Does carbon price affect risk spillovers between the energy and industry stock markets?

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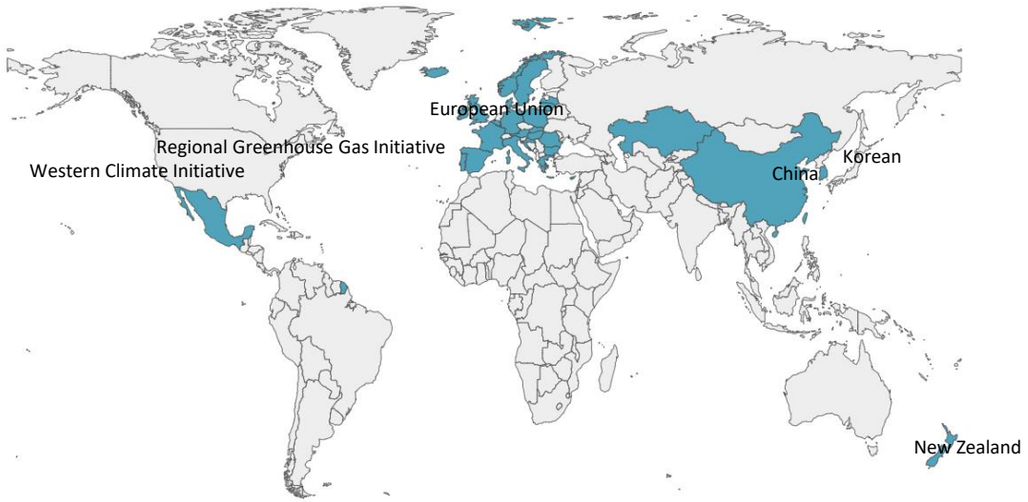
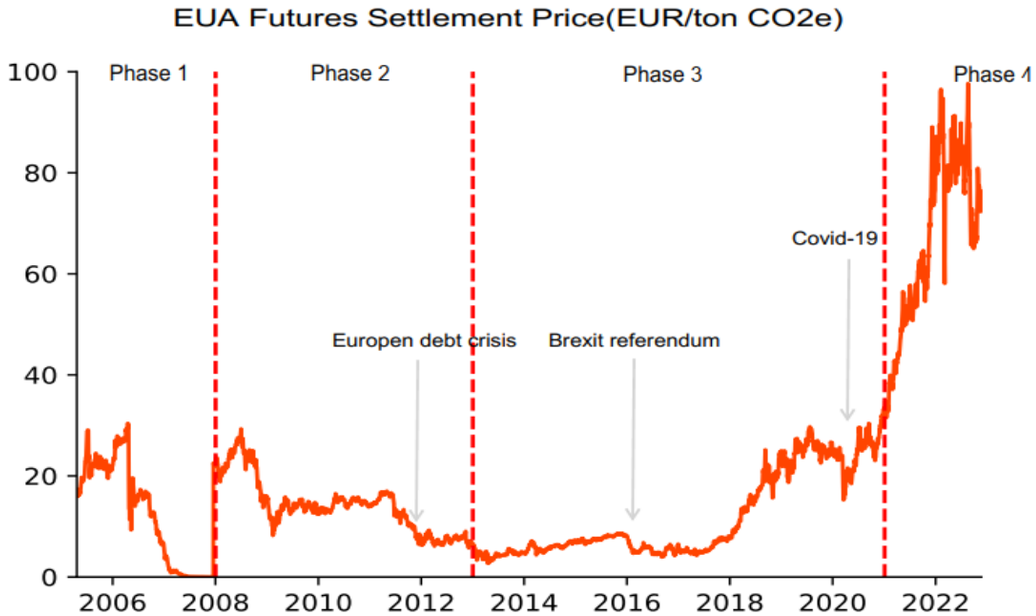
Part 01 Introduction

Research background

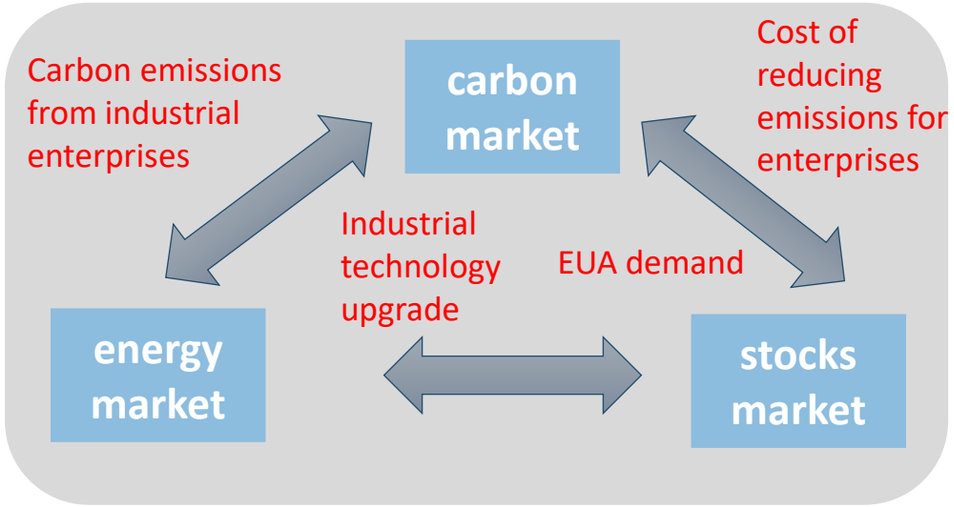
Global emissions trading system



Notes: This figure contains the major carbon markets.



The linkages among carbon and other markets?



The impact of the crisis events on the linkages among markets?

The numerous studies have examined the relationship between carbon markets and stock markets at the aggregated market level.

For the research between carbon market and other markets, the current literature mainly focus on the following aspects:

- Carbon price was driven by energy price, and there were significant spillovers between carbon and **energy** markets. (Gong et al., 2021 , Zhang and Sun, 2016; Wu et al., 2020)
- The **stock** market has had a significant impact on the EU carbon market.(Zhang et al., 2022) In addition, there were literatures on the impact of carbon markets on stock markets in different countries. (Luo and Wu, 2016)
- While some studies have investigated the linkage between carbon market and **sector stock markets**, these studies have focused on clean energy or power sector stocks. There was a strong information interdependence between carbon prices and stock markets for electricity and clean energy. (Ji et al., 2019, Ding et al., 2022)

Scholars have concentrated on the spillovers between carbon and other markets in time domain.

Current research methods of the relationship between markets are mainly divided into the following categories:

- Based on the **traditional cointegration equation and vector autoregression (VAR) model**, one strand of research has investigated the dynamic linkages, causality, contagion, and co-movement between markets. The studies on this subject were mostly **in time domain**. (Zeng et al., 2021;Gong et al., 2021; Wu et al., 2020)
- Based on the **multivariate GARCH model** (BEKK-GARCH,DCC-GARCH, etc.) model, another strand of studies has examined the volatility spillover effects between markets. (Zhang and Sun, 2016; Zhao et al., 2023; Zeng et al., 2021)
- **Wavelet coherence** have been widely used to analyze interdependence between markets in the time-frequency domain. (Meng et al., 2022； Cui et al., 2021)
- **Diebold and Yilmaz (2012) and Baruník and Krehlík (2018)** have been widely used to analyze risk spillovers between markets. The models can capture time-varying, directional and quantitative spillovers, and can analyze risk spillovers in frequency domain. (Wang and Guo, 2018； Adekoya et al., 2021； Ding et al., 2022)

Literature review

Literature review：

- Few literature have evaluated the relationship among carbon, energy and stock markets at the level of **segmented stock industry**. The heterogeneity at the sector level is indispensable to abundant portfolio strategies.
- Due to the heterogeneity of the diverse market participants, it is necessary to explore the risk spillovers between markets in **frequency domain**.

