Finance Research Letters 70 (2024) 106315

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

The connectedness features of German electricity futures over short and long maturities

Angelica Gianfreda [a,b], Giacomo Scandolo [c,*], Derek Bunn [d,b]

[a] Department of Economics and Management, University of Padua, via del Santo 33, 35123, Padova, Italy
[b] Energy Markets Group, London Business School, London, United Kingdom
[c] Department of Economics, University of Florence, via delle Pandette 32, 50127, Firenze, Italy
[d] Department of Management Science and Operations, London Business School, Regent's Park, London, NW1 4SA, United Kingdom

ARTICLE INFO

MSC:
C13
C32
C44
C58
F36
Q41

Keywords:
Electricity futures
Contagion
Commodities
Energy crises
Connectedness
Sentiment

ABSTRACT

This research provides an extensive characterization of the contagion between electricity, energy commodities, financial assets and economic indicators across several maturities. Despite the widespread importance of electricity futures, this has been an under-researched topic. The evolution of connectedness is investigated between 2006 and 2023. With a special focus on electricity forward base and peak contracts, results show that the contagion effects are moderate but evolve through time, with greater impacts observed during the crisis years. We confirm that electricity forward prices are more sensitive to operators' future expectations on fundamental market conditions than to financial and economic shocks.

1. Introduction

Electricity futures have wide-ranging economic and social ramifications. For the operators, hedging forward is essential for supply chain resilience and risk management optimization; for the energy regulators, retail price controls, if applied, are usually benchmarked against the forward purchasing of retailers; and for investors in energy commodities, the trading of power futures alongside gas and other commodities, adds a useful component to their portfolios. Despite all these implications, the characteristics of electricity futures across the range of its maturities have been surprisingly under-researched. In particular, from a financial economics perspective, the extent to which electricity is idiosyncratic, relating mainly to the specificities of its operational constraints, or whether it has become more connected to wider economic factors and the contagion of financial sentiment, is an open question. At the beginning of this century, the issue of the financialization of oil was a major topic, as portfolio investors caused it to acquire more of the characteristics of financial assets. Thus, it is timely to investigate if similar features are emerging in electricity. The dominant research has generally been on short term maturities, mostly close to delivery, by analysing day-ahead prices, volatility spillovers or the connectedness among the stock prices of energy firms (Nazlioglu et al., 2013; Figueiredo et al., 2016; Gianfreda et al., 2016; de Menezes et al., 2016; Apergis et al., 2017; Gugler et al., 2018; Chuliá et al., 2019; Do et al., 2020; Han et al., 2020; Gong and Xu, 2022; Uribe et al., 2022; Ma et al., 2022; Dai et al., 2023; Sikorska-Pastuszka and Papiez, 2023; Lyu et al., 2024; among many others).

* Corresponding author.
E-mail address: giacomo.scandolo@unifi.it (G. Scandolo).

https://doi.org/10.1016/j.frl.2024.106315
Received 29 May 2024; Received in revised form 13 October 2024; Accepted 15 October 2024
Available online 23 October 2024
1544-6123/

Empirical findings have emphasized that the overall connectedness among electricity markets and between electricity and fuel markets is time-varying and sensitive to structural changes in the markets, such as the increasing penetration of renewable energy sources, or fluctuations in exchange rates, and to economic and geopolitical events. Only a few papers have inspected electricity futures with longer maturities; see Bunn and Gianfreda (2010), Jaeck and Lautier (2016) and Wang et al. (2019), but these have not looked at broader contagion with longer maturities. A more extensive analysis of this question is therefore the motivation for this research. Since we are interested in assessing the degree of connectedness between electricity, energy commodities, financial assets and economic indicators, we adopt the Diebold and Yilmaz (2012) approach first in its static estimation, and then we map the evolution of the interconnectedness using a rolling window approach. The time-varying dynamics provide useful insights about the sensitivities of electricity forward prices. We look at a range of maturities from day ahead to 3 years. The paper is accordingly structured as follows. Section 2 describes the data used in our analysis. Section 3 recalls the methodology implemented, whereas results are presented and discussed in Section 4. Finally, Section 5 concludes.

2. Data

We analyse the German power market since it is the most liquid market in Europe. In particular, we use the German Phelix power futures traded at EEX, which have only financial fulfilment. Note that these are quoted ‘futures’ prices and not ‘auction’ prices. Auction-based, day-ahead prices are commonly used as spot prices and are reported elsewhere on the EPEX platform.[1] Instead, in this analysis, we use ‘futures’ or ‘derivatives’, and, to be precise, these are reported as the EEX European Power Futures for Germany; that is the *EEX German Power Futures*.[2] These prices are determined at the end of the day (‘EoD’) as normal. Hence, all prices and indexes in the empirical investigation are properly synchronized. We use their daily settlement prices for both base and peak periods, and contracts covering short-term (day and week) and standard (month and year) maturities. Base contracts involve all 24h for all days over the selected maturity, whereas peak contracts refer to the daytime hours from 8 to 20 for Monday to Friday only. We investigate the connectedness between electricity, energy commodities, financial assets, and economic indicators. Among the energy assets, we consider futures for the ICE Europe Brent for crude oil, the TTF for natural gas, the ICE API2 CIF ARA for coal, and the EUA carbon emissions. As for the financial assets, we use the $/€ exchange rates, the VIX volatility index, and the DAX30. Furthermore, to account for trends in economic sentiment, we consider the Google trend indicator for the German economic situation (GTEPI[3]); for the growth in renewable energies, we use the RENIXX price index, which is a global stock index tracking the 30 largest world companies in the renewable energy sector; and to account for the geopolitical risk, we use the GPR indicator provided by Caldara and Iacoviello (2022). The dataset covers several years with time series differing in length according to the maturities investigated. These are derived from the EEX Power Futures, that is: one day-ahead (1 DA); one, two and three week-ahead (1-2-3 WA); one, three and six month-ahead (1-3-6 MA); and one, two and three years ahead (1-2-3 YA) when both electricity base and peak periods are considered. When short maturities are not available for other assets, we use the first available contract (for instance we use 1 month ahead crude oil futures in the analysis of day- and week-ahead contracts). Alternatively, when longer maturities are not available, we use the previous available contract or the average price of relevant contracts (for instance 2 year ahead crude oil future price is obtained as the average price of the first 24 month-ahead contracts). Missing observations have been interpolated as necessary. Finally, since there are no financial trades on weekends and holidays, they have been excluded; hence, all our series have daily frequency with five observations per week. Electricity Futures have been obtained from EEX, the German economic perception index was downloaded from `www.trendecon.org`, and the daily geopolitical risk indicator for Europe (GPR) from `www.matteoiacoviello.com`. All other time series have been collected from Refinitiv. Table 1 presents the relevant information on the futures contracts; whereas, details on missing observation treatments, descriptive statistics of the time series and their plots are provided in Appendix A. We analyse the data as simple returns.[4] Descriptive statistics of electricity return series are reported in Table 2, together with the Augmented Dickey–Fuller (ADF) test. Because of the pandemic period 2020–2021 and the energy crisis resulting from the Ukraine war beginning in 2022, we investigated the connectedness not only on the whole sample but also on a subset from January 01, 2020 to December 29, 2023. All sample sizes are indicated across maturities in Tables 3–4.

