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Connectedness between fossil and renewable energy stock indices: The impact of the COP policies

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ABSTRACT

Switching from fossil to renewable energy is essential to reduce global warming. The existing literature has found evidence of connectedness between fossil and renewable energy stock indices but has not considered the possible impact of climate policies on those linkages. This paper provides evidence on the latter issue to fill this gap. Specifically, in addition to full sample estimation, endogenous break tests and sub-sample estimation are carried out using daily data for a wide range of indices over the last decade. The results suggest that renewable energy stock indices play a significant role in terms of connectedness; moreover, the two detected breaks indicate that both the unsuccessful COP17 held in Durban in 2011 and the anticipation of decisive action at the COP26 in Glasgow affected connectedness, namely spillovers are stronger during periods characterized by more effective climate policies. This confirms the crucial importance of policy intervention to tackle climate change.

1. Introduction

The use of renewable instead of fossil energy is being increasingly advocated by experts, governments and public opinion as a necessary choice to address climate change, namely the observed large-scale, long-term shift in temperatures and weather patterns. This is because one of its main drivers since the start of the industrial revolution in the late 18th century has been the burning of fossil fuels such as coal, oil and gas. These generate greenhouse gas emissions, including carbon dioxide (CO2) and methane, which bring about rising temperatures and global warming; as a result, the Earth is now about 1.1 degrees Celsius warmer than in the late 1800s, the latest decade having been the warmest on record. The 2018 UN Climate Change Annual Report concluded that it was essential to decrease global temperature rise to no more than 1.5 degrees Celsius (from the expected 2.7 by the end of the century without any measures) to slow down the effects of climate change. However, in October 2018, the Intergovernmental Panel on Climate Change (IPCC) warned in its "Global Warming of 1.5 °C" report that even if that target were achieved the impact of global warming on the environment would be far greater than expected, and in January 2019 The World Economic Forum for a third year in a row identified climate change as the main threat to the planet in its Global Risks Report.

To tackle these issues since 1995 Annual UN Climate Change Conferences have been held within the UN Framework Convention on Climate Change (UNFCCC); each of these meetings is known as a Conference of the Parties (COP), the latest having taken place in Glasgow, 31 October–13 November 2021 (COP26). Over the years a number of COP protocols have been signed with the aim of reducing reliance on fossil fuels and encouraging the transition to renewable energy, which comes from the Earth's natural resources (sunlight, wind, waves, the tides and geothermal heat from within the planet), is inexhaustible and does not pollute the environment; moreover, new clean energy technologies are reducing its costs compared to fossil fuels and making it more affordable. The International Energy Agency (IAE) reported in its "Global Energy Review 2021" that a record amount of renewable electricity was added to energy systems globally in 2021, despite higher commodity prices increasing production and transportation costs for solar panels and wind turbines.

It is clear that governments have an important role to play in accelerating the shift to clean energy by providing more support and incentives for investment in renewables as well as by adopting measures at the very least to "phase down" polluting energy sources such as coal as agreed at COP26. In particular, one would expect the decisions taken

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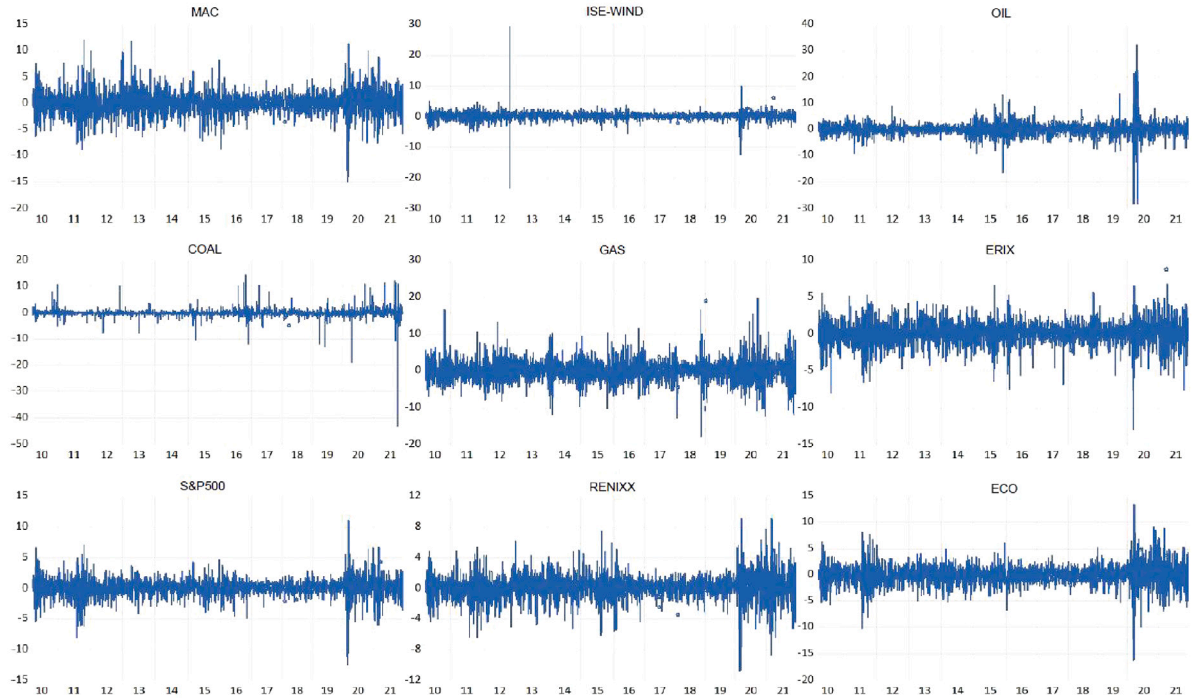

Fig. 1. Plots of the Return Series.

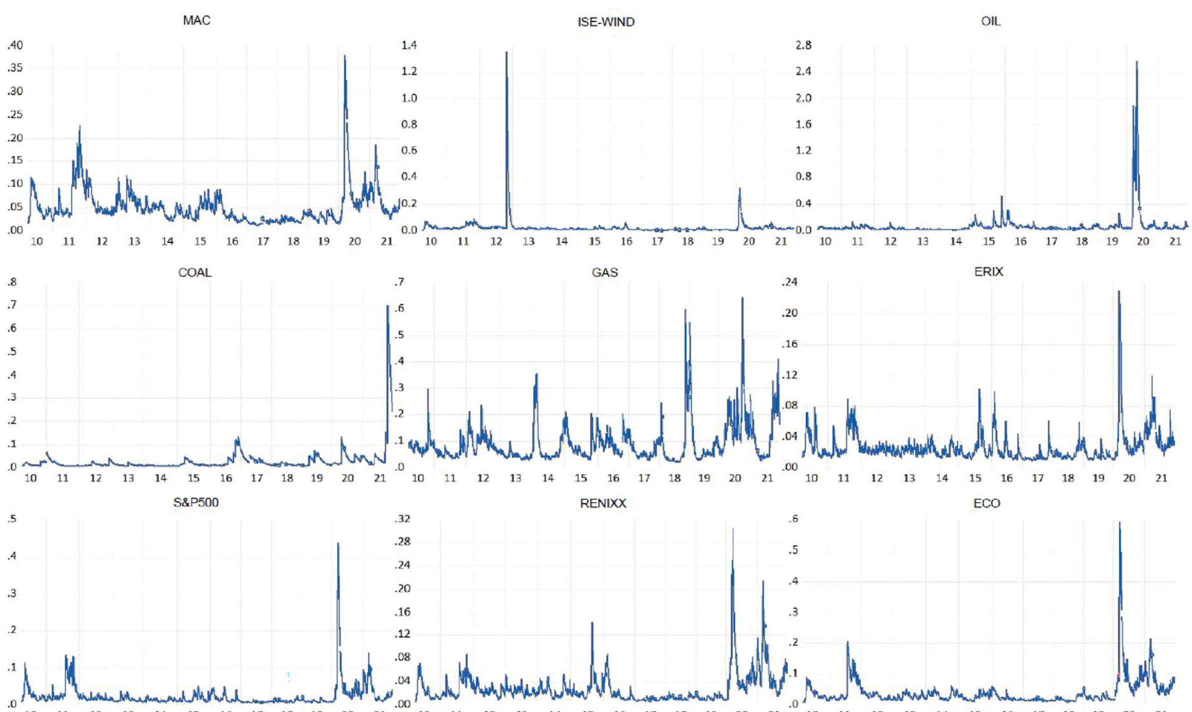

Fig. 2. Plots of the Volatility Series.

at such meetings with the aim of reducing carbon emissions (binding thresholds, fiscal incentives etc.) to make investment in clean energy more profitable relative to that in polluting energy sources and thus to drive up stock returns for the former sector relative to those for the latter. Therefore effective policies to combat climate change should strengthen (negative) spillovers between those two sets of markets, which should instead remain relatively weak when no decisive action is taken to cut down emissions. More precisely, a preliminary analysis of the data as well as the existing empirical evidence which is discussed below in the literature review, lead us to formulate two hypotheses of interest: the first concerns the presence of significant static and dynamic linkages between stocks issued for two different forms of energy markets, namely fossil fuels and renewable energy respectively; the second postulates the existence of significant effects of the outcomes of the COP meetings on the relationships being examined (specifically, that effective climate policies should make them stronger). To preview the results, the obtained evidence supports those hypotheses: we find that spillovers between the two sets of markets are sizeable; moreover,

Table 1
Variables sources and definitions.

Index	Definition	Source
MAC Global Energy Index	The MAC Global Solar Energy Index is a rules-based stock index tracking the performance of companies in global solar energy businesses.	The "MAC Global Solar Energy Stock Index" is the tracking Index for the "Invesco Solar ETF" which is an exchange-traded fund (ETF) that is traded on the New York Stock Exchange ARCA. MAC includes 43 companies.
ISE Global Wind Energy Index	The ISE Global Wind Energy Index is designed to track public companies that are active in the wind energy industry based on analysis of the products and services offered by those companies. The Index began on December 16, 2005 with a base value of 100.00.	It is one of the Nasdaq ISE indices. ISE includes 52 companies.
Crude Oil	West Taxes Intermediate crude oil.	New York Mercantile Exchange (NYMEX).
Coal	Newcastle Coal Index.	New York Mercantile Exchange (NYMEX).
Natural Gas	Natural Gas Index.	It is listed on the Chicago Mercantile Exchange.
European Renewable Energy Index	ERIX tracks the performance of European renewable energy companies that are active in either or several of the following six investment clusters: biofuels, geothermal, marine, solar, water, and wind.	The Index is provided by Societe Generale, which has contracted with S&P Opco, LLC (a subsidiary of S&P Dow Jones Indices LLC) ("S&P Dow Jones Indices") to maintain and calculate the Index. The index members are the 10 largest and most liquid stocks from the list of eligible companies. ERIX is rebalanced every quarter and an index review takes place every six months.
S&P500 Global Clean Energy Index	It is designed to measure the performance of the one hundred largest companies by market capitalization in global clean energy-related businesses from both developed and emerging markets , with target constituent count of 100.	It is one of the S&P DOW JONES indices. S&P500 has a target constituent count of 100 companies.
The World Renewable Energy Index	Renewable energy tracks the 30 largest companies of the renewable energy industry worldwide by market capitalization. The RENIXX comprises stocks such as sectors as wind energy, solar energy industry, hydropower, geothermal energy, bio-energy or fuel cell technology.	RENIXX has been created and is calculated by IWR, a renewable energy institute. RENIXX comprises the world's 30 largest companies in the renewable energy industry whose weighting in the index is based on the market capitalization.
Wilder Hill Clean Energy Index	Renewable Energy Supplies, Power Energy Delivery,Storage, Clean Fuels, as well as Green Utilities.	The WilderHill Clean Energy Index (ECO), live since 2004, and is calculated by the New York Stock Exchange (NYSE). ECO includes 78 stocks.

Note: The series used are daily and span the period from 25/03/2010 to 23/12/2021 for a total of 2943 observations.

connectedness appears to change around the time of key COP meetings, which most likely reflects the impact of the policy decisions adopted at those events.

The layout of the paper is as follows. Section 2 briefly reviews the relevant literature. Section 3 provides some information about the COP meetings and the key policy decisions adopted on those occasions. Section 4 outlines the Diebold and Yilmaz (2014) method used for the analysis. Section 5 presents the data and the empirical results. Section 6 offers some concluding remarks.

2. Literature review

Linkages between the fossil and renewable energy markets have been investigated in numerous papers. For instance, Henriques and Sadorsky (2008) estimated a VAR and found causal effects of oil prices and technology stock prices on those of renewable energy companies. Sadorsky (2012) adopted a GARCH framework to examine volatility spillovers and concluded that the stock prices of clean energy companies in their second moments are linked more strongly to technology ones than to oil prices. Kumar et al. (2012) showed that renewable

Table 2
Descriptive statistics.

Fossil and renewable energy stock index returns						
Variables	Mean	S.D.	Min	Max	Skewness	Kurtosis
MAC	0.01	2.23	−14.96	11.95	−0.14	6.53
ISE Wind	0.02	1.40	−23.42	11.95	1.11	97.12
Crude Oil	0.02	2.64	−28.22	31.96	0.17	31.87
Coal	0.02	1.59	−43.25	14.49	−6.49	29.25
Gas	0.01	2.98	−18.05	19.80	0.33	6.95
ERIX	0.03	1.62	−12.97	8.76	−0.41	6.51
S&P500	0.01	1.51	−12.50	11.03	−0.55	10.15
RENIXX	0.03	1.65	−10.79	9.12	−0.26	6.71
ECO	0.01	2.00	−16.24	13.40	−0.48	8.76

Note: The series used are daily and span from 25/03/2010 to 23/12/2021, for a total of 2943 observations.

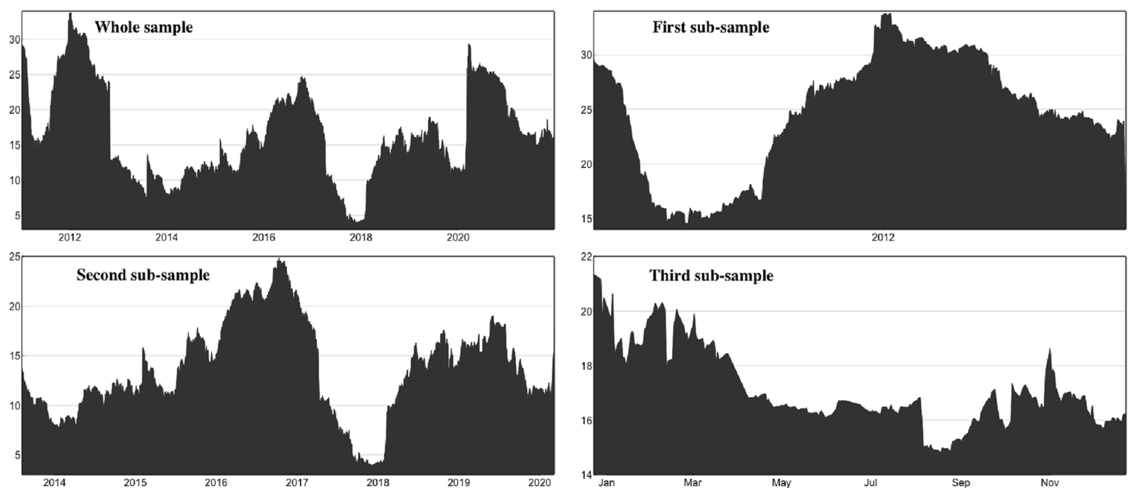

Fig. 3. Benchmark model overall spillover (Return System).

