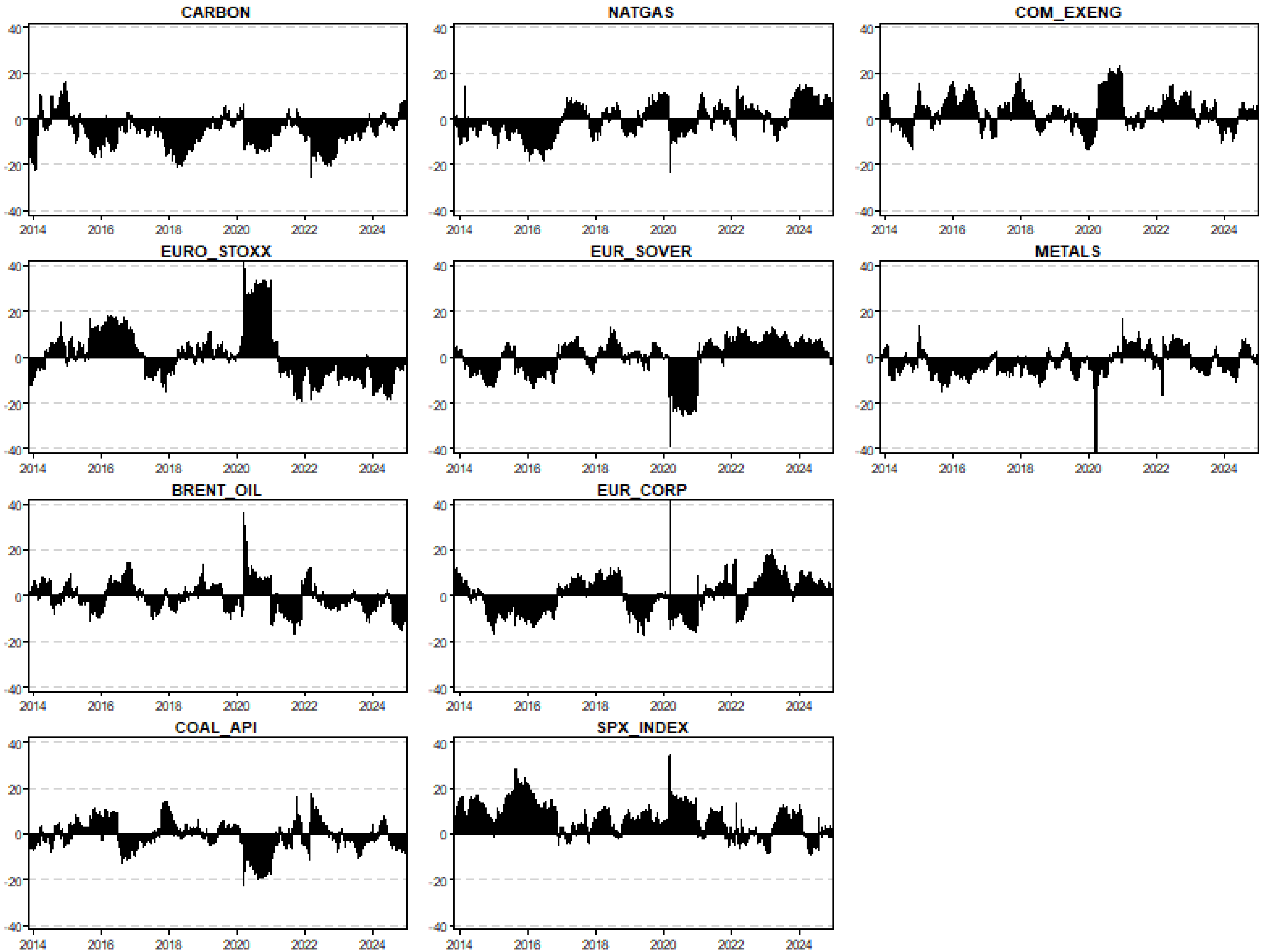
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	57.82	4.6	3.99	7.25	6.77	3.43	3.28	4.71	3.77	4.37	42.18
EUROSTOXX	3.26	48.44	4.96	3.2	3.12	4.95	4.06	17.08	5.26	5.68	51.56
BRENTOIL	3.71	6.49	54.56	4.78	3.39	3.48	4.09	6.32	7.29	5.9	45.44
COALAPI	4.61	5.41	3.49	60.67	7.47	3.55	2.54	4.17	3	5.09	39.33
NATGAS	4.33	4.33	3.04	8.15	62.01	3.2	3.63	4.47	3.24	3.6	37.99
EURSOVER	1.88	6.07	3.1	2.09	1.59	46.2	25.84	5.5	3.43	4.3	53.8
EURCORP	2.48	5.69	2.46	1.93	1.95	28.91	43.34	5.93	4.14	3.17	56.66
SPXINDEX	3.03	15.53	4.64	2.83	1.51	4.32	3.72	55.36	4.18	4.88	44.64
COMEXENG	2.16	7.92	4.69	3.69	3.6	4.81	4.93	6.45	51.6	10.15	48.4
METALS	3.68	8.12	4.08	3.63	3.45	4.91	5.83	5.71	10.35	50.22	49.78
DST(TO)	29.15	64.17	34.46	37.57	32.84	61.55	57.91	60.35	44.66	47.14	469.8
Inc. Own	86.97	112.61	89.02	98.23	94.85	107.74	101.25	115.71	96.26	97.36	cTCI/TCI
NS (NET)	-13.03	12.61	-10.98	-1.77	-5.15	7.74	1.25	15.71	-3.74	-2.64	52.20/46.98

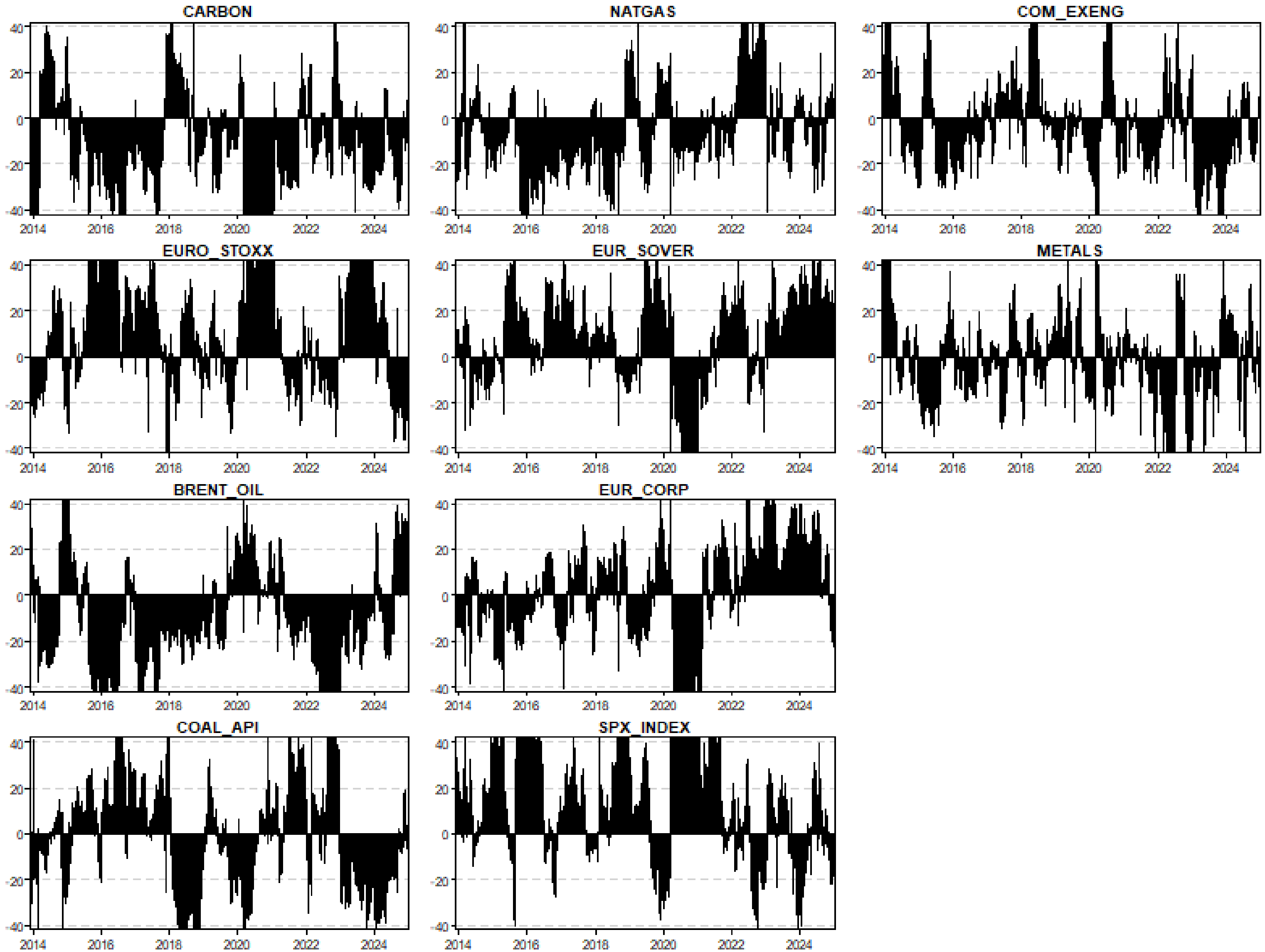
Appendix D.2.2. Dynamic Return and Volatility Net Directional Connectedness

Figure D.11: Dynamic Net Directional Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



(b) Dynamic volatility net directional connectedness

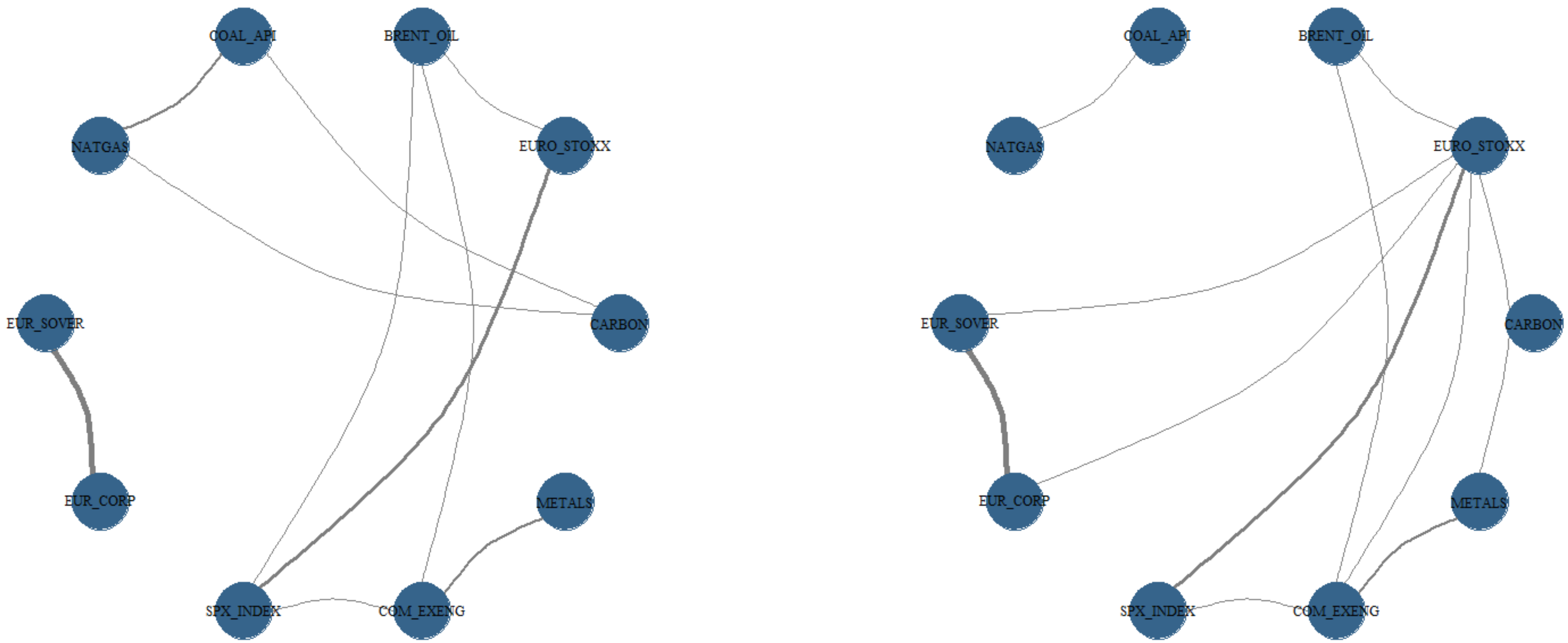


Appendix D.2.3. Static Return and Volatility Pairwise Directional Connectedness

Figure D.12: Network Representation of Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Static Return PCI network

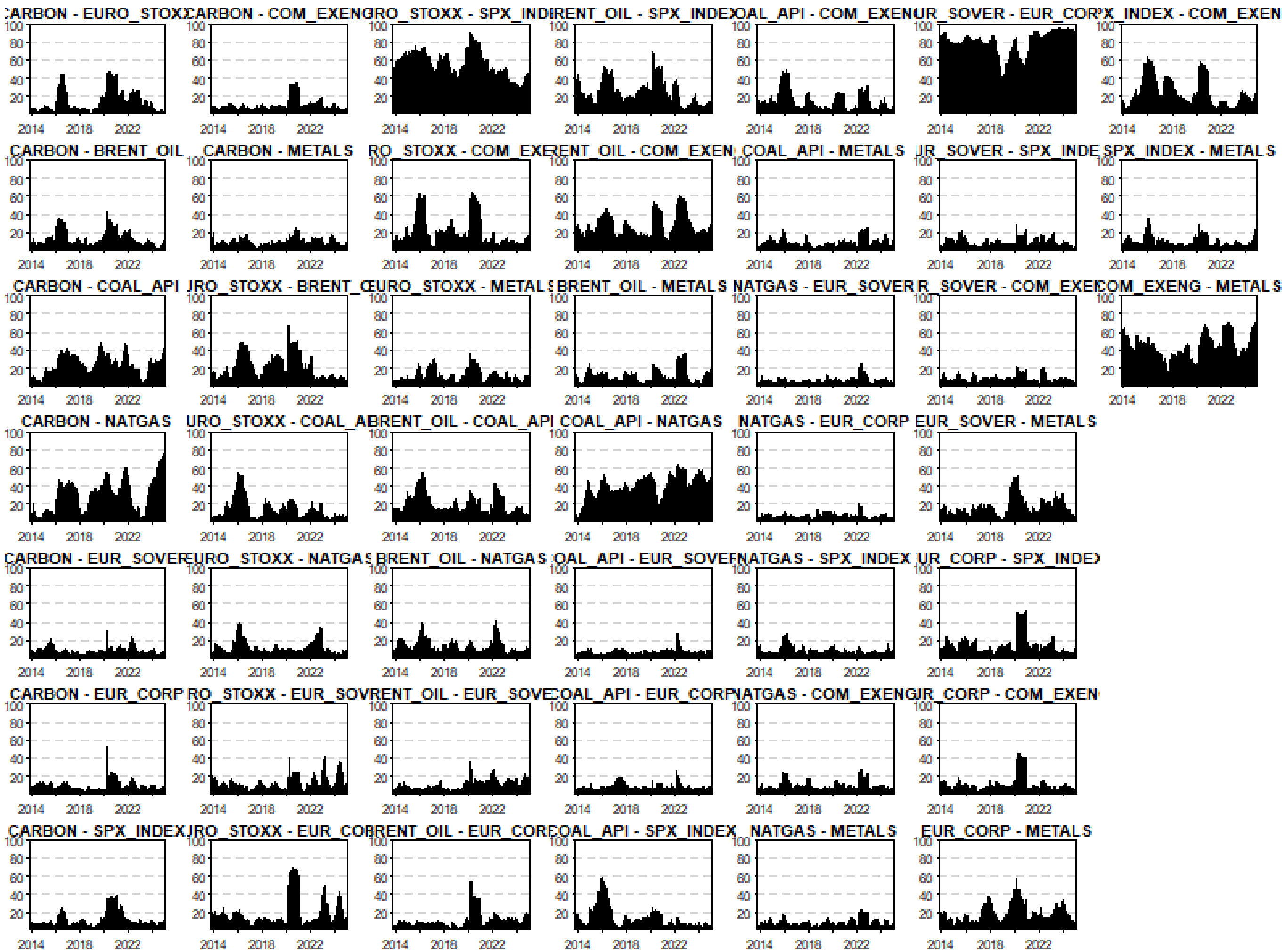
(b) Static Volatility PCI network



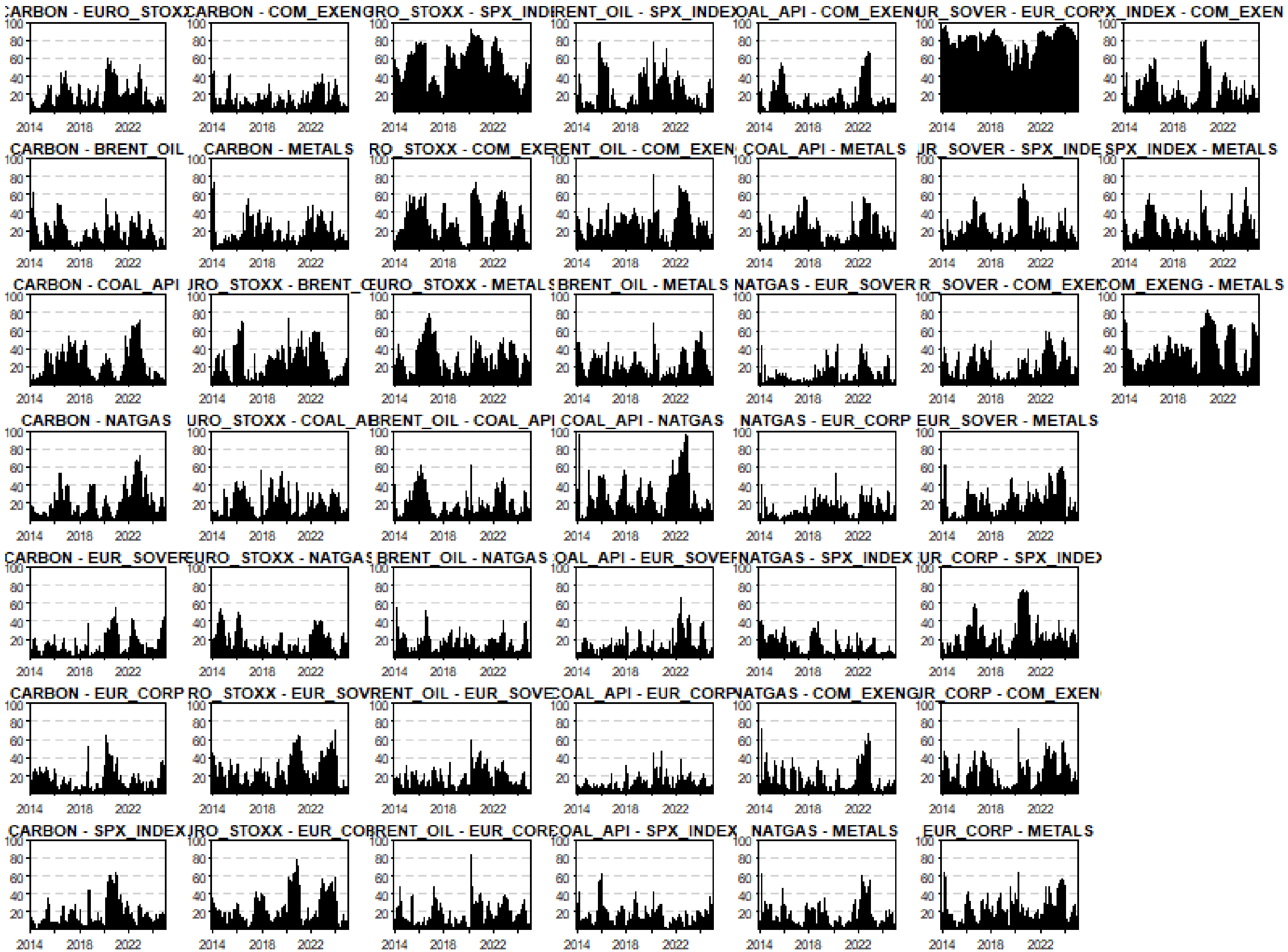
Appendix D.2.4. Dynamic Return and Volatility Pairwise Directional Connectedness