3. Methodology

We adopt the approach in Diebold and Yilmaz (2012). Recalling their framework, a covariance stationary VAR(p) model for a N-dimensional time series $\mathbf{x}_t$ with $p \geq 1$ lags is specified as $\mathbf{x}_t = \sum_{k=1}^{p} \boldsymbol{\Phi}_k \mathbf{x}_{t-k} + \boldsymbol{\varepsilon}_t$, where each $\boldsymbol{\Phi}_k$ is an $N \times N$ matrix and $\boldsymbol{\varepsilon}_t$ is an IID sequence of N-dimensional disturbances with nil mean and covariance matrix Σ. Under appropriate, mild conditions on the matrices $\boldsymbol{\Phi}_k$, the model can be rewritten as an infinite moving average $\mathbf{x}_t = \sum_{k=0}^{\infty} A_k \boldsymbol{\varepsilon}_{t-k}$. In the above representation, the $N \times N$ matrices A_k are defined recursively by A_0 being the identity matrix and by $A_k = \sum_{m=1}^{p} \boldsymbol{\Phi}_m A_{k-m}$ for $k \geq 1$, where, in the previous summation, A_{k-m} is the zero matrix when $k - m < 0$. Given an horizon $H \geq 1$, Pesaran and Shin (1998) propose a generalized

[1] Available at https://webshop.eex-group.com/data-type/de-day-ahead-auction-prices-and-volumes-eod.

[2] These can be collected from https://webshop.eex-group.com/data-type/eex-german-power-futures-eod.

[3] As described on the website, this indicator includes search terms that reflect popular concerns about the economy; considering, for instance, ‘economic crisis’, ‘short-time work’, ‘unemployment’, or ‘insolvency’. For this reason, we consider it as a general economic sentiment index for Germany.

[4] Note that for this reason, we have shifted GTEPI up by 5.2 units to have only positive values.

Table 1
Summary information on employed daily futures contracts.

Acronym	Assets	Units	Future contracts
ELE	Electricity	€/MWh	Base & peak: 1 DA, 1-2-3 WA, 1-3-6 MA 1-3-6 YA
COAL	Coal ICE API2 CIF ARA	$/MT	1MA (used for DA & WAs) 1-3 MA 2QA (used for 6 MA) 1-2-3 YA
OIL	ICE Europe Brent crude oil	c$/bbl	1MA (used for DA & WAs), 1-3-6 MA, 12 MA (used for 1YA), 24 MA (used for 2 YA), 36 MA (used for 3 YA)
GAS	TTF natural gas	€/MWh	1 DA, 1 WA (1 WA used for 2WA, 1MA used for 3WA), 1-3 MA, 2QA (used for 6 MA), 1-2-3 YA
CO2	EEX-EU CO_2 Emissions & FEUA	€/t	1 DA, 1-3-6 MA, 12 MA (used for 1 YA)
VIX	CBOE Volatility Index	index	1MA (used for DA & WAs), 1-3-6 MA, 10 MA (used for 1YA)
EXC	US $ to €	exchange rate	1DA, 1-2-3 WA, 1-3-6 MA, 1-2-3 YA

Table 2
Descriptive statistics for electricity power futures returns.

		Mean	St.Dev	Max	Min	Skew	Kurt	ADF
Base	1DA	0.0658	0.5553	11.6892	−0.8665	8.932	134.233	−96.239***
	1WA	0.0039	0.0864	0.9733	−0.5510	1.859	22.928	−72.879***
	2WA	0.0026	0.0655	0.5238	−0.5023	1.146	17.757	−59.247***
	3WA	0.0020	0.0567	0.6244	−0.4148	1.653	25.854	−60.346***
	1MA	0.0007	0.0380	0.4952	−0.2869	1.837	23.645	−64.045***
	3MA	0.0007	0.0339	0.4745	−0.2987	1.834	31.369	−64.763***
	6MA	0.0006	0.0324	0.4470	−0.3821	0.905	38.443	−61.889***
	1YA	0.0004	0.0211	0.3161	−0.2877	0.086	44.169	−55.743***
	2YA	0.0003	0.0167	0.2023	−0.2573	−1.242	42.021	−57.267***
	3YA	0.0002	0.0133	0.1257	−0.1902	−0.205	24.863	−53.943***
Peak	1DA	0.1008	0.7564	15.7061	−0.9178	9.031	127.196	−117.801***
	1WA	0.0036	0.0825	0.8081	−0.5642	1.003	15.008	−69.004***
	2WA	0.0026	0.0654	0.5273	−0.4904	1.052	18.554	−62.893***
	3WA	0.0021	0.0594	0.8181	−0.3926	2.484	37.101	−67.953***
	1MA	0.0008	0.0404	0.5484	−0.2662	2.429	29.910	−66.428***
	3MA	0.0007	0.0352	0.5391	−0.2991	2.398	40.896	−63.603***
	6MA	0.0006	0.0326	0.5211	−0.4624	0.651	43.470	−63.998***
	1YA	0.0003	0.0187	0.2351	−0.3026	0.089	51.727	−55.545***
	2YA	0.0002	0.0151	0.1648	−0.2247	−0.846	50.820	−60.399***
	3YA	0.0002	0.0112	0.1437	−0.2131	−0.751	48.563	−57.631***