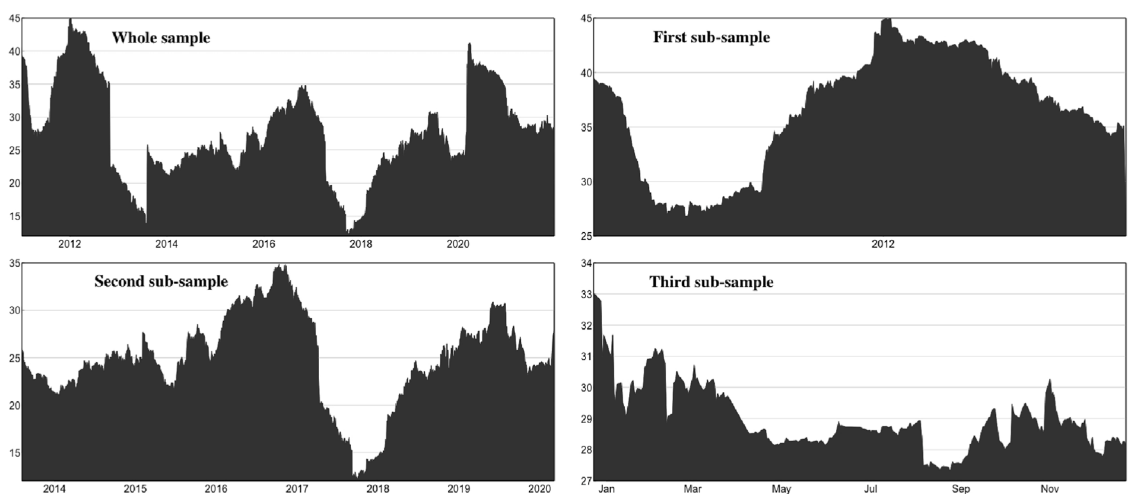

Fig. 4. Benchmark model including ERIX overall spillover (Return System).

energy stock prices are responsive to interest rates, past oil price changes and technology stock prices. Wen et al. (2014) focused on China and found volatility spillovers between oil prices and renewable energy company stock prices using a GARCH model incorporating asymmetries. Bondia et al. (2016) applied threshold cointegration tests allowing for endogenous structural breaks and reported that the stock prices of alternative energy companies are affected by technology stock prices, oil prices and interest rates only in the short run.

Reboredo et al. (2017) implemented instead a wavelet decomposition approach and detected stronger dependence between oil and renewable energy returns in the long run compared to the short run, whilst Reboredo and Ugolini (2018) used a multivariate vine-copula dependence setup and found that during the period 2009–2016 oil and electricity prices were the main drivers of clean energy stock returns in the US and the EU, respectively. Dutta (2017) reported that clean energy stock market returns are affected by changes in the crude oil volatility index (OVX) in the long run. Ferrer et al. (2018) analysed connectedness between crude oil prices, the stock prices of US clean energy companies and various financial variables in the frequency domain and found linkages mainly in the short run, whilst he could

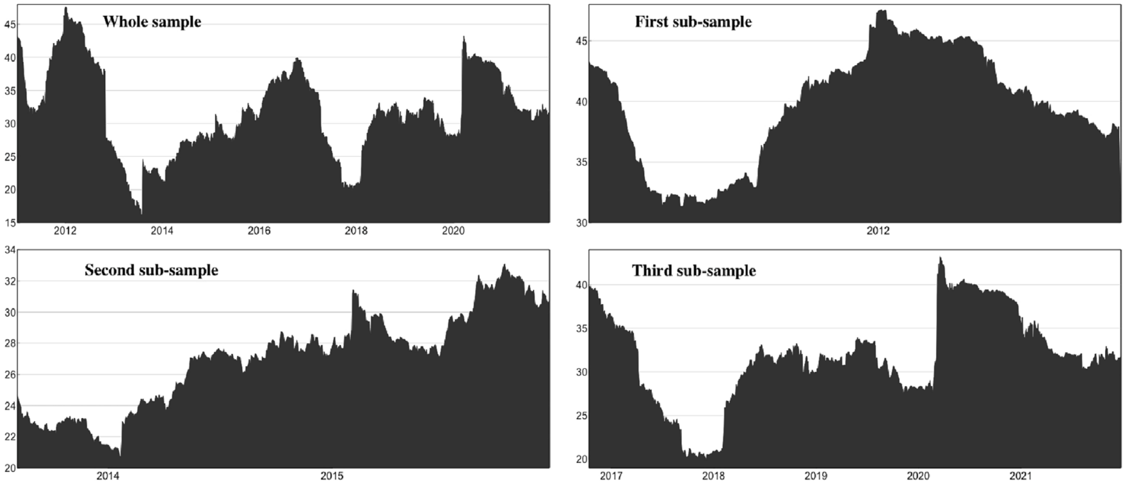

Fig. 5. Benchmark model including S&P500 overall spillover (Return System).

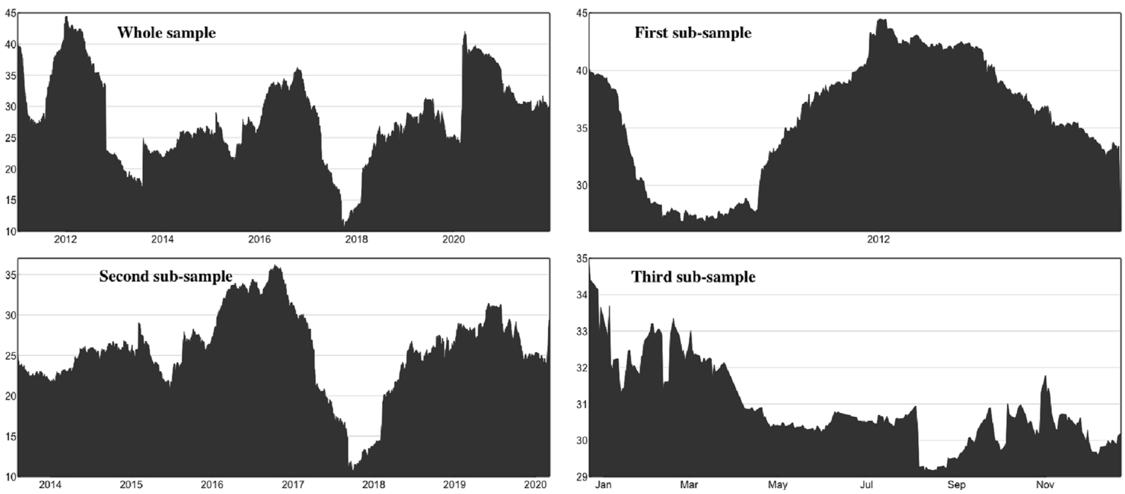

Fig. 6. Benchmark model including RENIXX overall spillover (Return System).

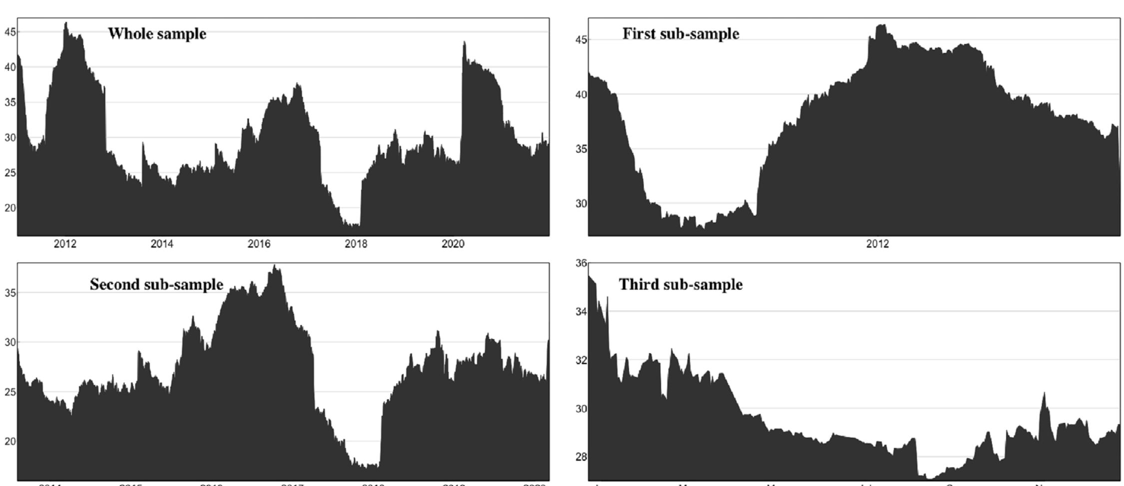

Fig. 7. Benchmark model including ECO overall spillover (Return System).

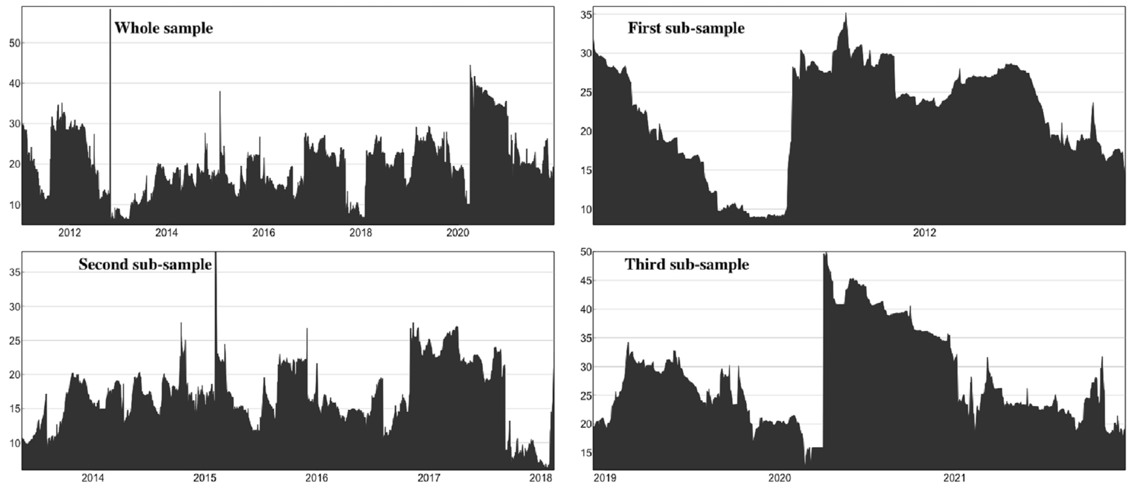

Fig. 8. Benchmark model overall spillover (Volatility System).

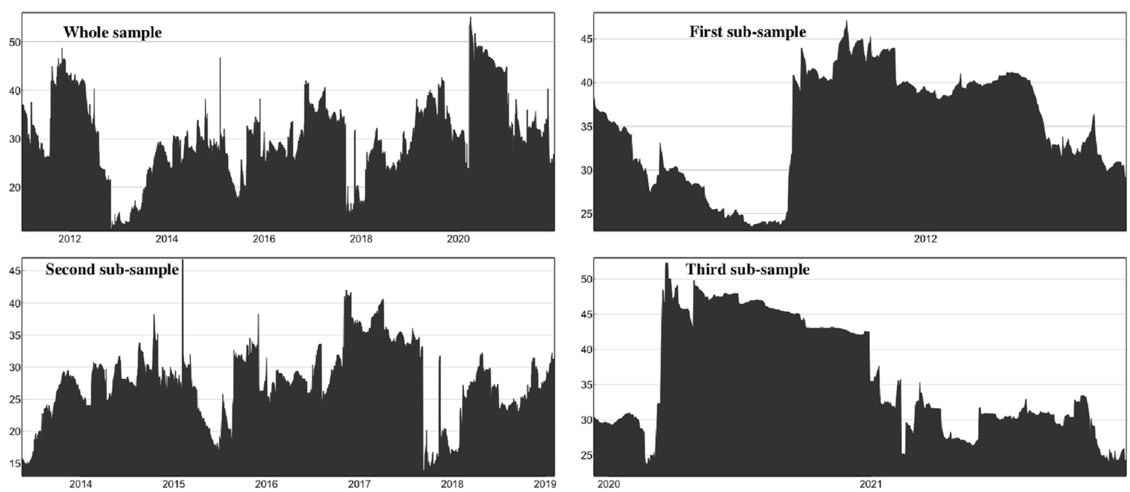

Fig. 9. Benchmark model including ERIX overall spillover (Volatility System).

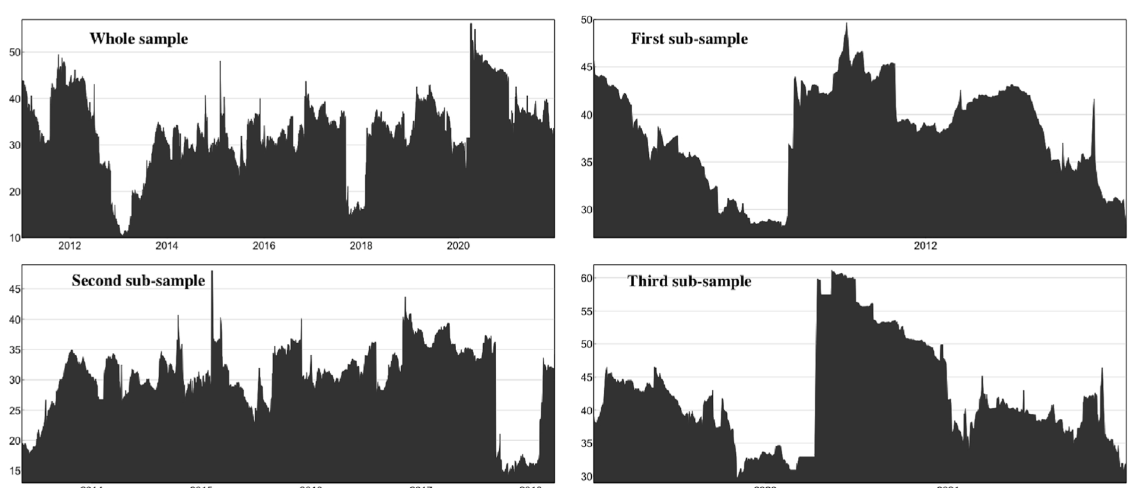

Fig. 10. Benchmark model including S&P500 overall spillover (Volatility System).

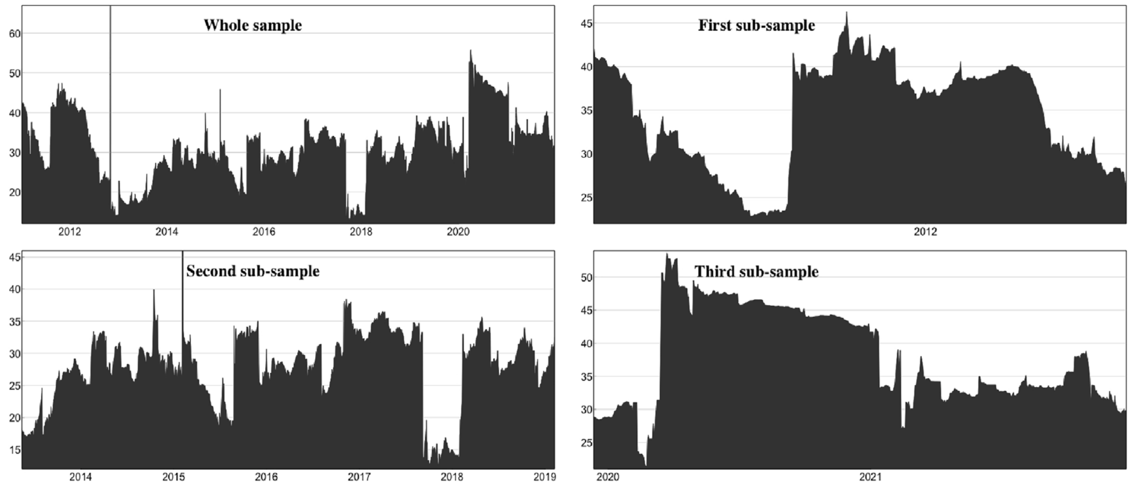

Fig. 11. Benchmark model including RENIXX overall spillover (Volatility System).