Hypothesis:

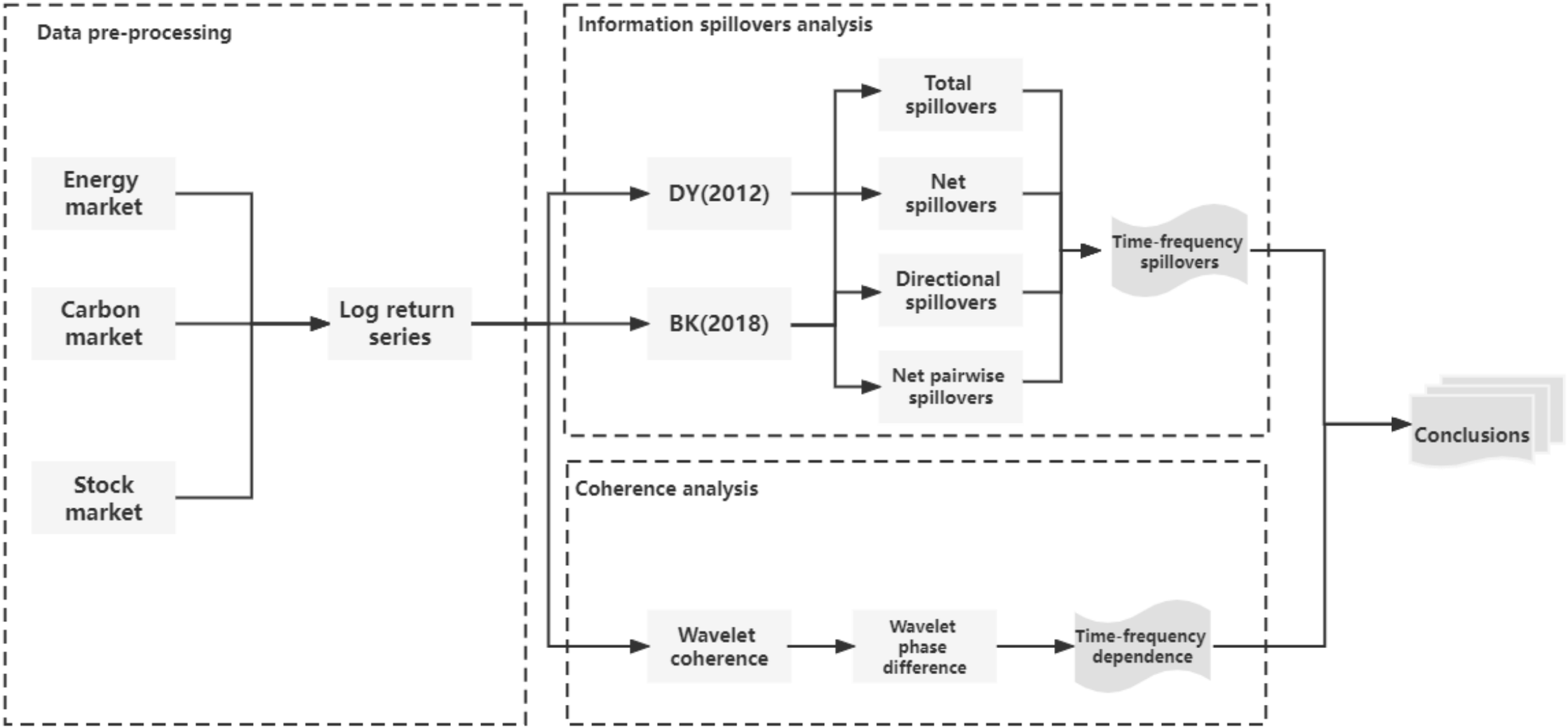
- **H1:** There is a strong connectedness among the carbon, energy and industry stock markets.
- **H2:** There is frequency-domain heterogeneity in the spillovers among carbon, energy and industry stock markets.
- **H3:** The crisis events affect the spillovers among carbon, energy and industry stock markets.

This paper systematically explores the among carbon, energy and **industry stock markets.**

This paper investigates the **time-frequency** dependence and risk connectedness among carbon, energy and industry stock markets using the wavelet coherence, Diebold and Yilmaz (2012) and Baruník and Krehlík (2018) methods.

Part02 Methodologies

Framework


Data pre-processing
Energy market
Carbon market
Stock market
Log return series
Information spillovers analysis
DY(2012)
BK(2018)
Total spillovers
Net spillovers
Directional spillovers
Net pairwise spillovers
Time-frequency spillovers
Coherence analysis
Wavelet coherence
Wavelet phase difference
Time-frequency dependence
Conclusions

Wavelet coherence

➢ Continuous wavelet transform (CWT)

Continuous wavelet transform uses wavelet basis function to decompose data into wavelet coefficients of different scales.

$$\Psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi(\frac{t-\tau}{s})$$

where τ is a translation parameter., s is a scaling factor.

continuous wavelet transform:

$$W_x(\tau,s)=\int_{-\infty}^{\infty} x(t)\psi_{\tau,s}^{*}(t)dt$$

➢ Wavelet coherence

cross-wavelet transform:

$$W_{xy}(\tau,s) = W_x\ (\tau,s)W_y^{*}(\tau,s)$$

wavelet coherence：

$$R^2(\tau,s) = \frac{\left|S(s^{-1}W_{xy}(\tau,s))\right|^2}{S(s^{-1}|W_x(\tau,s))|)S(s^{-1}\left|W_y(\tau,s))\right|)}$$

➢ Wavelet phase difference

wavelet phase：

$$\phi_x = tan^{-1}\ (\frac{I(W_x(\tau,s))}{R(W_x(\tau,s))})\ ,\phi_x \in [-\pi,\pi]$$

wavelet phase difference:

$$\phi_{xy} = tan^{-1}\ (\frac{I(W_{xy}(\tau,s))}{R(W_{xy}(\tau,s))})\ ,\phi_x \in [-\pi,\pi]$$

$$\phi_{xy} \in \begin{cases} \left(0,\frac{\pi}{2}\right), y(t)\ leads\ x\ \ (t) \\ \left(\frac{\pi}{2},\pi\right), x(t)\ leads\ y\ \ (t) \\ \left(-\frac{\pi}{2},0\right), x(t)\ leads\ y\ \ (t) \\ \left(-\pi,-\frac{\pi}{2}\right), y(t)\ leads\ x\ \ (t) \end{cases}$$

Time connectedness approach

Diebold and Yilmaz (2012) quantifies spillovers.

- GFEVD

the moving average form of VAR model:

$$x_t = \sum_{i=0}^{\infty} A_i \, \varepsilon_{t-i}$$

GFEVD:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \qquad \tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}$$

- Diebold and Yilmaz (2012)

(1)total spillovers: measure the contribution of spillovers of shocks across markets to the total forecast error variance.

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100$$

(2)directional spillovers: measure the directional spillovers received by market i from all other markets j.

$$S_{i\cdot}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100$$

(3)net spillovers: are simply the difference between the gross shocks transmitted to and those received from all other markets.

$$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H)$$

(4)net pairwise spillovers : provide summary information about how much each market contributes to the volatility in other markets, in net terms.

$$S_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)} \right) \cdot 100$$

$$= \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} \right) \cdot 100.$$

Frequency connectedness approach

Baruník and Krehlík (2018) quantifies spillovers in the frequency domain.

the moving-average specification of the VAR process:

$$\mathbf{x}_t = \Psi(L)\boldsymbol{\epsilon}_t$$

GFEVD:

$$(\theta_H)_{j,k} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}\left((\Psi_h\boldsymbol{\Sigma})_{j,k}\right)^2}{\sum_{h=0}^{H}(\Psi_h\boldsymbol{\Sigma}\Psi_h{}')_{j,j}}$$

- Baruník and Krehlík(2018)

frequency response function (FRF):

$$\Psi(e^{-iw}) = \sum_h e^{-iwh}\Psi_h$$

generalized causation spectrum over the frequencies:

$$(f(\omega))_{j,k} \equiv \left\{\sigma_{kk}^{-1}\left|\left(\Psi\left(e^{-iw}\right)\Sigma\right)_{j,k}\right|^2\right\} \Big/ \left(\Psi\left(\omega^{-iw}\right)\Sigma\Psi'\left(e^{+iw}\right)\right)_{j,j}$$

GFEVD at the frequency band d:

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_d \Gamma_j(\omega)(f(\omega))_{j,k}d\omega \qquad \left(\tilde{\Theta}_d\right)_{j,k} = (\Theta_d)_{j,k} \Big/ \sum_k (\Theta_\infty)_{j,k}$$

frequency spillovers at the frequency band d:

$$C_d^F = 100 \times \left(\frac{\sum_{j\neq k}(\sim\Theta_d)_{j,k}}{\sum(\sim\Theta_\infty)_{j,k}} - \frac{\mathrm{Tr}\{\sim\Theta_d\}}{\sum(\sim\Theta_\infty)_{j,k}}\right)$$

total spillovers within the frequency band d:

$$C_d^W = 100 \times \left(1 - \frac{\mathrm{Tr}\{\tilde{\Theta}_d\}}{\sum(\tilde{\Theta}_d)_{j,k}}\right)$$

Part 03 Empirical results

Data

Table 1. Data sources.