*** Denotes significance at the 1% level.

decomposition of the total H-step-ahead error variance in forecasting x_i. Specifically, the "fraction" of this total variance due to a shock to the component x_j (at time t and equal to the standard deviation of ε_j) is given by

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

where σ_{jj} is the jth diagonal element in Σ (i.e. the variance of ε_j) and e_i denotes the N-dimensional vector, with 1 for i and 0 elsewhere. Since $\sum_{j=1}^{N} \theta_{ij}^{g}(H)$ need not be unity, the quantity $\theta_{ij}^{g}(H)$ must be normalized, thus obtaining $\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{k=1}^{N} \theta_{ik}^{g}(H)}$. Diebold and Yilmaz (2012) define the *Total Spillover Index* (TSI) as

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

They define the measurement of *directional* spillovers as follows. For fixed i and j,

$$S^g_{i\cdot}(H) = \frac{100}{N}\sum_{\substack{k=1\\k\neq i}}^{N}\tilde{\theta}^g_{ik}(H) \qquad\qquad S^g_{\cdot j}(H) = \frac{100}{N}\sum_{\substack{k=1\\k\neq j}}^{N}\tilde{\theta}^g_{kj}(H)$$

measure the amount of directional volatility spillovers transmitted, respectively, to x_i FROM all other components, and from x_j TO all other components. In our analysis, we consider the simple returns $x_{t,i} = \frac{P_{t,i}-P_{t-1,i}}{P_{t-1,i}}$, where $P_{t,i}$ is the settlement price or the index value for $i = 1,\dots,N$ with $N = 11$ for the analysis over the whole set of electricity, energy, financial assets and economic indicators, whereas $N = 6$ when we use only the energy assets and the geopolitical risk indicator. We perform both static and dynamic analyses. In the dynamic investigation, we estimate a VAR(p) over a rolling window of 260 daily observations and use the Bayesian Information Criterion to select p within the range 1 to 5 (our data frequency); and we observe that $p = 5$ is always selected. Accordingly, we also perform the static analysis by estimating a VAR(5) on the selected samples. As in previous studies, we fix the horizon H at 10 days. Estimations have been undertaken in MatLab using the commands VARM and FEVD from the econometrics toolbox.

4. Empirical results

Our results report, for the first time, the connectedness in the information spillovers between electricity, energy and financial futures, together with economic indicators, across short, medium, and long-term maturities, with a focus on both base and peak electricity contracts. In this way, we are able to identify the extent to which variations in simple electricity returns are influenced by the dynamics of variations in energy, financial and economic indicators.

4.1. Static connectedness

We first consider all assets and indexes, then we restrict the further investigations only to electricity, energy assets and geopolitical risk. Results for base electricity contracts are reported in Table 3, whereas those for peak contracts are in Table 4. Given our interest in electricity and its risk sources, we have collected only the first rows of all connectedness tables, adding the information *FROM others*, *TO others* and the Total Spillover Index *TSI* in three columns. In this way, we are able to compare the levels of linkages across maturities. Each entry in columns 3–12 represents the estimated contribution to the forecast error variance of the electricity contracts coming from the innovations to the asset j. For instance, the first row shows that 95.27% of the total variation in electricity one day-ahead returns is due to its own shocks, whereas coal contributes only for 0.56%, oil for 0.08%, CO_2 for 0.17%, natural gas for 0.35%, DAX for 0.18%, exchange rates for 0.14%, the economic perception for 0.21%, the renewable energy index for 0.23%, VIX for 0.32% and the geopolitical risk for 2.5%. This can be seen to be the highest contribution across maturities. In general, we observe that all energy, financial and economic assets have an extremely low contribution to the forecast error variance of the electricity futures. The assets with a marginal relevance of 10%–30% are natural gas futures, and more for base than for peak contracts when the analysis is restricted to only energy assets over the reduced sample 2020–2023. The spillovers *FROM others* are the directional spillovers received by electricity from all other assets (that is 0.0473*100/11 = 0.43) and indexes are indeed very low and marginal (against the maximum value of 9.1 = 100/11). This fraction raises in the reduced sample when only energy and geopolitical risk are considered. Similarly in the directional *TO others*, we can see that the directional spillovers transmitted by electricity to all other assets/indexes are also very low (0.4614 against 90.91 = 100*10/11 the maximum amount of electricity shocks transmitted to all other assets. Considering the total spillovers in the last columns, the TSI values ranging between 4 and 30 for both base and peak periods show that, on average, there is low total forecast error variance coming from spillovers across the futures contracts of these assets and indexes; with higher contagion during the crisis years, as also noted in Abdullah et al. (2023). As expected and consistently across maturities, our average spillover indexes assess limited transfers to the other futures and indexes, confirming a view that electricity is an idiosyncratic product with its own characteristics, more driven by its own fundamental factors (capacity, congestions, generation mix and forecasted levels of demand) than interdependencies with other markets. Indeed, our results show that the cross variance shares (defined as the fractions of the 10-step-ahead error variances in forecasting electricity simple returns on all maturities) are due to shocks within electricity itself and not to shocks in other assets/indexes. In detail, the own-variable effects account for a minimum of 57.50% and 61.57% to a maximum of 96.28 and 96.31% in base and peak contracts, respectively. From the low averaged TSI values, we deduce that there is a limited connection across the various futures and indexes over the samples investigated. This suggests the useful conclusion that in a portfolio context, electricity assets can introduce value by having lower correlated returns, hence supporting the previous findings in Naeem et al. (2020).