Figure D.13: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



Appendix D.3. 8-period forecast horizon and a rolling window of 180 observations

Appendix D.3.1. Static Return and Volatility Connectedness Matrix

Table D.6: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	58.73	4.12	3.91	7.88	10.34	2.69	2.43	3.68	2.92	3.3	41.27
EUROSTOXX	3.39	48.68	5.76	3.42	3.3	3.36	3.91	19.61	5.29	3.28	51.32
BRENTOIL	3.7	6.12	56.35	5.5	3.71	2.85	2.46	7.32	8.25	3.74	43.65
COALAPI	6.46	3.9	5.87	54.95	13.64	2.04	2.22	3.99	4.08	2.87	45.05
NATGAS	10.06	3.2	4.03	13.38	57.41	2.03	1.95	2.71	2.77	2.45	42.59
EURSOVER	2.21	3.22	2.9	1.85	1.87	47.39	31.45	2.41	2.25	4.43	52.61
EURCORP	2.16	5.13	2.86	1.94	1.99	30.01	44.76	4.01	2.69	4.47	55.24
SPXINDEX	2.58	17.81	6.93	3.46	2.26	2.47	2.89	52.51	6.38	2.71	47.49
COMEXENG	2.66	5.13	7.45	3.6	2.65	2.37	2.51	6.56	52.2	14.86	47.8
METALS	2.55	3.37	3.34	2.48	2.67	4.89	5.64	3.13	15.99	55.95	44.05
DST(TO)	35.76	51.99	43.06	43.51	42.42	52.71	55.46	53.43	50.61	42.12	471.08
Inc. Own	94.5	100.68	99.41	98.45	99.83	100.1	100.22	105.94	102.81	98.07	cTCI/TCI
NS (NET)	-5.5	0.68	-0.59	-1.55	-0.17	0.1	0.22	5.94	2.81	-1.93	52.34/47.11

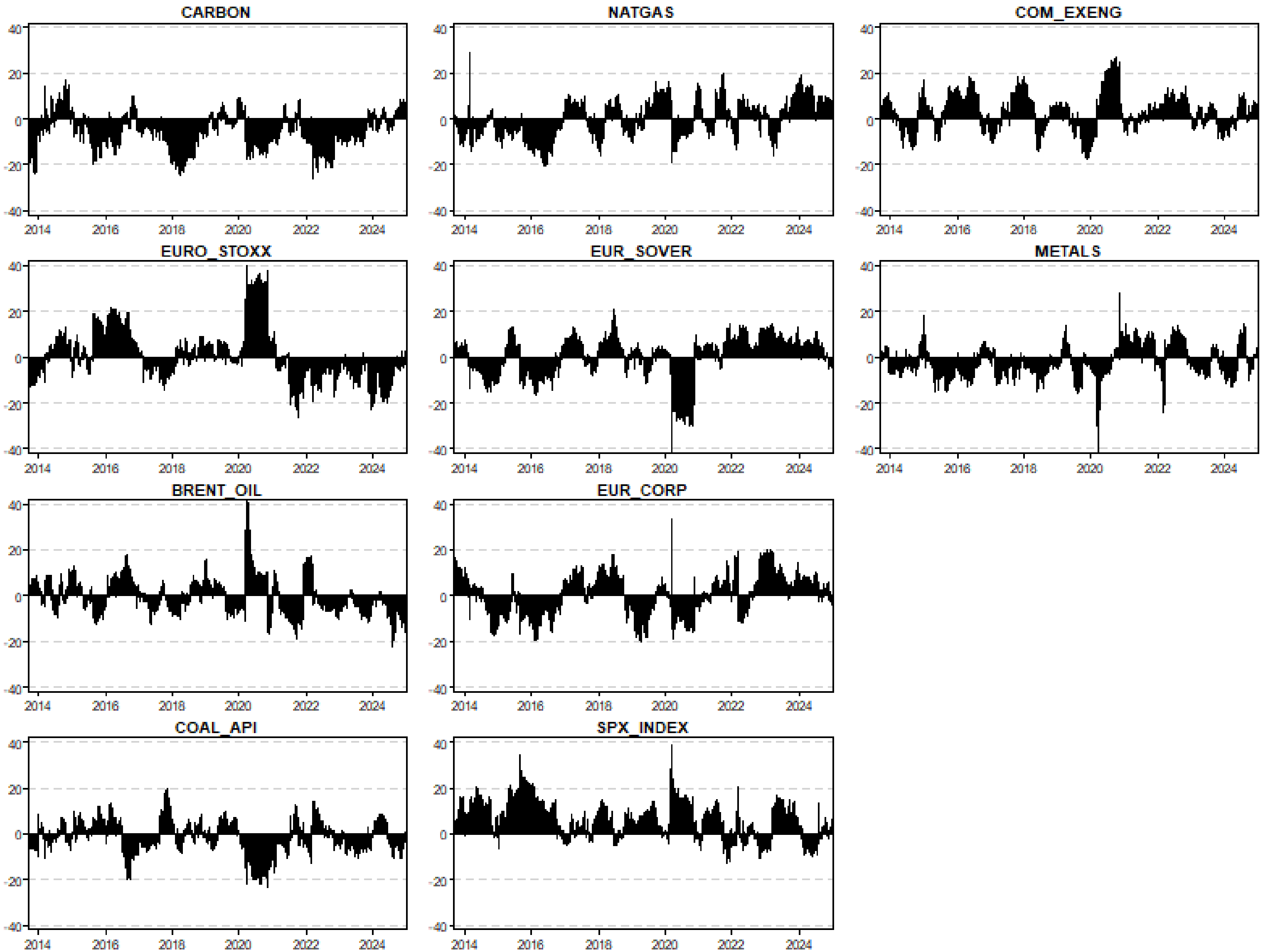
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	57.54	4.29	4.24	6.61	7.04	3.68	3.29	4.63	3.58	5.1	42.46
EUROSTOXX	3.64	47.92	5.2	3.73	3.31	5.24	4.1	16.18	4.86	5.81	52.08
BRENTOIL	4.54	6.27	54.13	4.66	3.32	3.65	4.43	6.37	6.68	5.96	45.87
COALAPI	4.31	5.16	4.37	59.14	7.71	3.82	2.8	4.58	3.16	4.95	40.86
NATGAS	4.37	4.61	3.24	7.83	61.1	3.29	3.43	4.7	3.63	3.81	38.9
EURSOVER	2.2	5.98	3.36	2.47	2.19	44.51	25.76	5.33	3.96	4.24	55.49
EURCORP	2.95	5.35	2.3	2.49	2.54	28.14	42.31	5.81	4.68	3.43	57.69
SPXINDEX	3.08	15.12	5.25	2.88	1.77	4.81	4.19	53.9	4.15	4.85	46.1
COMEXENG	2.82	7.63	4.56	4.09	4.03	5.57	5.32	6.51	49.19	10.29	50.81
METALS	3.96	7.74	4.37	3.92	3.82	5.1	6.4	6.17	9.52	49.01	50.99
DST(TO)	31.86	62.14	36.9	38.68	35.72	63.29	59.73	60.27	44.22	48.44	481.25
Inc. Own	89.41	110.06	91.03	97.82	96.83	107.8	102.03	114.17	93.41	97.45	cTCI/TCI
NS (NET)	-10.59	10.06	-8.97	-2.18	-3.17	7.8	2.03	14.17	-6.59	-2.55	53.47/48.12

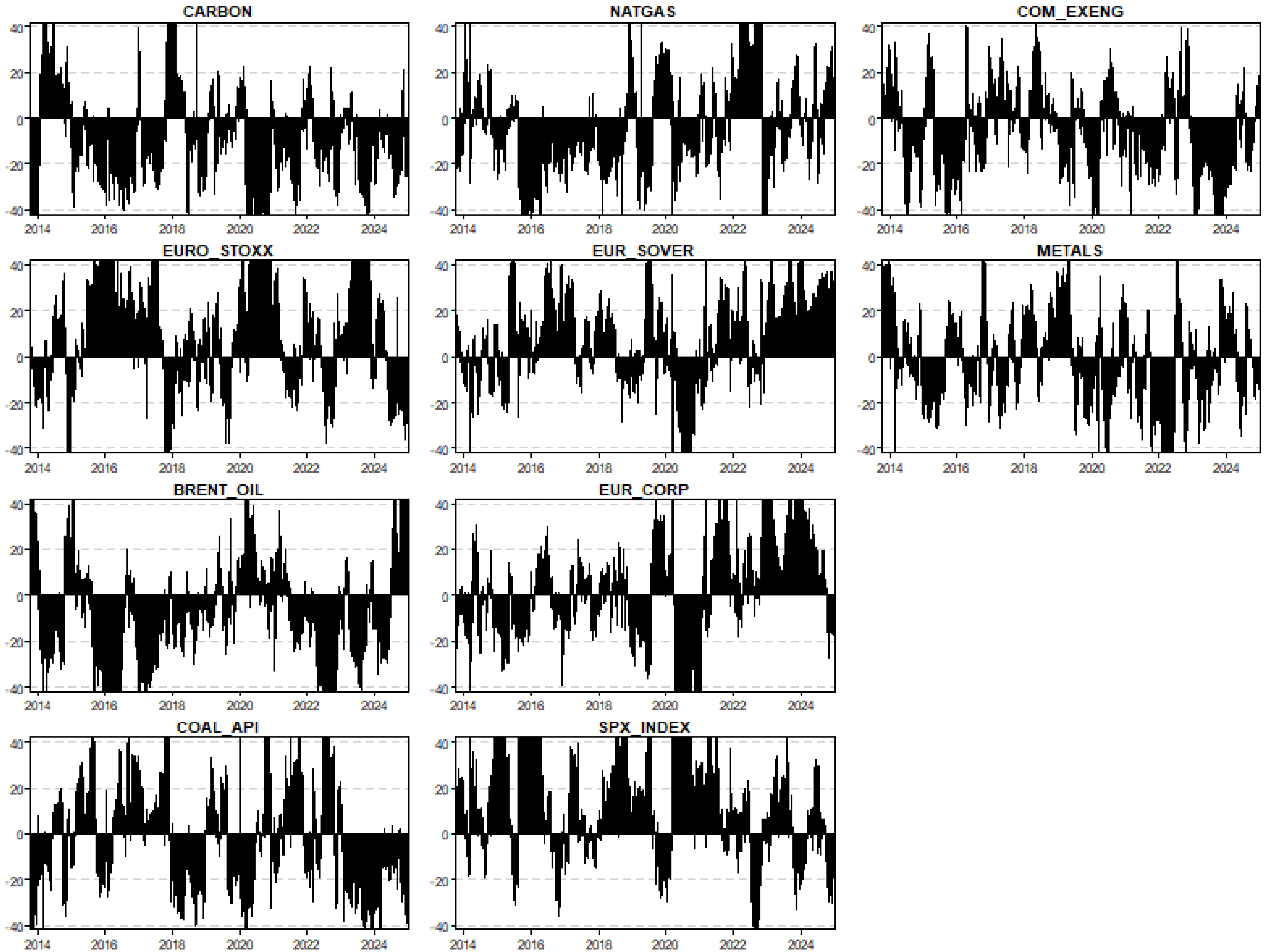
Appendix D.3.2. Dynamic Return and Volatility Net Directional Connectedness

Figure D.14: Dynamic Net Directional Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



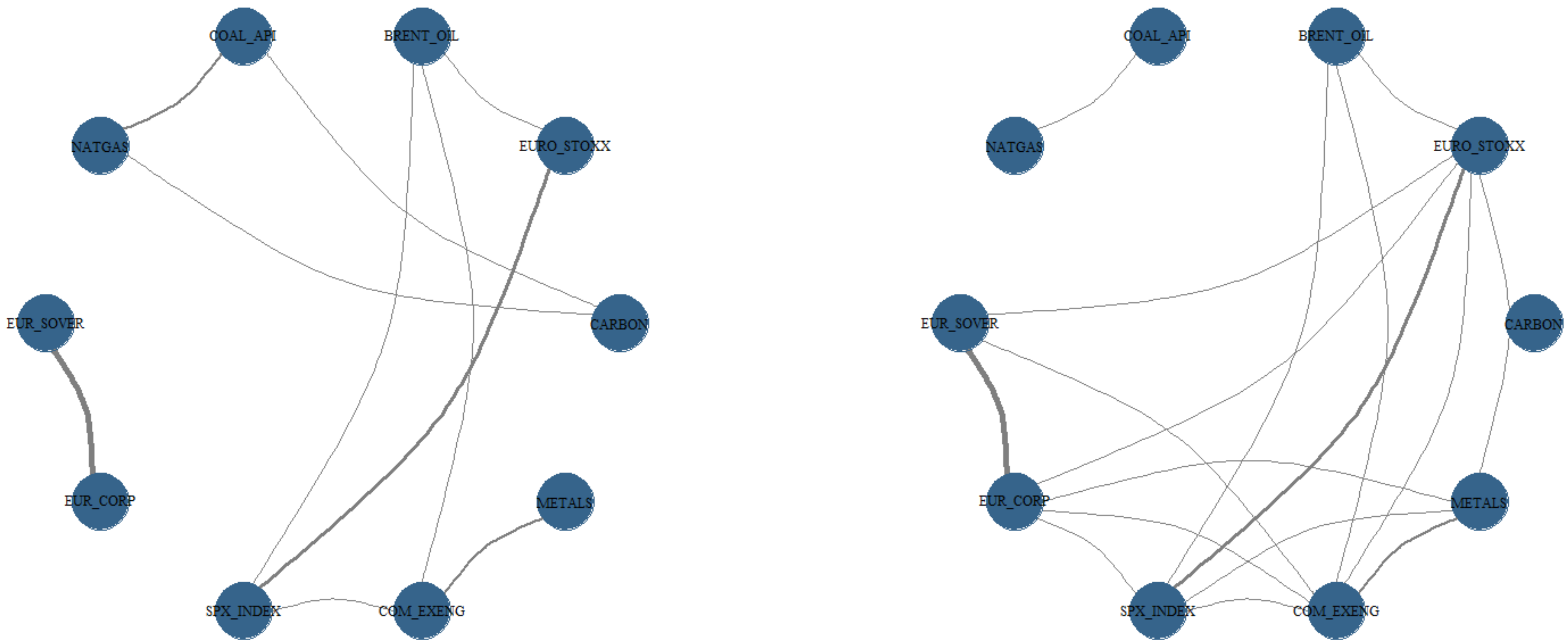
(b) Dynamic volatility net directional connectedness



Appendix D.3.3. Static Return and Volatility Pairwise Directional Connectedness

Figure D.15: Network Representation of Pairwise Connectedness Index (Jan 2013 – Jan 2025)

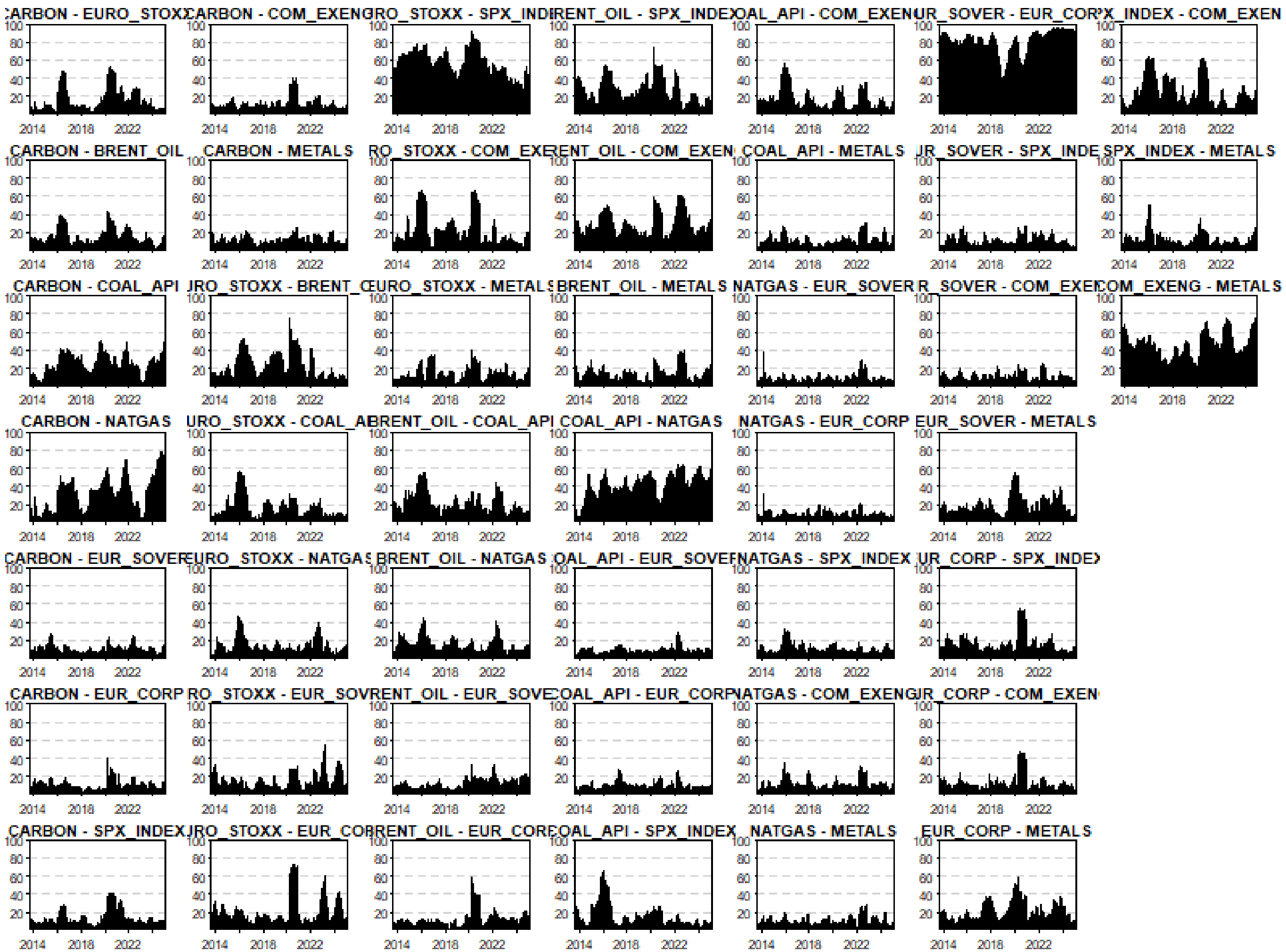
(a) Static Return PCI network　　　　(b) Static Volatility PCI network