Market	Variable	Date
Carbon	EUA	
Energy	Brent crude oil	
	Natural gas futures	
	Euronext ARA coal futures	
Stock	STOXX Europe 600 index (Oil & Gas, Industrial Goods & Services, Technology, Utilities, Telecommunications, Financial Services, Real Estate, Automobiles & Parts, etc.)	2010-01-04~2022-11-16

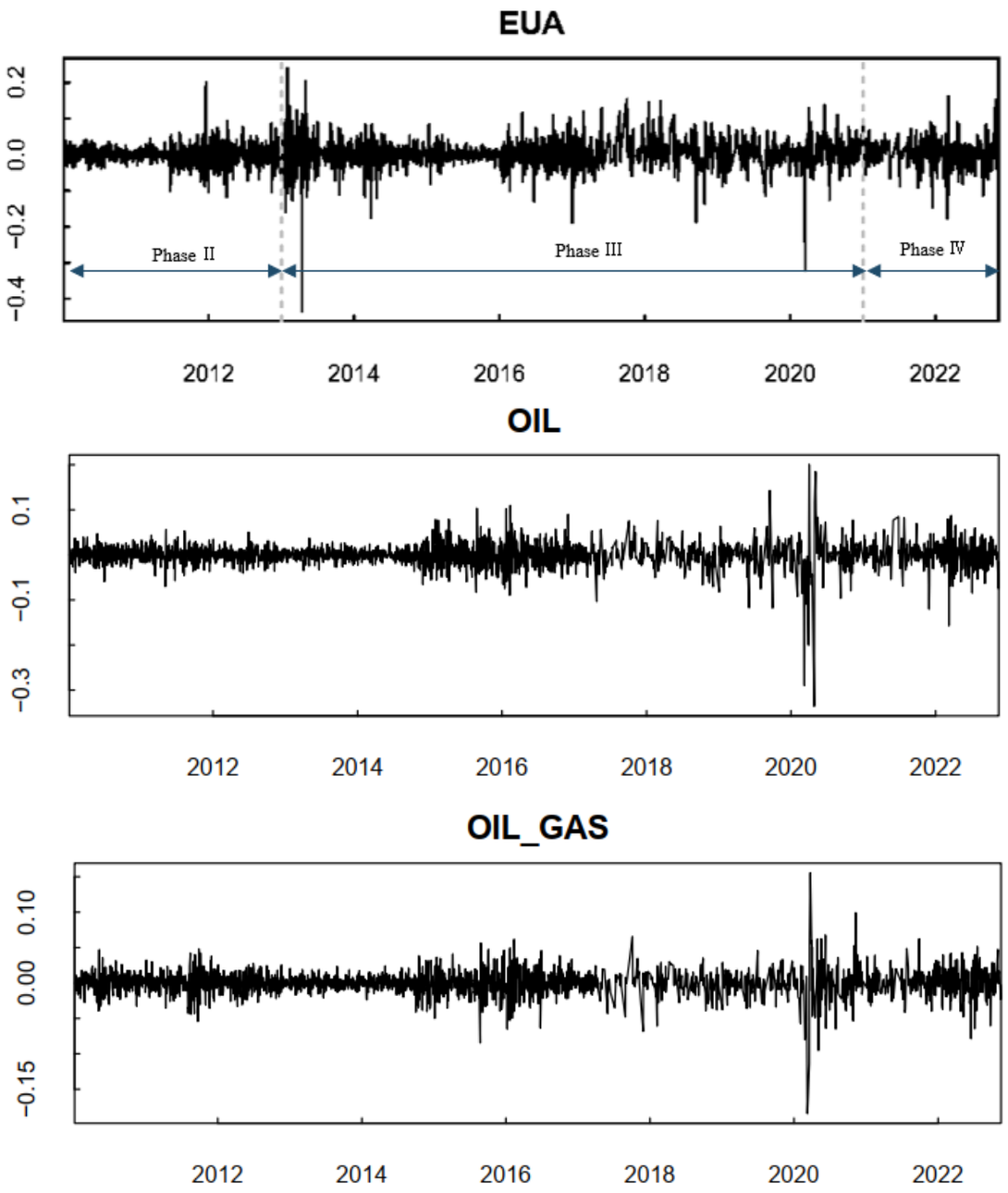


Fig.1. Dynamics of carbon, energy and stock price index returns.

Descriptive statistics and correlations

Table 2. Summary descriptive statistics and unit root tests.

	Mean	Std. Dev.	Skewness	Kurtosis	JB	ADF	Q(20)	Q2(20)	ARCH
EUA	0. 001	0. 036	−0. 851	14. 472	23100. 359***	−13. 944***	23. 628***	107. 053***	119. 115***
OIL	0. 000	0. 026	−1. 306	23. 806	62395. 237***	−13. 946***	43. 947***	773. 925***	608. 553***
COAL	0. 000	0. 026	−1. 911	80. 139	700269. 799***	−12. 456***	37. 318***	99. 464***	122. 681***
GAS	0. 001	0. 032	1. 246	62. 689	428216. 813***	−11. 042***	83. 197***	22. 364***	96. 027***
AUTO_PARTS	0. 000	0. 020	−0. 371	5. 172	2970. 012***	−14. 491***	20. 966**	950. 982***	507. 409***
OIL_GAS	0. 000	0. 017	−0. 812	14. 342	22663. 387***	−14. 913***	61. 390***	1510. 045***	804. 371***
INDSGDS_SVS	0. 000	0. 014	−0. 793	8. 305	7778. 210***	−14. 073***	28. 830***	974. 393***	627. 443***
TECH	0. 000	0. 016	−0. 093	6. 264	4271. 981***	−13. 653***	23. 762***	305. 375***	219. 676***
UTILITIES	0. 000	0. 013	−1. 834	29. 456	95857. 269***	−14. 939***	34. 804***	97. 756***	92. 247***
TECHNOLOGY	0. 000	0. 012	−1. 076	16. 089	28665. 516***	−15. 282***	23. 671***	494. 231***	450. 953***
RETAIL	0. 000	0. 013	−0. 602	10. 313	11728. 821***	−13. 672***	22. 471***	193. 651***	176. 307***
FINANCIAL_SVS	0. 000	0. 015	−0. 954	10. 128	11554. 989***	−15. 101***	46. 461***	842. 525***	605. 005***
BASIC_MATS	0. 000	0. 015	−0. 444	3. 743	1609. 831***	−14. 748***	15. 111	599. 983***	380. 730***
REAL_ESTATE	0. 000	0. 014	−1. 290	15. 658	27395. 949***	−14. 370***	47. 940***	814. 159***	734. 599***
BANKS	0. 000	0. 019	−0. 366	7. 250	5776. 794***	−14. 545***	13. 685	425. 269***	280. 897***
CHEMICALS	0. 000	0. 013	−0. 324	3. 887	1689. 606***	−14. 296***	6. 881	426. 963***	279. 954***
FOOD_BEV	0. 000	0. 010	−0. 684	9. 030	9075. 807***	−14. 427***	22. 437***	548. 569***	394. 291***
Basic_Resources	0. 000	0. 021	−0. 320	3. 315	1240. 368***	−15. 159***	17. 404**	498. 403***	333. 203***
CON_MAT	0. 000	0. 015	−0. 797	9. 617	10337. 961***	−14. 842***	31. 309***	605. 010***	411. 370***
INSURANCE	0. 000	0. 016	−0. 844	11. 550	14822. 728***	−15. 248***	60. 100***	1034. 206***	636. 395***
MEDIA	0. 000	0. 013	−0. 789	10. 532	12337. 079***	−14. 752***	33. 465***	580. 401***	428. 214***
TRAVEL	0. 000	0. 017	−1. 956	27. 741	85383. 334***	−14. 906***	53. 003***	1174. 964***	960. 524***
HEALTH_CARE	0. 000	0. 011	−0. 295	6. 781	5039. 548***	−15. 366***	17. 345*	465. 702***	310. 763***

