



# Connectedness of energy markets around the world during the COVID-19 pandemic

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## ABSTRACT

This paper studies the connectedness among energy equity indices of oil-exporting and oil-importing countries around the world. For each country, we construct time-varying measures of how much shocks this country transmits to other countries and how much shocks this country receives from other countries. We analyze the network of countries and find that, on average, oil-exporting countries are mainly transmitting shocks, and oil-importing countries are mainly receiving shocks. Furthermore, we use panel data regressions to evaluate whether the connectedness among countries is influenced by economic sentiment, uncertainty, and the global COVID-19 pandemic. We find that the connectedness among countries increases significantly in periods of uncertainty, low economic sentiment, and COVID-19 problems. This implies that diversification benefits across countries are severely reduced exactly during crises, that is, during the times when diversification benefits are most important.

## 1. Introduction

The global COVID-19 pandemic has caused disruptions in all sectors of the economy. One of the most strongly affected sectors is the energy sector. As the general economic outlook worsened, oil prices plummeted, hitting energy sectors strongly in most countries. This unprecedented situation allows us to study what happens to the connectedness among energy sectors of countries around the world in case of a global economic crisis. Accordingly, we utilize data on the energy equity indices of 29 developed and developing countries and study the connectedness among these indices before and during this period. Hence, our paper relates to two strands of literature: the impact of COVID-19 on energy markets and the connectedness among energy markets. In particular, we aim to examine the interconnectedness in the energy sector globally as the energy market integration has increased recently through global trade and production networks. Considering that the energy sector is the center of all production processes, the global fluctuations in energy prices are quickly reflected in the stock prices of the energy companies operating locally, making the energy

companies more exposed to international spillovers, especially during elevated uncertainty. Furthermore, the COVID-19 pandemic has had a debilitating impact on global output due to the lockdown strategies of countries. Accordingly, the lockdown policy implemented in one country also affects other countries through global value chains. Energy prices are exposed to the drag from the lockdown policies, which directly influence the demand and supply conditions of the energy market. Hence, understanding how the financial performance of the countries' energy sector is connected and how shocks are transmitted during the pandemic remains an open question for portfolio managers and policymakers.

The relationship between energy and other asset classes has been extensively investigated in the literature, see, e.g., Ashfaq et al. (2019), Bašta and Molnár (2018), Bigerna et al. (2021), Cevik et al. (2020), Cui et al. (2021), Qin (2020), Jiang and Yoon (2020), Khalfaoui et al. (2019), Li et al. (2020), Liu et al. (2020), Mokni (2020), Nazlioglu et al. (2020), Pavlova et al. (2018), Qin (2020), Sarwar et al. (2020)

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and Wen et al. (2020). However, less attention has been paid to the connectedness of energy sectors of various countries. The paper most closely related to our work is Singh et al. (2019), which calculate the connectedness among MSCI energy indices. However, our paper takes the analysis one step further and studies which variables can explain the connectedness, focusing on the COVID-19 pandemic.

Recently, several studies have focused on the impact of the COVID-19 on the financial markets. During the COVID-19 pandemic, financial markets experienced increased volatility (Lyócsa et al., 2020; Lyócsa and Molnár, 2020). For instance, Guo et al. (2021) analyze the tail risk contagion and find that the COVID-19 epidemic increases the contagion channels in the financial markets. Zhang and Hamori (2021) study the connectedness among the stock market, the crude oil market, and the COVID-19 pandemic and observe that the impact of COVID-19 on the volatility of the oil and stock markets exceeds that of the 2008 global financial crisis. Sharif et al. (2020) examine the dynamic connectedness between the oil and major asset classes under several measures of uncertainties, including the spread of COVID-19, geopolitical risk, and economic policy uncertainty, and demonstrate that the spread of COVID-19 is an important driver of uncertainty.