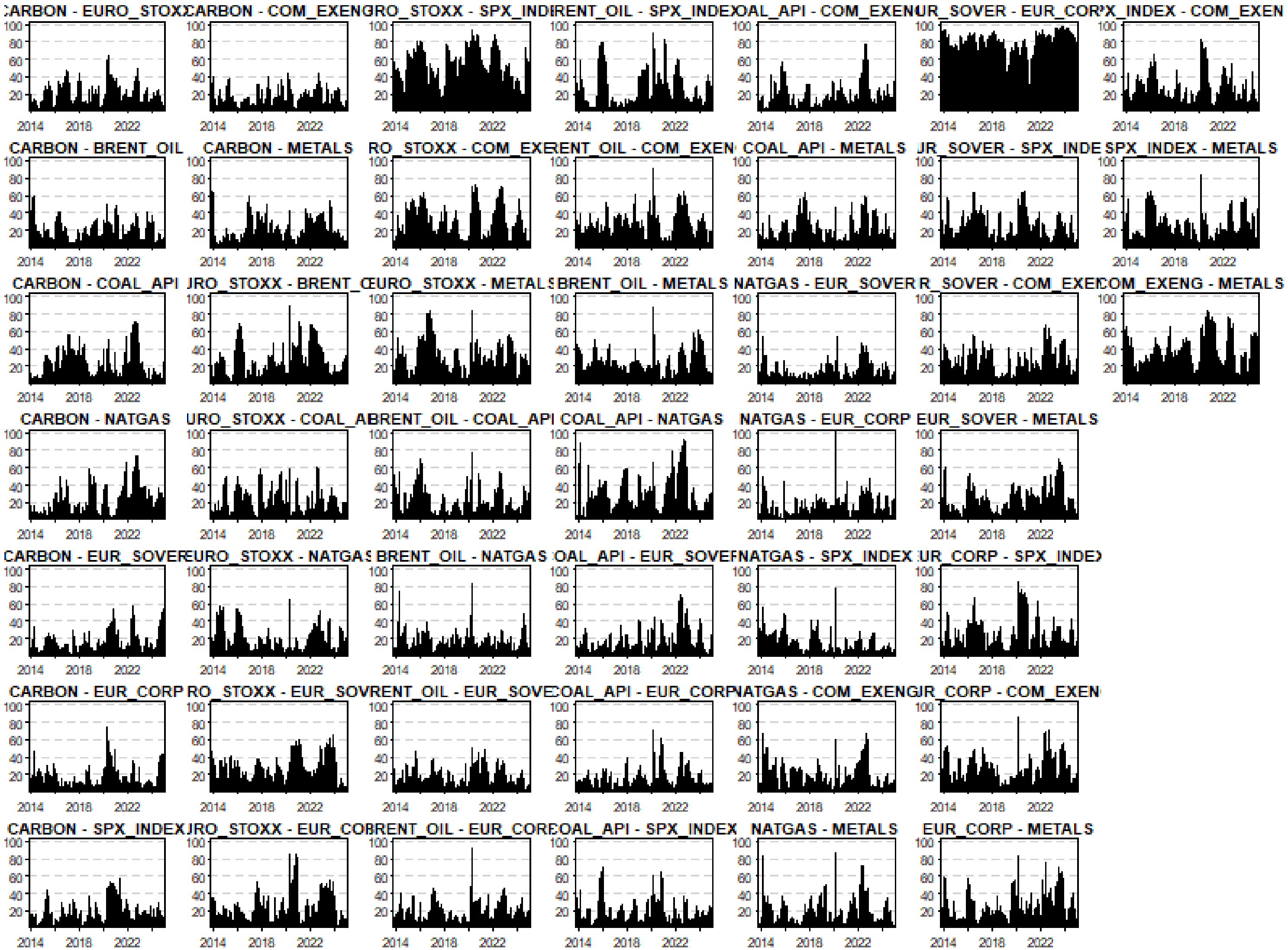
Appendix D.3.4. Dynamic Return and Volatility Pairwise Directional Connectedness

Figure D.16: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



Appendix D.4. 8-period forecast horizon and a rolling window of 200 observations

Appendix D.4.1. Static Return and Volatility Connectedness Matrix

Table D.7: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	60.33	3.99	3.77	7.83	10.23	2.42	2.21	3.44	2.72	3.05	39.67
EUROSTOXX	3.26	49.92	5.7	3.3	3.08	3.01	3.64	19.93	5.19	2.98	50.08
BRENTOIL	3.47	5.98	57.62	5.41	3.57	2.65	2.3	7.25	8.28	3.46	42.38
COALAPI	6.33	3.75	5.78	56.18	13.78	1.83	2.01	3.82	3.94	2.59	43.82
NATGAS	9.94	3	3.86	13.6	58.93	1.78	1.72	2.44	2.52	2.21	41.07
EURSOVER	1.99	2.97	2.64	1.64	1.63	48.54	32.01	2.25	2	4.33	51.46
EURCORP	1.94	5.03	2.68	1.71	1.75	30.44	45.63	3.94	2.53	4.33	54.37
SPXINDEX	2.38	17.98	6.82	3.32	2	2.25	2.7	53.68	6.39	2.47	46.32
COMEXENG	2.47	5.04	7.42	3.46	2.38	2.12	2.33	6.56	53.26	14.96	46.74
METALS	2.34	3.1	3.07	2.25	2.42	4.81	5.56	2.9	16.18	57.37	42.63
DST(TO)	34.12	50.84	41.75	42.53	40.82	51.31	54.49	52.53	49.76	40.39	458.54
Inc. Own	94.45	100.75	99.37	98.71	99.76	99.85	100.12	106.21	103.02	97.76	cTCI/TCI
NS (NET)	-5.55	0.75	-0.63	-1.29	-0.24	-0.15	0.12	6.21	3.02	-2.24	50.95/45.85

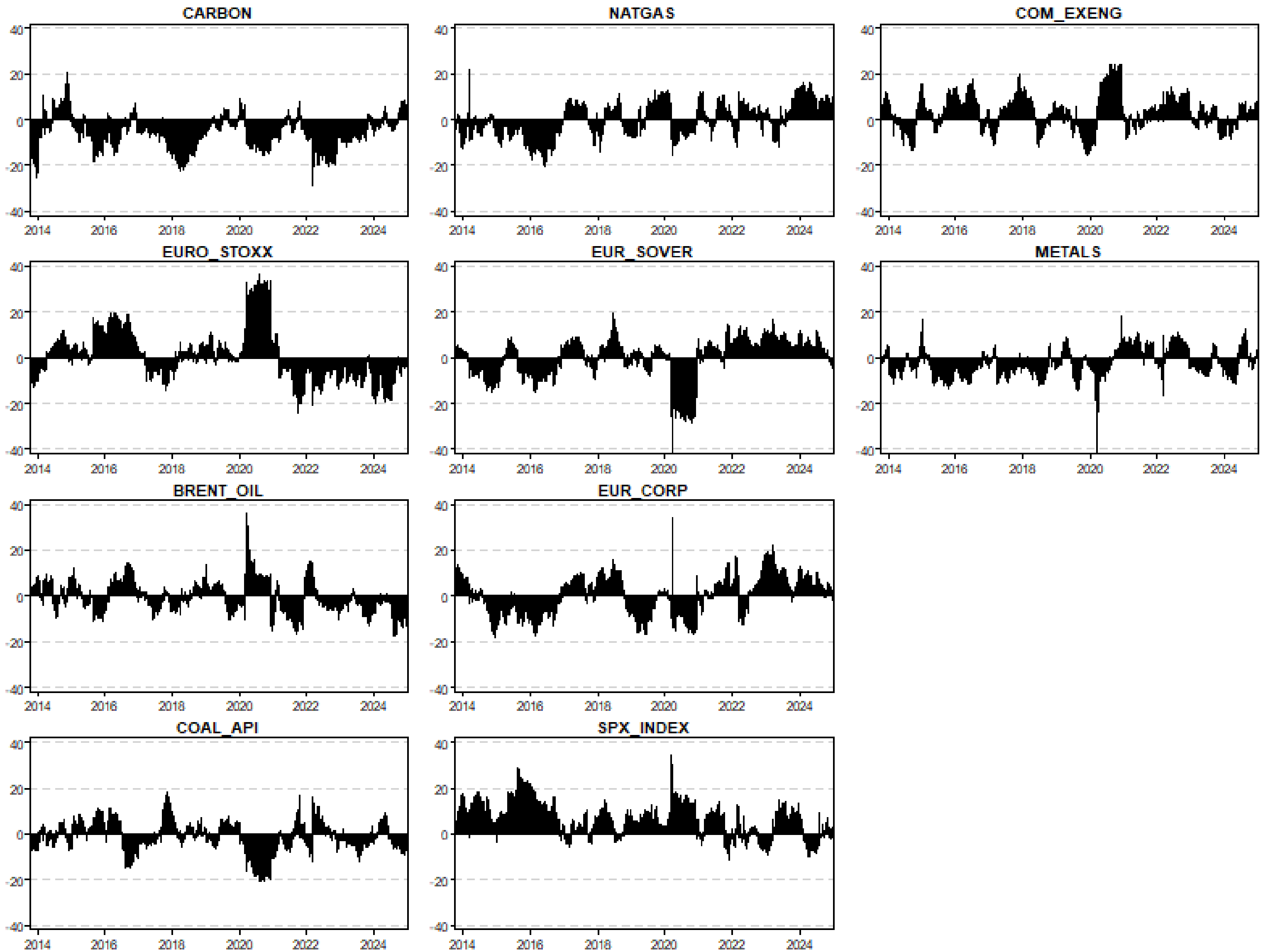
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	60.17	4.17	3.78	6.68	6.57	3.32	3.11	4.33	3.26	4.61	39.83
EUROSTOXX	3.29	49.69	5.1	3.09	2.94	4.86	3.93	16.76	4.8	5.55	50.31
BRENTOIL	4.03	6.12	56.72	4.48	3.04	3.25	4.01	6.11	6.72	5.54	43.28
COALAPI	4.14	4.95	3.92	62.24	7.35	3.39	2.39	4.07	2.83	4.7	37.76
NATGAS	4.18	4.25	2.96	7.77	63.79	2.87	3.22	4.26	3.21	3.49	36.21
EURSOVER	1.94	5.82	3.08	2.1	1.74	46.3	26.28	5.1	3.44	4.21	53.7
EURCORP	2.58	5.27	2.19	2.05	2.04	28.8	44.04	5.7	4.16	3.17	55.96
SPXINDEX	2.84	15.41	4.97	2.56	1.49	4.35	3.82	56.19	3.92	4.45	43.81
COMEXENG	2.32	7.68	4.52	3.73	3.57	4.87	4.97	6.12	51.84	10.37	48.16
METALS	3.62	7.62	4.07	3.51	3.33	4.94	5.95	5.62	9.94	51.42	48.58
DST(TO)	28.93	61.29	34.59	35.97	32.07	60.65	57.69	58.07	42.27	46.09	457.61
Inc. Own	89.1	110.98	91.3	98.21	95.85	106.95	101.73	114.26	94.11	97.51	cTCI/TCI
NS (NET)	-10.9	10.98	-8.7	-1.79	-4.15	6.95	1.73	14.26	-5.89	-2.49	50.85/45.76

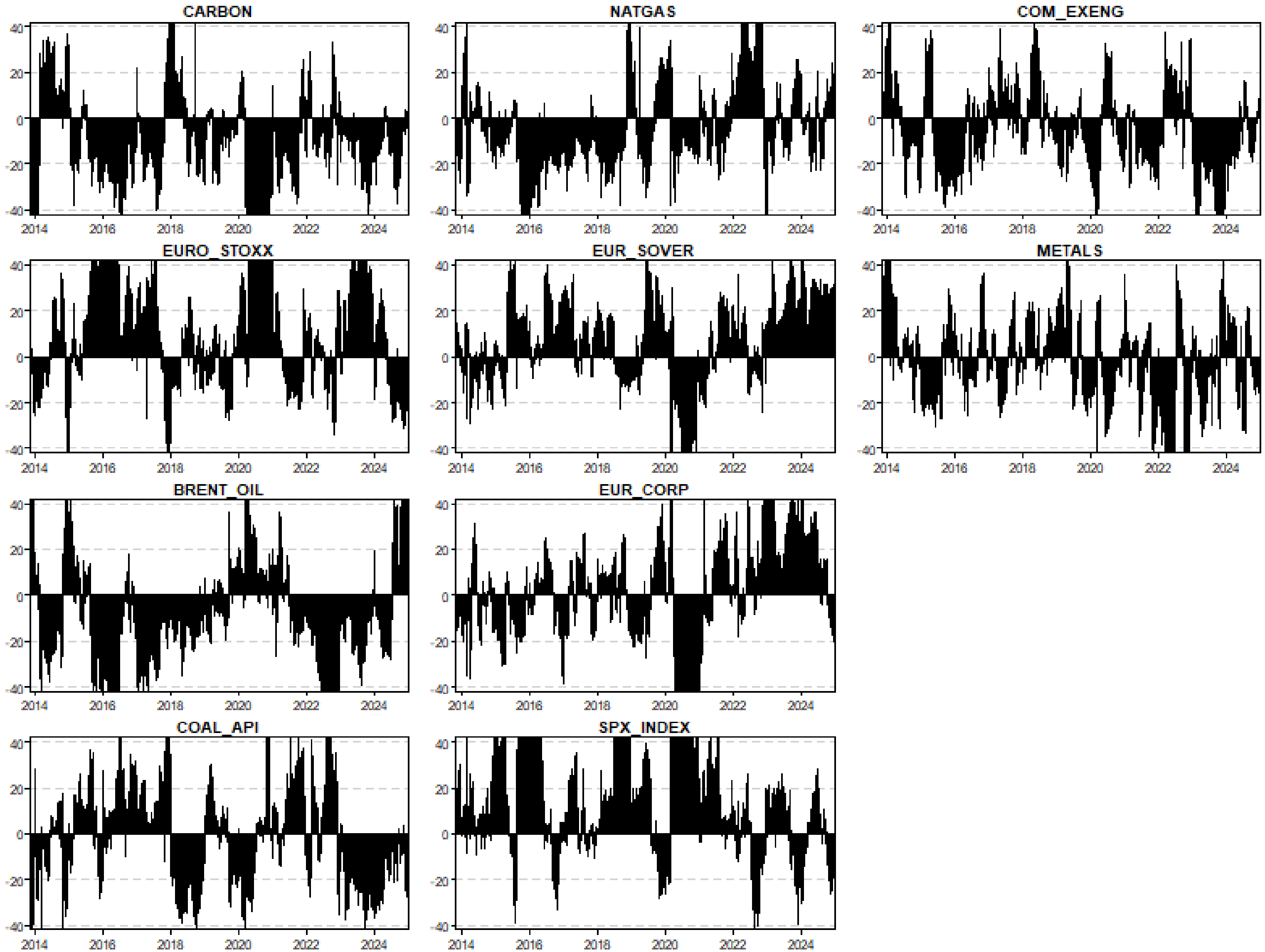
Appendix D.4.2. Dynamic Return and Volatility Net Directional Connectedness

Figure D.17: Dynamic Net Directional Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



(b) Dynamic volatility net directional connectedness

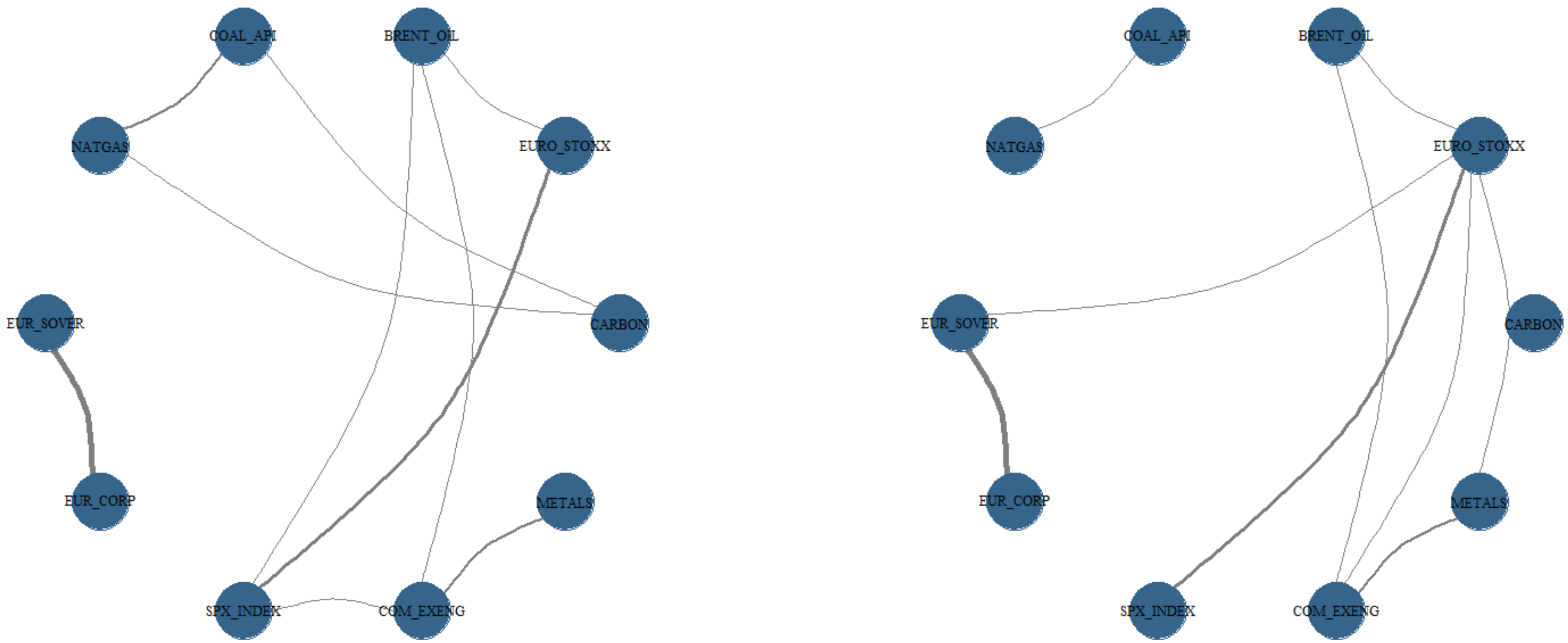


Appendix D.4.3. Static Return and Volatility Pairwise Directional Connectedness

Figure D.18: Network Representation of Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Static Return PCI network