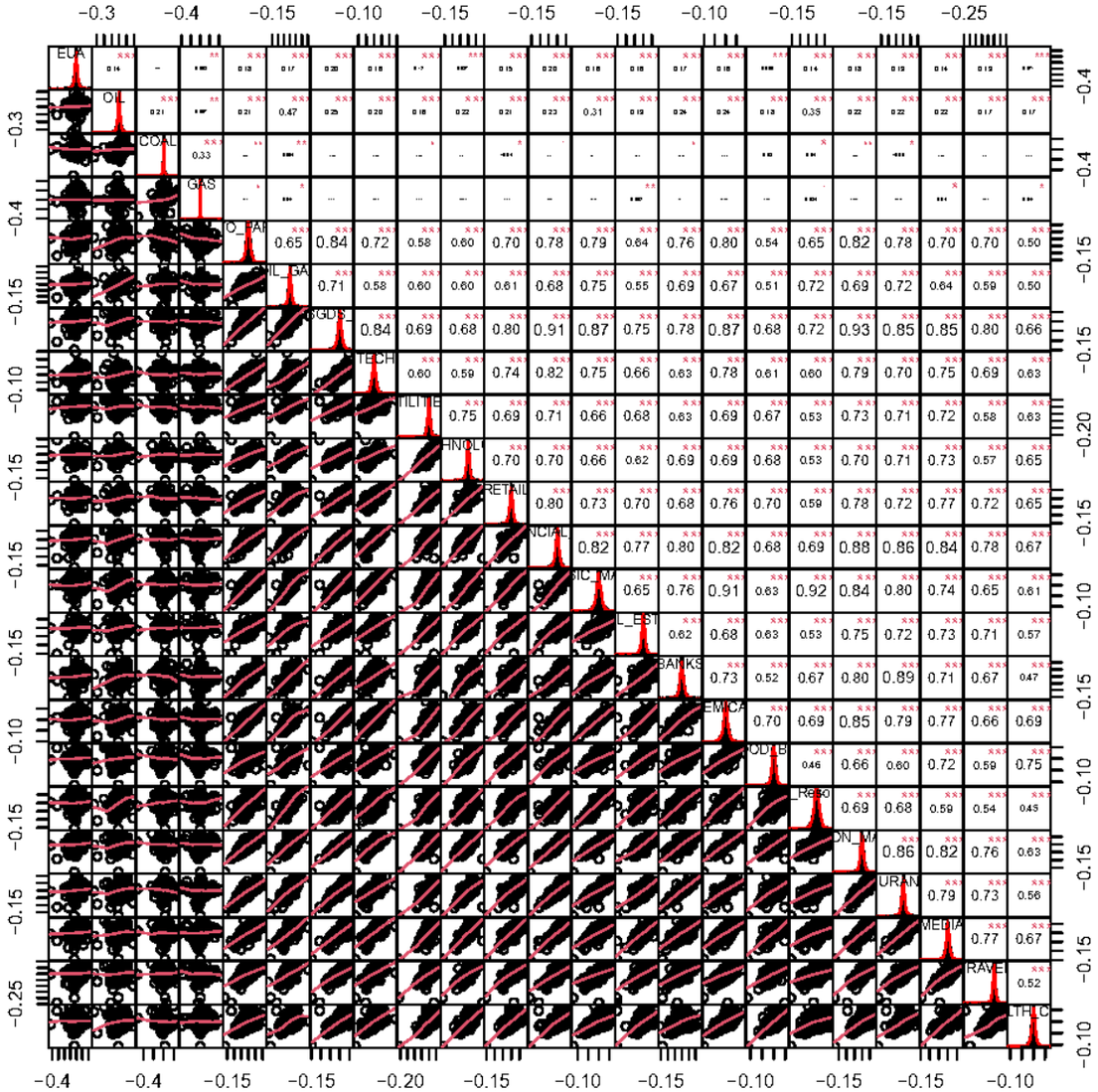


Fig.2. Correlations among daily returns of carbon, energy and stock prices.

Wavelet coherence

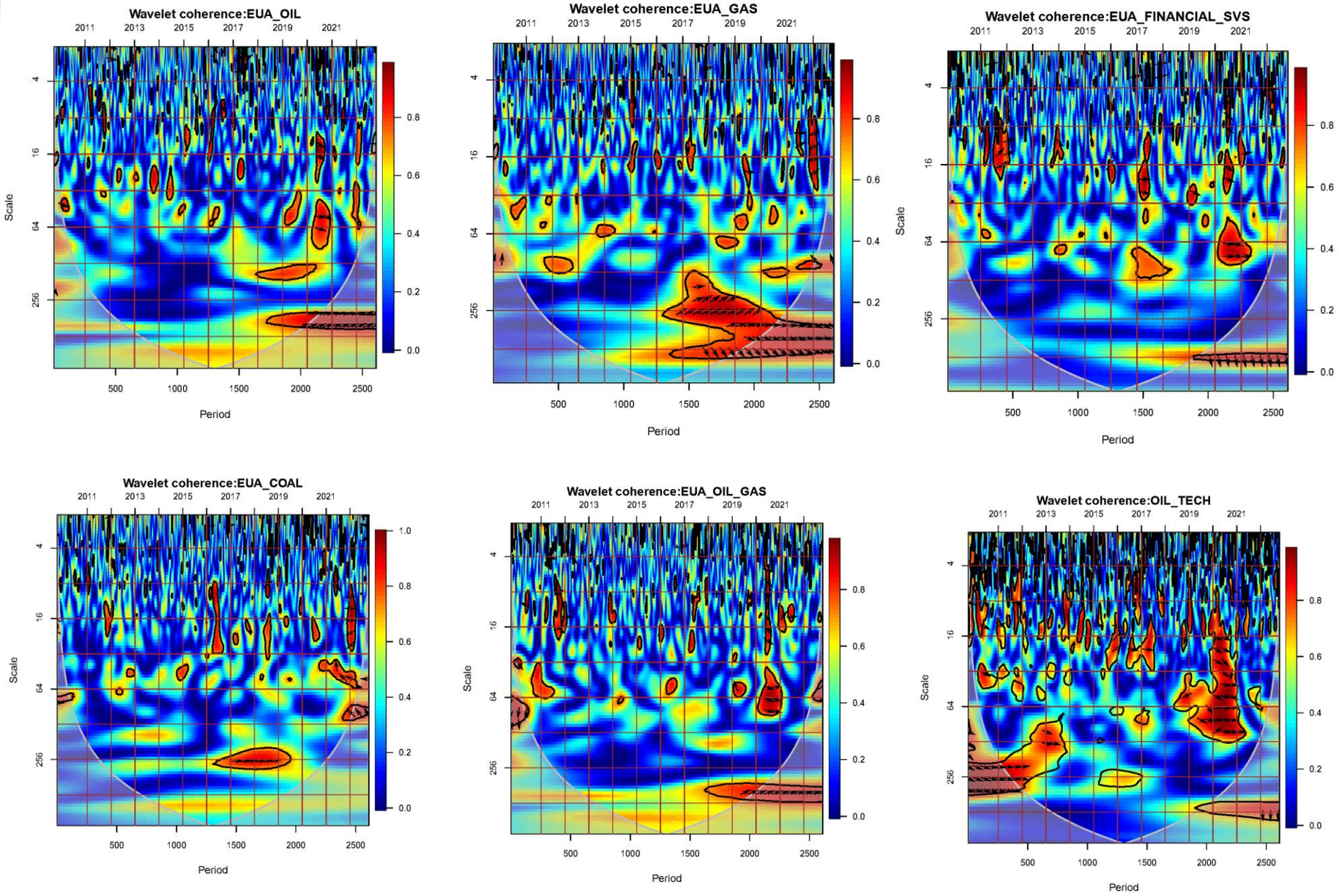


Fig.3. Wavelet coherence among carbon, energy and stock markets.

- The dependence among carbon, energy and stock markets is mainly strong at a long-term scale.
- The carbon market presents low coherence with the energy and stock markets, while the dependence between crude oil market and stock market is relatively high.
- The COVID-19 intensified the dependence.