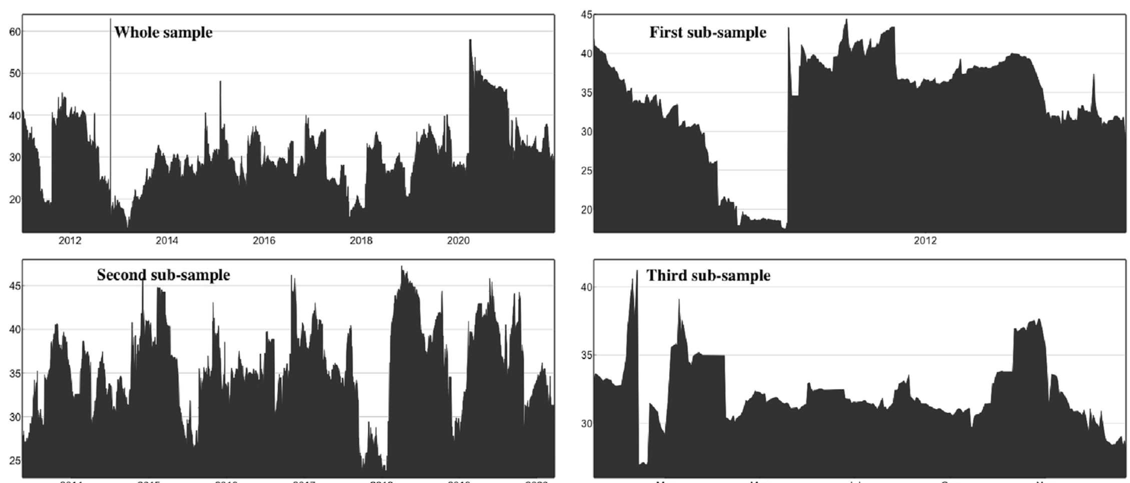

Fig. 12. Benchmark model including ECO overall spillover (Volatility System).

Table 3
Structural breaks dates.

Systems	First break	Second break
Panel A: Return		
Five Variable System	29/10/2012	06/03/2020
First System	29/10/2012	06/03/2020
Second System	29/10/2012	21/12/2015
Third System	29/10/2012	05/03/2020
Fourth System	29/10/2012	06/03/2020
Panel B: Volatility		
Five Variable System	06/08/2012	12/02/2018
First System	06/08/2012	06/02/2019
Second System	06/08/2012	21/03/2018
Third System	06/08/2012	07/02/2019
Fourth System	06/08/2012	24/03/2020

Note: The break dates have been obtained by carrying out the Bai and Perron (1998) tests.

not detect any impact of crude oil prices on the stock prices of renewable energy companies. Alkathery and Chaudhiri (2021) estimated multivariate GARCH models to analyse the co-movement between oil price, EU carbon allowance prices, the global clean energy index and the equity index in three GCC countries (Kuwait, Saudi Arabia and the United Arab Emirates) and found evidence of significant volatility spillovers in all three markets.

Liu and Shigeyuki (2020) applied the Diebold and Yilmaz (2014) approach to examine return and volatility spillovers from fossil fuel (crude oil and natural gas) and traditional stock markets to renewable stock markets in the US and Europe and estimated stronger spillovers in the case of the US and from traditional stock markets to renewable energy stocks in both regions. Hanif et al. (2021) investigated frequency volatility spillovers, connectedness and the nonlinear dependence between the European emission allowance (EUA) prices and renewable energy indices using a time-scale spillover index and different copula functions. They found stronger short-run spillovers in the case of carbon prices and both S&P clean energy and wind energy indices in the short, and stronger long-run ones in the case of the clean energy indices and carbon price. Finally, Geng et al. (2021) applied the connectedness network approach to Europe and found high interdependence between crude oil returns and clean energy companies' returns and also a greater impact of bad news on information connectedness compared to good news.

Ozcan et al. (2020) employed the Generalized Method of Moments (GMM) to estimate a panel Vector Autoregressive Regression (PVAR) for a sample of 35 OECD economies from 2000 to 2014 and found that economic growth and energy consumption patterns affect the environmental performance of countries. González-Álvarez and Montañés (2023) examined the relationship between energy consumption, carbon dioxide (CO2) emissions and economic growth using a sample of 31 countries and reported that, for the majority of the countries

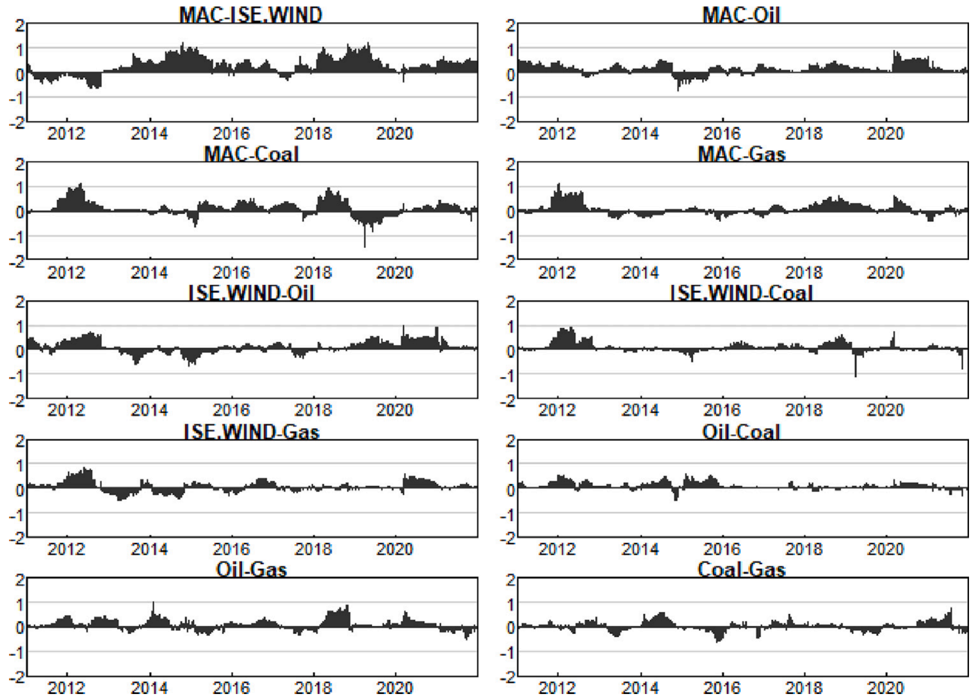

Fig. 13. Benchmark model Net Pairwise (Return System).

Table 4
Benchmark model (Returns).

Variables	MAC	ISE.Wind	Crude Oil	Coal	Gas	From
	Whole sample					
MAC	75.23	19.27	5.28	0.05	0.17	24.77
ISE.Wind	20.96	74.79	4.09	0.07	0.09	25.21
Crude Oil	6.12	4.45	88.00	0.53	0.91	12.00
Coal	0.04	0.15	0.62	98.84	0.35	1.16
Gas	0.11	0.09	1.00	0.09	98.69	1.31
Directional to others	27.23	23.96	11.00	0.74	1.53	64.45
Net Directional Con.	2.46	−1.25	−1.00	−0.42	0.22	**12.89**
	First Sub-sample					
	MAC	ISE.Wind	Crude Oil	Coal	Gas	From
MAC	70.31	16.98	12.21	0.48	0.03	29.69
ISE.Wind	17.21	72.87	9.08	0.74	0.10	27.13
Crude Oil	13.02	9.46	74.87	1.39	1.26	25.13
Coal	0.99	1.42	2.29	94.82	0.48	5.18
Gas	0.57	1.04	1.67	0.60	96.12	3.88
Directional to others	31.79	28.90	25.26	3.21	1.87	91.03
Net Directional Con.	2.09	1.77	0.12	−1.98	−2.01	**18.21**
	Second Sub-sample					
	MAC	ISE.Wind	Crude Oil	Coal	Gas	From
MAC	77.39	15.90	6.66	0.03	0.03	22.61
ISE.Wind	18.31	75.03	6.47	0.10	0.09	24.97
Crude Oil	6.91	6.67	85.61	0.03	0.78	14.39
Coal	0.01	0.18	0.17	99.26	0.38	0.74
Gas	0.04	0.18	0.91	0.14	98.73	1.27
Directional to others	25.27	22.92	14.21	0.29	1.27	63.97
Net Directional Con.	2.66	−2.05	−0.18	−0.44	0.01	**12.79**
	Third Sub-sample					
	MAC	ISE.Wind	Crude Oil	Coal	Gas	From
MAC	64.25	32.47	1.69	0.03	1.56	35.75
ISE.Wind	33.77	64.35	1.33	0.05	0.50	35.65
Crude Oil	3.02	3.15	91.71	1.34	0.78	8.29
Coal	0.01	0.07	1.42	97.65	0.84	2.35
Gas	1.11	0.43	0.80	0.51	97.15	2.85
Directional to others	37.91	36.12	5.24	1.93	3.68	84.88
Net Directional Con.	2.16	0.47	−3.05	−0.42	0.84	**16.98**

Note: The table reports in each case the contributions from i to j. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

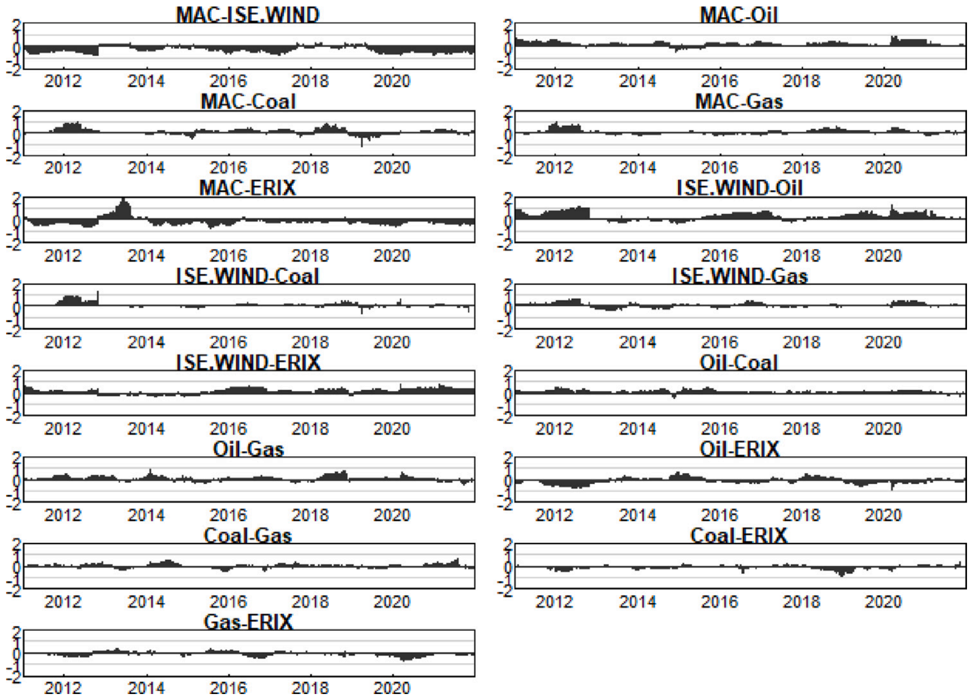

Fig. 14. Benchmark model including ERIX Net Pairwise (Return System).

Table 5
Benchmark model including ERIX (Returns).

Variables	MAC	ISE.Wind	Crude Oil	Coal	Gas	ERIX	From
Whole sample							
MAC	62.15	15.98	4.36	0.04	0.14	17.32	37.85
ISE.Wind	15.37	54.65	3.02	0.05	0.08	26.83	45.33
Crude Oil	5.95	4.36	85.58	0.51	0.89	2.71	14.42
Coal	0.04	0.14	0.62	98.76	0.35	0.08	1.24
Gas	0.12	0.12	1.00	0.10	98.60	0.07	1.40
ERIX	16.73	26.62	1.89	0.04	0.05	54.67	45.35
Directional to others	38.21	47.22	10.90	0.74	1.51	47.01	145.59
Net Directional Con.	0.36	1.87	−3.53	−0.50	0.11	1.68	**24.26**
First Sub-sample	MAC	ISE.Wind	Crude Oil	Coal	Gas	ERIX	From
MAC	53.87	14.14	9.31	0.36	0.02	22.30	46.13
ISE.Wind	14.15	56.86	7.58	0.73	0.15	20.55	43.14
Crude Oil	11.61	9.32	67.06	1.22	1.10	9.68	32.94
Coal	0.96	1.72	2.24	94.06	0.45	0.57	5.94
Gas	0.57	1.23	1.62	0.59	95.74	0.24	4.26
ERIX	22.39	19.61	7.48	0.26	0.07	50.19	49.81
Directional to others	49.68	46.03	28.23	3.15	1.79	53.34	182.22
Net Directional Con.	3.55	2.88	−4.71	−2.79	−2.47	3.53	**30.37**
Second Sub-sample	MAC	ISE.Wind	Crude Oil	Coal	Gas	ERIX	From
MAC	68.08	13.97	5.88	0.02	0.02	12.03	31.92
ISE.Wind	12.56	51.50	4.47	0.06	0.07	31.34	48.50
Crude Oil	6.70	6.49	82.73	0.04	0.74	3.29	17.27
Coal	0.01	0.17	0.17	99.14	0.37	0.13	0.86
Gas	0.04	0.20	0.89	0.13	98.49	0.25	1.51
ERIX	11.08	32.58	2.35	0.03	0.03	53.92	46.08
Directional to others	30.39	53.42	13.77	0.28	1.23	47.05	146.14
Net Directional Con.	−1.53	4.92	−3.50	−0.58	−0.28	0.97	**24.36**
Third Sub-sample	MAC	ISE.Wind	Crude Oil	Coal	Gas	ERIX	From

(continued on next page)

considered, CO2 emissions levels are not clearly linked to economic growth. Song et al. (2022) used the VAR-GARCH framework to examine the connectedness between wind and solar generation and found dynamic volatility spillovers between wind and solar power; moreover, these appear to be trending and periodic, with reliance on wind and solar capacity resulting from new installations. Tzeremes et al. (2023)

Table 5 (*continued*).

MAC	51.96	26.76	1.29	0.02	1.23	18.75	48.04
ISE.Wind	23.34	43.70	1.00	0.03	0.36	31.56	56.30
Crude Oil	2.90	3.40	91.12	1.31	0.70	0.56	8.88
Coal	0.01	0.07	1.38	97.58	0.83	0.12	2.42
Gas	1.06	0.47	0.73	0.50	97.10	0.15	2.90
ERIX	17.74	34.30	0.20	0.11	0.11	47.54	52.46
Directional to others	45.05	65.00	4.60	1.97	3.23	51.15	171.00
Net Directional Con.	−2.99	8.71	−4.28	−0.45	0.33	−1.31	**28.50**

Note: The table reports in each case the contributions from *i* to *j*. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

Table 6
Benchmark model including S&P500 (Returns).