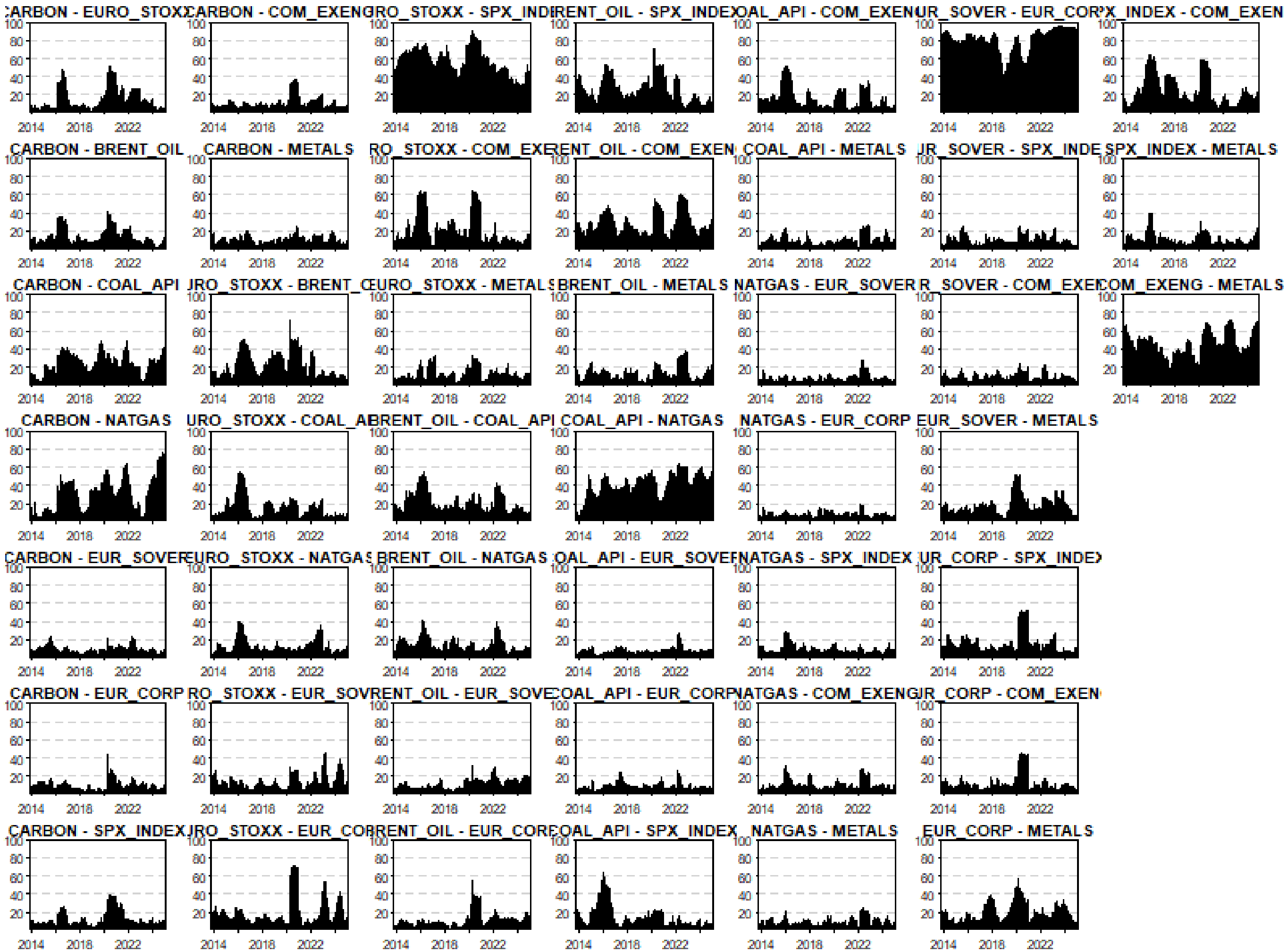
(b) Static Volatility PCI network



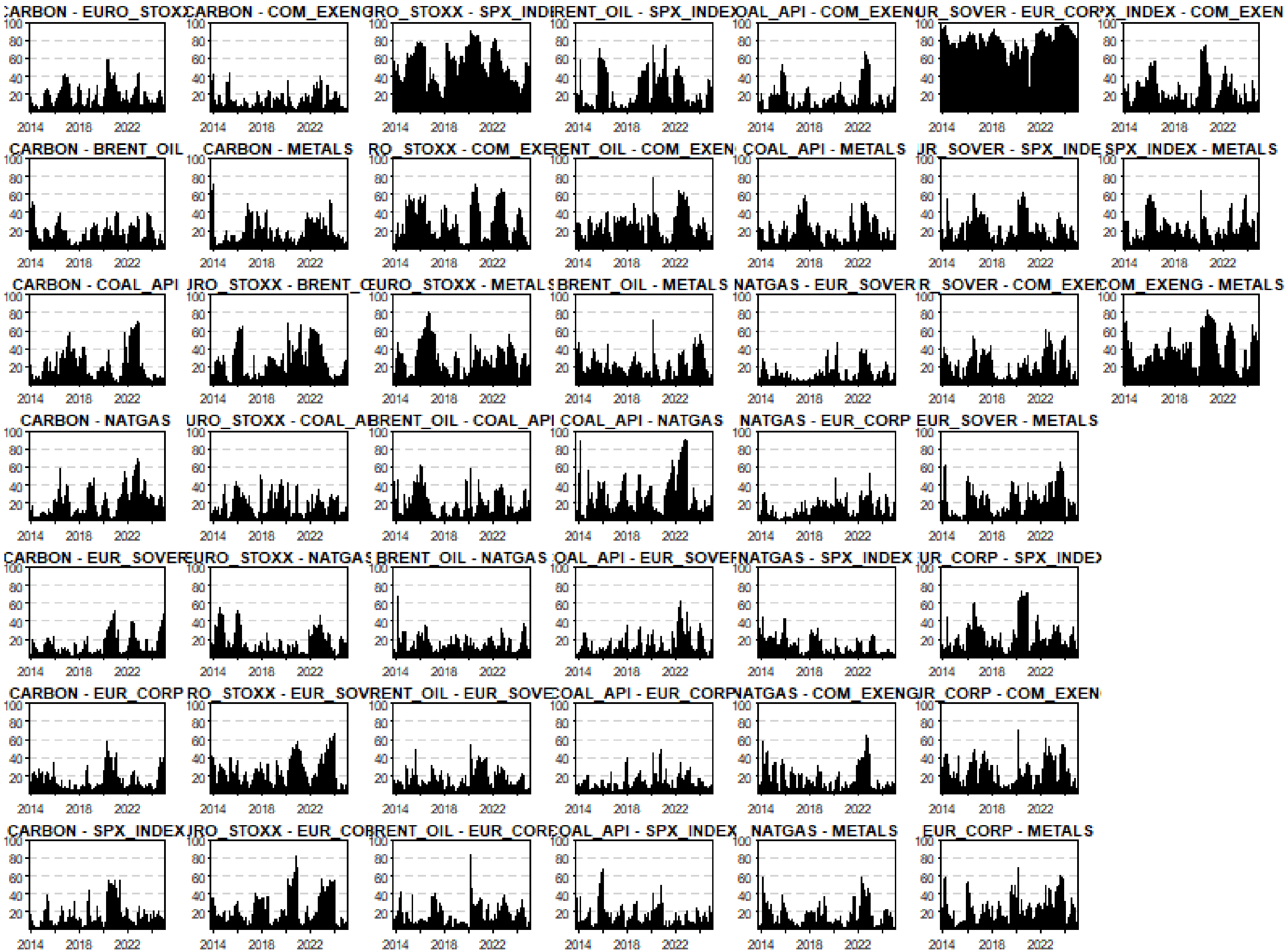
Appendix D.4.4. Dynamic Return and Volatility Pairwise Directional Connectedness

Figure D.19: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



Appendix D.5. 8-period forecast horizon and a rolling window of 220 observations

Appendix D.5.1. Static Return and Volatility Connectedness Matrix

Table D.8: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	61.59	3.93	3.64	7.76	10.08	2.24	2.07	3.26	2.57	2.86	38.41
EUROSTOXX	3.15	50.93	5.67	3.2	2.9	2.71	3.41	20.17	5.13	2.73	49.07
BRENTOIL	3.3	5.9	58.62	5.37	3.45	2.48	2.19	7.17	8.31	3.22	41.38
COALAPI	6.2	3.63	5.73	57.17	13.87	1.69	1.86	3.68	3.8	2.36	42.83
NATGAS	9.8	2.83	3.73	13.77	60.14	1.6	1.57	2.19	2.34	2.03	39.86
EURSOVER	1.83	2.76	2.44	1.47	1.43	49.48	32.44	2.12	1.8	4.23	50.52
EURCORP	1.81	4.98	2.57	1.53	1.55	30.74	46.27	3.9	2.43	4.21	53.73
SPXINDEX	2.22	18.15	6.71	3.18	1.78	2.07	2.56	54.62	6.44	2.26	45.38
COMEXENG	2.31	4.99	7.41	3.32	2.15	1.93	2.17	6.6	54.09	15.02	45.91
METALS	2.19	2.85	2.84	2.05	2.2	4.76	5.48	2.69	16.34	58.6	41.4
DST(TO)	32.81	50.03	40.74	41.65	39.42	50.23	53.75	51.77	49.15	38.94	448.48
Inc. Own	94.4	100.96	99.36	98.83	99.56	99.71	100.02	106.39	103.24	97.54	cTCI/TCI
NS (NET)	-5.6	0.96	-0.64	-1.17	-0.44	-0.29	0.02	6.39	3.24	-2.46	49.83/44.85

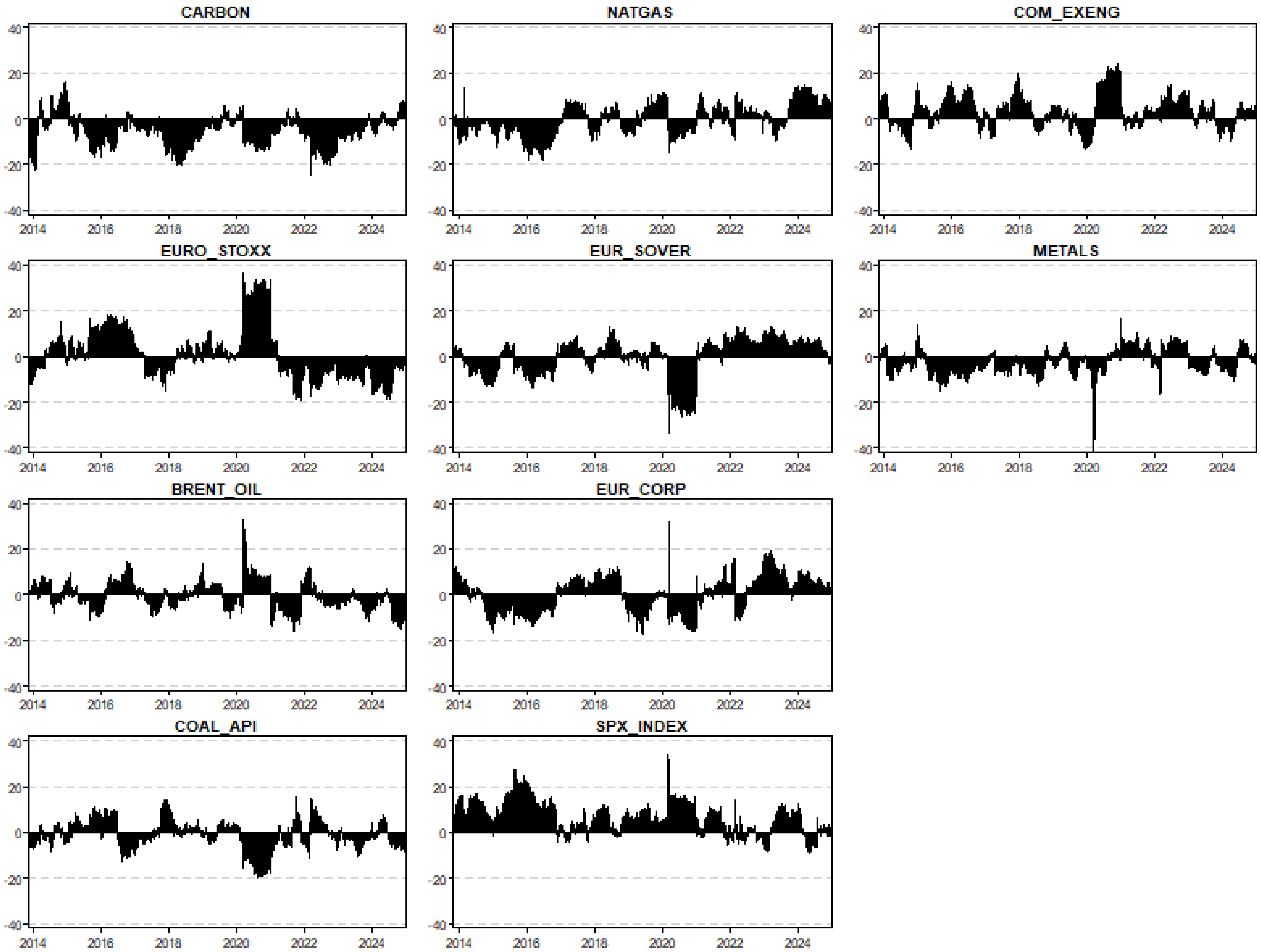
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	62.2	4.14	3.49	6.68	6.23	3.06	2.83	4.04	3.14	4.2	37.8
EUROSTOXX	2.95	50.86	4.93	2.73	2.66	4.69	3.87	17.15	4.84	5.33	49.14
BRENTOIL	3.56	6.04	58.65	4.31	2.84	2.92	3.59	5.91	6.93	5.24	41.35
COALAPI	4.12	4.62	3.28	64.8	7	3.13	2.22	3.66	2.66	4.52	35.2
NATGAS	4.07	3.96	2.61	7.59	66.13	2.57	3.05	3.93	2.92	3.16	33.87
EURSOVER	1.71	5.66	2.88	1.82	1.5	47.64	26.63	4.99	3.08	4.09	52.36
EURCORP	2.3	5.25	2.14	1.71	1.66	29.27	45.3	5.68	3.66	3.02	54.7
SPXINDEX	2.61	15.47	4.61	2.36	1.32	4.01	3.62	58.11	3.72	4.17	41.89
COMEXENG	1.91	7.65	4.54	3.52	3.19	4.42	4.56	5.92	53.86	10.43	46.14
METALS	3.41	7.37	3.76	3.24	2.95	4.79	5.5	5.17	10.24	53.57	46.43
DST(TO)	26.64	60.17	32.23	33.96	29.35	58.88	55.87	56.45	41.18	44.17	438.89
Inc. Own	88.84	111.02	90.88	98.75	95.49	106.52	101.17	114.56	95.04	97.73	cTCI/TCI
NS (NET)	-11.16	11.02	-9.12	-1.25	-4.51	6.52	1.17	14.56	-4.96	-2.27	48.77/43.89

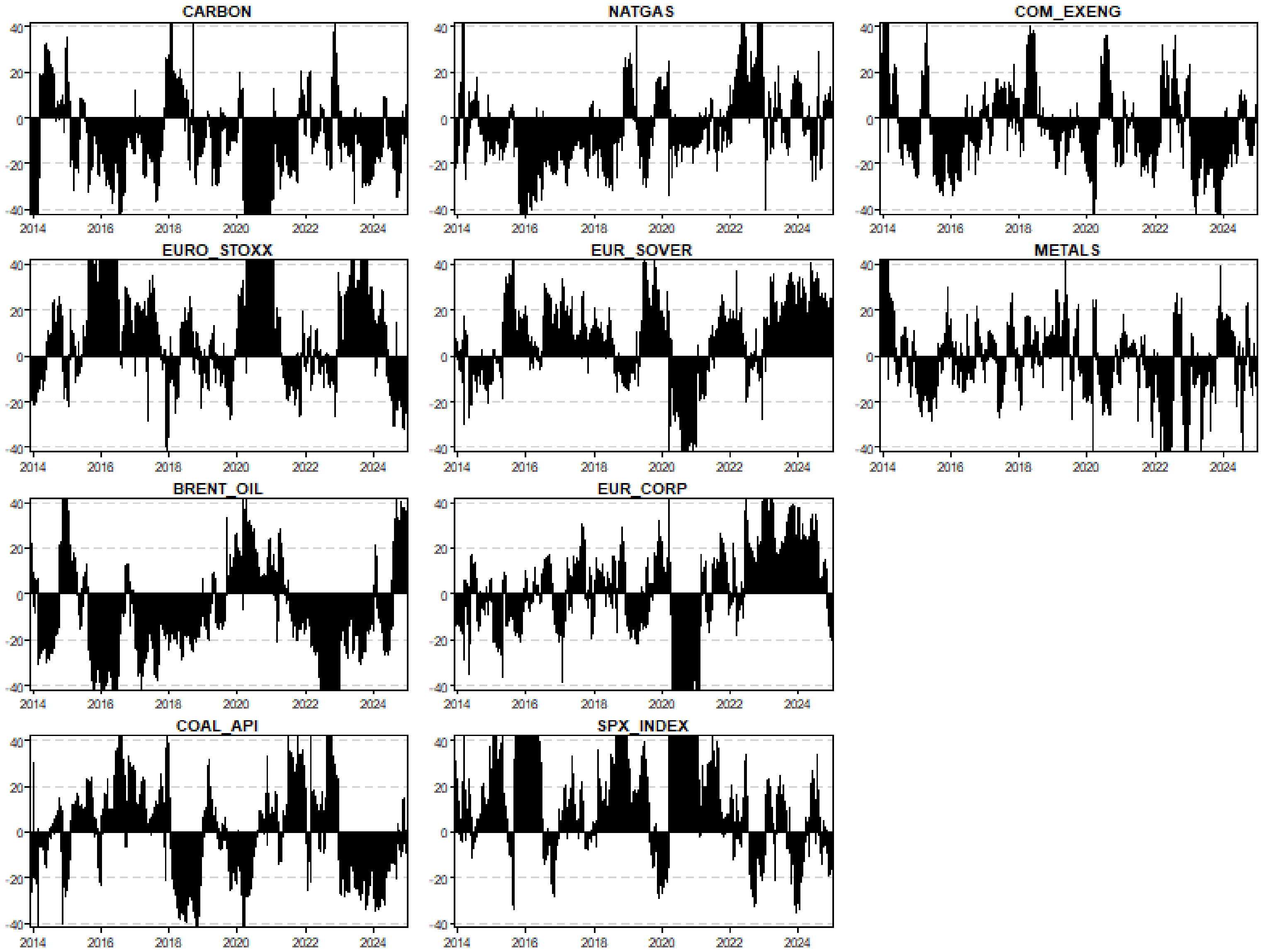
Appendix D.5.2. Dynamic Return and Volatility Net Directional Connectedness

Figure D.20: Dynamic Net Directional Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



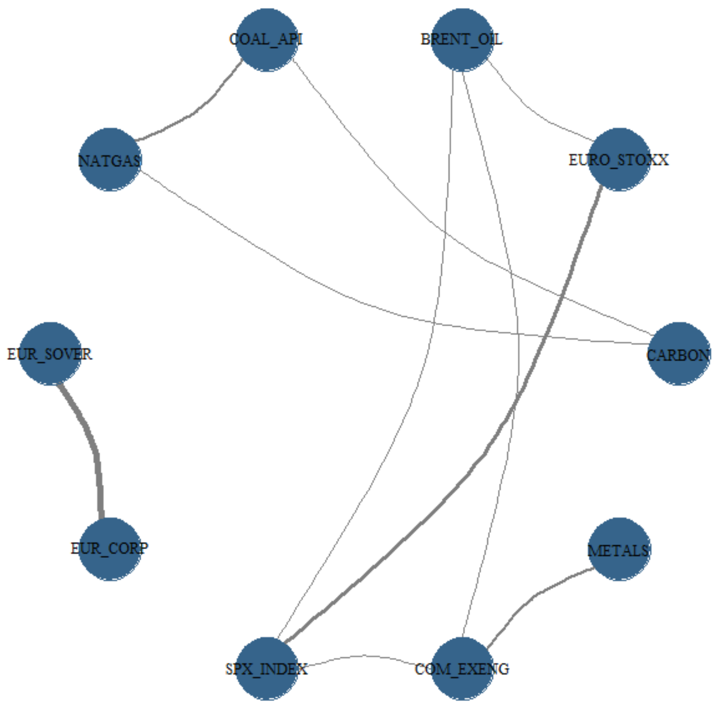
(b) Dynamic volatility net directional connectedness