Two recent papers closely related to our work are Corbet et al. (2020) and Szczygielski et al. (2021). Corbet et al. (2020) (p.23) argue that “The COVID-19 pandemic by itself provides an unprecedented background to re-examine spillovers between energy firms during a very sharp downturn in short-term and long-term expectations of global energy use.” and therefore, they study the connectedness among US energy stocks. With the same motivation, we investigate the connectedness among energy sectors of various countries. In terms of data, Corbet et al. (2020) and our paper complement each other. Otherwise, our paper builds upon Corbet et al. (2020) in the following aspect: while they document connectedness, we go one step further and study which factors can explain connectedness. Similarly, Szczygielski et al. (2021) examine MSCI energy indices. However, they study the impact of COVID-19 on returns and volatility of energy indices, while we focus on the impact of COVID-19 on the connectedness among MSCI energy indices. Therefore, our works complement each other.

Understanding the connectedness among energy sectors from various countries is crucial for security reasons, for policymakers from a macroeconomic perspective, as well as for investors seeking diversification benefits. The unprecedented global economic contraction due to the spread of COVID-19 has resulted in massive challenges for the whole world, and particularly for the oil-exporting countries due to the rapid decline in oil prices. The elevated uncertainties of global economies and lockdown measures have severely interrupted the global supply chain network and influenced the economic and financial activities (McKee and Stuckler, 2020). Furthermore, global shock in the financial and economic sectors triggered by COVID-19 is significantly different from the earlier financial and economic crises, including the global financial crisis and the European debt crisis. In particular, the financial stress and market uncertainties in the energy sector have led to disequilibrium in demand and supply. Therefore, understanding the impact of COVID-19 lockdown measures on the energy markets is of significant importance for both the market participants, academics, and policymakers.

This study uncovers the impact of the COVID-19 on the degree of energy markets' connectedness by incorporating a set of explanatory variables, including market sentiment and uncertainty measures. The COVID-19 pandemic is measured by the severity of lockdown, using the Oxford COVID-19 Government Response Tracker and Google Mobility Reports. We implement the spillover approach of Antonakakis et al. (2020) to compute the connectedness index for the network of energy markets around the world. Our results reveal that oil-exporting countries as net shock transmitters and oil-importing countries as net shock receivers. Furthermore, we study determinants of the connectedness among energy markets and find that energy markets worldwide become more connected when uncertainty is high and economic sentiment is

low, and also when COVID-19 problems are most severe. These results provide useful insights for not only the market participants in the energy markets but also for the policymakers.

The remainder of the paper is structured as follows. Section 2 introduces data and preliminary statistics, followed by methodology in Section 3. The results are reported in Section 4. Finally, Section 5 concludes the paper.

## 2. Data

We collect data on MSCI energy equity indices for 29 countries around the world. The selection of sample countries is based on the availability of the MSCI energy indices data. In particular, we chose the date that enables us to cover as many countries and use more historical data. Selected countries also have higher rankings based on the energy consumption data.<sup>1</sup> These indices are not available for the Middle East countries, hence there is no country from that region included in our sample. We compute the daily log-returns,  $r(t) = \ln(p_t/p_{t-1})$ , from energy index level  $p_t$ . The data is obtained from Bloomberg for the period from 23/08/2006 until 5/11/2021. Table 1 reports summary statistics for the return series of all energy indices together with the Bloomberg codes for the data and abbreviations that we use for the countries. From Table 1, we observe that most of the countries have positive mean returns. This can be attributed to our data period that covers the quantitative easing policies implemented by central banks, especially after the COVID-19 related shutdown period starting from March 2020. While Russia attains the largest maximal value of returns, the minimal value of returns is obtained by Argentina. Almost all return series are negatively skewed except for Finland, Hungary and Korea. Hence, as the mean and median values also support it, the distributions have a longer tail on the left side of the distribution. The kurtosis statistics are also high for almost all countries, showing the heavier tails as a clear indication of extreme events in the period considered.