4.2. Dynamic connectedness

The static connectedness analysis might mask the dynamic evolution of all our connectedness measures. Given the COVID-19 pandemic and the Russian invasion of Ukraine, we have estimated the spillovers using a 260-day rolling window approach to assess the spillover variation over time and we have inspected the corresponding time series. Our inspections unveil the dependence structure and information spillover mechanisms between the electricity and other assets, showing that differences are more clearly visible when short and long horizons are contrasted. The *total spillover plots* are represented in Fig. 1 when several maturities are considered for base electricity contracts, assets and indexes. We quantify an overall connectedness between a minimum of 26.20

Table 3
Spillovers for electricity base contracts across maturities & assets. Samples for simple returns start on: 23 Nov 2012 for 1DA, for a total of 2974 observations; 5 Jan 2015 for 1-2-3WA, for a total of 2270 observations; 3 Jan 2006 for 1-3-6MA and 1-2-3YA, for a total of 4544 observations. The reduced sample starts on 2 Jan 2020 and ends on 29 Dec 2023, with a total of 1013 observations.

	ELE	COAL	OIL	CO2	GAS	DAX	EXC	EPI	REN	VIX	GPI	FROM	TO	TSI
All samples (N = 11)														
1DA	0.9527	0.0056	0.0008	0.0017	0.0035	0.0018	0.0014	0.0021	0.0023	0.0032	0.0249	0.4302	0.4614	13.1100
1WA	0.8715	0.0218	0.0049	0.0107	0.0691	0.0027	0.0009	0.0029	0.0074	0.0023	0.0057	1.1678	1.1400	16.9861
2WA	0.8030	0.0333	0.0057	0.0295	0.1017	0.0032	0.0022	0.0017	0.0085	0.0045	0.0067	1.7906	1.7866	18.2360
3WA	0.7911	0.0471	0.0079	0.0226	0.1047	0.0033	0.0032	0.0023	0.0054	0.0033	0.0091	1.8991	2.0576	18.6148
1MA	0.8758	0.0711	0.0107	0.0005	0.0335	0.0006	0.0008	0.0005	0.0041	0.0008	0.0015	1.1289	1.1612	14.3465
3MA	0.7262	0.0498	0.0093	0.0007	0.2081	0.0003	0.0012	0.0004	0.0015	0.0005	0.0021	2.4893	2.4655	18.6019
6MA	0.7655	0.0420	0.0148	0.0003	0.1691	0.0020	0.0003	0.0006	0.0039	0.0013	0.0003	2.1316	2.2232	18.0490
1YA	0.7989	0.1126	0.0264	0.0284	0.0160	0.0058	0.0008	0.0009	0.0070	0.0012	0.0019	1.8284	1.8768	14.2726
2AY	0.7597	0.0127	0.0272	0.0316	0.1431	0.0113	0.0015	0.0013	0.0080	0.0015	0.0021	2.1844	2.1001	14.9806
3YA	0.7545	0.0070	0.0261	0.0341	0.1544	0.0126	0.0010	0.0012	0.0063	0.0017	0.0011	2.2316	2.3465	15.4751
Only energy assets over the whole reported samples (N = 6)														
1DA	0.9628	0.0058	0.0009	0.0017	0.0034						0.0254	0.6203	0.6111	4.8230
1WA	0.8864	0.0214	0.0043	0.0105	0.0717						0.0057	1.8935	1.7997	8.2404
2WA	0.8185	0.0334	0.0058	0.0291	0.1064						0.0068	3.0242	3.1628	10.5888
3WA	0.8057	0.0469	0.0076	0.0226	0.1084						0.0087	3.2385	3.4544	11.0771
1MA	0.8831	0.0706	0.0105	0.0004	0.0339						0.0015	1.9490	2.0666	5.3394
3MA	0.7297	0.0491	0.0091	0.0006	0.2095						0.0020	4.5057	4.4863	12.1971
6MA	0.7725	0.0421	0.0150	0.0002	0.1699						0.0003	3.7916	4.0095	10.8073
1YA	0.8123	0.1142	0.0263	0.0289	0.0163						0.0020	3.1290	3.3313	8.5842
2YA	0.7783	0.0130	0.0279	0.0322	0.1463						0.0022	3.6947	3.5576	9.3117
3YA	0.7729	0.0073	0.0272	0.0348	0.1567						0.0011	3.7847	4.0665	10.0493
Over the reduced sample (N = 11)														
1DA	0.9276	0.0070	0.0006	0.0044	0.0077	0.0057	0.0067	0.0031	0.0088	0.0085	0.0199	0.6583	0.5715	20.9569
1WA	0.7996	0.0278	0.0084	0.0246	0.0869	0.0077	0.0062	0.0027	0.0121	0.0086	0.0152	1.8214	1.6611	23.7221
2WA	0.7205	0.0341	0.0082	0.0393	0.1454	0.0098	0.0078	0.0038	0.0114	0.0057	0.0139	2.5406	2.5641	25.3915
3WA	0.7135	0.0513	0.0121	0.0285	0.1395	0.0069	0.0098	0.0030	0.0107	0.0071	0.0176	2.6049	2.9381	25.7466
1MA	0.7548	0.0901	0.0239	0.0478	0.0437	0.0090	0.0066	0.0031	0.0100	0.0045	0.0065	2.2294	2.2230	23.0265
3MA	0.5750	0.0630	0.0206	0.0308	0.2741	0.0076	0.0120	0.0019	0.0075	0.0007	0.0068	3.8634	4.2958	30.4048
6MA	0.6333	0.0593	0.0124	0.0274	0.2372	0.0068	0.0079	0.0062	0.0072	0.0017	0.0007	3.3340	3.5564	28.5432
1YA	0.7476	0.0854	0.0187	0.1027	0.0180	0.0015	0.0088	0.0031	0.0089	0.0022	0.0030	2.2944	2.5306	22.7020
2YA	0.6796	0.0056	0.0206	0.1181	0.1441	0.0050	0.0121	0.0030	0.0052	0.0027	0.0041	2.9126	2.8227	24.9391
3YA	0.6646	0.0099	0.0189	0.1266	0.1439	0.0099	0.0136	0.0037	0.0024	0.0041	0.0026	3.0493	3.3359	25.6052
Only energy assets on the reduced sample (N = 6)														
1DA	0.9574	0.0087	0.0011	0.0045	0.0070						0.0212	0.7096	0.6423	6.3455
1WA	0.8320	0.0275	0.0077	0.0250	0.0928						0.0151	2.7999	2.6828	10.6681
2WA	0.7497	0.0349	0.0083	0.0370	0.1558						0.0143	4.1718	4.4929	13.7082
3WA	0.7426	0.0527	0.0116	0.0283	0.1478						0.0170	4.2901	4.7756	14.0538
1MA	0.7871	0.0896	0.0252	0.0473	0.0451						0.0057	3.5479	3.8466	10.9727
3MA	0.5923	0.0656	0.0208	0.0330	0.2825						0.0058	6.7944	7.6471	22.6448
6MA	0.6493	0.0616	0.0117	0.0295	0.2473						0.0006	5.8443	6.2870	19.2884
1YA	0.7665	0.0870	0.0185	0.1065	0.0184						0.0031	3.8919	4.3833	11.7918
2YA	0.6953	0.0055	0.0208	0.1204	0.1539						0.0041	5.0791	4.9899	14.9874
3YA	0.6910	0.0095	0.0205	0.1332	0.1434						0.0024	5.1493	5.8870	16.2893