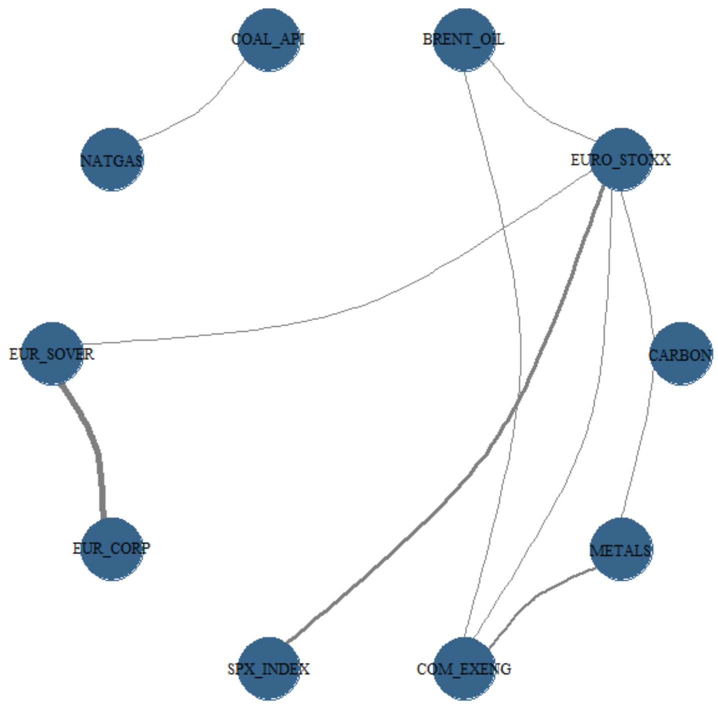
Appendix D.5.3. Static Return and Volatility Pairwise Directional Connectedness

Figure D.21: Network Representation of Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Static Return PCI network



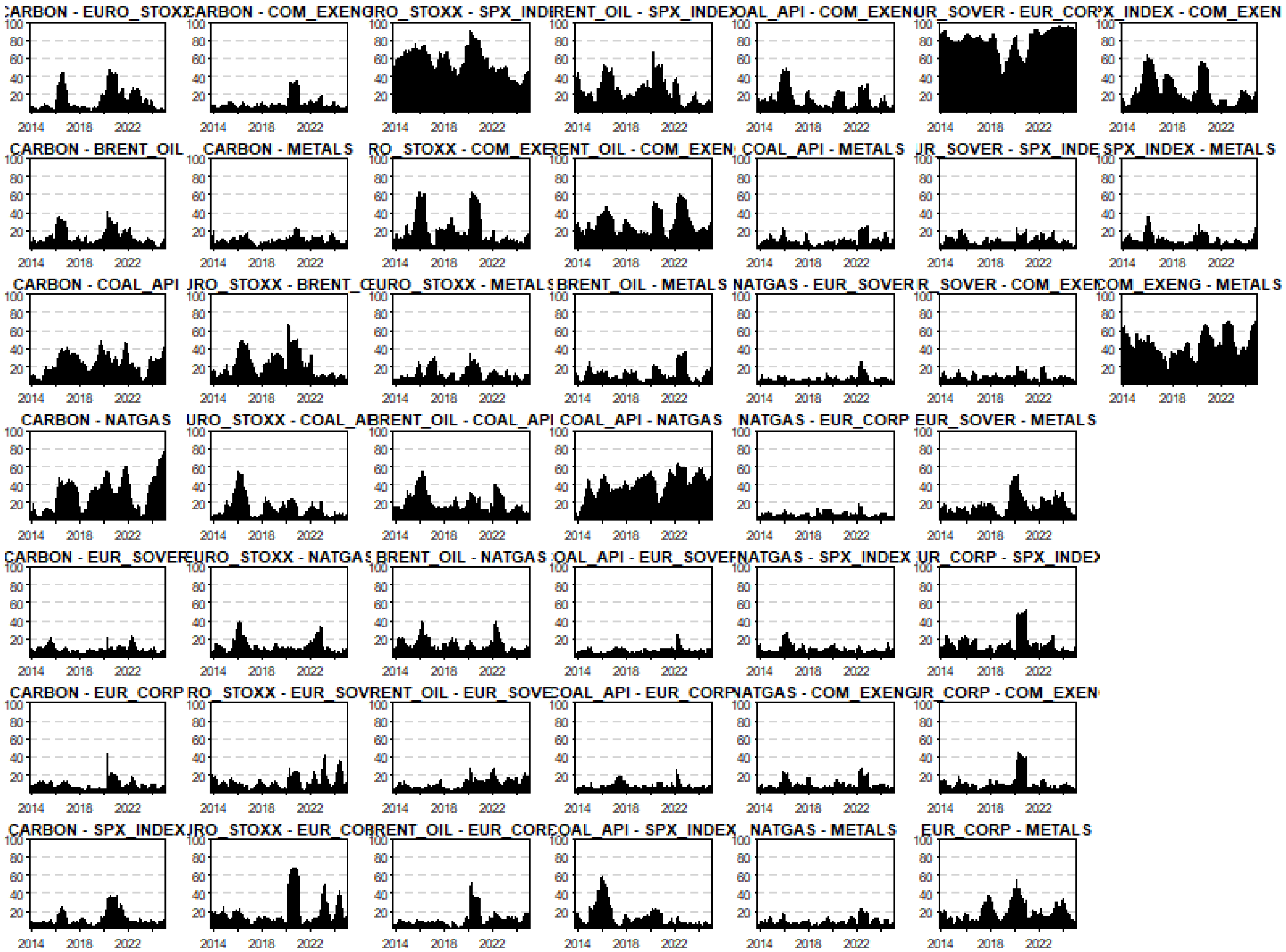
(b) Static Volatility PCI network



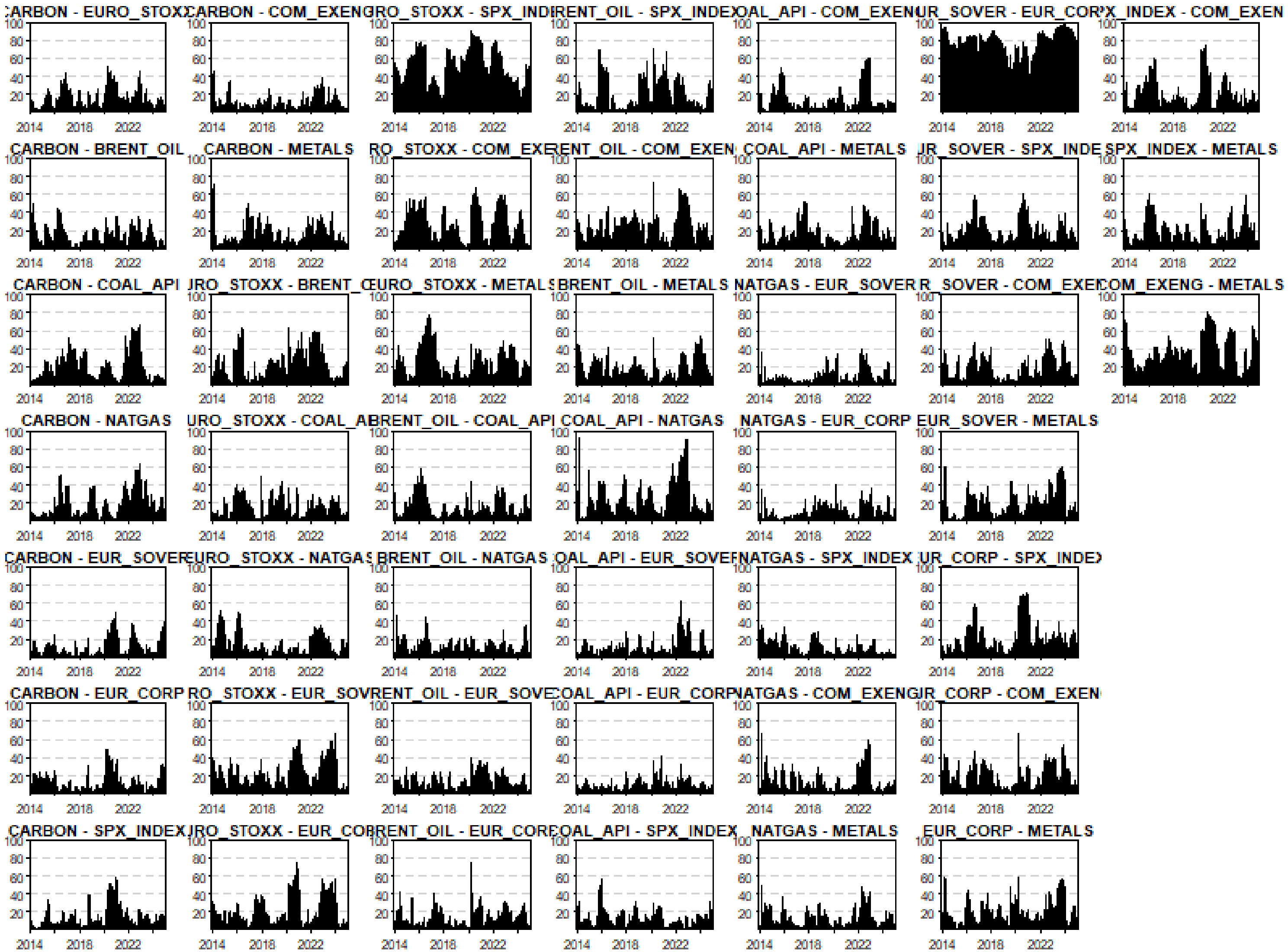
Appendix D.5.4. Dynamic Return and Volatility Pairwise Directional Connectedness

Figure D.22: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



Appendix D.6. 12-period forecast horizon and a rolling window of 180 observations

Appendix D.6.1. Static Return and Volatility Connectedness Matrix

Table D.9: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	58.33	4.13	3.97	7.9	10.32	2.77	2.5	3.72	2.98	3.39	41.67
EUROSTOXX	3.43	48.44	5.78	3.45	3.36	3.41	3.95	19.53	5.31	3.33	51.56
BRENTOIL	3.74	6.15	55.99	5.54	3.77	2.9	2.52	7.35	8.26	3.79	44.01
COALAPI	6.48	3.93	5.89	54.66	13.62	2.09	2.26	4.03	4.12	2.93	45.34
NATGAS	10.05	3.25	4.07	13.36	57.07	2.08	2.01	2.78	2.84	2.5	42.93
EURSOVER	2.27	3.27	2.96	1.9	1.95	47.08	31.3	2.47	2.32	4.48	52.92
EURCORP	2.19	5.15	2.91	1.99	2.07	29.9	44.54	4.04	2.71	4.5	55.46
SPXINDEX	2.63	17.76	6.94	3.51	2.3	2.54	2.93	52.24	6.4	2.76	47.76
COMEXENG	2.69	5.18	7.48	3.64	2.69	2.43	2.57	6.6	51.91	14.81	48.09
METALS	2.58	3.45	3.41	2.53	2.74	4.92	5.68	3.22	15.92	55.54	44.46
DST(TO)	36.06	52.28	43.39	43.82	42.82	53.03	55.73	53.74	50.85	42.49	474.2
Inc. Own	94.39	100.72	99.38	98.47	99.89	100.11	100.27	105.98	102.76	98.03	cTCI/TCI
NS (NET)	-5.61	0.72	-0.62	-1.53	-0.11	0.11	0.27	5.98	2.76	-1.97	52.69/47.42

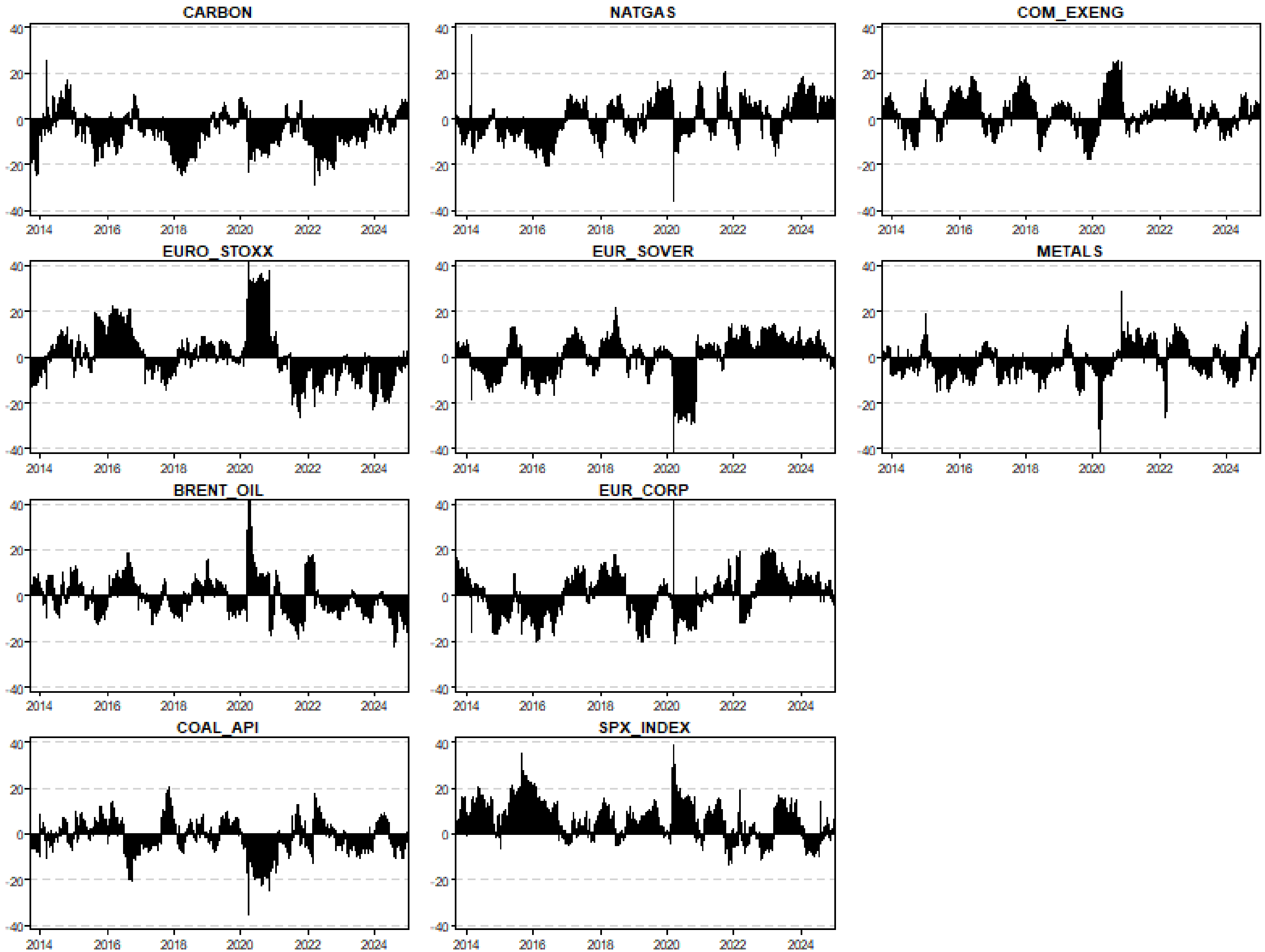
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	49.07	5.05	5.04	7.53	8.1	4.71	4.25	6.24	4.55	5.47	50.93
EUROSTOXX	4.34	42.48	5.5	4.66	4.47	5.91	4.68	15.49	5.76	6.72	57.52
BRENTOIL	4.91	7.05	46.16	5.52	4.3	4.89	5.5	7.04	7.5	7.13	53.84
COALAPI	5.42	6.83	4.96	50.79	8.67	4.61	3.48	5.51	3.82	5.91	49.21
NATGAS	5.12	5.38	4.23	8.78	52.69	4.47	4.44	5.78	4.38	4.72	47.31
EURSOVER	2.74	6.84	3.83	3.16	2.59	41.18	23.89	6.2	4.83	4.75	58.82
EURCORP	3.51	6.06	2.89	3.07	3.37	26.97	38.08	6.43	5.71	3.9	61.92
SPXINDEX	4	14.79	5.55	3.89	2.41	5.65	4.67	47.45	5.22	6.37	52.55
COMEXENG	3.54	8.03	4.9	4.53	4.92	6.48	6.13	7.47	44.23	9.77	55.77
METALS	4.45	8.84	5.11	4.64	4.75	5.52	7.13	7.41	9.82	42.32	57.68
DST(TO)	38.03	68.87	42.02	45.78	43.58	69.22	64.17	67.57	51.57	54.74	545.55
Inc. Own	87.1	111.35	88.18	96.57	96.27	110.4	102.26	115.01	95.8	97.06	cTCI/TCI
NS (NET)	-12.9	11.35	-11.82	-3.43	-3.73	10.4	2.26	15.01	-4.2	-2.94	60.62/54.55

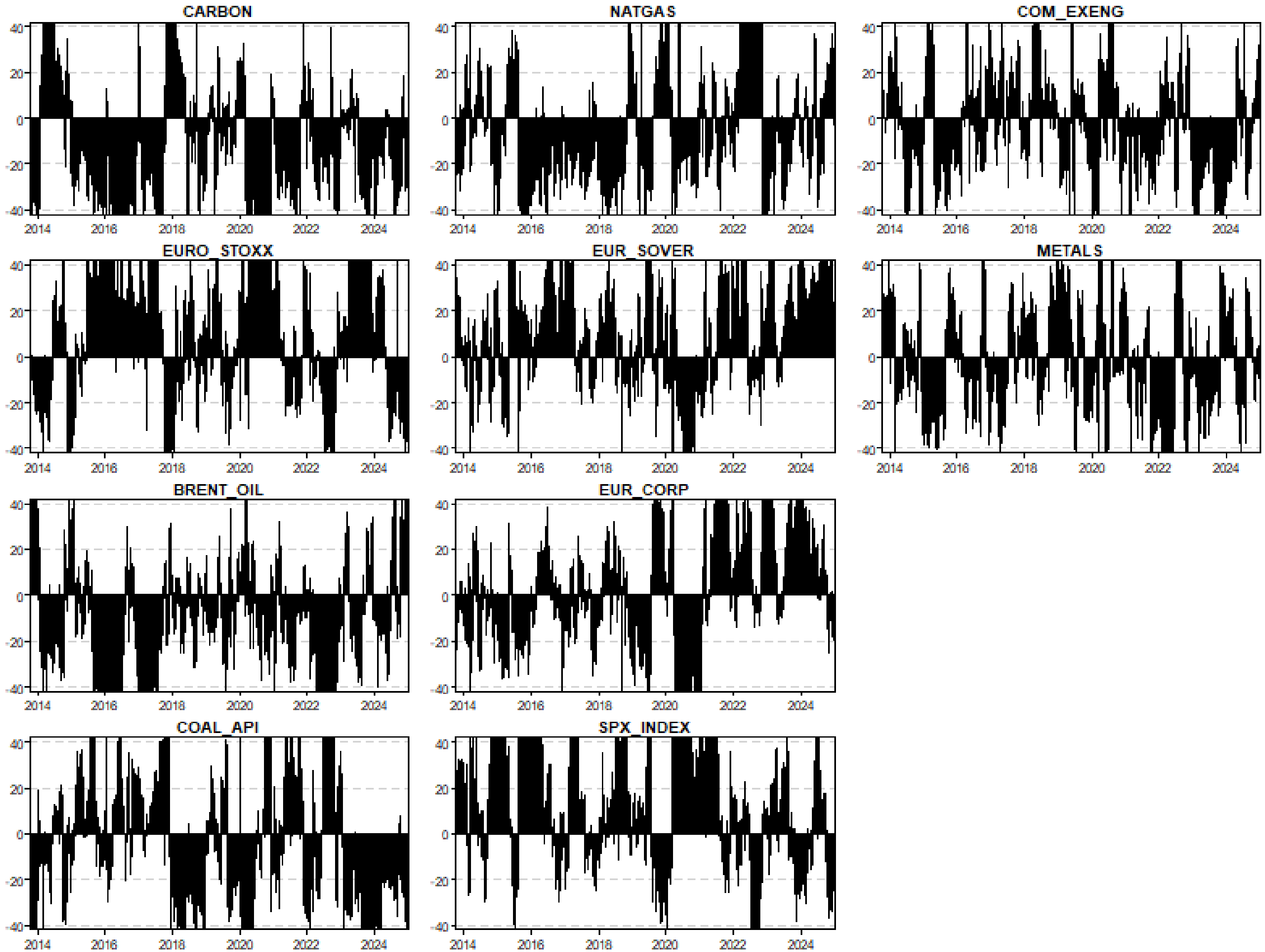
Appendix D.6.2. Dynamic Return and Volatility Net Directional Connectedness