Static spillovers

TSI=79.38

	EUA	OIL	COAL	GAS	AUTO_PARTS	OIL_GAS	INDSGDS_SVS	TECH	UTILITIES	TECHNOLOGY	RETAIL	FINANCIAL_SVS	BASIC_MATS	REAL_ESTATE	BANKS	CHEMICALS	FOOD_BEV	Basic_Resources	CON_MAT	INSURANCE	MEDIA	TRAVEL	HEALTH_CARE	FROM
EUA	66.90	1.24	0.42	0.49	2.02	2.01	2.52	1.59	1.13	0.56	1.44	2.46	1.59	1.58	1.96	1.60	0.60	1.21	2.13	2.37	1.38	2.44	0.35	33.10
OIL	0.81	44.43	2.00	0.21	1.99	9.80	3.07	1.81	1.24	2.14	1.95	2.40	4.50	1.71	2.57	2.66	1.70	5.41	2.35	2.26	2.28	1.47	1.24	55.57
COAL	0.09	4.12	84.34	9.02	0.28	0.22	0.09	0.10	0.19	0.02	0.12	0.10	0.10	0.04	0.18	0.08	0.11	0.21	0.30	0.20	0.01	0.06	0.04	15.66
GAS	0.56	0.87	9.80	86.90	0.12	0.18	0.05	0.10	0.15	0.01	0.01	0.10	0.08	0.45	0.01	0.02	0.01	0.17	0.02	0.01	0.19	0.01	0.18	13.10
AUTO_PARTS	0.29	0.44	0.06	0.01	9.93	4.22	7.04	5.15	3.44	3.67	4.85	6.12	6.23	4.02	5.84	6.44	2.92	4.29	6.66	6.11	4.89	4.86	2.52	90.07
OIL_GAS	0.34	2.54	0.03	0.02	4.85	11.56	5.89	3.88	4.29	4.16	4.23	5.35	6.49	3.50	5.48	5.20	3.06	6.01	5.49	6.02	4.71	4.06	2.85	88.44
INDSGDS_SVS	0.29	0.53	0.03	0.00	5.65	4.11	7.96	5.61	3.91	3.74	5.14	6.56	6.02	4.53	4.86	6.15	3.73	4.19	6.85	5.72	5.73	5.14	3.52	92.04
TECH	0.24	0.42	0.03	0.01	5.29	3.43	7.16	10.13	3.77	3.59	5.51	6.75	5.72	4.35	4.04	6.23	3.84	3.63	6.28	4.94	5.69	4.85	4.11	89.87
UTILITIES	0.17	0.41	0.07	0.00	3.82	4.20	5.41	4.11	11.16	6.26	5.26	5.57	4.86	5.27	4.46	5.31	4.97	3.16	5.91	5.63	5.80	3.88	4.31	88.84
TECHNOLOGY	0.09	0.59	0.00	0.00	4.08	4.02	5.18	3.92	6.23	11.10	5.44	5.54	4.84	4.42	5.34	5.28	5.10	3.12	5.52	5.72	6.04	3.69	4.74	88.90
RETAIL	0.20	0.46	0.06	0.00	4.75	3.66	6.28	5.27	4.61	4.78	9.71	6.19	5.19	4.75	4.45	5.60	4.72	3.40	5.85	5.03	5.78	5.12	4.11	90.29
FINANCIAL_SVS	0.29	0.46	0.05	0.01	5.11	3.92	6.80	5.48	4.17	4.13	5.24	8.20	5.61	4.92	5.27	5.64	3.74	3.93	6.43	6.13	5.79	5.03	3.67	91.80
BASIC_MATS	0.20	0.87	0.02	0.01	5.45	4.93	6.56	4.90	3.78	3.80	4.62	5.89	8.72	3.76	4.97	7.30	3.41	7.34	6.15	5.53	4.78	3.75	3.27	91.28
REAL_ESTATE	0.24	0.41	0.04	0.05	4.42	3.40	6.22	4.67	5.26	4.41	5.32	6.48	4.77	10.83	4.21	5.11	4.39	3.12	6.11	5.62	5.83	5.49	3.58	89.17
BANKS	0.29	0.57	0.06	0.00	5.89	4.82	6.12	3.99	4.01	4.83	4.56	6.41	5.74	3.85	10.05	5.32	2.76	4.44	6.44	8.01	5.06	4.53	2.24	89.95
CHEMICALS	0.20	0.52	0.03	0.01	5.66	3.95	6.73	5.35	4.15	4.15	5.02	5.96	7.31	4.07	4.62	8.73	4.24	4.20	6.37	5.45	5.20	3.95	4.14	91.27
FOOD_BEV	0.11	0.50	0.03	0.00	3.55	3.23	5.65	4.56	5.35	5.51	5.85	5.49	4.73	4.81	3.31	5.84	11.99	2.59	5.19	4.37	6.30	4.29	6.76	88.01
Basic_Resources	0.21	1.43	0.02	0.02	5.13	6.25	6.22	4.25	3.36	3.35	4.12	5.62	10.05	3.34	5.27	5.74	2.55	11.91	5.70	5.47	4.17	3.45	2.37	88.09
CON_MAT	0.25	0.42	0.05	0.00	5.55	3.99	7.12	5.12	4.46	4.15	4.99	6.45	5.88	4.62	5.33	6.06	3.57	4.00	8.30	6.08	5.55	4.78	3.26	91.70
INSURANCE	0.30	0.45	0.06	0.00	5.43	4.71	6.32	4.30	4.51	4.56	4.54	6.53	5.63	4.53	7.04	5.53	3.18	4.08	6.46	8.82	5.52	4.69	2.79	91.18
MEDIA	0.17	0.46	0.03	0.02	4.49	3.79	6.52	5.10	4.73	4.93	5.38	6.36	5.00	4.84	4.58	5.40	4.72	3.21	6.07	5.69	9.03	5.40	4.09	90.97
TRAVEL	0.36	0.31	0.05	0.00	5.22	3.85	6.88	5.10	3.85	3.69	5.65	6.51	4.65	5.37	4.84	4.85	3.83	3.15	6.18	5.71	6.35	10.57	3.03	89.43
HEALTH_CARE	0.06	0.46	0.00	0.02	3.32	3.24	5.76	5.29	5.02	5.54	5.51	5.81	4.90	4.26	2.91	6.17	7.31	2.62	5.13	4.13	5.89	3.64	12.98	87.02
TO	5.77	18.48	12.96	9.93	92.08	85.93	119.56	89.65	81.61	81.98	94.74	114.65	109.91	82.98	91.53	107.52	74.46	77.49	113.59	106.21	102.95	84.59	67.20	79.38

Fig.4. Static spillovers.

- **H1**: There is a strong connectedness among the carbon, energy and industry stock markets.

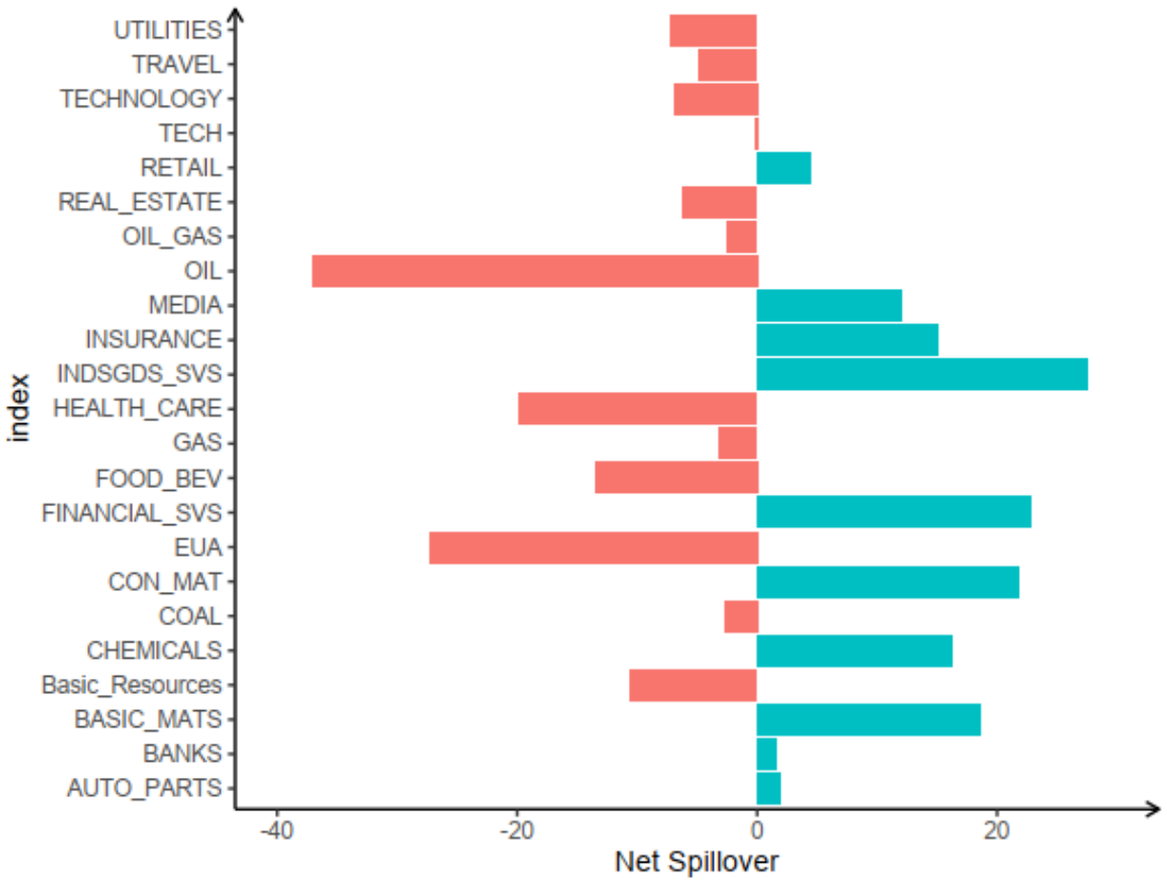


Fig.5. Net spillovers.