and a maximum of 59 for base contracts; and between 26.42 and 58.38 for peak contracts; with all other dynamics reported in Appendix A. In general, we observe that the TSIs increase with maturity, and clearer dynamics are evident over year-ahead contracts. In addition, we see that the dynamic total connectedness reaches its extraordinary high levels in March 2020, at the beginning of the COVID-19 pandemic when demand levels were extremely low, thus making electricity markets more sensitive to news and consequently more connected to other markets (Mazur et al., 2021; Zhang and Wang, 2022). We have investigated the estimated contribution to the forecast error variance of electricity simple returns coming from the innovations to simple returns of electricity itself, coal, oil, gas, CO_2, RENIXX, VIX, DAX30, exchange rates, the economic perception index, and the geopolitical risk indicator. Results clearly show that the electricity spillover due to its own contribution decreases with maturity, hence confirming more connection with other markets as soon as the increasing horizon makes structural fundamental factors less relevant (Fig. 1). When we look at other fundamental power drivers, it is interesting to observe that the time-varying connections with coal and gas show maximum values of 25% (30% in peak) and 25%, and again that the linkages are increasing with longer maturities (Fig. 2). In Fig. 3, spillovers from CO_2 to electricity show maxima values of about 25% with remarkable increments when moving from DA to YA contracts. In 2018, we observe only substantial self-induced electricity spillovers especially in the short term maturities, whereas those from coal, oil and CO_2 drop because Germany reduced energy consumption in response to increased fuel prices, mild weather conditions and better energy efficiency (Fraunhofer, 2018, at https://www.energy-charts.de/ren_share_de.htm). We also

Table 4
Spillovers for electricity peak contracts across maturities & assets. Samples for simple returns start on: 23 Nov 2012 for 1DA, for a total of 2974 observations; 5 Jan 2015 for 1-2-3WA, for a total of 2270 observations; 3 Jan 2006 for 1-3-6MA and 1-2-3YA, for a total of 4544 observations. The reduced sample starts on 2 Jan 2020 and ends on 29 Dec 2023, with a total of 1013 observations.