To assess how government responses have evolved and how the extent of residents' behavior changes in each country, we construct a Lockdown index by exploiting two newly created data sets; The Oxford COVID-19 Government Response Tracker (OxCGRT) and Google Mobility Reports (GMR). The OxCGRT stringency index is computed as the average of nine sub-indexes, restrictions on gathering size, including school closing, cancellation of public events, workplace closing, closure of public transportation, restrictions on internal movement, staying at home requirements, public information campaigns and restrictions on international travel, each ranging from 0 (the least stringent) to 100 (the most stringent) responses (Hale et al., 2020). The OxCGRT data set's key advantages are its consistent cross-country approach, daily frequency and coverage (with over 73 countries included).<sup>2</sup> Besides, we use the GMR to assess how citizen mobility is shifted. The GMR also shows what has changed in reaction to policies targeting to limit the effect of the COVID-19 by creating reports on the frequency of visits to workplaces, parks, public transportation, retail centers, and residences compared to the baseline period which is an average of, January 3 -February 6, 2020.<sup>3</sup> This shows us a comprehensive picture of how residents are reacting to related government policy measures and coronavirus threat. Using the GMR data, we create an index of by taking the average change in the frequency of visits to retail centers, workplaces and public transportation. Then, we compute our Lockdown index indicator by taking the equal-weighted average of OxCGRT stringency index and the Google mobility index for a given country.

<sup>1</sup> see, <https://solarpower.guide/solar-energy-insights/countries-energy-consumption-per-capita>.

<sup>2</sup> The OxCGRT data can be downloaded from: <https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker>.

<sup>3</sup> The GMR data is publicly available on <https://www.google.com/covid19/mobility/>.

**Table 1**  
Descriptive statistics for the log-returns of 29 countries MSCI equity energy index.

Country	Bloomberg code	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB Prob.	Observations
ARGENTINA (ARG)	MXAR0EN Index	-0.0007	0.0000	0.171	-0.444	0.031	-1.62	22.41	0.00	3967
AUSTRALIA (AUS)	MXAU0EN Index	-0.0002	0.0000	0.086	-0.230	0.017	-0.99	13.65	0.00	3967
AUSTRIA (AUT)	MXAT0EN Index	0.0001	0.0000	0.187	-0.213	0.022	-0.50	10.86	0.00	3967
BRAZIL (BRA)	MXBR0EN Index	-0.0002	0.0002	0.218	-0.346	0.031	-0.77	10.75	0.00	3967
CANADA (CAN)	MXCA0EN Index	-0.0001	0.0000	0.148	-0.212	0.017	-1.12	20.85	0.00	3967
CHINA (CHN)	MXCN0EN Index	-0.0001	0.0000	0.179	-0.174	0.020	-0.04	7.75	0.00	3967
COLOMBIA (COL)	MXCO0EN Index	-0.0001	0.0000	0.133	-0.278	0.022	-0.82	13.39	0.00	3967
FINLAND (FIN)	MXFI0EN Index	0.0004	0.0000	0.213	-0.127	0.022	0.17	6.35	0.00	3967
FRANCE (FRA)	MXFR0EN Index	-0.0001	0.0003	0.140	-0.182	0.017	-0.24	12.78	0.00	3967
HUNGARY (HUN)	MXHU0EN Index	0.0000	0.0000	0.140	-0.162	0.020	0.08	7.69	0.00	3967
INDIA (IND)	MXIN0EN Index	0.0004	0.0000	0.181	-0.173	0.018	-0.22	9.93	0.00	3967
INDONESIA (IDN)	MXID0EN Index	0.0001	0.0000	0.190	-0.370	0.028	-0.16	11.56	0.00	3967
ITALY (ITA)	MXIT0EN Index	-0.0002	0.0002	0.162	-0.235	0.018	-0.62	18.21	0.00	3967
JAPAN (JPN)	MXJP0EN Index	-0.0002	0.0000	0.127	-0.144	0.019	-0.23	4.31	0.00	3967
KOREA (KOR)	MXKR0EN Index	0.0003	0.0000	0.226	-0.148	0.023	0.45	7.57	0.00	3967
MALAYSIA (MYS)	MXMY0EN Index	-0.0001	0.0000	0.078	-0.158	0.015	-0.69	8.98	0.00	3967
NETHERLANDS (NLD)	MXNL0EN Index	-0.0002	0.0000	0.169	-0.168	0.020	-0.55	11.16	0.00	3967
NORWAY (NOR)	MXNO0EN Index	0.0000	0.0000	0.128	-0.213	0.019	-0.51	7.69	0.00	3967
PAKISTAN (PAK)	MXPK0EN Index	-0.0001	0.0000	0.095	-0.084	0.016	-0.02	3.47	0.00	3967
POLAND (POL)	MXPL0EN Index	0.0001	0.0000	0.275	-0.280	0.019	-0.11	25.05	0.00	3967
PORTUGAL (PRT)	MXPT0EN Index	0.0000	0.0000	0.160	-0.180	0.017	-0.03	8.50	0.00	3967
RUSSIA (RUS)	MXRU0EN Index	-0.0001	0.0001	0.292	-0.271	0.023	-0.10	17.91	0.00	3967
SOUTH AFRICA (ZAF)	MXZA0EN Index	0.0003	0.0000	0.124	-0.139	0.023	-0.07	3.73	0.00	3967
SPAIN (SPA)	MXSE0EN Index	-0.0001	0.0000	0.167	-0.171	0.020	-0.06	8.30	0.00	3967
SWEDEN (SWE)	MXSE0EN Index	0.0000	0.0000	0.178	-0.264	0.024	-0.53	12.30	0.00	3967
TAIWAN (TWN)	MXTW0EN Index	0.0001	0.0000	0.094	-0.112	0.016	-0.06	3.74	0.00	3967
THAILAND (THA)	MXTH0EN Index	0.0000	0.0000	0.134	-0.293	0.019	-1.22	24.18	0.00	3967
TURKEY (TUR)	MXTR0EN Index	0.0004	0.0000	0.151	-0.164	0.022	-0.41	4.89	0.00	3967
USA (USA)	MXUS0EN Index	0.0000	0.0000	0.172	-0.227	0.019	-0.71	16.24	0.00	3967