Figure D.23: Dynamic Net Directional Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



(b) Dynamic volatility net directional connectedness

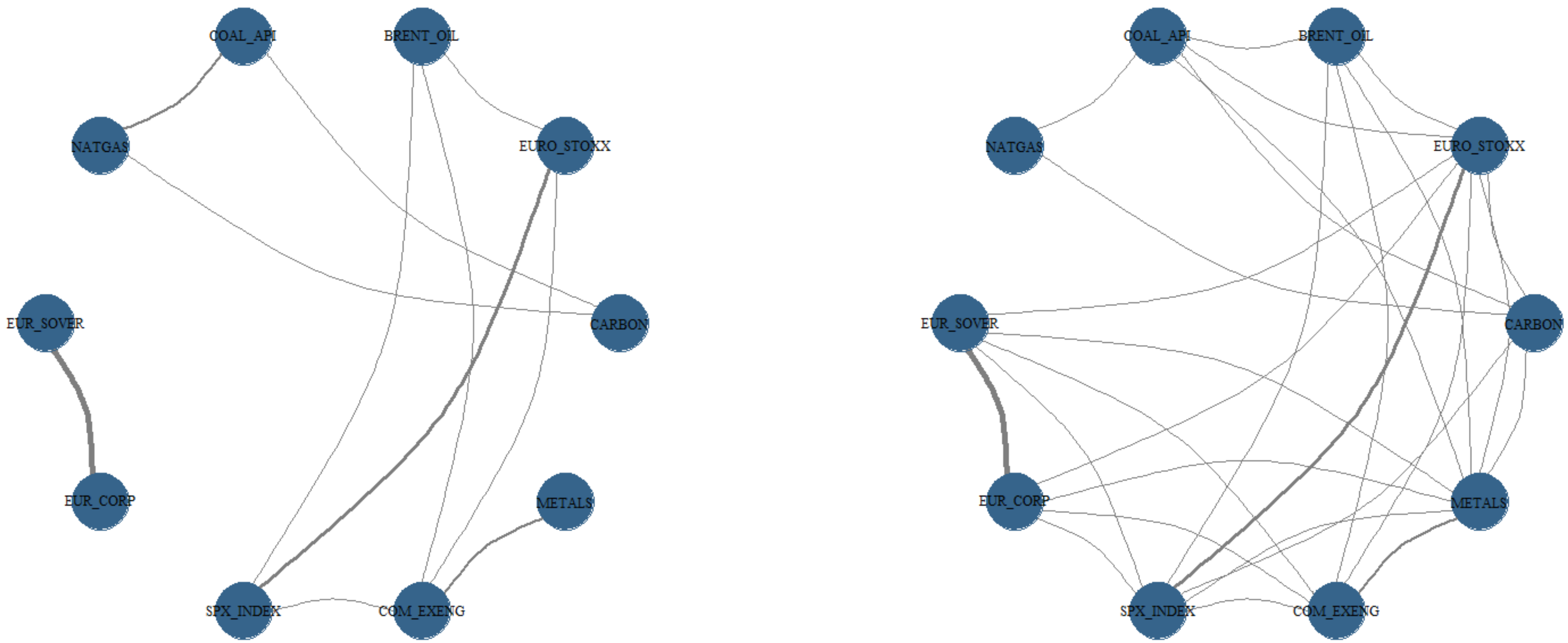


Appendix D.6.3. Static Return and Volatility Pairwise Directional Connectedness

Figure D.24: Network Representation of Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Static Return PCI network

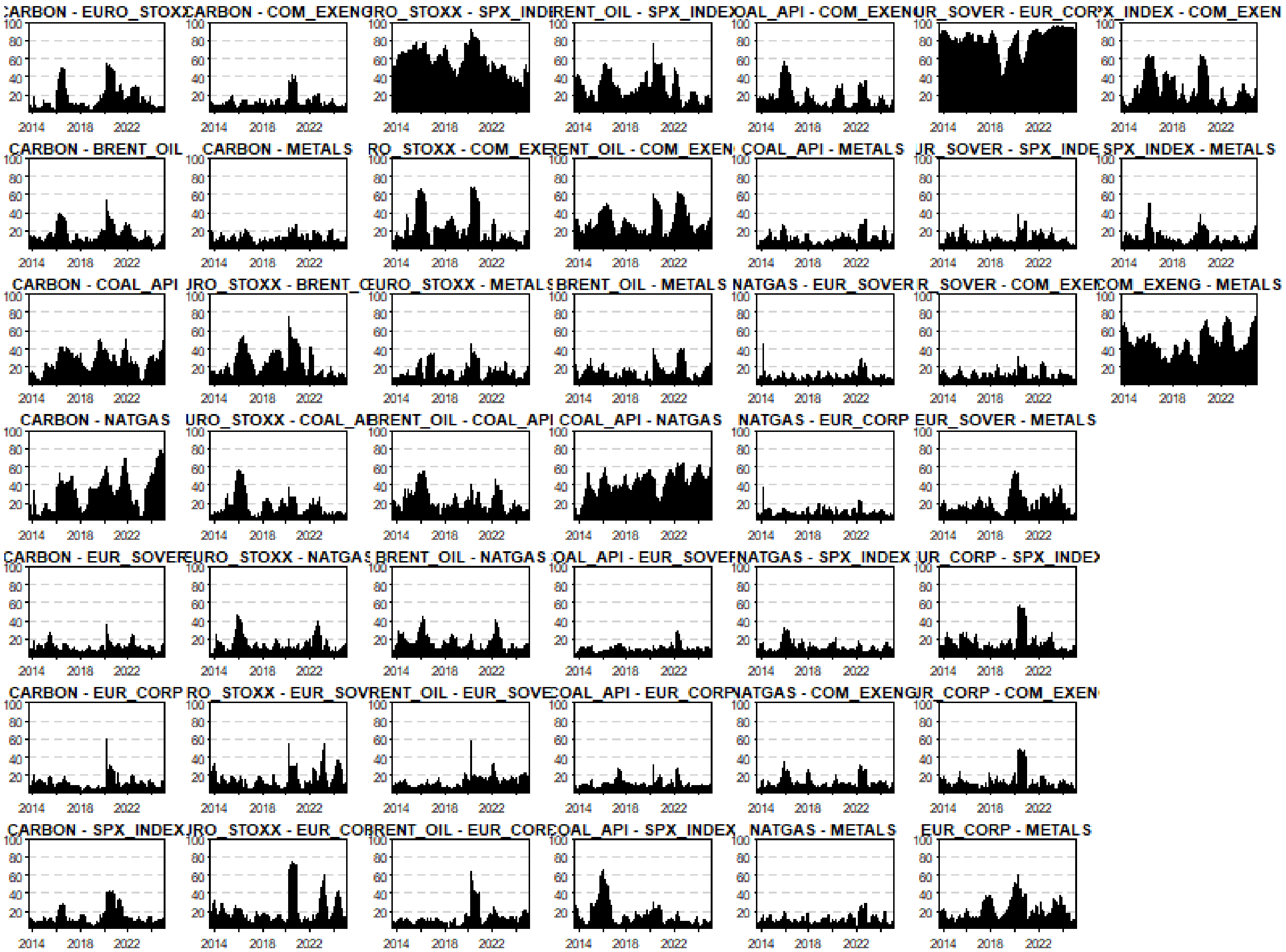
(b) Static Volatility PCI network



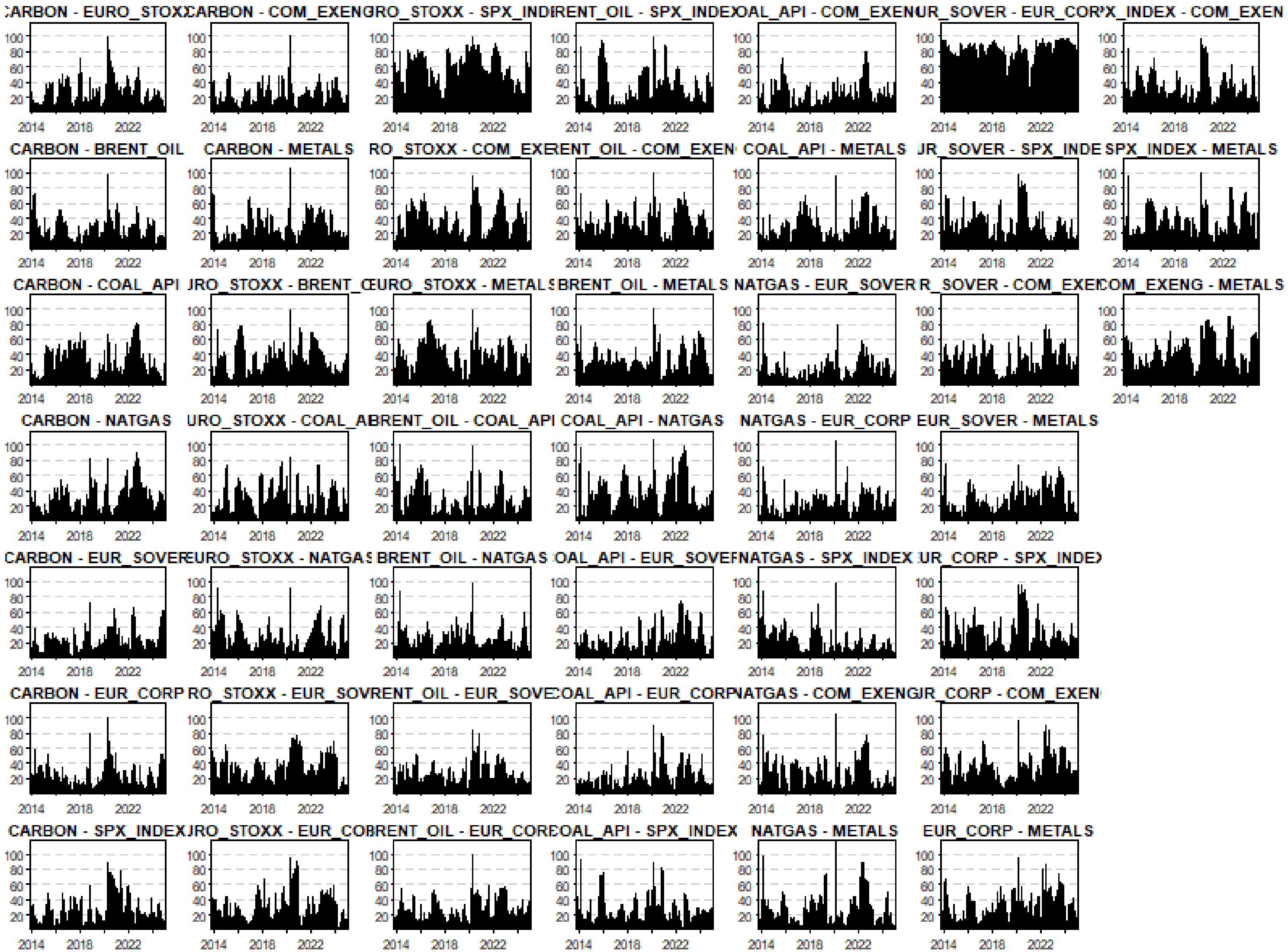
Appendix D.6.4. Dynamic Return and Volatility Pairwise Directional Connectedness

Figure D.25: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



Appendix D.7. 12-period forecast horizon and a rolling window of 200 observations

Appendix D.7.1. Static Return and Volatility Connectedness Matrix

Table D.10: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	59.98	4	3.81	7.85	10.21	2.49	2.28	3.48	2.77	3.13	40.02
EUROSTOXX	3.28	49.71	5.71	3.34	3.13	3.05	3.68	19.85	5.21	3.03	50.29
BRENTOIL	3.5	6.01	57.33	5.44	3.62	2.69	2.35	7.28	8.29	3.5	42.67
COALAPI	6.34	3.78	5.8	55.96	13.77	1.86	2.05	3.84	3.96	2.64	44.04
NATGAS	9.93	3.04	3.89	13.57	58.66	1.81	1.77	2.5	2.57	2.25	41.34
EURSOVER	2.04	3.01	2.69	1.68	1.69	48.28	31.89	2.3	2.06	4.36	51.72
EURCORP	1.98	5.05	2.72	1.75	1.82	30.35	45.45	3.97	2.55	4.36	54.55
SPXINDEX	2.43	17.94	6.82	3.36	2.04	2.32	2.74	53.46	6.4	2.51	46.54
COMEXENG	2.49	5.09	7.45	3.49	2.41	2.17	2.38	6.6	53.02	14.9	46.98
METALS	2.38	3.18	3.13	2.29	2.47	4.84	5.59	2.98	16.13	57.02	42.98
DST(TO)	34.37	51.09	42.02	42.78	41.16	51.58	54.72	52.79	49.94	40.68	461.13
Inc. Own	94.35	100.8	99.35	98.74	99.82	99.86	100.17	106.25	102.96	97.69	cTCI/TCI
NS (NET)	-5.65	0.8	-0.65	-1.26	-0.18	-0.14	0.17	6.25	2.96	-2.31	51.24/46.11

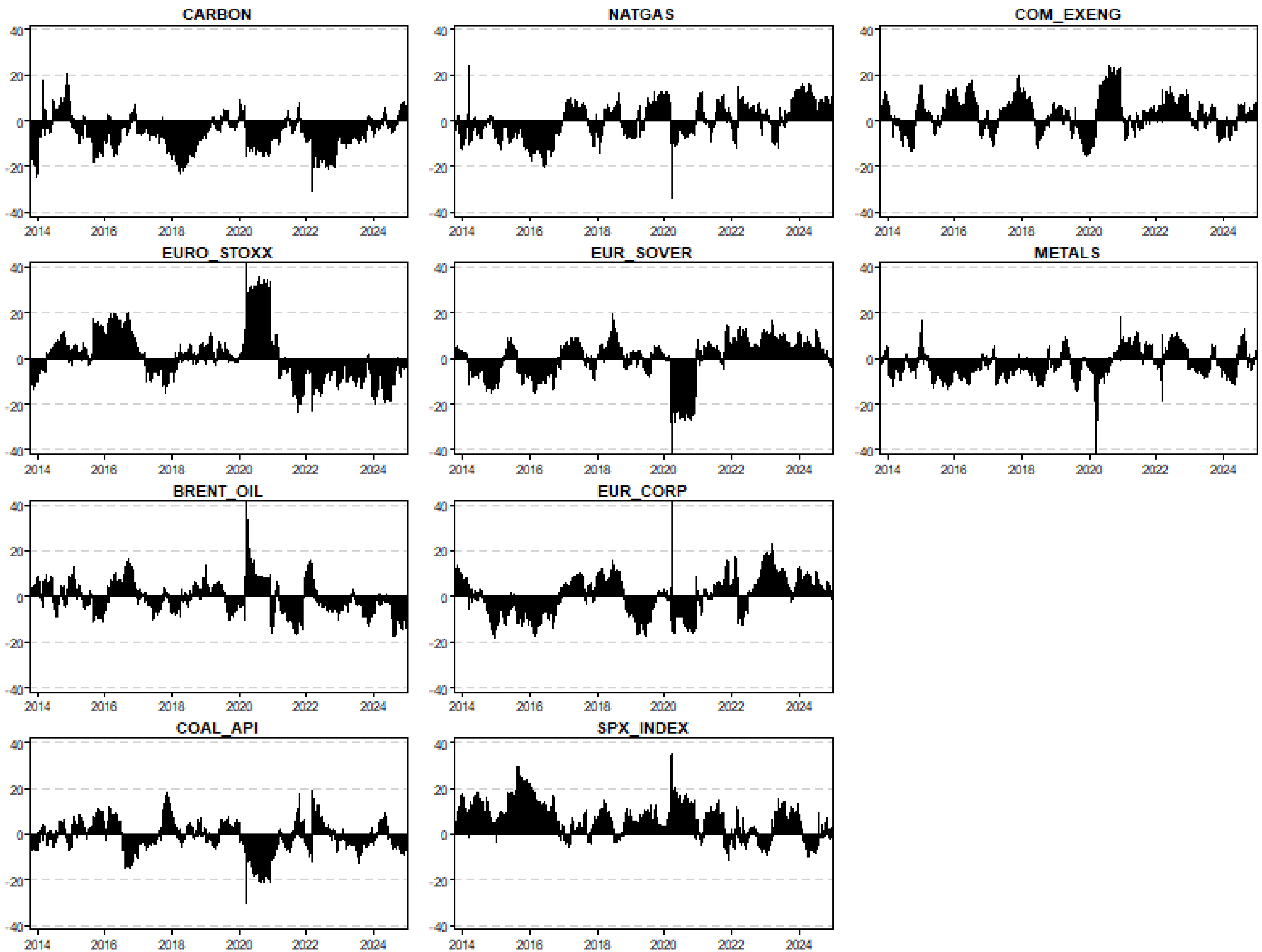
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	51.77	4.95	4.62	7.64	7.57	4.25	4.08	5.87	4.28	4.97	48.23
EUROSTOXX	3.95	44.7	5.26	4	4.01	5.47	4.39	16.25	5.63	6.33	55.3
BRENTOIL	4.33	6.94	48.98	5.34	4.07	4.39	5.01	6.77	7.45	6.73	51.02
COALAPI	5.18	6.48	4.42	54.18	8.27	4.19	3.09	5.01	3.51	5.67	45.82
NATGAS	4.87	5.04	3.94	8.7	55.58	4.08	4.28	5.31	3.85	4.35	44.42
EURSOVER	2.39	6.61	3.52	2.68	2.03	43.31	24.59	5.95	4.24	4.68	56.69
EURCORP	3.04	6.01	2.75	2.55	2.71	27.87	40.08	6.26	5.14	3.58	59.92
SPXINDEX	3.75	15.2	5.1	3.55	2.01	5.11	4.18	50.28	4.96	5.87	49.72
COMEXENG	2.95	8.09	4.83	4.12	4.36	5.67	5.7	7.07	47.39	9.81	52.61
METALS	4.08	8.78	4.77	4.27	4.3	5.29	6.67	6.72	10.22	44.9	55.1
DST(TO)	34.53	68.1	39.22	42.85	39.32	66.32	61.99	65.21	49.29	51.99	518.82
Inc. Own	86.3	112.8	88.19	97.03	94.9	109.63	102.07	115.49	96.68	96.89	cTCI/TCI
NS (NET)	-13.7	12.8	-11.81	-2.97	-5.1	9.63	2.07	15.49	-3.32	-3.11	57.65/51.88