	ELE	COAL	OIL	CO2	GAS	DAX	EXC	EPI	REN	VIX	GPI	FROM	TO	TSI
All samples (N = 11)														
1DA	0.9514	0.0040	0.0008	0.0020	0.0016	0.0025	0.0025	0.0012	0.0007	0.0032	0.0300	0.4420	0.4419	13.1016
1WA	0.8731	0.0255	0.0040	0.0101	0.0667	0.0027	0.0009	0.0021	0.0069	0.0009	0.0071	1.1538	1.1126	16.9778
2WA	0.8339	0.0309	0.0047	0.0254	0.0802	0.0027	0.0026	0.0017	0.0065	0.0055	0.0059	1.5100	1.4505	17.6821
3WA	0.8302	0.0342	0.0086	0.0177	0.0816	0.0023	0.0034	0.0004	0.0060	0.0051	0.0105	1.5435	1.5829	17.8386
1MA	0.8939	0.0602	0.0081	0.0005	0.0299	0.0005	0.0009	0.0005	0.0032	0.0007	0.0017	0.9647	0.9451	13.9846
3MA	0.7663	0.0413	0.0063	0.0006	0.1781	0.0012	0.0015	0.0002	0.0011	0.0002	0.0032	2.1246	1.8436	17.6938
6MA	0.8144	0.0420	0.0111	0.0001	0.1247	0.0015	0.0006	0.0015	0.0023	0.0011	0.0006	1.6871	1.6859	17.1285
1YA	0.7965	0.1291	0.0244	0.0249	0.0106	0.0037	0.0010	0.0005	0.0063	0.0011	0.0020	1.8498	1.8538	14.2734
2YA	0.7711	0.0126	0.0232	0.0283	0.1453	0.0071	0.0017	0.0011	0.0069	0.0010	0.0018	2.0813	1.9081	14.7244
3YA	0.7631	0.0057	0.0221	0.0276	0.1584	0.0100	0.0015	0.0018	0.0078	0.0014	0.0008	2.1540	2.2137	15.2841
Only energy assets over the whole reported samples (N = 6)														
1DA	0.9608	0.0041	0.0008	0.0019	0.0017						0.0308	0.6529	0.6090	4.8643
1WA	0.8855	0.0251	0.0033	0.0100	0.0687						0.0072	1.9078	1.7867	8.2491
2WA	0.8490	0.0310	0.0047	0.0249	0.0841						0.0063	2.5162	2.5812	9.5520
3WA	0.8444	0.0342	0.0083	0.0177	0.0852						0.0103	2.5939	2.5873	9.6362
1MA	0.9001	0.0598	0.0079	0.0005	0.0301						0.0016	1.6642	1.6559	4.6692
3MA	0.7706	0.0404	0.0060	0.0005	0.1794						0.0031	3.8225	3.3321	10.4874
6MA	0.8209	0.0421	0.0113	0.0001	0.1250						0.0006	2.9851	3.0640	9.1257
1YA	0.8075	0.1301	0.0242	0.0254	0.0108						0.0021	3.2075	3.3264	8.6445
2YA	0.7846	0.0126	0.0238	0.0287	0.1484						0.0019	3.5896	3.3424	9.0277
3YA	0.7812	0.0058	0.0228	0.0282	0.1611						0.0008	3.6467	3.8411	9.6931
Over the reduced sample (N = 11)														
1DA	0.9363	0.0042	0.0008	0.0033	0.0028	0.0042	0.0086	0.0025	0.0062	0.0070	0.0241	0.5794	0.5349	20.8145
1WA	0.7880	0.0358	0.0077	0.0225	0.0899	0.0077	0.0051	0.0037	0.0128	0.0050	0.0218	1.9269	1.7066	23.9020
2WA	0.7571	0.0350	0.0079	0.0312	0.1203	0.0075	0.0080	0.0040	0.0097	0.0060	0.0133	2.2083	2.1434	24.7215
3WA	0.7525	0.0374	0.0123	0.0228	0.1141	0.0075	0.0100	0.0012	0.0128	0.0086	0.0208	2.2502	2.2997	24.8461
1MA	0.7635	0.0937	0.0231	0.0352	0.0416	0.0084	0.0068	0.0040	0.0121	0.0031	0.0085	2.1500	1.9147	22.6715
3MA	0.6157	0.0609	0.0178	0.0190	0.2379	0.0100	0.0138	0.0032	0.0071	0.0005	0.0141	3.4935	3.2660	29.2223
6MA	0.6602	0.0616	0.0100	0.0194	0.2025	0.0107	0.0117	0.0085	0.0109	0.0036	0.0011	3.0892	3.0391	27.9349
1YA	0.7451	0.1050	0.0190	0.0926	0.0112	0.0006	0.0123	0.0032	0.0068	0.0012	0.0030	2.3169	2.4696	22.6686
2YA	0.6988	0.0057	0.0202	0.1043	0.1410	0.0024	0.0145	0.0039	0.0047	0.0020	0.0026	2.7384	2.4315	24.4264
3YA	0.7074	0.0061	0.0162	0.0892	0.1520	0.0054	0.0135	0.0014	0.0026	0.0024	0.0039	2.6598	2.8933	24.8789
Only energy assets on the reduced sample (N = 6)														
1DA	0.9631	0.0048	0.0010	0.0033	0.0027						0.0250	0.6148	0.6502	6.2656
1WA	0.8168	0.0353	0.0068	0.0240	0.0953						0.0218	3.0541	2.6896	10.9262
2WA	0.7851	0.0359	0.0072	0.0285	0.1287						0.0146	3.5810	3.7450	12.4232
3WA	0.7822	0.0391	0.0118	0.0225	0.1233						0.0210	3.6298	3.7923	12.4652
1MA	0.7972	0.0924	0.0245	0.0353	0.0424						0.0081	3.3803	3.2517	10.2430
3MA	0.6394	0.0624	0.0182	0.0222	0.2447						0.0130	6.0094	5.8397	20.3955
6MA	0.6871	0.0648	0.0095	0.0217	0.2160						0.0008	5.2142	5.4294	17.9135
1YA	0.7629	0.1058	0.0197	0.0975	0.0111						0.0030	3.9509	4.3524	11.8074
2YA	0.7128	0.0060	0.0205	0.1061	0.1521						0.0025	4.7865	4.4447	14.3026
3YA	0.7258	0.0058	0.0166	0.0943	0.1538						0.0038	4.5697	5.0084	14.8479

report RENIXX with its spillovers, reaching the maximum of 25% in peak between 2019 and 2020, when the shortest maturities are considered. It is worth recalling that this index works as barometer of the growing worldwide concern about climate change, providing signals of an increasing global trend towards green investments. As far as the other contributions are concerned, we observe that they are extremely low and below 10%, with GPR reaching 14% and 18% over peak 1DA and 1MA base maturities. All spillover dynamics are reported in Appendix A.