- Carbon and crude oil markets are the main spillover receiver, while industrial products and services and financial services sector are the main net transmitters of spillovers in the system.

Time-frequency spillovers

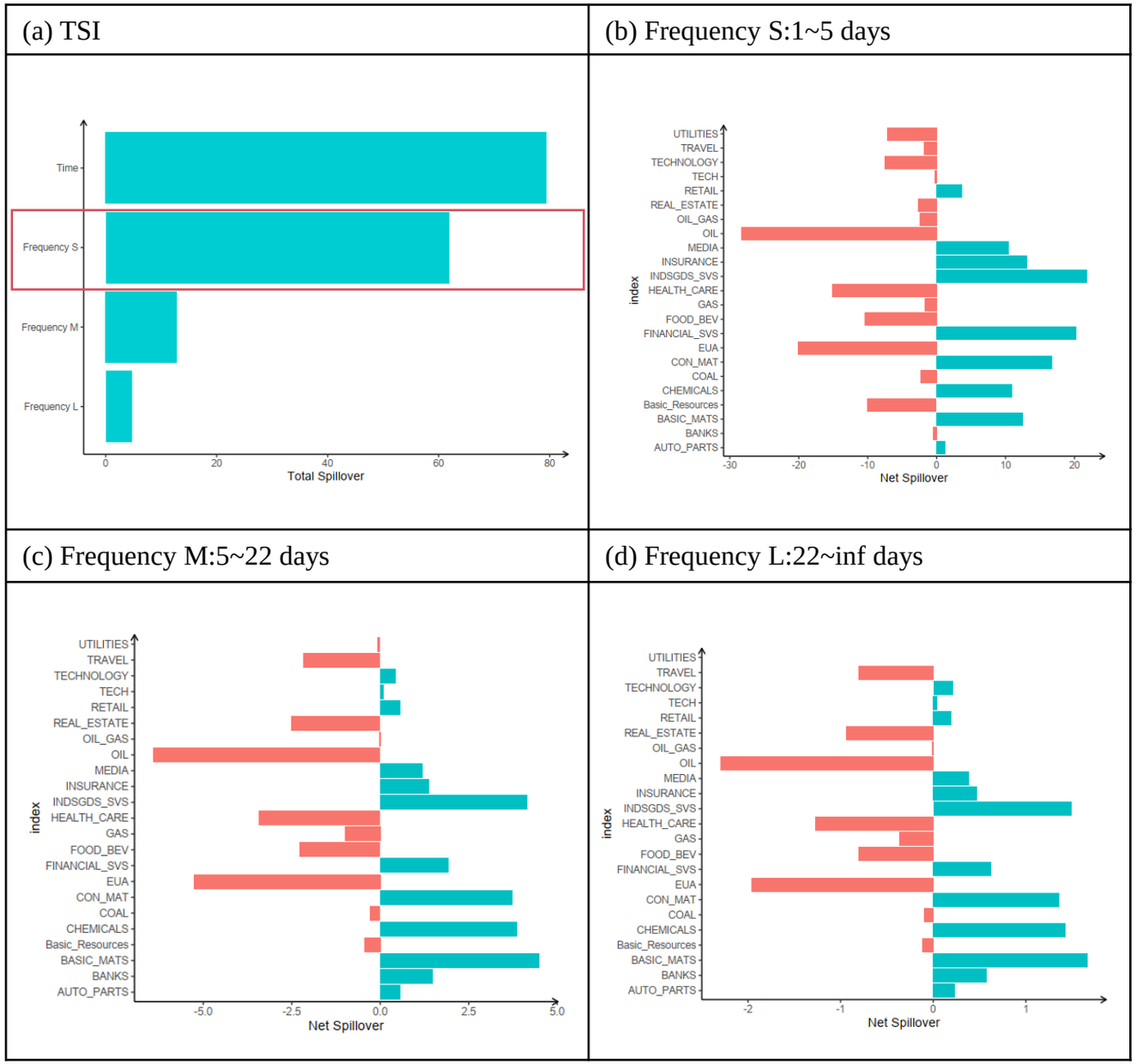


Fig.6. Time-frequency spillovers.

- H2: There is frequency-domain heterogeneity in the spillovers among carbon, energy and industry stock markets.