Variables	Whole sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	S&P500	From
MAC	48.63	12.70	3.39	0.03	0.11	35.14	51.37
ISE.Wind	15.63	54.78	3.06	0.05	0.07	26.41	45.22
Crude Oil	5.67	4.24	82.00	0.50	0.84	6.75	18.00
Coal	0.04	0.14	0.63	98.74	0.36	0.09	1.26
Gas	0.11	0.11	0.99	0.10	98.48	0.22	1.52
S&P500	32.26	20.24	3.71	0.04	0.16	43.59	56.41
Directional to others	53.71	37.44	11.79	0.71	1.53	68.60	173.78
Net Directional Con.	2.33	−7.78	−6.21	−0.55	0.01	12.19	**28.96**
	First Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	S&P500	From
MAC	44.13	11.07	7.68	0.30	0.02	36.80	55.87
ISE.Wind	13.92	57.43	7.19	0.63	0.14	20.69	42.57
Crude Oil	11.12	8.15	63.79	1.19	1.10	14.65	36.21
Coal	0.97	1.51	2.27	93.48	0.46	1.30	6.52
Gas	0.57	1.24	1.70	0.59	95.46	0.44	4.54
S&P500	34.07	15.51	9.45	0.41	0.07	40.51	59.49
Directional to others	60.64	37.48	28.28	3.12	1.78	73.89	205.20
Net Directional Con.	4.77	−5.09	−7.93	−3.39	−2.75	14.40	**34.20**
	Second Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	S&P500	From
MAC	57.30	10.07	2.46	0.05	0.21	29.91	42.70
ISE.Wind	13.04	58.78	2.02	0.19	0.07	25.89	41.22
Crude Oil	3.58	2.50	88.94	0.37	1.06	3.55	11.06
Coal	0.09	0.17	0.85	98.56	0.12	0.21	1.44
Gas	0.28	0.10	1.22	0.30	98.05	0.05	1.95
S&P500	28.09	20.23	2.73	0.05	0.05	48.84	51.16
Directional to others	45.09	33.08	9.27	0.96	1.51	59.61	149.53
Net Directional Con.	2.38	−8.14	−1.78	−0.48	−0.44	8.45	**24.92**
	Third Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	S&P500	From
MAC	44.46	17.20	2.99	0.05	0.55	34.76	55.54
ISE.Wind	19.19	46.42	2.84	0.02	0.29	31.25	53.58
Crude Oil	5.52	4.81	82.43	0.48	0.75	6.00	17.57
Coal	0.01	0.07	0.57	98.77	0.51	0.07	1.23
Gas	0.42	0.38	0.86	0.13	97.68	0.52	2.32
S&P500	31.27	25.90	2.85	0.05	0.41	39.53	60.47
Directional to others	56.41	48.35	10.11	0.73	2.51	72.61	190.71
Net Directional Con.	0.86	−5.22	−7.47	−0.51	0.19	12.14	**31.79**

Note: The table reports in each case the contributions from *i* to *j*. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

studied the relationship between energy transition, CO2 emissions, economic growth and information and communications technology (ICT) in the BRICS countries using the GMM-PVAR method for the period 2000–2017. Their results indicate that energy transition is significantly affected by carbon emissions and economic growth. Dogan et al. (2022) examined the nexus between green finance and five types of renewable energy (biofuels, fuel cell, geothermal, solar, and wind) using the TVPVAR method and concluded that dynamic connectedness fluctuates over time and is affected by economic events and news. Some other studies also take into account for the possible role of investment sentiment. In particular, Songa et al. (2019) used the Diebold and Yilmaz (2014) connectedness measure to investigate the relationship between the fossil energy and renewable energy markets as well as investor sentiment. They found that there are stronger linkages between volatilities compared to returns, and also that the fossil energy market, especially crude oil, has a greater impact on the renewable energy stock market than investor sentiment. Our analysis below extends their study by considering an updated sample as well as a wider set of indices and examining the possible impact of the COP policy decisions on the evolution of the connectedness parameters by testing for breaks and doing sub-sample estimation as well.

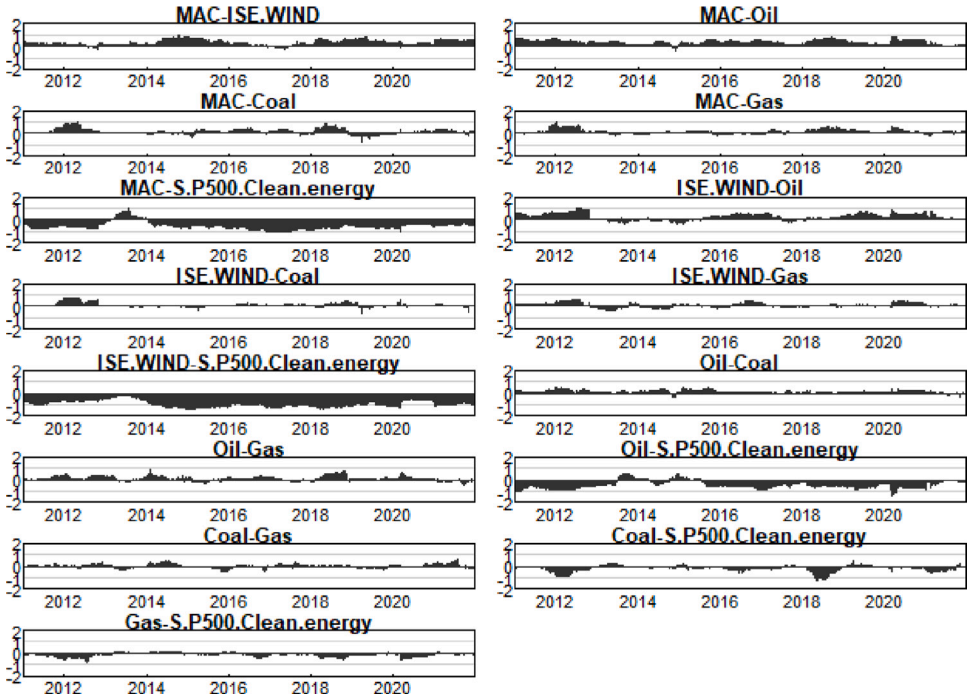

Fig. 15. Benchmark model including S&P500 Net Pairwise (Return System).

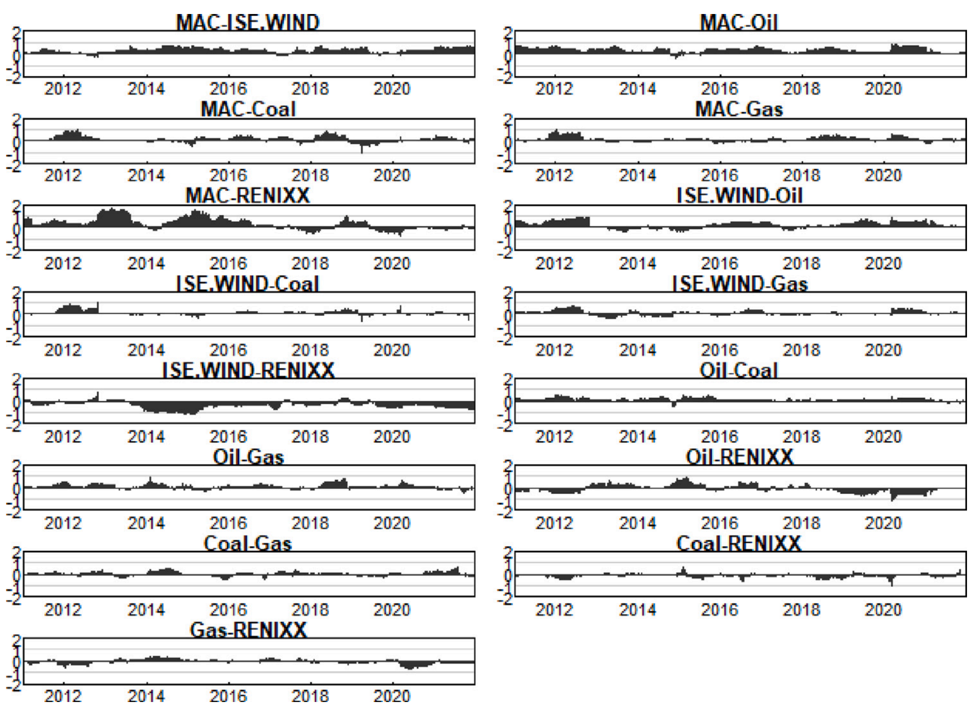

Fig. 16. Benchmark model including RENIXX Net Pairwise (Return System).

3. The United Nations Framework Convention on Climate Change

In June 1992, years of diplomatic efforts finally led to holding the UN Conference on the Environment and Development (UNCED), also known as the Earth Summit, and to the creation of three frameworks: the UN Framework Convention on Climate Change (UNFCCC), the UN Convention on Biological Diversity (UNCBD), and the UN Convention to Combat Desertification (UNCCD). The governments of the signatory countries became parties to these legally binding conventions and began to meet regularly to discuss progress at the so-called Conferences of Parties (COPs) on climate, biodiversity, and desertification.

The UNFCCC, signed by 197 countries as of 2015, has since become the best known of the three conventions, with the 197 national delegations being divided into five regional groups: Africa, Asia, Latin America, Western Europe, Eastern Europe and Other States. Starting with COP1 in Berlin in 1995, the UNFCCC Secretariat has been convening its signatories yearly at what has become the world's largest climate event. Growing interest from civil society groups, journalists,

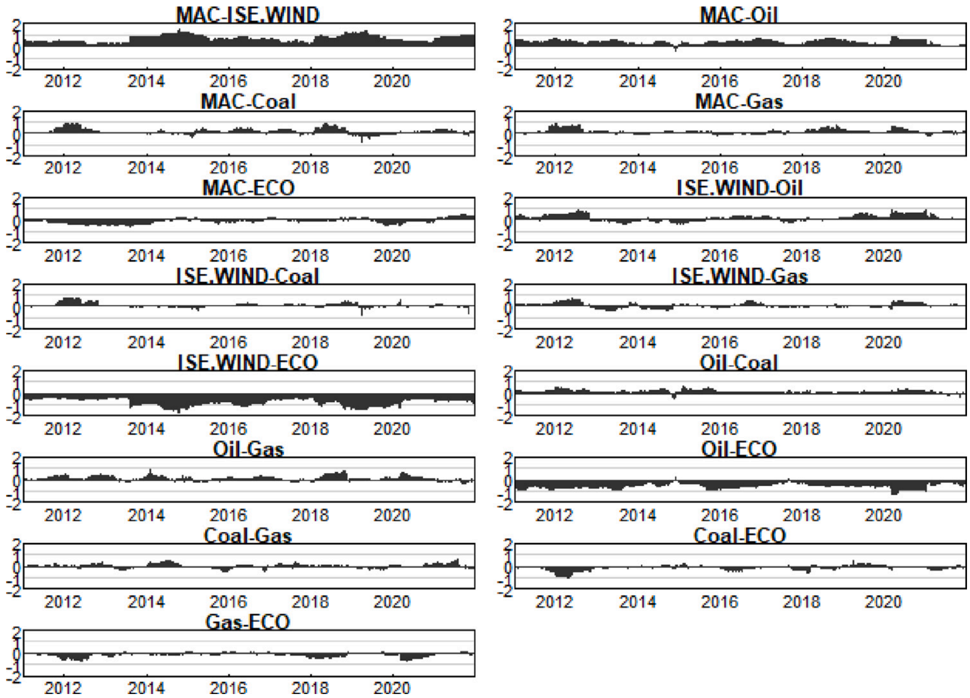

Fig. 17. Benchmark model including ECO Net Pairwise (Return System).

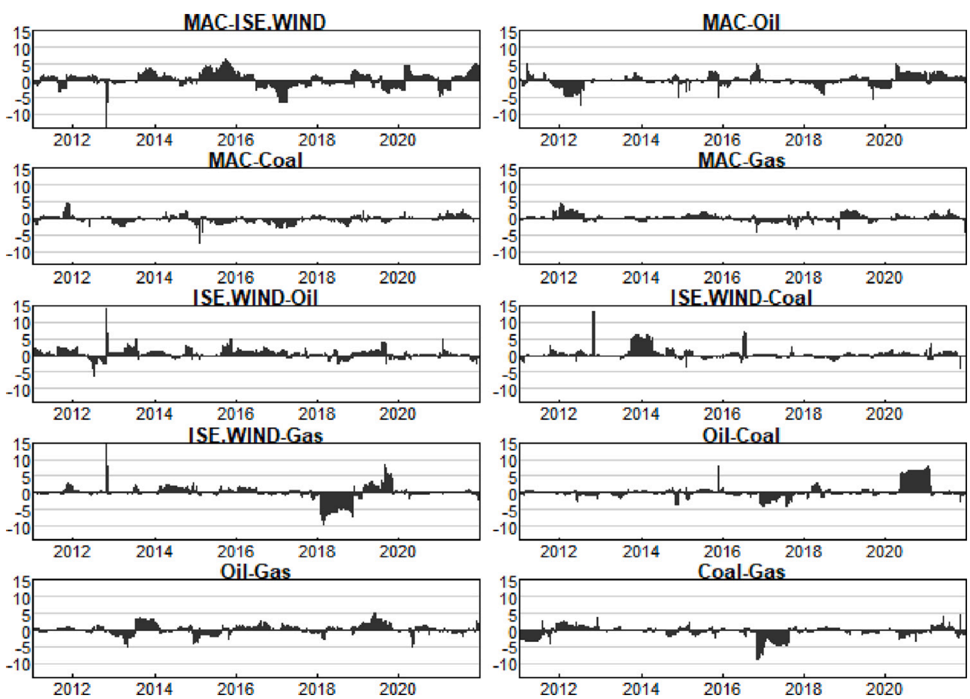

Fig. 18. Benchmark model Net Pairwise (Volatility System).

business representatives, academics, and others has meant that recent COP meetings have attracted thousands of participants worldwide.

The pace of progress in tackling climate change has differed across the 197 signatories. In some cases, individual countries have been developing and publishing new versions of their national action plans to deal with climate issues. The departure of the US, the second largest emitter of greenhouse gases, from the Paris Agreement in 2019 severely affected the global community's overall ability to address climate change. The US re-joined the agreement in early 2021, thus bringing renewed focus and momentum. Therefore, COP26, which was held in Glasgow on 31 October–13 November 2021, marked an important milestone. By its conclusion, 151 countries had submitted new climate plans (nationally determined contributions) to reduce their emissions by 2030. The goal of limiting temperature rise to 1.5 degrees *C* would require reducing global emissions by half by 2030. The 2030 targets previously set by various major emitters were still very weak (especially in the case of Australia, China, Saudi Arabia, Brazil and Russia) and in those countries credible pathways to achieve net-zero targets were still lacking. The COP26 agreements represent some encouraging progress in this direction: all countries have been

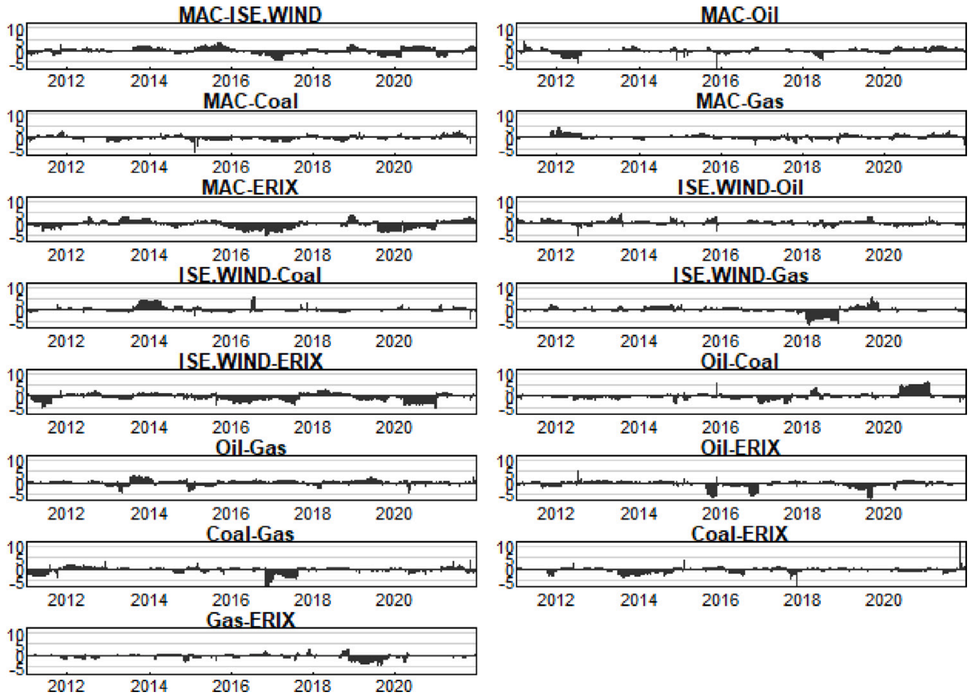

Fig. 19. Benchmark model including ERIX Net Pairwise (Volatility System).