Since the COVID-19 pandemic has caused severe disruptions in macroeconomic conditions, we use the daily News Sentiment Index (NSI) of Buckman et al. (2020) which is a timely proxy of economic sentiment based on counting of a string of words related to economic activity in the newspapers. More specifically, Buckman et al. (2020) construct sentiment scores from economics-related news in 16 major U.S. newspapers using the LexisNexis tool.<sup>4</sup> We also consider the Twitter-based economic uncertainty index (TEU) of Baker et al. (2020a) which is extracted by scraping English-language tweets including terms such as ‘uncertainty’, ‘economy’, ‘finance’, investor, and ‘market’ etc.,<sup>5</sup> capturing the shifts in the sentiment related to economic uncertainty in a more timely manner.

To quantify the role of news about infectious disease outbreaks, we use the daily Infectious Disease Equity Market Volatility Tracker (EMVID) constructed by Baker et al. (2020b). The EMVID index counts the number of articles including infectious disease related keywords such as coronavirus, pandemic, flu, virus, disease, and so on (the complete list of keywords can be accessible from: [https://www.policyuncertainty.com/infectious\\_EMV.html](https://www.policyuncertainty.com/infectious_EMV.html)) by searching approximately 3000 US Newspapers. Then, EMVID index is normalized by the total numbers of articles for a given day. We also rely on the CBOE Energy Sector ETF Volatility Index (VXXLE), which is computed as the implied volatility of CBOE Energy Sector ETF index options over the next 30 calendar days. This index is well-known among financial practitioners as a proxy of market expectations of near-term volatility in the energy sector. All data is downloaded from Bloomberg Terminal.

It is important to emphasize the relationship between the variables LOCKDOWN, NSI, EMVID, VXXLE and TEU. Variables EMVID, VXXLE and TEU are uncertainty measures, and therefore they are high when uncertainty is high. Periods of high uncertainty often coincide with

<sup>4</sup> Buckman et al. (2020) chose articles with at least 200 words where LexisNexis picked the country subject as “United States and” the article’s topic as “economics”. For a detailed explanation, see <https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/>.

<sup>5</sup> The full list of keywords is available at [http://www.policyuncertainty.com/twitter\\_uncert.html](http://www.policyuncertainty.com/twitter_uncert.html).