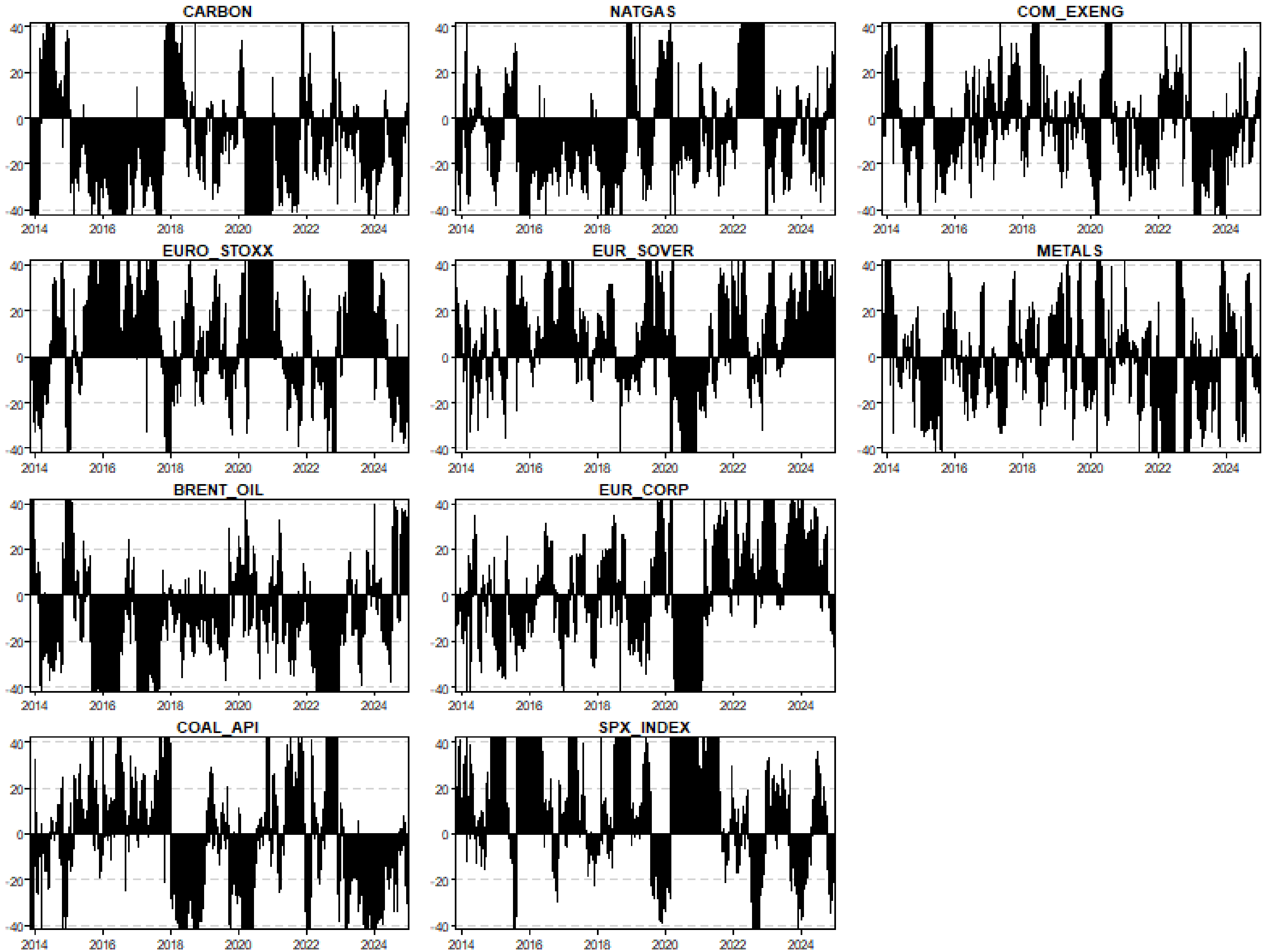
Appendix D.7.2. Dynamic Return and Volatility Net Directional Connectedness

Figure D.26: Dynamic Net Directional Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



(b) Dynamic volatility net directional connectedness

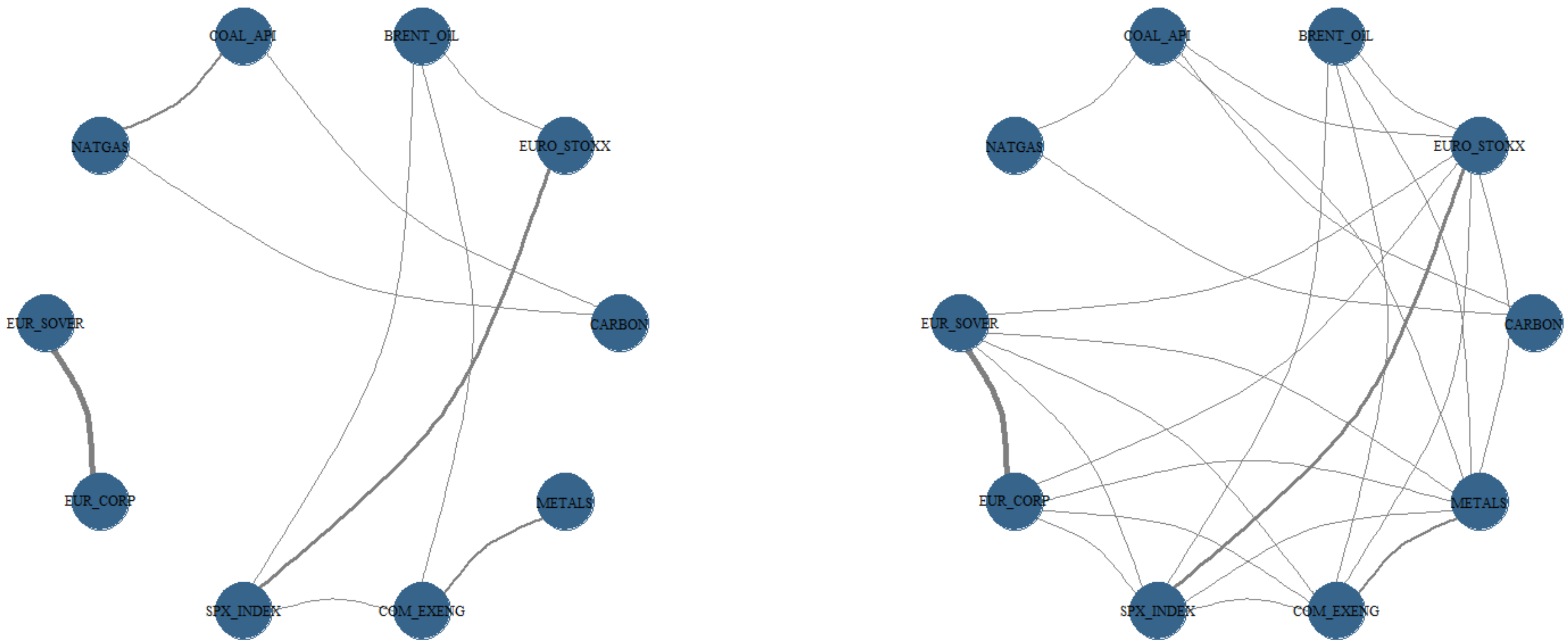


Appendix D.7.3. Static Return and Volatility Pairwise Directional Connectedness

Figure D.27: Network Representation of Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Static Return PCI network

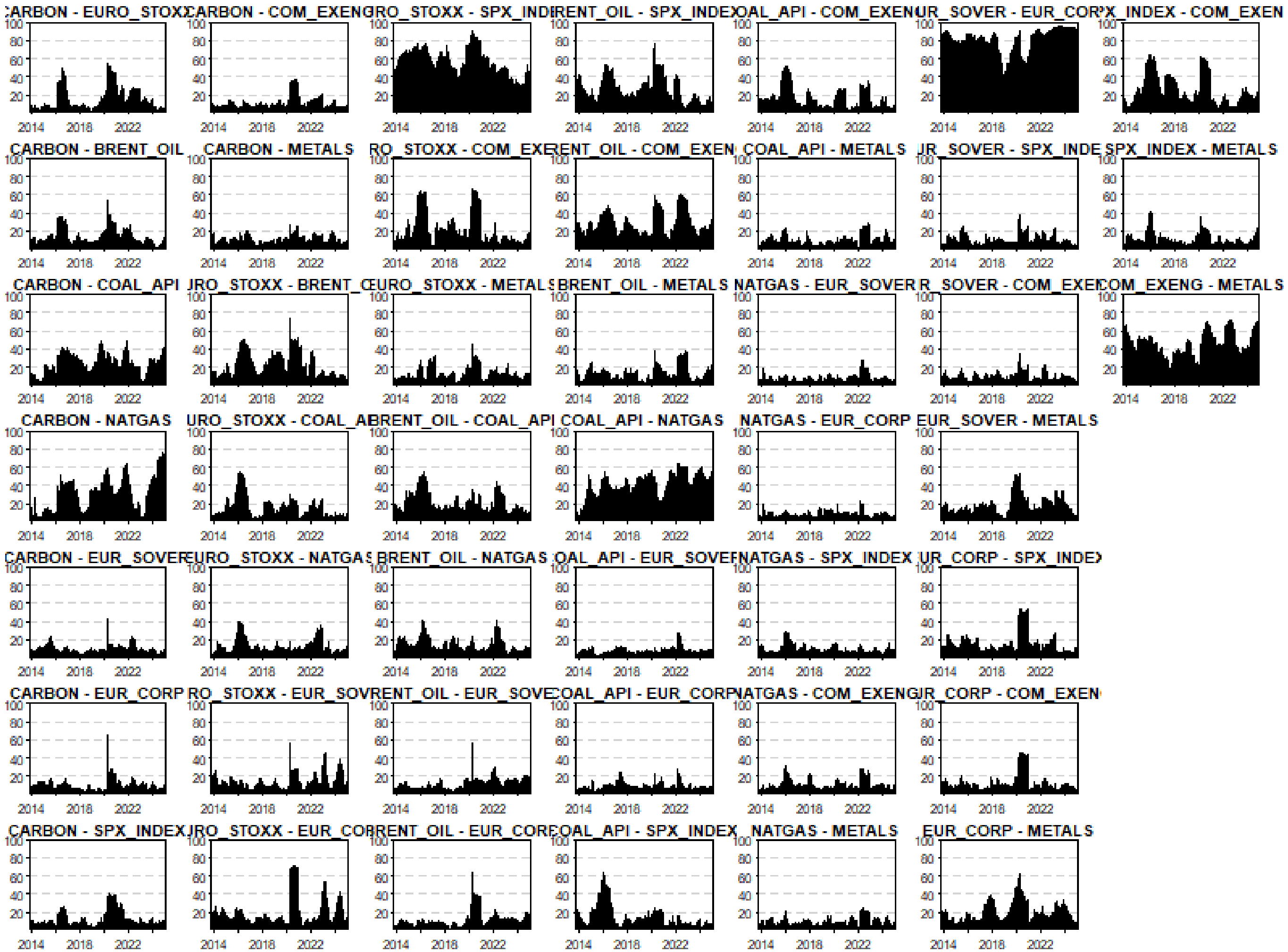
(b) Static Volatility PCI network



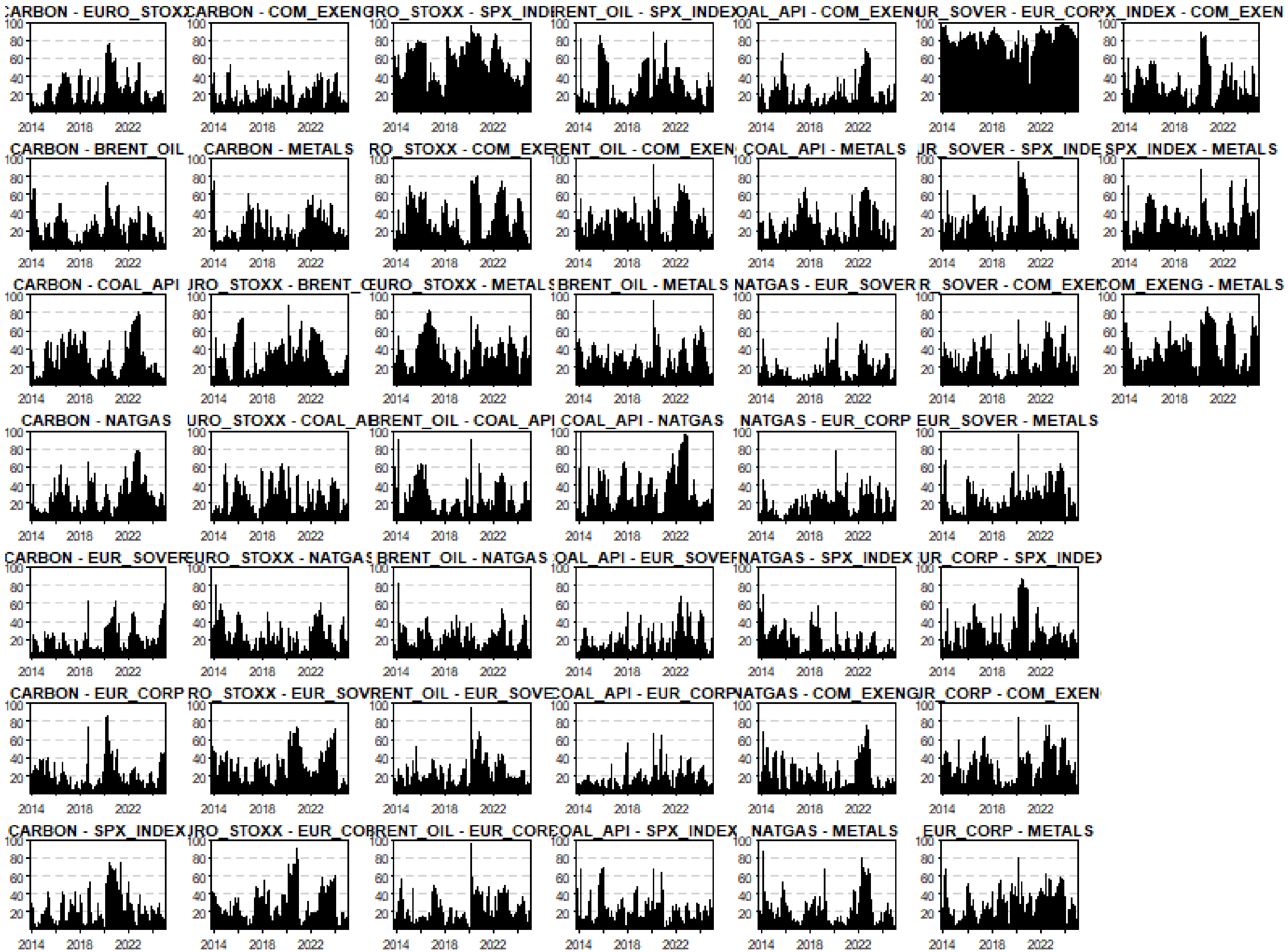
Appendix D.7.4. Dynamic Return and Volatility Pairwise Directional Connectedness

Figure D.28: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



Appendix D.8. 12-period forecast horizon and a rolling window of 220 observations

Appendix D.8.1. Static Return and Volatility Connectedness Matrix

Table D.11: Static Return and Volatility Connectedness Matrix (Jan 2013 - Jan 2025)

(a) Carbon returns connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	61.29	3.94	3.67	7.78	10.07	2.3	2.13	3.29	2.61	2.93	38.71
EUROSTOXX	3.18	50.75	5.67	3.23	2.95	2.75	3.44	20.11	5.14	2.78	49.25
BRENTOIL	3.31	5.92	58.37	5.39	3.49	2.52	2.23	7.2	8.31	3.26	41.63
COALAPI	6.22	3.66	5.74	56.99	13.87	1.72	1.89	3.7	3.83	2.39	43.01
NATGAS	9.79	2.87	3.75	13.75	59.92	1.63	1.61	2.24	2.38	2.06	40.08
EURSOVER	1.87	2.8	2.48	1.5	1.48	49.27	32.33	2.16	1.85	4.26	50.73
EURCORP	1.84	5	2.61	1.57	1.62	30.67	46.12	3.92	2.43	4.23	53.88
SPXINDEX	2.26	18.11	6.71	3.22	1.81	2.14	2.59	54.44	6.44	2.29	45.56
COMEXENG	2.33	5.03	7.43	3.35	2.18	1.97	2.22	6.63	53.89	14.98	46.11
METALS	2.22	2.93	2.91	2.08	2.25	4.77	5.51	2.77	16.29	58.28	41.72
DST(TO)	33.01	50.26	40.96	41.87	39.71	50.46	53.95	52	49.28	39.18	450.7
Inc. Own	94.3	101.01	99.33	98.86	99.62	99.73	100.06	106.44	103.17	97.47	cTCI/TCI
NS (NET)	-5.7	1.01	-0.67	-1.14	-0.38	-0.27	0.06	6.44	3.17	-2.53	50.08/45.07