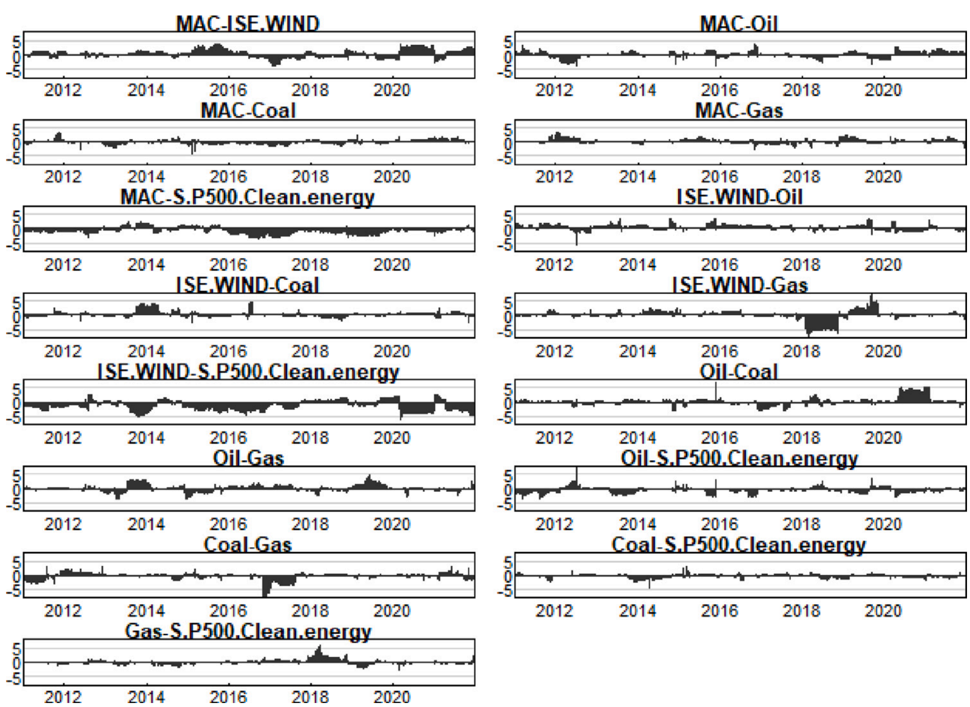

Fig. 20. Benchmark model including S&P500 Net Pairwise (Volatility System).

asked to strengthen their 2030 targets by the end of 2022 to align them with the Paris Agreement's temperature goals, and those that had not yet done so have also been asked to submit long-term strategies aiming to reach net-zero emissions by 2050.

4. The model

We use the methodology proposed by Diebold and Yilmaz (2014) to examine the connectedness between the fossil and renewable energy indices considered in this study and their dynamic spillovers. This approach is based on a vector auto-regression (VAR) model specified as follows:

$$A_t = \sum_{i=1}^{P} \Psi_i A_{t-1} + \epsilon_t, \tag{1}$$

where A_t is an $N \times 1$ vector of endogenous variables, i indicates the VAR order, and ϵ_t is a vector of iid error terms. The moving average

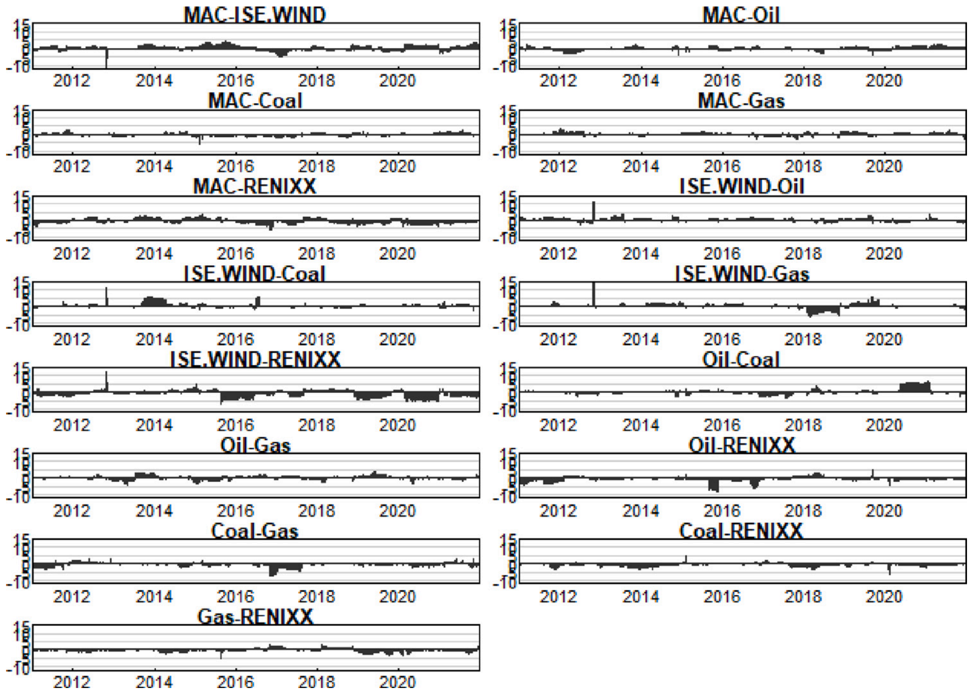

Fig. 21. Benchmark model including RENIXX Net Pairwise (Volatility System).

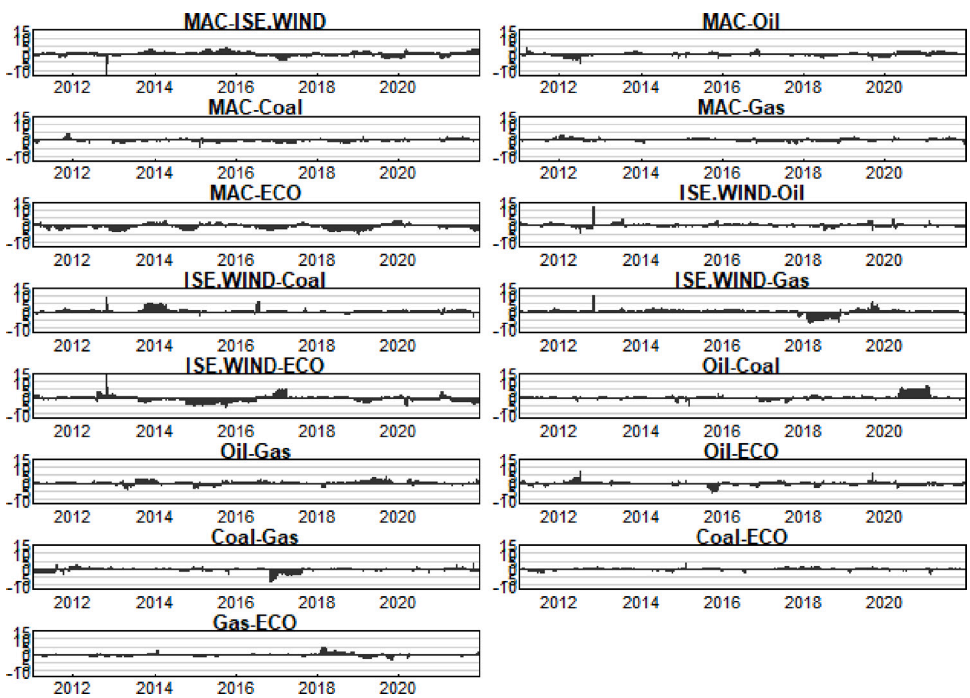

Fig. 22. Benchmark model including ECO Net Pairwise (Volatility System).

representation of the VAR(p) process is given by:

$$A_t = \sum_{i=1}^{\infty} Z_i \epsilon_{t-1}, \tag{2}$$

where the $N \times N$ coefficient matrices Z_i are recursively defined as $Z_i = \sum_{k=1}^{P} Z_{i-k}$ with Z_0 being the $N \times N$ identity matrix. We use the generalized decomposition of the covariance matrix of ϵ_t calculated as in Koop et al. (1996) and Pesaran and Shin (1998). The main advantage of this method over the Cholesky decomposition is that the resulting spillover indices are robust to the ordering of the variables. The generalized version of the H-step-ahead forecast-error variance decomposition has the following form:

$$c_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\epsilon_i' Z_h \sum \epsilon_j\right)^2}{\sum_{h=0}^{H-1} \left(\epsilon_i' Z_h \sum Z_h' \epsilon_j\right)}, \tag{3}$$

where the term σ_{jj} is a vector of standard deviations of the error terms for the jth equation and ith is an $N \times 1$ vector, with 1 for the ith equation

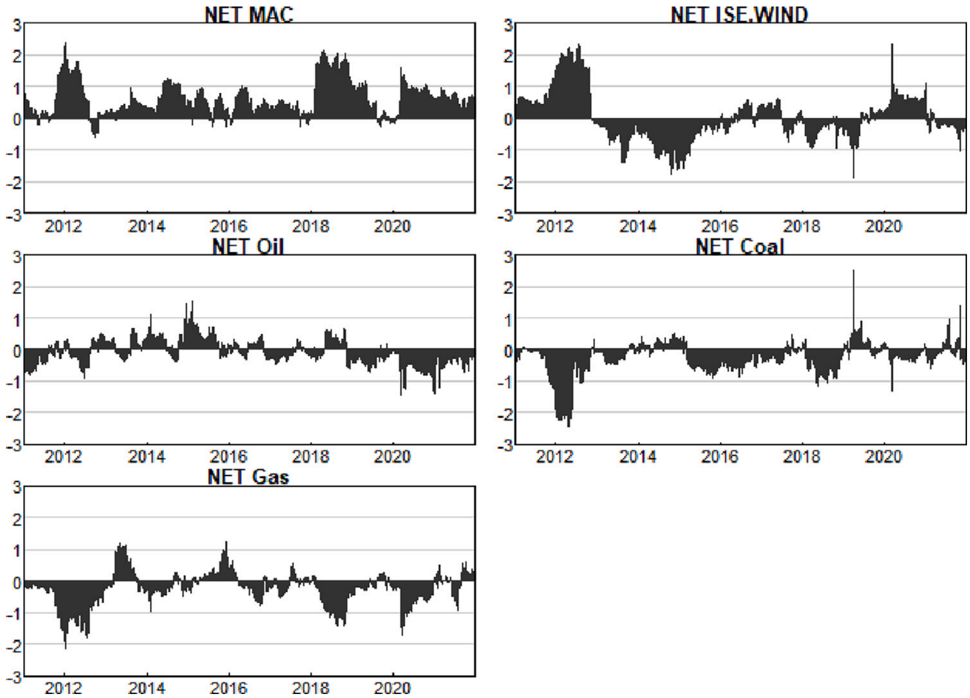

Fig. 23. Benchmark model Net Directional (Return System).

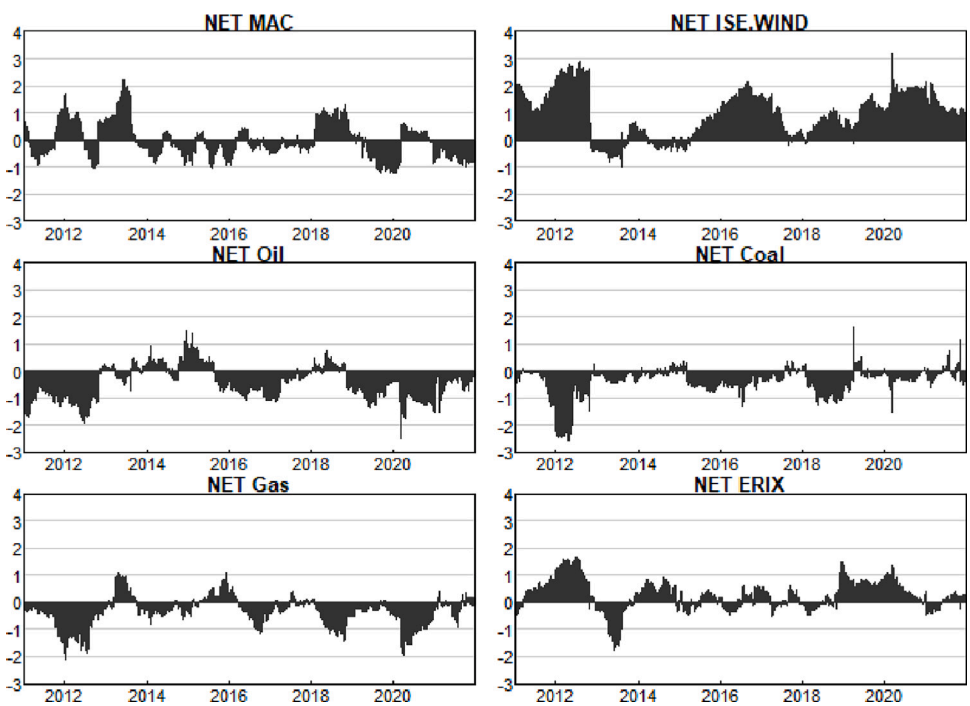

Fig. 24. Benchmark model including ERIX Net Directional (Return System).

and 0 elsewhere. In order to create spillover indices, each entry of the variance decomposition table is normalized by its row sum as follows:

$$\ddot{c}_{ij}^{g}(H) = \frac{c_{ij}^{g}(H)}{\sum_{j=1}^{N} c_{ij}^{g}(H)} \tag{4}$$

Having calculated the spillovers from market j to market i, for all i and j, three spillover indices are then constructed, namely: (i) the total spillover index, which measures spillovers across all markets, and has the following form:

$$S^{g}(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \ddot{c}_{ij}^{g}(H)}{N} * 100 \tag{5}$$

(ii) the spillover to market i from all other markets, which is defined as

$$S_{i,0}^{g}(H) = \frac{\sum_{j=1,i\neq j}^{N} \ddot{c}_{ij}^{g}(H)}{N} * 100 \tag{6}$$

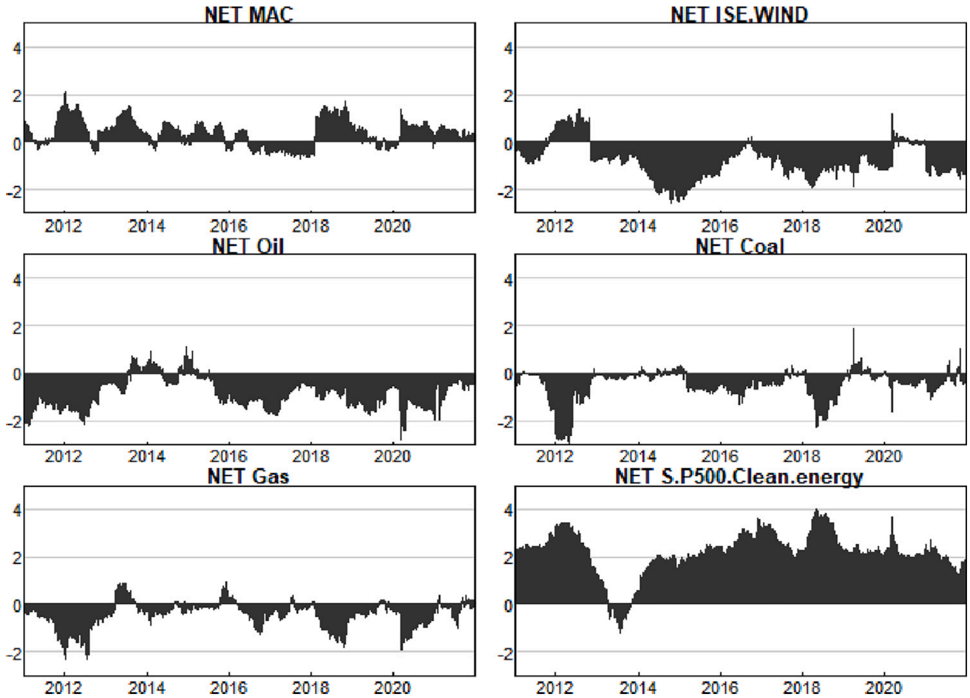

Fig. 25. Benchmark model including S&P500 Net Directional (Return System).