Net-pairwise spillovers

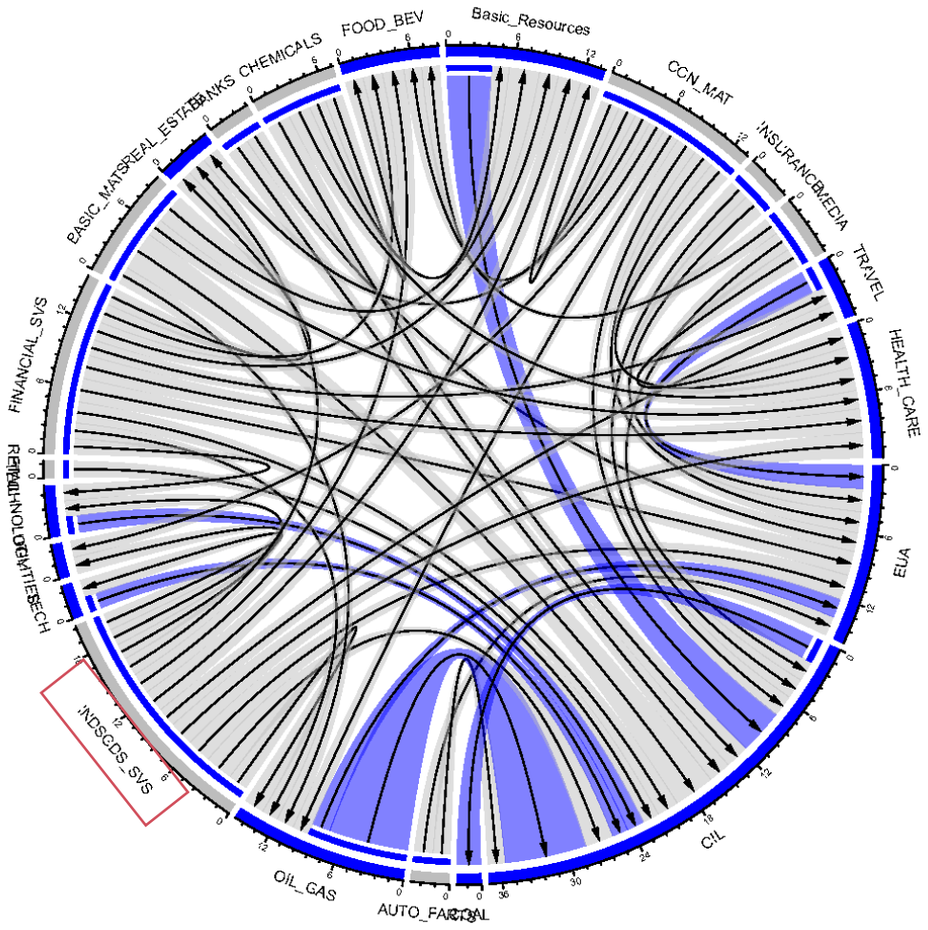
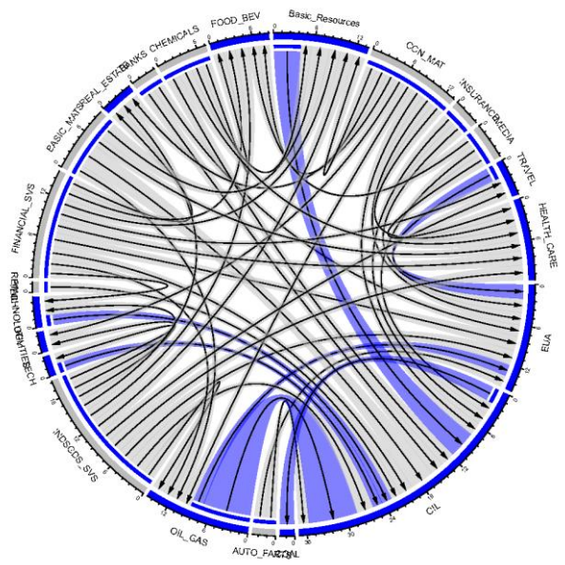
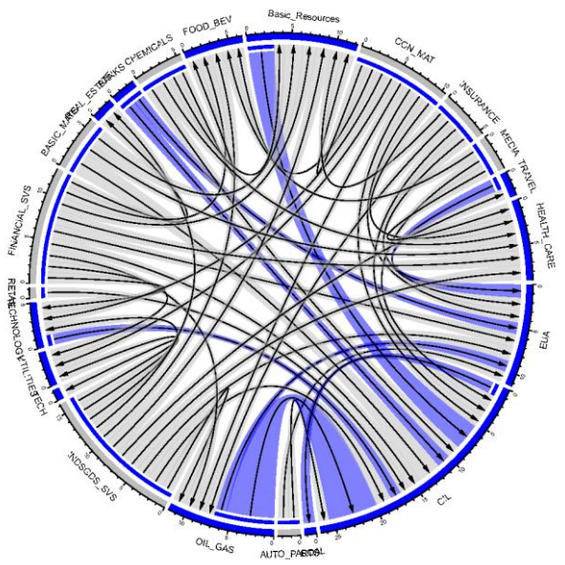
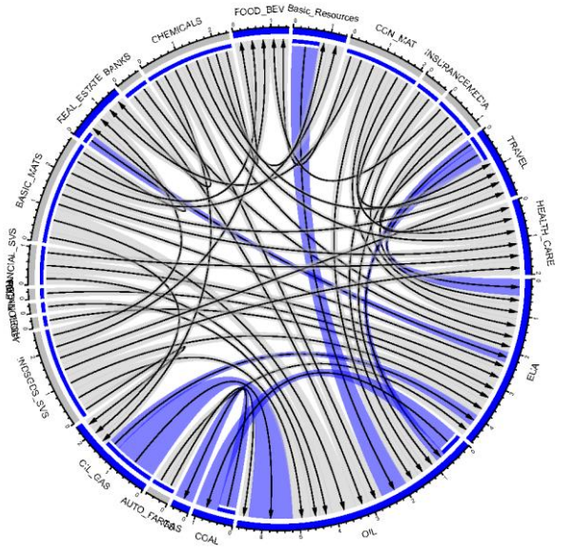
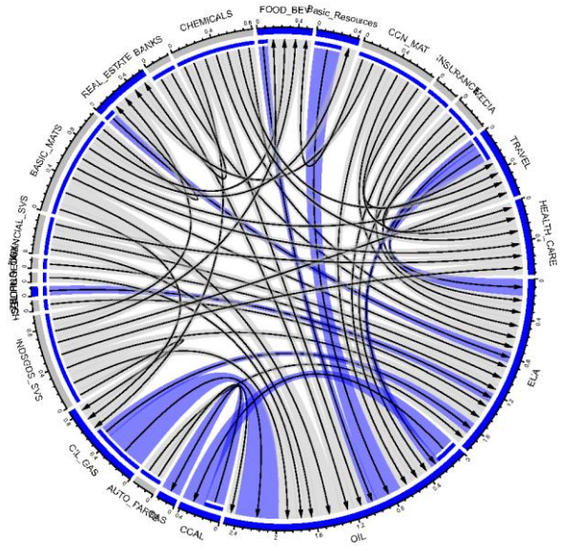


Fig.7. Net-pairwise spillovers networks.

Time	Frequency S:1~5 days
	
Frequency M:5~22 days	Frequency L:22~inf days
	

Dynamic spillovers

- **H3:** The crisis events affect spillovers among carbon, energy and industry stock markets.

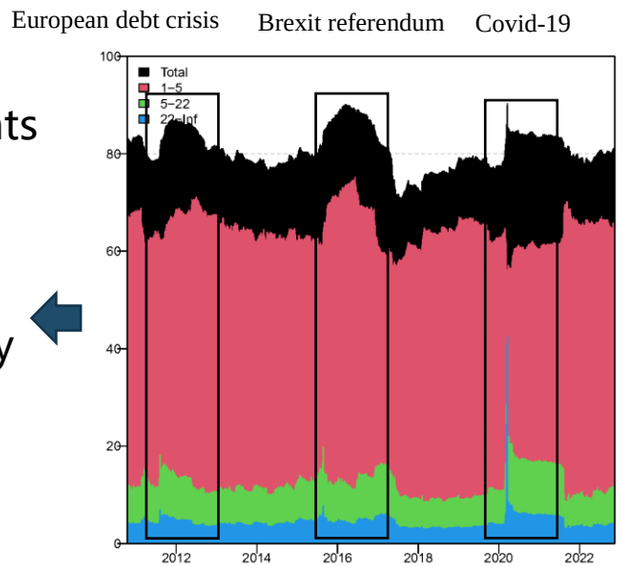


Fig.8. Dynamic total spillovers.

Table 3. Summary statistics of dynamic net spillovers.

	Mean	Std. Dev	P
EUA	−26. 704	16. 728	0. 000
COAl	−35. 193	8. 661	0. 000
OIL	−23. 504	14. 088	0. 001
GAS	−20. 672	12. 838	0. 009
OIL_GAS	2.574	10.136	0.650
INDSGDS_SVS	28.066	5.887	1.000
BASIC_MATS	19.314	4.372	1.000
FOOD_BEV	-11.251	9.246	0.132