**Table 2**  
Correlations of uncertainty measures.

	LOCKDOWN	TEU	VXXLE	EMVID	NSI
LOCKDOWN	1				
TEU	0.209	1			
VXXLE	0.523	0.709	1		
EMVID	0.520	0.503	0.800	1	
NSI	-0.298	-0.830	-0.657	-0.490	1

strict LOCKDOWN, as countries impose lockdowns during most problematic periods. Therefore, these four variables should exhibit positive correlations. On the other hand, NSI is measuring overall economic sentiment, where high numbers represent positive sentiment, and low numbers represent negative sentiment. Therefore, this variable should be negatively correlated with remaining variables. Table 2 presents the actual correlation among these variables, and we see that the signs are as expected.

### 3. Methodology

#### 3.1. Dynamic connectedness index: TVP- VAR based approach

To construct the connectedness measures, we implement a time-varying parameter vector auto-regressions (TVP-VAR) model as proposed by Antonakakis et al. (2020), which is a modified version of the connectedness measure suggested by Diebold and Yilmaz (2009, 2012, 2014). The main benefit of the TVP-VAR based connectedness approach are (i) the outlier sensitivity problem is solved by employing the Kalman filter approach, (ii) it helps to overcome the arbitrarily choosing the rolling-window length, and (iii) it overcomes the issue of losing observations, hence rendering it useful for a short-samples. In particular, the TVP-VAR can be outlined as:

$$z_t = B_t z_{t-1} + u_t \quad u_t \sim N(0, S_t) \quad (1)$$

$$vec(B_t) = vec(B_{t-1}) + v_t \quad v_t \sim N(0, R_t) \quad (2)$$

where  $z_t$ ,  $z_{t-1}$  and  $u_t$  are vectors of dimension  $k \times 1$  and  $B_t$  and  $S_t$  are matrices of dimension  $k \times k$ .  $vec(B_t)$  and  $v_t$  are  $k^2 \times 1$  dimensional vectors whereas  $R_t$  is a  $k^2 \times k^2$  dimensional matrix.<sup>6</sup>

For the initialization of the Kalman filter, we utilize an uninformative prior for parameters  $B_0$  and  $S_0$ . Subsequently, the Kalman filter algorithm relies on forgetting factor controlling how the estimated parameter coefficients vary over time. Considering that our parameters are not changing significantly across periods, forgetting factor is set equal to 0.99 to maintain numerical stability as suggested by Koop and Korobilis (2014). Although it is possible to estimate forgetting factors from the data, it is computationally more demanding and the existence of value added in very limited and questionable from such a procedure (Koop and Korobilis, 2013).

Thereafter, F-step generalized forecast error variance decomposition (GFEVD) is calculated using the framework developed by Koop et al. (1996). It is important to note that GFEVD methodology is entirely independent of the ordering of the variables in contrast to the orthogonalized forecast error variance decomposition (see, Diebold and Yilmaz (2009)). Based on the Wold Decomposition theorem, TVP-VAR is converted into its vector moving average (VMA) representation by using the following equality:  $z_t = \sum_{i=1}^p B_{it} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{jt} u_{t-j}$ . The (scaled) GFEVD is obtained by normalizing the (unscaled) GFEVD,  $\psi_{ij,t}^g(F)$  so that each row adds up to one. Hence,  $\tilde{\psi}_{ij,t}^g(F)$  indicates the impact of country  $j$  has on country  $i$  regarding its forecast error variance share which is described as the *pairwise directional connectedness from country  $j$  to country  $i$* . This measure is calculated by,

$$\psi_{ij,t}^g(F) = \frac{S_{ii,t}^{-1} \sum_{l=1}^{F-1} (t_l' A_l S_l t_l)^2}{\sum_{k=1}^k \sum_{l=1}^{F-1} (t_l' A_l S_l A_l' t_l)} \quad \tilde{\psi}_{ij,t}^g(F) = \frac{\psi_{ij,t}^g(F)}{\sum_{j=1}^k \psi_{ij,t}^g(F)}$$