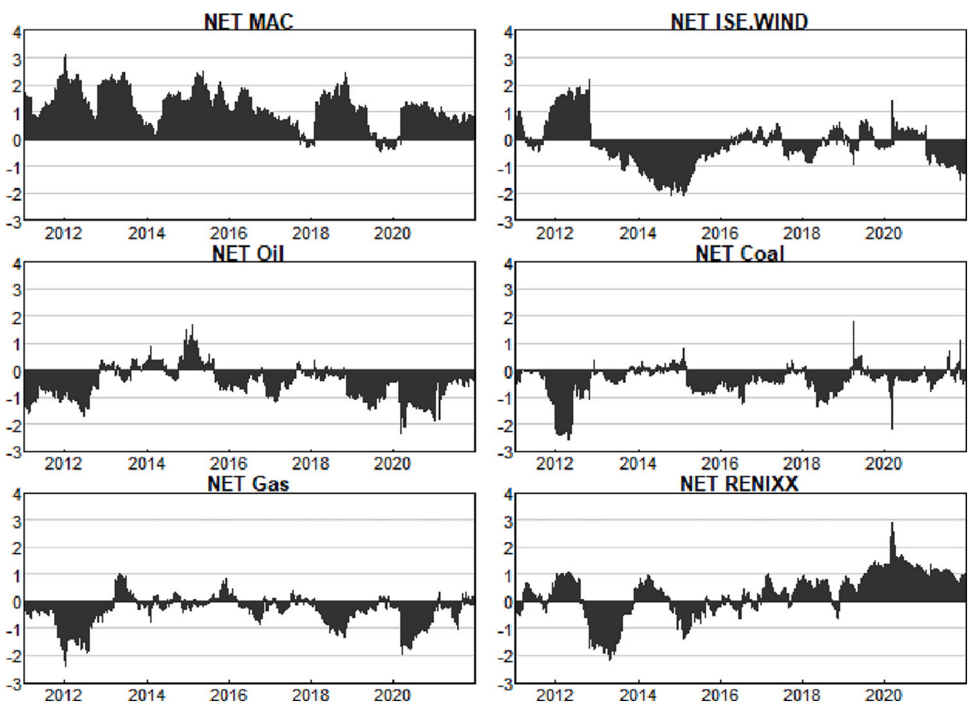

Fig. 26. Benchmark model including RENIXX Net Directional (Return System).

and (iii) the spillover from market i to all other markets, which is equal to

$$S^g_{0,i}(H) = \frac{\sum_{j=1,i\neq j}^{N} \ddot{c}^g_{ji}(H)}{N} * 100 \tag{7}$$

In the analysis that follows, we provide estimates of the spillover indices given by Eqs. 5–(7) for both the returns and volatilities of all the fossil and renewable energy indices selected.

Furthermore, we use a rolling window approach to estimate 10-step ahead dynamic spillover indices based on a 40-week window.

5. Empirical analysis

The dataset used for the analysis includes conventional and renewable energy daily indices retrieved from Bloomberg. More specifically, the benchmark model comprises five indices, namely: the MAC Global Solar Energy Index (MAC), the ISE Global Wind Energy Index (ISE Wind), the West Texas Intermediate Crude Oil Index, the Newcastle Coal Index, and the Natural Gas Index. One of the following four renewable energy indices is then added in turn to the benchmark model: the European Renewable Energy Index (ERIX), the S&P500

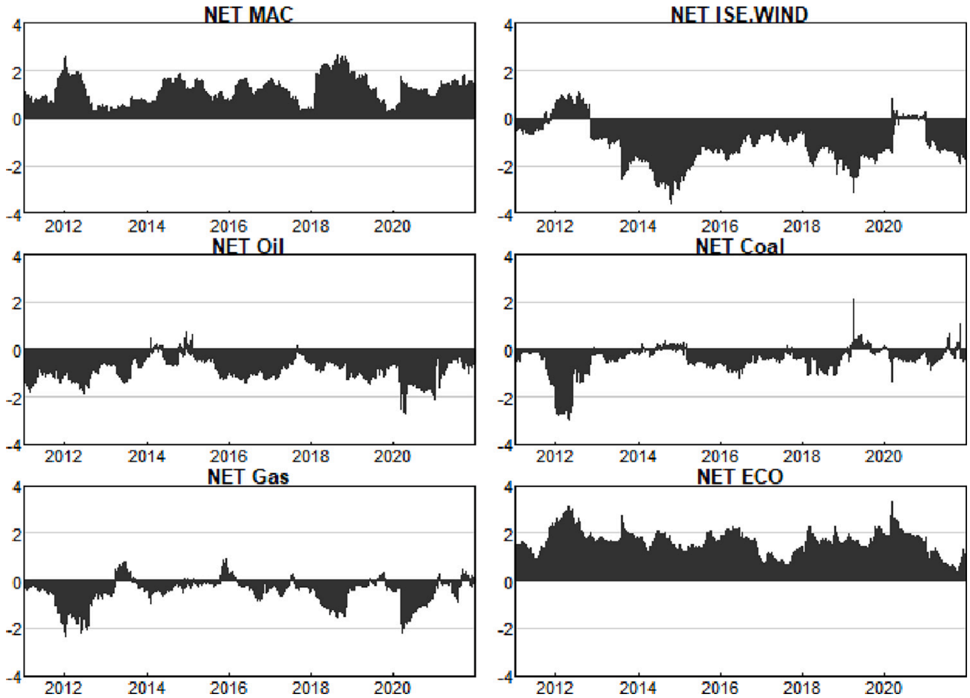

Fig. 27. Benchmark model including ECO Net Directional (Return System).

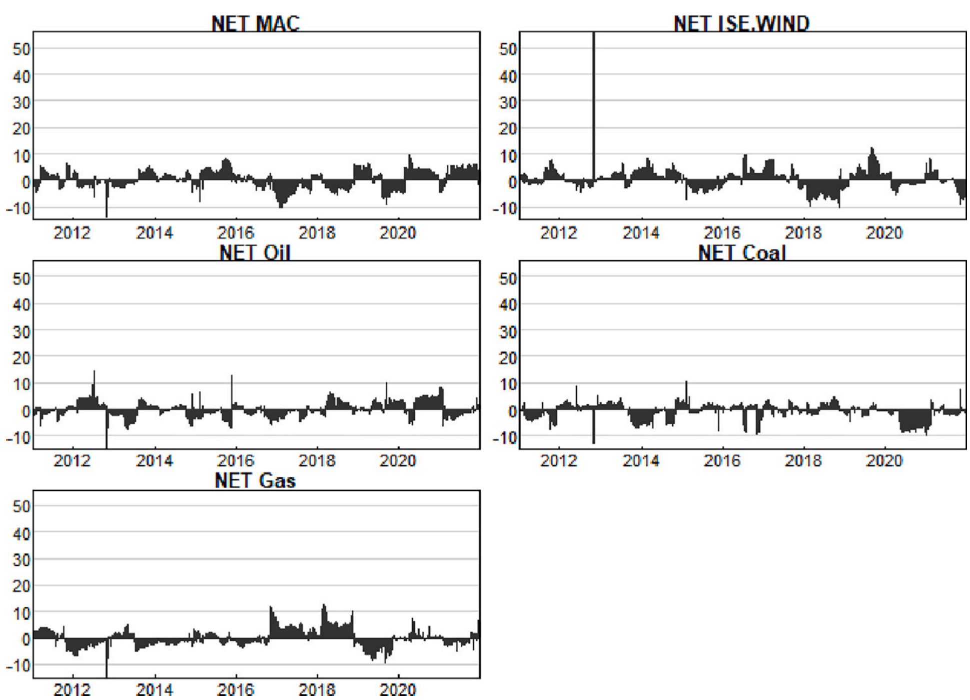

Fig. 28. Benchmark model Net Directional (Volatility System).

Global Clean Energy Index (S&P500), the World Renewable Energy Index (RENIXX), and the Wilder Hill Clean Energy Index (ECO). The sample period goes from 25/03/2010 to 23/12/2021, for a total of 2943 observations. The rationale for ending the sample in December 2021 is that the most recent key policy decisions with a possible impact on the linkages of interest were taken at COP 26 in Glasgow, 31 October–12 November 2021, whilst the following COP27, held in Sharm el-Sheik, Egypt, on 6–18 November 2022 was inconclusive (specifically, no commitments to phase out fossil fuels were made), and thus extending the sample size would not provide any important additional information concerning the issues being examined. Table 1 provides precise variable definitions and data sources. Daily returns are then calculated as the log difference of consecutive daily prices indices, whereas their volatility is modelled as a GARCH (1,1) process. Figs. 1 and 2 show returns and volatility for both fossil and renewable energy stock indices. Visual inspection reveals similar patterns for the two sets of series and the presence of spikes, which generally correspond to the dates of COP meetings. These observations, together with the evidence discussed in the literature review, leads us to formulate the following two hypotheses to be tested: (1) there exist statistically significant

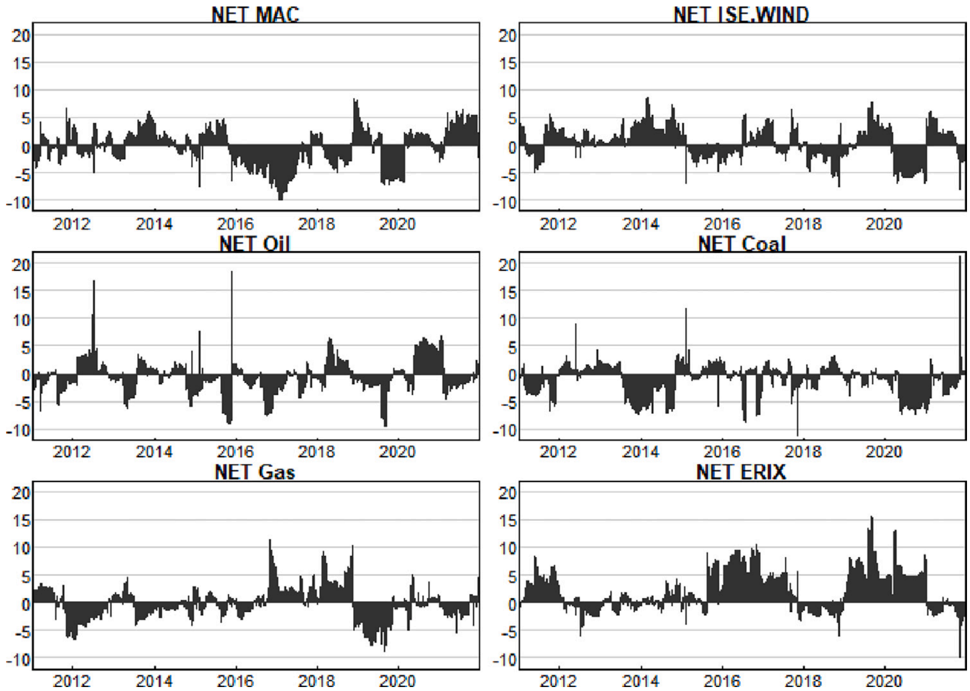

Fig. 29. Benchmark model including ERIX Net Directional (Volatility System).

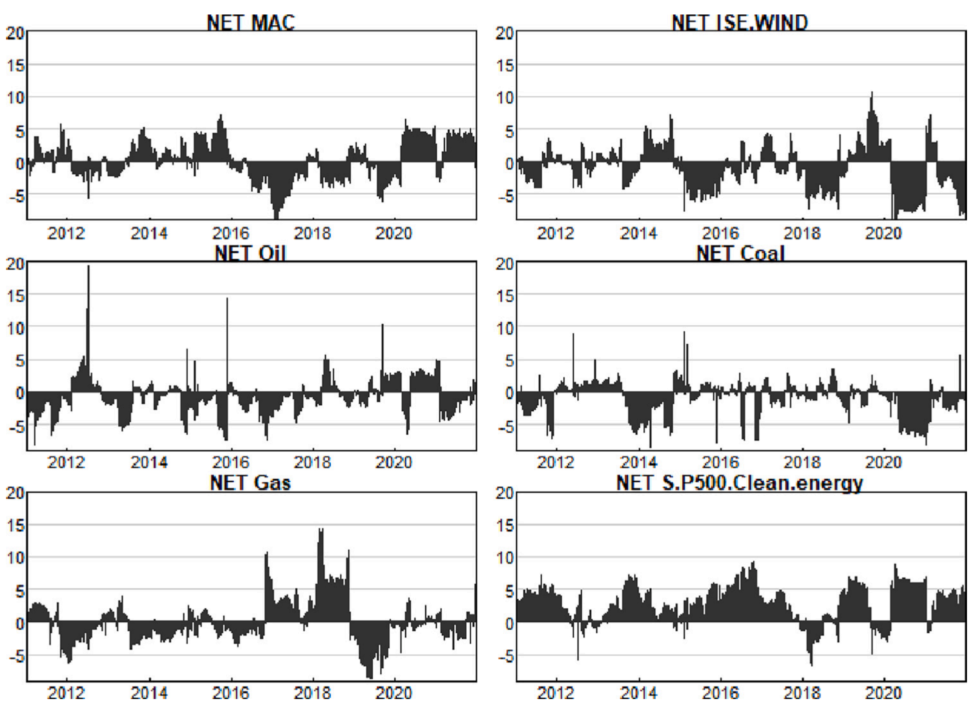

Fig. 30. Benchmark model including S&P500 Net Directional (Volatility System).

static and dynamic linkages between the fossil and renewable energy markets, which can be measured by their degree of connectedness; (2) the degree of connectedness varies over time in response to policy decisions taken at the COP meetings, becoming stronger when climate policies are effective. Table 2 reports descriptive statistics for fossil and renewable energy stock index returns. It can be seen that ERIX and RENIXX exhibit the highest daily mean (0.03%), followed by ISE Wind, Crude Oil, and Coal (0.02%). The Natural Gas Index has the highest standard deviation (2.98%), followed by Crude Oil (2.64%) and MAC (2.23%). Of the renewable energy indices, ECO is the most volatile (2.00%), whereas S&P500 has the lowest mean returns (0.01%) and volatility (1.51%). Excess skewness is exhibited by ISE Wind and Coal, whilst all series appear to be leptokurtic, especially in the case of ISE Wind, Crude Oil and Coal.

The first (benchmark) model estimated to investigate both static and dynamic connectedness following the approach of Diebold and Yilmaz (2014) includes five widely used energy indices for both renewable and fossil energy sources (MAC, ISE, Crude Oil, Coal and Natural Gas). As

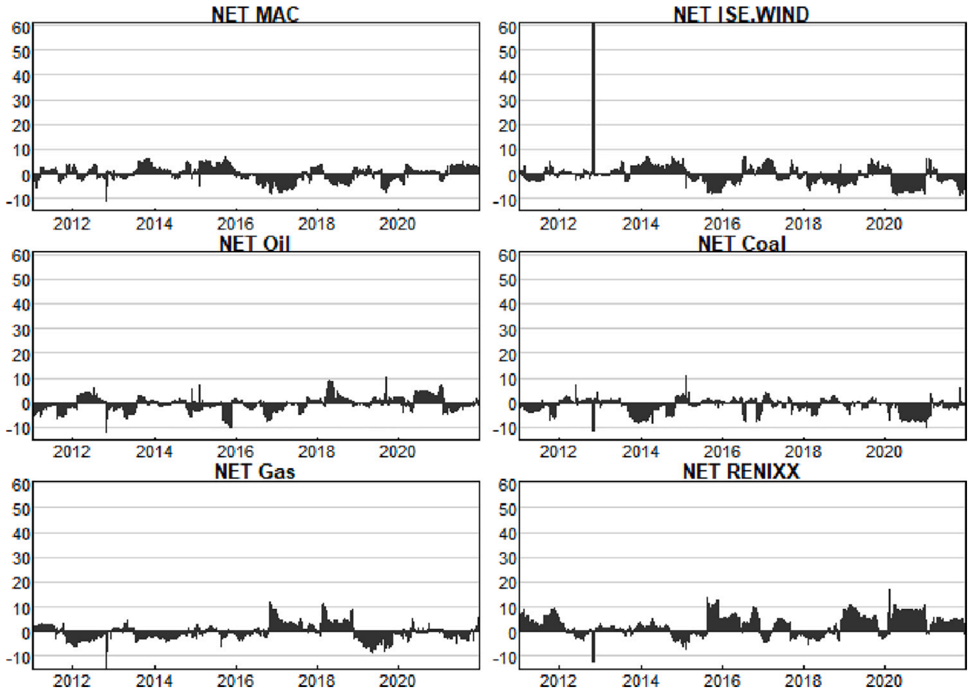

Fig. 31. Benchmark model including RENIXX Net Directional (Volatility System).