5. Conclusions

Following a comprehensive analysis, our results, as discussed above, have confirmed the special operational characteristics of electricity and the relative lack of contagion under normal circumstances between its returns and those of other energy commodities as well as between other economic indicators. Under crisis conditions, however, there is a stronger interaction, and this is intuitively consistent with evidence that geopolitical risks are closely connected with the dynamics of oil prices. A stream of literature (see Wegener et al., 2016; Ngene et al., 2021, among others) reveals the inter-relationship between oil price volatility and sovereign credit risk. Since government bond yields are often used as proxies for risk-free rates, the oil price volatility leads to a link between geopolitical risks and financial market prices. Nevertheless, from the perspective of energy investors under normal, non-crisis,

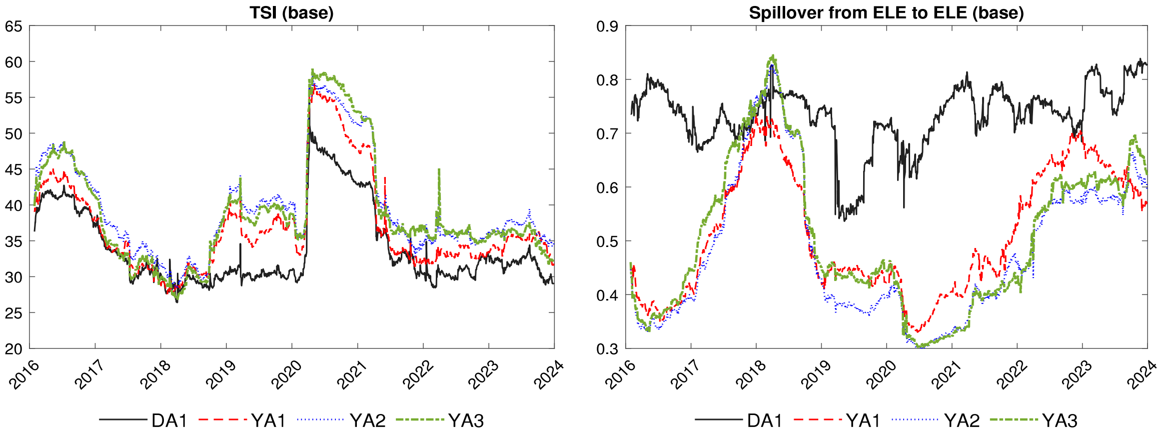

Fig. 1. On the left: Total Spillover Index plots when electricity base contracts are considered. On the right: Historical Spillovers FROM Electricity to Electricity, when one day ahead (DA1), one, two and three year ahead (YA1, YA2, YA3) are considered.

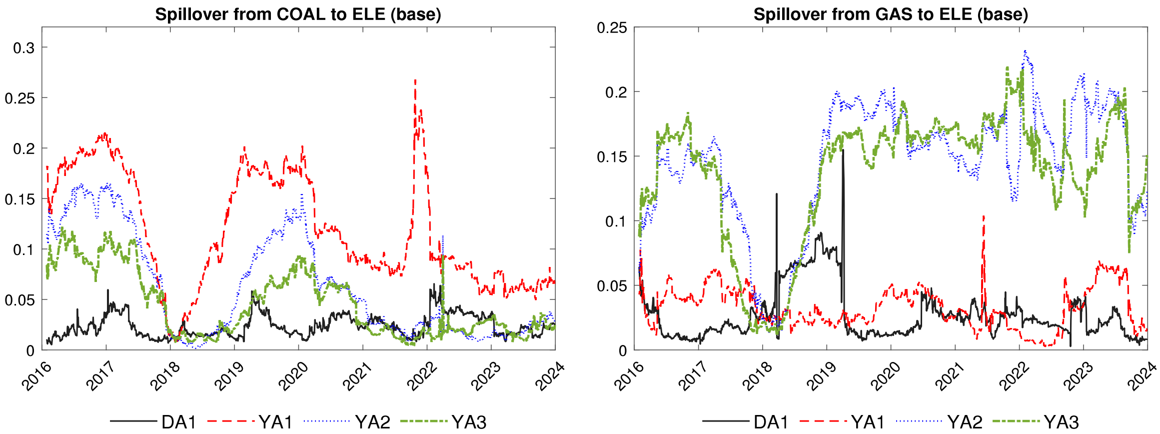

Fig. 2. Historical Spillovers FROM Coal (on the left) and FROM Gas (on the right) to Electricity, when one day ahead (DA1), one, two and three year ahead (YA1, YA2, YA3) are considered.

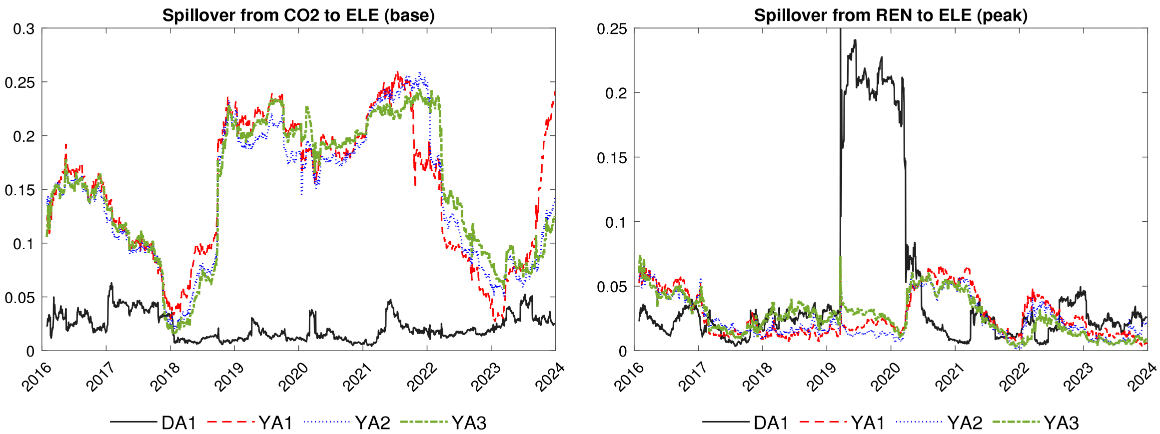

Fig. 3. Historical Spillovers FROM CO_2 to base electricity contracts (on the left) and FROM RENIXX to peak electricity contracts (on the right), when one day ahead (DA1), one, two and three year ahead (YA1, YA2, YA3) are considered.

circumstances, our results suggest that electricity futures can provide relatively uncorrelated risks within the energy investment portfolios. This result is useful in the financial economics context as it defines electricity as a distinct asset class and provides risk managers with a low correlation product. There is some evidence that contagion is slightly higher at longer maturities and that they are sensitive to environmental concerns with respect to carbon emissions and new investments in green and renewable generation. Overall, the conjecture that electricity is ready to follow oil in its commodity financialization has not (yet) been established.