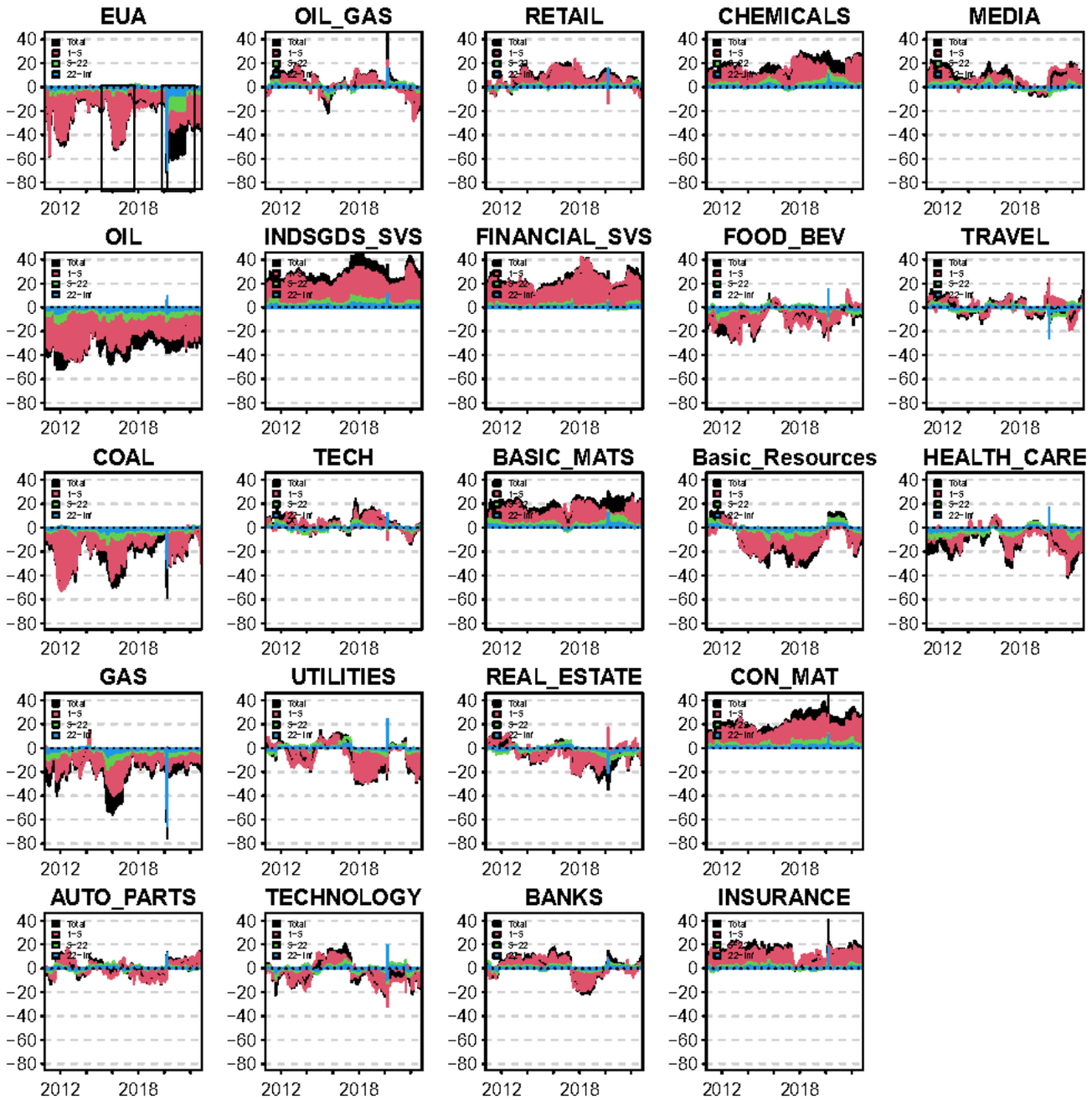


Fig.9. Dynamic net frequency spillovers.

Dynamic net pairwise spillovers

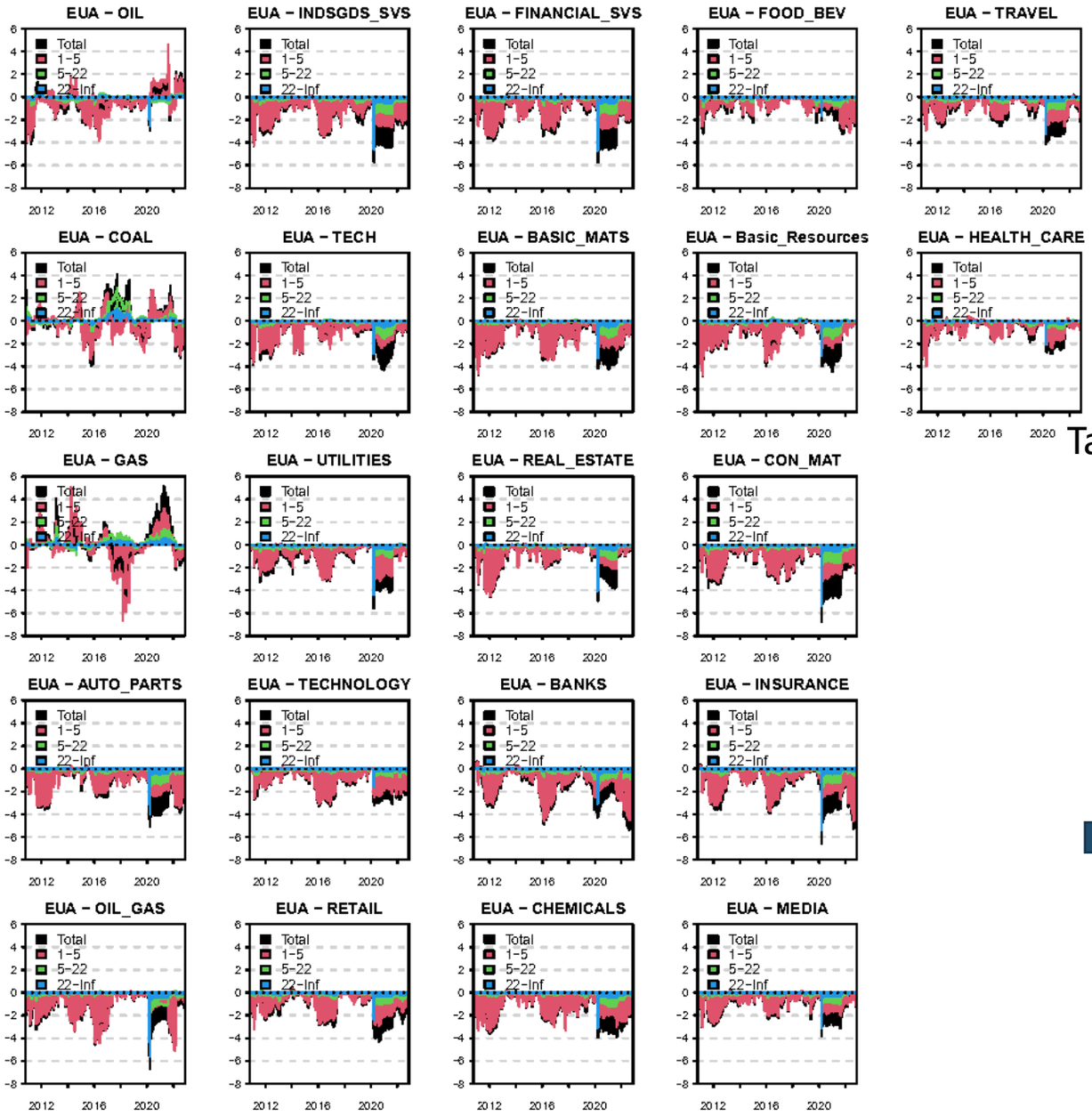


Fig.10. Dynamic net-pairwise frequency spillovers.

- Carbon market has a weaker impact on fossil energy markets. In the fossil energy market, the crude oil market has a strong influence on the carbon market.
- Carbon market is a recipient of net connectedness from other sectors in the stock market. Energy-intensive and financial industries are most influential in the connectedness of the EUA future price.

Table 4. Summary statistics of dynamic net-pairwise spillovers.

	mean	std.Dev	P
OIL	-0.65	1.18	0.00
COAL	0.03	1.33	0.00
GAS	0.38	1.51	0.01
AUTO_PARTS	-1.52	1.25	0.57
OIL_GAS	-1.55	1.14	0.65
INDSGDS_SVS	-1.77	1.26	1.00
TECH	-1.34	1.07	0.68
UTILITIES	-1.30	1.10	0.45
TECHNOLOGY	-1.20	0.98	0.31
RETAIL	-1.27	1.06	0.86
FINANCIAL_SVS	-1.71	1.31	1.00
BASIC_MATS	-1.64	1.23	1.00
REAL_ESTATE	-1.24	1.20	0.36
BANKS	-1.69	1.47	0.77
CHEMICALS	-1.59	1.14	1.00
FOOD_BEV	-0.92	0.73	0.13
Basic_Resources	-1.37	1.18	0.32
CON_MAT	-1.65	1.32	1.00
INSURANCE	-1.64	1.42	1.00
MEDIA	-1.13	0.87	0.89
TRAVEL	-1.17	0.97	0.53
HEALTH_CARE	-0.77	0.81	0.13

Rolling-window analysis

Fig.11. Robustness check-rolling window size.

Table 5. Summary statistics of dynamic total spillovers.

Rolling window	TSI
150 days	81.734（4.018）
175 days	81.499（3.975）
200 days	81.357（3.882）
225 days	81.274（3.792）
250 days	81.219（3.720）

Part 04 Conclusions

Conclusions

Hypothesis:

- **H1:** There is a strong connectedness among the carbon, energy and industry stock markets.
- **H2:** There is frequency-domain heterogeneity in the spillovers among carbon energy and industry stock markets.
- **H3:** The crisis events affect spillovers among carbon, energy and industry equity markets.

The dependence among carbon, energy and stock markets is mainly strong on a long-term scale.

The total return spillover index is 79.38%, indicating higher connectedness among carbon, energy and stock markets. The net spillover analysis shows that the main net recipients of return spillovers are carbon (-27.33%) and oil markets (-37.09%), while industrial products and services (27.52%) and financial services sector (22.85%) are major source of risk spillover.

The short-term total spillover index is 61.88%, accounting for 78% of the total connectedness. The total risk connectedness among markets is mainly transmitted on shorter time-horizons.

The major international crisis events, such as the European sovereign debt crisis, Brexit referendum, and the COVID-19 pandemic have greatly intensified the risk spillover magnitude.

Thanks

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