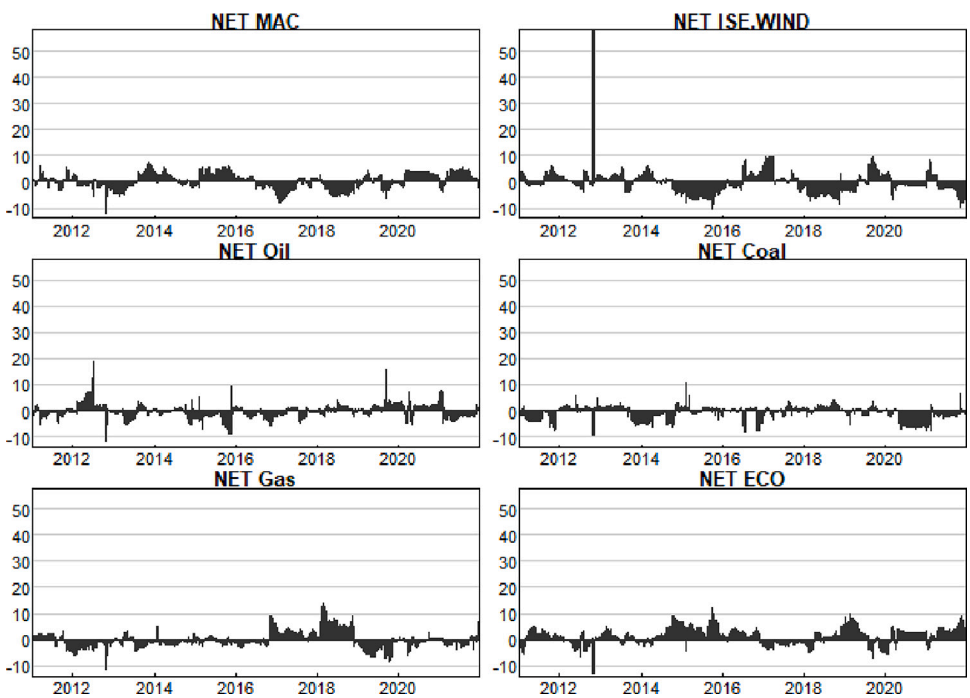

Fig. 32. Benchmark model including ECO Net Directional (Volatility System).

already mentioned, the analysis is carried out for both returns and their volatilities, the latter being modelled as a GARCH(1,1)".[2]

The static results are presented in Tables 4–8 for returns, and in Tables 9–13 for their volatilities. These tables report the percentage contribution from *i* to *j* in each case. The row "Directional to others" presents the total spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each series from all others. Total connectedness is in bold (see Figs. 11 and 12).

The benchmark model for returns yields an estimate of total connectedness of 12.89%, with MAC having a strong effect on ISE Wind (20.96%). MAC and Gas appear to be the two givers, whereas ISE Wind, Crude Oil and Coal are the receivers. In the extended system including in turn ERIX, S&P500, RENIXX and ECO the results (Tables 5–8) suggest that the additional variable is in each case the biggest giver in the corresponding system, with ERIX contributing 45.35%, S&P500 56.41%, RENIXX 49.35%, and ECO 52.00%. Furthermore, total connectedness is higher (on average, twice as big) in all cases

[2] These results are not reported for space reasons but are available upon request.

Table 7
Benchmark model including RENIXX (Returns).

Variables	Whole sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	RENIXX	From
MAC	53.98	13.82	3.80	0.02	0.12	28.25	46.02
ISE.Wind	16.78	59.96	3.30	0.06	0.07	19.83	40.04
Crude Oil	5.91	4.30	84.70	0.51	0.88	3.71	15.30
Coal	0.04	0.15	0.62	98.83	0.35	0.01	1.17
Gas	0.12	0.10	1.00	0.09	98.62	0.07	1.38
RENIXX	29.87	16.78	2.57	0.05	0.08	50.65	49.35
Directional to others	52.72	35.14	11.29	0.74	1.50	51.87	153.26
Net Directional Con.	6.69	−4.90	−4.01	−0.43	0.12	2.52	**25.54**
	First Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	RENIXX	From
MAC	50.69	12.34	8.80	0.34	0.02	27.81	49.31
ISE.Wind	14.58	61.77	7.65	0.65	0.09	15.27	38.23
Crude Oil	12.00	8.73	68.95	1.28	1.16	7.88	31.05
Coal	0.98	1.49	2.28	94.29	0.47	0.50	5.71
Gas	0.57	1.10	1.66	0.60	95.77	0.31	4.23
RENIXX	31.36	13.75	6.45	0.19	0.04	48.21	51.79
Directional to others	59.47	37.40	26.84	3.06	1.79	51.77	180.33
Net Directional Con.	10.16	−0.84	−4.21	−2.66	−2.44	−0.02	**30.05**
	Second Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	RENIXX	From
MAC	60.17	11.55	4.05	0.02	0.01	24.19	39.83
ISE.Wind	13.97	60.84	3.97	0.07	0.09	21.06	39.16
Crude Oil	5.50	5.13	85.42	0.02	1.03	2.89	14.58
Coal	0.01	0.15	0.14	99.26	0.37	0.06	0.74
Gas	0.03	0.21	1.22	0.13	98.40	0.00	1.60
RENIXX	26.07	18.54	2.50	0.07	0.02	52.80	47.20
Directional to others	45.58	35.59	11.89	0.31	1.52	48.21	143.10
Net Directional Con.	5.75	−3.57	−2.69	−0.43	−0.08	1.01	**23.85**
	Third Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	RENIXX	From
MAC	43.97	22.26	1.20	0.02	1.08	31.47	56.03
ISE.Wind	25.10	47.66	1.01	0.03	0.36	25.85	52.34
Crude Oil	3.36	3.42	88.21	1.27	0.93	2.80	11.79
Coal	0.00	0.08	1.38	97.66	0.84	0.04	2.34
Gas	1.10	0.47	1.11	0.51	96.00	0.82	4.00
RENIXX	31.88	23.12	0.70	0.12	0.70	43.48	56.52
Directional to others	61.45	49.34	5.41	1.95	3.91	60.98	183.03
Net Directional Con.	5.42	−3.01	−6.39	−0.39	−0.09	4.45	**30.50**

Note: The table reports in each case the contributions from *i* to *j*. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

Table 8
Benchmark model including ECO (Returns).

Variables	Whole sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ECO	From
MAC	48.88	12.61	3.43	0.03	0.11	34.94	51.12
ISE.Wind	17.35	61.37	3.42	0.05	0.08	17.72	38.63
Crude Oil	5.61	4.17	80.75	0.49	0.83	8.16	19.25
Coal	0.04	0.15	0.63	98.80	0.35	0.03	1.20
Gas	0.12	0.11	0.99	0.09	98.48	0.21	1.52
ECO	34.41	12.62	4.82	0.03	0.12	48.00	52.00
Directional to others	57.53	29.65	13.29	0.70	1.49	61.07	173.72
Net Directional Con.	6.40	−8.97	−5.96	−0.50	−0.03	9.07	**27.29**
	First Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ECO	From
MAC	45.96	11.13	7.99	0.31	0.02	34.58	54.04
ISE.Wind	14.66	61.64	7.71	0.59	0.09	15.32	38.36
Crude Oil	11.03	7.94	63.30	1.14	1.08	15.51	36.70
Coal	0.99	1.37	2.22	93.14	0.48	1.80	6.86
Gas	0.57	1.03	1.68	0.60	95.55	0.58	4.45
ECO	33.20	11.35	10.76	0.50	0.13	44.05	55.95

(*continued on next page*)

compared to the benchmark model, which implies that the aggregate renewable energy indices play a major role. By contrast, in the case of the corresponding volatilities (Tables 10–13), although the same indices are still the main givers, total connectedness is lower compared

Table 8 (*continued*).

	MAC	ISE.Wind	Crude Oil	Coal	Gas	ECO	From
Directional to others	60.44	32.83	30.37	3.14	1.79	67.79	196.36
Net Directional Con.	6.40	−5.53	−6.34	−3.72	−2.66	11.84	**32.73**
	Second Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ECO	From
MAC	50.07	10.20	4.26	0.02	0.02	35.44	49.93
ISE.Wind	15.20	60.51	5.27	0.07	0.08	16.87	37.49
Crude Oil	6.19	5.89	77.72	0.03	0.72	9.46	22.28
Coal	0.01	0.16	0.17	99.24	0.37	0.05	0.76
Gas	0.04	0.19	0.92	0.13	98.71	0.01	1.29
ECO	34.39	10.45	6.03	0.01	0.01	49.12	50.88
Directional to others	55.82	26.90	16.65	0.26	1.19	61.82	162.64
Net Directional Con.	5.89	−10.59	−5.63	−0.51	−0.09	10.94	**27.11**
	Third Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ECO	From
MAC	43.15	22.10	1.10	0.02	1.03	32.60	56.85
ISE.Wind	25.96	48.82	1.09	0.04	0.39	23.70	51.18
Crude Oil	2.76	3.20	87.03	1.27	0.66	5.09	12.97
Coal	0.01	0.07	1.41	97.55	0.84	0.12	2.45
Gas	1.06	0.49	0.70	0.50	96.11	1.13	3.89
ECO	33.02	20.37	2.10	0.08	0.62	43.81	56.19
Directional to others	62.81	46.23	6.40	1.91	3.54	62.63	183.53
Net Directional Con.	5.96	−4.95	−6.57	−0.54	−0.35	6.45	**30.59**

Note: The table reports in each case the contributions from *i* to *j*. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

Table 9
Benchmark model (Volatility).

Variables	Whole sample					
	MAC	ISE.Wind	Crude Oil	Coal	Gas	From
MAC	97.14	1.92	0.86	0.07	0.02	2.86
ISE.Wind	1.29	98.61	0.09	0.00	0.01	1.39
Crude Oil	4.06	0.36	95.41	0.10	0.07	4.59
Coal	0.05	0.00	0.36	98.86	0.73	1.14
Gas	0.06	0.04	0.48	0.28	99.14	0.86
Directional to others	5.45	2.33	1.78	0.44	0.83	10.84
Net Directional Con.	2.59	0.94	−2.80	−0.70	−0.02	**2.17**
	First Sub-sample					
	MAC	ISE.Wind	Crude Oil	Coal	Gas	From
MAC	68.70	21.41	9.61	0.02	0.26	31.30
ISE.Wind	18.57	69.65	11.32	0.06	0.39	30.35
Crude Oil	4.97	16.45	78.44	0.01	0.13	21.56
Coal	0.16	0.09	0.46	93.08	6.21	6.92
Gas	0.06	2.11	0.74	0.54	96.56	3.44
Directional to others	23.75	40.06	22.13	0.64	6.99	93.57
Net Directional Con.	−7.55	9.71	0.57	−6.28	3.55	**18.71**
	Second Sub-sample					
	MAC	ISE.Wind	Crude Oil	Coal	Gas	From
MAC	99.42	0.22	0.19	0.15	0.02	0.58
ISE.Wind	0.24	99.70	0.04	0.00	0.02	0.30
Crude Oil	2.07	0.19	97.50	0.03	0.21	2.50
Coal	0.30	0.02	0.04	98.20	1.44	1.80
Gas	0.09	0.19	0.45	0.12	99.14	0.86
Directional to others	2.70	0.62	0.72	0.31	1.68	6.03
Net Directional Con.	2.12	0.32	−1.78	−1.49	0.83	**1.21**
	Third Sub-sample					
	MAC	ISE.Wind	Crude Oil	Coal	Gas	From
MAC	55.42	36.54	7.28	0.52	0.24	44.58
ISE.Wind	38.11	52.57	9.18	0.08	0.07	47.43
Crude Oil	14.05	7.52	77.75	0.42	0.26	22.25
Coal	0.26	0.18	1.13	97.77	0.66	2.23
Gas	0.04	0.13	0.51	0.08	99.24	0.76
Directional to others	52.47	44.37	18.10	1.09	1.23	117.26
Net Directional Con.	7.89	−3.07	−4.15	−1.14	0.47	**23.45**

Note: The table reports in each case the contributions from *i* to *j*. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

Table 10
Benchmark model including ERIX (Volatility).

Variables	MAC	ISE.Wind	Crude Oil	Coal	Gas	ERIX	From
	Whole sample						
MAC	72.02	1.37	0.56	0.08	0.02	25.96	27.98
ISE.Wind	1.03	95.66	0.08	0.00	0.01	3.21	4.34
Crude Oil	3.61	0.33	93.62	0.09	0.07	2.27	6.38
Coal	0.04	0.00	0.37	98.79	0.73	0.08	1.21
Gas	0.04	0.04	0.47	0.27	99.11	0.06	0.89
ERIX	20.49	2.38	0.20	0.01	0.03	76.88	23.12
Directional to others	25.21	4.12	1.68	0.46	0.86	31.57	63.90
Net Directional Con.	−2.76	−0.22	−4.70	−0.75	−0.03	8.45	**10.65**
	First Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ERIX	From
MAC	56.91	18.26	7.82	0.02	0.17	16.81	43.09
ISE.Wind	13.31	50.47	8.10	0.05	0.27	27.80	49.53
Crude Oil	4.28	14.98	69.32	0.01	0.09	11.31	30.68
Coal	0.17	0.09	0.48	92.87	6.29	0.09	7.13
Gas	0.04	2.19	0.66	0.54	93.63	2.93	6.37
ERIX	13.76	32.60	6.31	0.04	0.48	46.81	53.19
Directional to others	31.56	68.13	23.38	0.65	7.31	58.95	189.97
Net Directional Con.	−11.52	18.61	−7.30	−6.48	0.94	5.76	**31.66**
	Second Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ERIX	From
MAC	91.52	0.17	0.01	0.19	0.04	8.06	8.48
ISE.Wind	0.27	99.30	0.01	0.01	0.01	0.41	0.70
Crude Oil	0.85	0.03	94.60	0.01	0.07	4.44	5.40
Coal	0.39	0.00	0.09	98.90	0.55	0.07	1.10
Gas	0.01	0.10	0.03	0.07	99.55	0.23	0.45
ERIX	10.60	0.18	0.21	0.18	0.06	88.77	11.23
Directional to others	12.12	0.49	0.35	0.47	0.72	13.21	27.36
Net Directional Con.	3.64	−0.22	−5.05	−0.63	0.28	1.98	**4.56**
	Third Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ERIX	From
MAC	41.29	26.46	2.14	0.26	0.56	29.29	58.71
ISE.Wind	22.18	37.76	1.74	0.00	0.10	38.23	62.24
Crude Oil	8.98	4.40	82.42	0.41	0.49	3.30	17.58
Coal	0.46	0.01	0.67	97.54	1.24	0.08	2.46
Gas	0.02	0.01	0.84	0.19	98.31	0.63	1.69
ERIX	22.05	27.95	1.13	0.09	0.05	48.73	51.27
Directional to others	53.68	58.83	6.53	0.96	2.44	71.52	193.95
Net Directional Con.	−5.33	−3.41	−11.06	−1.50	0.75	20.26	**32.33**

Note: The table reports in each case the contributions from *i* to *j*. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

to the model for returns. The dynamic analysis (see Figs. 3–7 for returns and Figs. 8–12 for their volatilities) suggests the possible presence of two structural breaks in the connectedness coefficients, which we investigate next by applying the Bai and Perron (1998) endogenous break tests. The results indicate that there are two breaks in all cases, for both returns and their volatilities, the first on 29/10/2012, and the second on 6/3/2020 (see Table 3). Therefore, we re-run both the static and the dynamic analysis for each of the three corresponding sub-samples (before the first break, between the first and the second break, and finally after the second break). These estimates suggest a higher degree of spillovers during the first and third sub-samples compared to the second one in all cases, for both returns and their volatilities. Interestingly, the first break follows the 2011 UNCCC (COP17) meeting held in Durban, South Africa, 28 November–11 December 2011, which was not very successful, despite a new legally binding treaty to limit carbon emissions being agreed, since experts soon concluded that this was not sufficient to avoid global warming beyond 2.0 degrees and that more decisive action would be required. The second break follows instead COP25, Madrid, 2–13 December 2019. This was also a disappointing event, since any decisions concerning carbon emission cuts were postponed to the next climate conference, namely COP26. However, precisely because of the perceived failure of this meeting, calls for further action soon gathered momentum and, in a briefing given exactly on 6/3/2020 about the UN Climate Change Conference COP26, expected to take place in Glasgow in November 2020 (then postponed to 31 October–13 November 2021 due to COVID-19), UN Secretary-General António Guterres called 2020 "a pivotal year for how we address climate change", adding that "success in Glasgow depends on countries, the private sector and civil society demonstrating that they are taking significant steps to raise ambition on cutting greenhouse gas emissions, building resilience to climate and financing both."[3] He listed four priorities for COP26: first, that national climate plans – the NDCs – should show that countries are working to implement the Paris Agreement, and that each new NDC should show more ambition than the previous one; second, that all nations should adopt strategies to reach net zero emissions by 2050; third, the development of a robust package of projects and initiatives to help communities and nations adapt to climate disruption and build resilience against future impacts; fourth, the provision of finance, with developed countries at COP26 delivering on their commitment to mobilize 100 billion dollars a year by 2020. Key measures towards achieving at least some of these goals

[3] See https://unfccc.int/news/2020-is-a-pivotal-year-for-climate-un-chief-and-cop26-president.