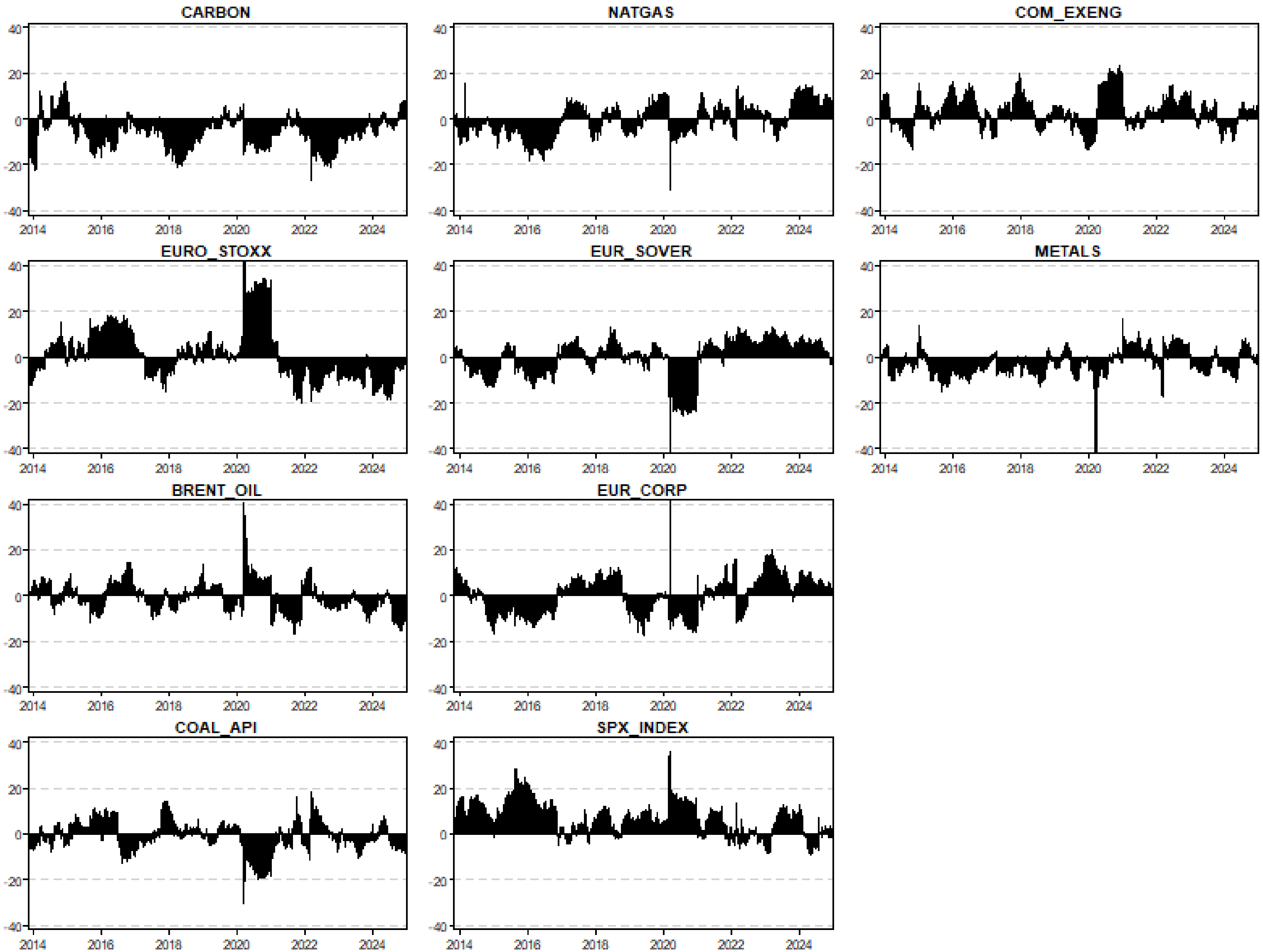
(b) Carbon volatility connectedness matrix

	CARBON	EUROSTOXX	BRENTOIL	COALAPI	NATGAS	EURSOVER	EURCORP	SPXINDEX	COMEXENG	METALS	FROM
CARBON	53.98	4.97	4.32	7.64	7.18	3.84	3.72	5.49	4.29	4.56	46.02
EUROSTOXX	3.55	46.21	4.99	3.61	3.61	5.32	4.27	16.81	5.63	6.01	53.79
BRENTOIL	3.82	6.9	51.01	5.18	3.86	3.98	4.53	6.63	7.62	6.47	48.99
COALAPI	5.06	5.98	3.68	57.01	7.87	3.96	2.92	4.6	3.39	5.53	42.99
NATGAS	4.63	4.71	3.52	8.47	58.3	3.77	4.15	4.94	3.53	3.99	41.7
EURSOVER	2.06	6.39	3.31	2.32	1.72	44.95	25.12	5.85	3.77	4.53	55.05
EURCORP	2.67	6.01	2.68	2.1	2.2	28.56	41.62	6.19	4.53	3.42	58.38
SPXINDEX	3.46	15.35	4.67	3.27	1.77	4.68	3.85	52.71	4.66	5.58	47.29
COMEXENG	2.45	8.05	4.81	3.83	3.94	5.14	5.21	6.79	49.88	9.9	50.12
METALS	3.87	8.67	4.35	4	3.91	5.1	6.19	6.11	10.51	47.28	52.72
DST(TO)	31.56	67.03	36.35	40.42	36.07	64.35	59.96	63.39	47.93	49.97	497.04
Inc. Own	85.54	113.25	87.36	97.43	94.38	109.3	101.59	116.09	97.81	97.25	cTCI/TCI
NS (NET)	-14.46	13.25	-12.64	-2.57	-5.62	9.3	1.59	16.09	-2.19	-2.75	55.23/49.70

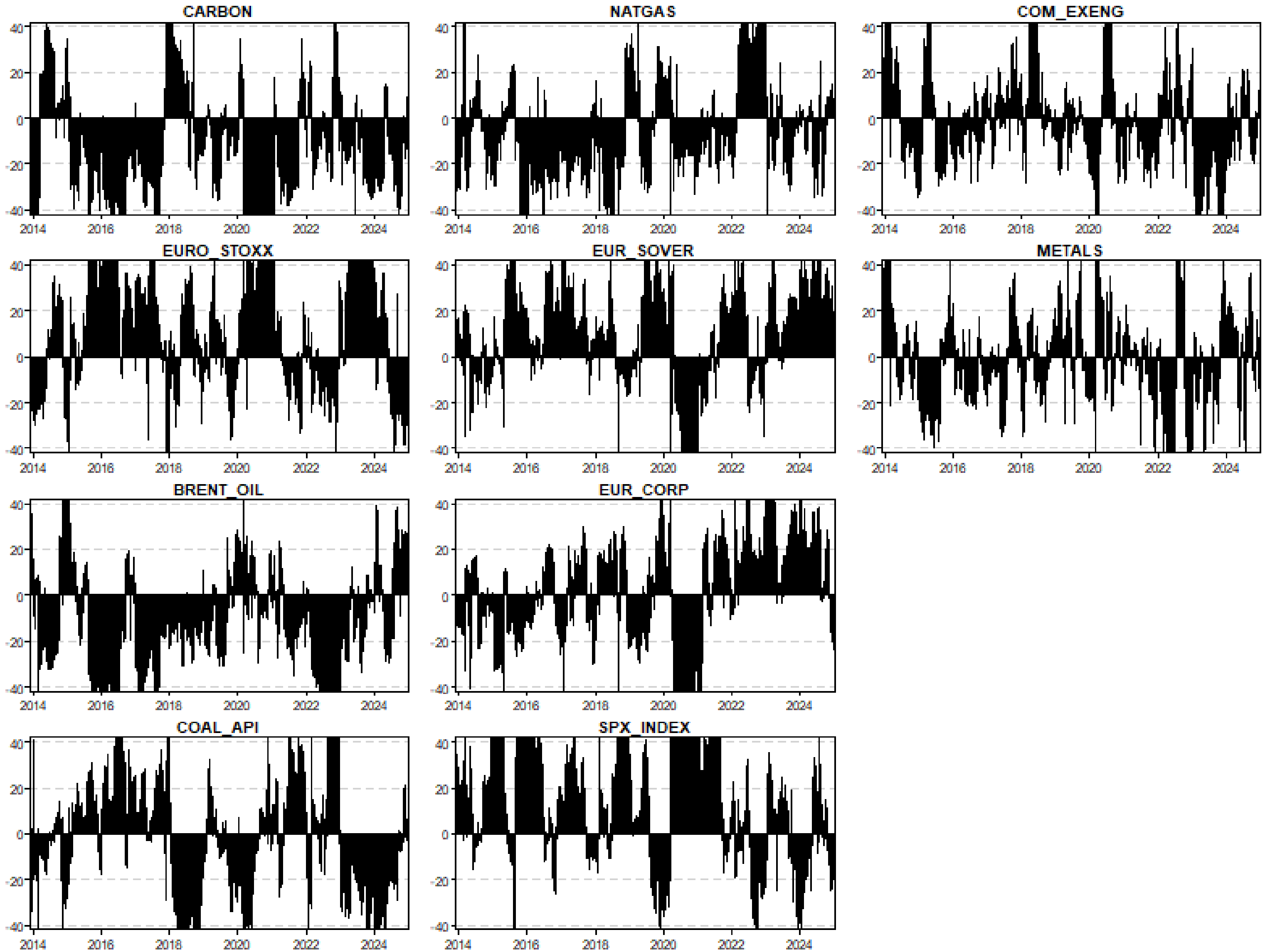
Appendix D.8.2. Dynamic Return and Volatility Net Directional Connectedness

Figure D.29: Dynamic Net Directional Connectedness (Jan 2013 – Jan 2025)

(a) Dynamic return net directional connectedness



(b) Dynamic volatility net directional connectedness

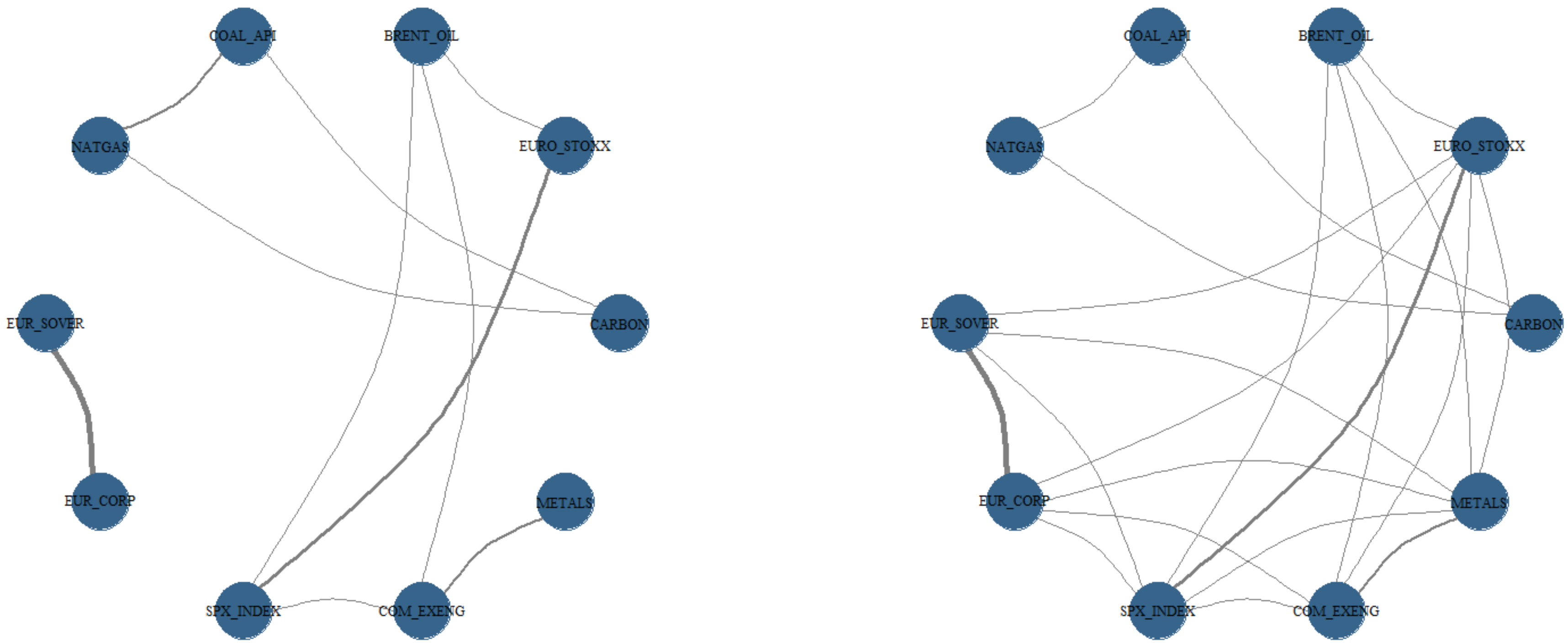


Appendix D.8.3. Static Return and Volatility Pairwise Directional Connectedness

Figure D.30: Network Representation of Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Static Return PCI network

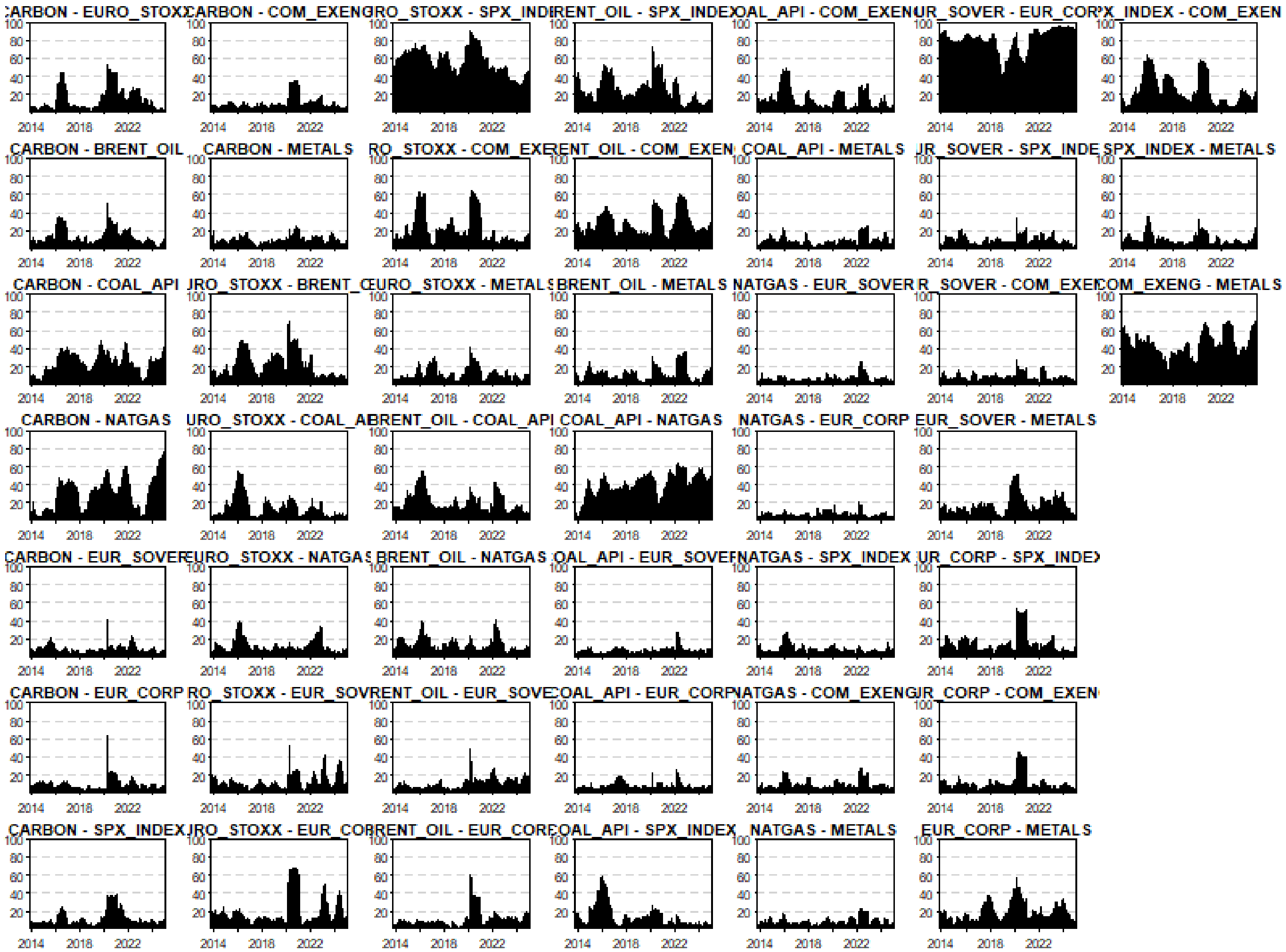
(b) Static Volatility PCI network



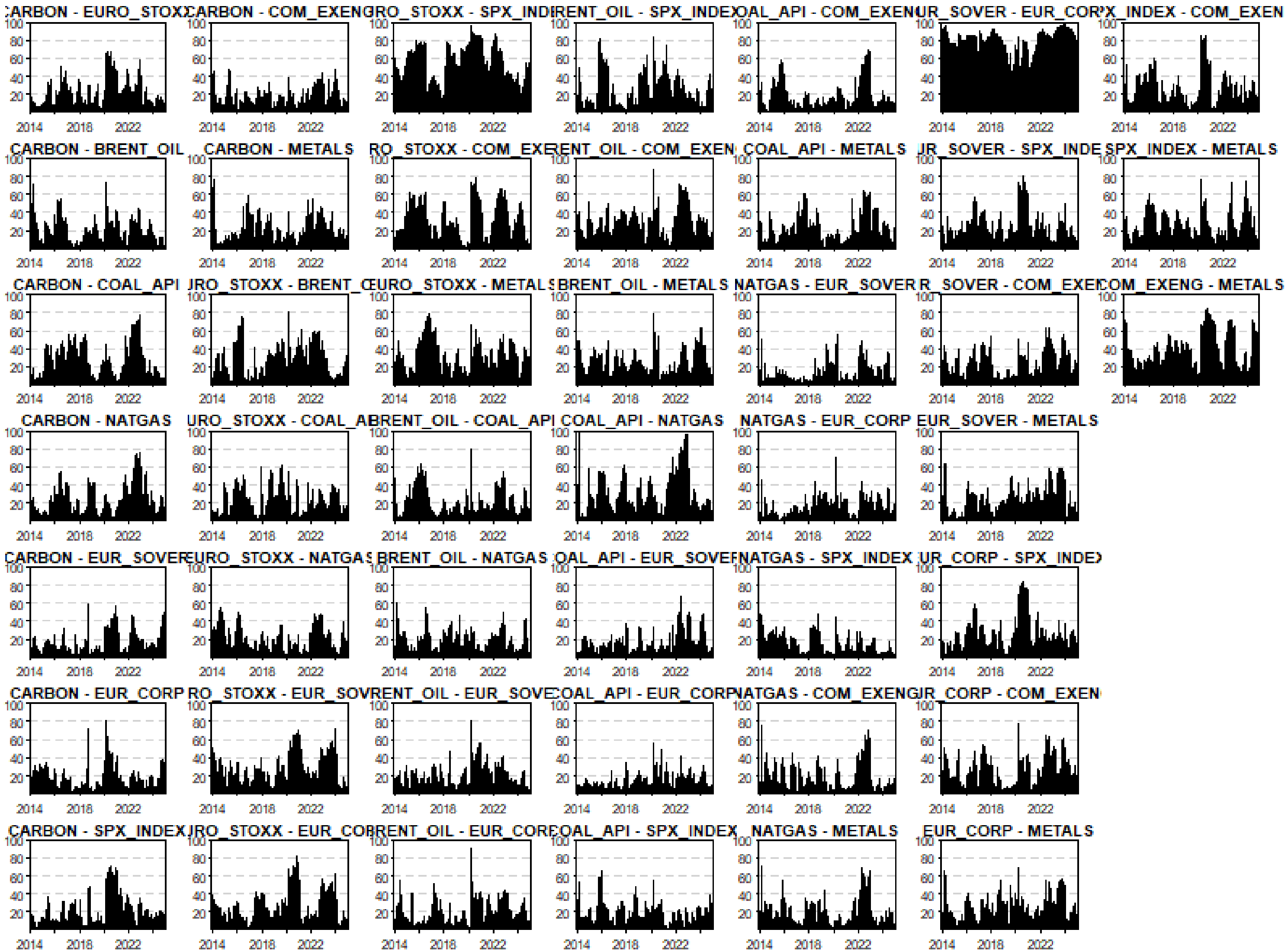
Appendix D.8.4. Dynamic Return and Volatility Pairwise Directional Connectedness

Figure D.31: Dynamic Return and Volatility Pairwise Connectedness Index (Jan 2013 – Jan 2025)

(a) Dynamic return PCI



(b) Dynamic volatility PCI



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