CRediT authorship contribution statement

Angelica Gianfreda: Writing – original draft, Methodology, Formal analysis, Conceptualization. **Giacomo Scandolo:** Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Derek Bunn:** Writing – original draft, Methodology, Conceptualization.

Declaration of competing interest

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed.

We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We understand that the Corresponding Author is the sole contact for the Editorial process. He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.frl.2024.106315.

Data availability

The authors do not have permission to share data.

References

Abdullah, M., Abakah, E.J.A., Wali Ullah, G.M., Tiwari, A.K., Khan, I., 2023. Tail risk contagion across electricity markets in crisis periods. Energy Econ. 127, 107100.

Apergis, N., Baruník, J., Lau, M.C.K., 2017. Good volatility, bad volatility: What drives the asymmetric connectedness of Australian electricity markets?. Energy Econ. 66, 108–115.

Bunn, D.W., Gianfreda, A., 2010. Integration and shock transmissions across European electricity forward markets Energy Econ. 32 (2), 278–291.

Caldara, D., Iacoviello, M., 2022. Measuring geopolitical risk Amer. Econ. Rev. 12 (4), 1194–1225.

Chuliá, H., Furió, D., Uribe, J.M., 2019. Volatility spillovers in energy markets Energy J. 40 (3), 173–198.

Dai, Z., Tang, R., Zhang, X., 2023. A new multilayer network for measuring interconnectedness among the energy firms Energy Econ. 124, 106880.

de Menezes, L.M., Houllier, M.A., Tamvakis, M., 2016. Time-varying convergence in European electricity spot markets and their association with carbon and fuel prices Energy Policy 88, 613–627.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers Int. J. Forecast. 28 (1), 57–66.

Do, H.X., Nepal, R., Jamasb, T., 2020. Electricity market integration, decarbonisation and security of supply: Dynamic volatility connectedness in the Irish and Great Britain markets Energy Econ. 92, 104947.

Figueiredo, N.C., da Silva, P.P., Cerqueira, P.A., 2016. It is windy in Denmark: Does market integration suffer? Energy 115, 1385–1399, Towards low carbon energy systems: engineering and economic perspectives.

Gianfreda, A., Parisio, L., Pelagatti, M., 2016. Revisiting long-run relations in power markets with high RES penetration Energy Policy 94, 432–445.

Gong, X., Xu, J., 2022. Geopolitical risk and dynamic connectedness between commodity markets Energy Econ. 110, 106028.

Gugler, K., Haxhimusa, A., Liebensteiner, M., 2018. Integration of European electricity markets: Evidence from spot prices Energy J. 39 (2_suppl), 41–66.

Han, L., Kordzakhia, N., Truck, S., 2020. Volatility spillovers in Australian electricity markets Energy Econ. 90, 104782.

Jaeck, E., Lautier, D., 2016. Volatility in electricity derivative markets: the Samuelson effect revisited Energy Econ. 59, 300–313.

Lyu, C., Do, H.X., Nepal, R., Jamasb, T., 2024. Volatility spillovers and carbon price in the Nordic wholesale electricity markets Energy Econ. 134, 107559.

Ma, R., Liu, Z., Zhai, P., 2022. Does economic policy uncertainty drive volatility spillovers in electricity markets: Time and frequency evidence Energy Econ. 107, 105848.

Mazur, M., Dang, M., Vega, M., 2021. COVID-19 and the march 2020 stock market crash. Evidence from S&P1500 Finance Res. Lett. 38, 101690.

Naeem, M.A., Peng, Z., Suleman, M.T., Nepal, R., Shahzad, S.J.H., 2020. Time and frequency connectedness among oil shocks, electricity and clean energy markets Energy Econ. 91, 104914.

Nazlioglu, S., Erdem, C., Soytas, U., 2013. Volatility spillover between oil and agricultural commodity markets Energy Econ. 36, 658–665.

Ngene, G., Wang, J., Hassan, M.K., Julio, I., Yu, J.-S., 2021. Oil and sovereign credit risk: Asymmetric nonlinear dynamic interactions Emerg. Mark. Finance Trade 57 (7), 2006–2022.

Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models Economics Letters 58 (1), 17–29. http://dx.doi.org/10.1016/S0165-1765(97)00214-0.

Sikorska-Pastuszka, M., Papiez, M., 2023. Dynamic volatility connectedness in the European electricity market Energy Econ. 127, 107045.

Uribe, J.M., Mosquera-Lopez, S., Arenas, O.J., 2022. Assessing the relationship between electricity and natural gas prices in European markets in times of distress Energy Policy 166, 113018.

Wang, B., Wei, Y., Xing, Y., Ding, W., 2019. Multifractal detrended cross-correlation analysis and frequency dynamics of connectedness for energy futures markets Phys. A 527, 121194.

Wegener, C., Basse, T., Kunze, F., von Mettenheim, H.-J., 2016. Oil prices and sovereign credit risk of oil producing countries: an empirical investigation Quant. Finance 16 (12), 1961–1968.

Zhang, Y., Wang, R., 2022. COVID-19 impact on commodity futures volatilities Finance Res. Lett. 47, 102624.