Table 11
Benchmark model including S&P500 (Volatility).

Variables	Whole sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	S&P500	From
MAC	56.78	0.85	0.35	0.04	0.04	41.93	43.22
ISE.Wind	1.22	95.52	0.06	0.00	0.00	3.19	4.48
Crude Oil	3.57	0.27	87.20	0.09	0.08	8.79	12.80
Coal	0.05	0.00	0.37	98.84	0.72	0.02	1.16
Gas	0.06	0.06	0.49	0.28	99.07	0.04	0.93
S&P500	36.33	1.50	1.25	0.01	0.03	60.89	39.11
Directional to others	41.21	2.68	2.53	0.42	0.88	53.97	101.69
Net Directional Con.	−2.00	−1.80	−10.27	−0.74	−0.05	14.87	**16.95**
	First Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	S&P500	From
MAC	46.42	13.65	5.31	0.03	0.14	34.45	53.58
ISE.Wind	14.87	46.92	6.20	0.06	0.22	31.73	53.08
Crude Oil	5.72	14.48	65.45	0.00	0.09	14.26	34.55
Coal	0.05	0.08	0.70	92.77	6.36	0.04	7.23
Gas	0.09	2.08	0.63	0.54	95.59	1.07	4.41
S&P500	26.22	23.74	6.75	0.04	0.23	43.01	56.99
Directional to others	46.95	54.03	19.60	0.68	7.04	81.55	209.85
Net Directional Con.	−6.63	0.95	−14.96	−6.55	2.63	24.57	**34.98**
	Second Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	S&P500	From
MAC	74.54	0.17	0.15	0.11	0.02	25.01	25.46
ISE.Wind	0.23	98.99	0.00	0.00	0.05	0.73	1.01
Crude Oil	1.93	0.06	93.78	0.03	0.27	4.04	6.22
Coal	0.31	0.00	0.03	98.20	1.44	0.02	1.80
Gas	0.12	0.15	0.26	0.06	99.28	0.13	0.72
S&P500	27.52	0.08	1.07	0.08	0.13	71.12	28.88
Directional to others	30.12	0.46	1.51	0.28	1.80	29.93	64.10
Net Directional Con.	4.65	−0.55	−4.71	−1.52	1.08	1.05	**10.68**
	Third Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	S&P500	From
MAC	36.42	23.17	5.44	0.31	0.16	34.50	63.58
ISE.Wind	25.77	32.28	7.16	0.03	0.03	34.74	67.72
Crude Oil	15.21	15.33	50.87	0.15	0.03	18.40	49.13
Coal	0.17	0.17	0.47	98.61	0.53	0.05	1.39
Gas	0.03	0.65	0.11	0.07	99.06	0.08	0.94
S&P500	31.03	24.79	7.16	0.08	0.08	36.86	63.14
Directional to others	72.22	64.10	20.34	0.64	0.82	87.78	245.90
Net Directional Con.	8.64	−3.62	−28.79	−0.74	−0.12	24.64	**40.98**

Note: The table reports in each case the contributions from *i* to *j*. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

were in fact agreed at COP26, as previously detailed (see Section 3 above).

Net pairwise connectedness, which measures how information is transmitted between markets, is shown in Figs. 13–17 for returns, and in Figs. 18–22 for their volatilities. As can be seen, the net pairwise contribution of all variables fluctuates between positive and negative, which possibly reflects policy changes as previously argued. It also appears that the transmission mechanism is not dominated by any particular market. For example, the results for the MAC-ISE WIND pair indicate that MAC was a recipient of information from ISE WIND at the beginning of the sample period, but subsequently became a contributor to ISE WIND. In general the degree of connectedness is weak at the beginning of the sample and over the period from 2019 to 2020, and slightly stronger afterwards.

Figs. 23 to 32 show the net directional spillovers for both the return and volatility systems, with positive spillovers indicating information transmission to all other markets, while negative ones measure the contribution from those. The results suggest that, in both sets of benchmark models, markets are mainly affected by MAC and also to some extent by ISE WIND, particularly during the periods around the COP17 and COP26 meetings. Moreover, the models including ERIX produce similar evidence. By contrast, all other specifications lead to the conclusion that the renewable energy indices were the main transmitters during most of the sample period, especially in the case of S&P500 and ECO; moreover, the contributions from these indices were slightly higher around the COP17 and COP26 meetings compared to other COP meeting periods. On the whole, the empirical evidence discussed above provides convincing support to the two hypotheses of interest, namely it confirms the existence of sizeable return and volatility spillovers between the two sets of markets considered, and also that such spillovers are generally stronger during periods characterized by more effective climate policies resulting from successful COP meetings.

6. Conclusions

This paper contributes to the literature on renewable energy and climate change by investigating static and dynamic connectedness between the first and second moments of fossil and renewable energy stock indices in the last decade at the daily frequency. For this purpose the Diebold and Yilmaz (2014) methodology is applied; in addition, endogenous break tests are implemented to detect any shifts that might have occurred over time and, two breaks having been identified, subsample estimates are also obtained and the findings are related to policies agreed in the COP meetings. The analysis extends in several ways that carried out by Songa et al. (2019) in an earlier study, since it considers a longer sample as well as a wider set of indices,

Table 12
Benchmark model including RENIXX (Volatility).

Variables	MAC	ISE.Wind	Crude Oil	Coal	Gas	RENIXX	From
	Whole sample						
MAC	63.62	1.19	0.65	0.08	0.04	34.43	36.38
ISE.Wind	1.19	96.83	0.10	0.00	0.01	1.87	3.17
Crude Oil	3.75	0.33	91.08	0.09	0.08	4.67	8.92
Coal	0.05	0.00	0.36	98.83	0.73	0.02	1.17
Gas	0.07	0.05	0.47	0.29	99.10	0.01	0.90
RENIXX	29.79	1.40	1.35	0.00	0.02	67.44	32.56
Directional to others	34.86	2.97	2.92	0.46	0.87	41.01	83.09
Net Directional Con.	−1.52	−0.20	−6.00	−0.71	−0.03	8.46	**13.85**
	First Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	RENIXX	From
MAC	52.23	16.20	6.95	0.03	0.16	24.44	47.77
ISE.Wind	14.64	54.82	8.63	0.05	0.27	21.59	45.18
Crude Oil	4.62	15.24	71.58	0.00	0.08	8.48	28.42
Coal	0.16	0.09	0.48	92.97	6.26	0.04	7.03
Gas	0.06	2.08	0.60	0.57	95.84	0.85	4.16
RENIXX	23.74	22.42	4.94	0.02	0.02	48.86	51.14
Directional to others	43.21	56.03	21.59	0.68	6.80	55.39	183.70
Net Directional Con.	−4.56	10.84	−6.82	−6.35	2.64	4.25	**30.62**
	Second Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	RENIXX	From
MAC	79.05	0.12	0.02	0.16	0.06	20.58	20.95
ISE.Wind	0.14	99.76	0.03	0.01	0.01	0.06	0.24
Crude Oil	1.14	0.09	91.10	0.02	0.11	7.53	8.90
Coal	0.36	0.00	0.11	98.94	0.58	0.01	1.06
Gas	0.05	0.15	0.02	0.07	99.69	0.03	0.31
RENIXX	23.29	0.06	1.30	0.28	0.78	28.21	55.97
Directional to others	24.97	0.43	1.30	0.28	0.78	28.21	55.97
Net Directional Con.	4.02	0.19	−7.60	−0.78	0.47	3.70	**9.33**
	Third Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	RENIXX	From
MAC	37.55	23.97	2.51	0.33	0.60	35.05	62.45
ISE.Wind	25.33	43.73	2.13	0.01	0.08	28.72	56.27
Crude Oil	10.15	4.69	78.48	0.47	0.26	5.94	21.52
Coal	0.44	0.01	0.79	97.15	1.36	0.25	2.85
Gas	0.00	0.01	0.83	0.21	98.71	0.24	1.29
RENIXX	28.42	17.37	2.44	0.02	0.06	51.69	48.31
Directional to others	64.34	46.06	8.70	1.04	2.36	70.20	192.70
Net Directional Con.	1.89	−10.21	−12.83	−1.81	1.06	21.89	**32.12**

Note: The table reports in each case the contributions from *i* to *j*. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

it allows for parameter shifts and provides a policy interpretation of the detected spillover changes. The results suggest that the renewable energy indices under examination play a significant role in terms of connectedness and that markets have reacted to the policy measures adopted at the COP meetings. In particular, both the unsuccessful COP17 held in Durban in 2011 and the anticipation of decisive action at the then forthcoming COP26 in Glasgow to be held in 2021 affected the degree of connectedness of the estimated systems including both fossil and renewable energy indices. These findings confirm the validity of the two hypotheses formulated at the outset concerning the existence of linkages between the two sets of markets considered and their strengthening in the presence of more decisive policy actions to combat climate change.

Although the existence of significant spillovers between the two types of markets had already been established in previous papers (see, e.g., Reboredo et al., 2017; Reboredo and Ugolini, 2018; Songa et al., 2019; Liu and Shigeyuki, 2020) , our analysis provides an additional, important piece of information, namely the fact that such linkages appear to be affected by policy changes. More specifically, it is clear that they are weaker during periods when less effective climate change policies are in place, whilst more decisive measures and tighter targets tend to strengthen spillover effects. The main transmission mechanism is likely to be through the impact of these policies on the relative value of stocks in the two sets of markets, specifically by driving up the price of those in the renewable sector. This confirms the crucial importance of policy intervention and support for renewable energy to tackle climate change. It is only to be hoped that the COP26 agreements will be fully implemented and followed by even more ambitious targets to promote the use of renewable energy and reduce global warming with its devastating effects on the environment. To be more precise, a variety of policy tools are available and should be considered by national governments. They include stringent emission ceilings to be imposed on industries as well as individual car users, and fiscal incentives for clean energy such as lower tax rates and direct subsidies to promote the production and usage of renewable energy. The adoption of such policies also affects the behaviour of market participants by making investment in renewable energy (as opposed to fossil fuel) stocks more appealing. This is important to promote sustainable development which is compatible with the preservation of the planet. Moreover, it implies that investors would be well advised to pay close attention to the decisions taken at the COP meetings and their implementation by national governments with the aim of constructing profitable asset portfolios. Finally, it should be acknowledged that the present study has some limitations. In particular, alternative model specifications, such as multivariate GARCH models, could be considered as a robustness check. Further, policy announcements, other than those made during

Table 13
Benchmark model including ECO (Volatility).

Variables	Whole sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ECO	From
MAC	60.65	1.07	0.39	0.05	0.02	37.83	39.35
ISE.Wind	1.13	97.00	0.06	0.00	0.01	1.81	3.00
Crude Oil	3.35	0.27	87.86	0.09	0.06	8.37	12.14
Coal	0.05	0.00	0.39	98.83	0.73	0.00	1.17
Gas	0.05	0.04	0.46	0.28	98.89	0.28	1.11
ECO	35.90	1.65	1.12	0.00	0.01	61.32	38.68
Directional to others	40.47	3.04	2.41	0.42	0.83	48.28	95.45
Net Directional Con.	1.12	0.03	−9.73	−0.75	−0.27	9.60	**15.91**
	First Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ECO	From
MAC	49.78	14.68	6.28	0.01	0.14	29.10	50.22
ISE.Wind	15.25	56.32	8.73	0.05	0.28	19.37	43.68
Crude Oil	4.51	14.23	70.42	0.02	0.08	10.73	29.58
Coal	0.15	0.09	0.44	93.01	6.19	0.13	6.99
Gas	0.05	1.93	0.62	0.53	96.42	0.44	3.58
ECO	22.46	19.96	9.33	0.02	0.16	48.07	51.93
Directional to others	42.43	50.90	25.39	0.63	6.84	59.77	185.97
Net Directional Con.	−7.78	7.22	−4.18	−6.35	3.26	7.84	**30.99**
	Second Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ECO	From
MAC	44.26	0.40	18.72	0.04	0.04	36.53	55.74
ISE.Wind	1.69	94.16	2.02	0.02	0.01	2.09	5.84
Crude Oil	15.17	0.93	55.86	0.02	0.04	27.98	44.14
Coal	0.27	0.01	0.02	98.84	0.74	0.12	1.16
Gas	0.03	0.04	0.24	0.19	99.43	0.07	0.57
ECO	28.13	1.10	26.36	0.02	0.05	44.34	55.66
Directional to others	45.28	2.49	47.36	0.30	0.89	66.80	163.11
Net Directional Con.	−10.45	−3.35	3.22	−0.87	0.32	11.13	**27.18**
	Third Sub-sample						
	MAC	ISE.Wind	Crude Oil	Coal	Gas	ECO	From
MAC	54.67	9.34	0.15	0.64	0.77	34.43	45.33
ISE.Wind	20.86	57.23	0.24	0.02	0.02	21.63	42.77
Crude Oil	0.14	0.08	98.73	0.37	0.52	0.16	1.27
Coal	0.42	0.01	1.63	93.69	4.18	0.07	6.31
Gas	1.63	0.04	0.56	0.94	96.67	0.16	3.33
ECO	34.03	11.17	0.14	0.07	0.07	54.51	45.49
Directional to others	57.09	20.63	2.73	2.03	5.56	56.45	144.49
Net Directional Con.	11.76	−22.14	1.47	−4.28	2.23	10.97	**24.08**

Note: The table reports in each case the contributions from i to j. The row "Directional to others" shows the spillover effects from each variable to all others, while the last column, "From", reports the total spillover received by each variable from all others. The total connectedness is in bold.

COP meetings, could be included since they could also affect the degree of connectedness between the stock indices and volatilities considered.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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