with  $\sum_{j=1}^k \tilde{\psi}_{ij,t}^g(F) = 1$ ,  $\sum_{i,j=1}^k \tilde{\psi}_{ij,t}^g(F) = k$ , and  $t_i$  corresponds to a selection vector with unity on the  $i$ th position and zero otherwise. Thereafter, we compute the total connectedness index through the use of the GFEVD as follows:

$$TO_{jt} = \sum_{i=1, i \neq j}^k \tilde{\psi}_{ij,t}^g(F) \tag{3}$$

$$FROM_{jt} = \sum_{i=1, i \neq j}^k \tilde{\psi}_{ji,t}^g(F) \tag{4}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{5}$$

$$TCI_t = k^{-1} \sum_{j=1}^k TO_{jt} \equiv k^{-1} \sum_{j=1}^k FROM_{jt}. \tag{6}$$

where  $\tilde{\psi}_{ij,t}^g(F)$  represents the influence of a shock in country  $j$  has on country  $i$ . As defined in Bouri et al. (2021, p.5), Eq. (3) illustrates the total influence a shock in country  $j$  has on all other countries, called as the *total directional connectedness to others*. Eq. (4) indicates the total impact of all other countries have on variable  $j$ , named as the *total directional connectedness from others*. Eq. (5) subtracts the impact of country  $j$  has on others by the impact of others have on country  $j$ , indicating the *net total directional connectedness* which provides information on whether a country is a net receiver or a net transmitter of shocks. Country  $j$  is a net transmitter (*receiver*) of shocks – and thus driving (*driven by*) the network – when the influence of country  $j$  has on others is bigger (*smaller*) than the impact of all others have on country  $j$ ,  $NET_{jt} > 0$  ( $NET_{jt} < 0$ ). Eq. (6) shows the *total connectedness index (TCI<sub>t</sub>)* that is the average influence of one country has on all others. The higher this number is the higher the inter-dependence of the network and hence the market risk is. This results from the fact that a shock given to one member of the network will propagate to whole network easily. We set the forecast horizon  $F = 10$ . We also compute the total connectedness

<sup>6</sup> The optimal 1-lag length is selected by the Bayesian information criterion (BIC).

index using alternative forecast horizons ( $F = 5, F = 15$ ). Our results are robust to the selection of forecast horizon. We present the total connectedness index for  $F = 5$  and  $F = 15$  in the Appendix A.

### 3.2. Quantile regression approach

To examine the effect of the outbreak of the COVID-19 on the total connectedness of the MSCI energy indices over different quantiles, we utilize the quantile regression (QR) technique suggested by Koenker and Bassett (1978) which presents a comprehensive understanding of the conditional distribution. Hence, this approach enables to obtain the response over the entire spectrum of the distribution. As suggested by Koenker and Hallock (2001), QR approach is more robust to outliers, heteroscedasticity and non-normality, compared to the OLS estimator.

The QR model can be outlined as:

$$TCI = x' \beta + \varepsilon \text{ with } Q_{TCI}(\tau | x) = x' \beta(\tau) \tag{7}$$

where  $TCI$  represents logarithm of the total connectedness index for MSCI energy indices,  $x$  represents the control variables including the logarithm of (1+EMVID Index), the logarithm of VXXLE Index, the logarithm of the TEU index and NSI index. Furthermore,  $Q_{TCI}(\tau | x)$  is the  $\tau$ th conditional quantile of TCI which is linearly dependent on the set of explanatory variables.

By optimizing the following minimization problem for a given quantile, the coefficients  $\beta(\tau)$  are estimated:

$$\hat{\beta}(\tau) = \arg \min \left[ \sum_{TCI \geq x' \beta} \tau |TCI - x' \beta| + \sum_{TCI < x' \beta} (1 - \tau) |TCI - x' \beta| \right] \tag{8}$$

### 3.3. Fixed effects panel regression model

To examine the determinants of the directional spillovers across countries, we estimate a panel fixed effect regression of the form:

$$Spillover_{i,t} = \alpha_i + \beta_1' Lockdown_{i,t} + \beta_2' NSI_t + \beta_3' EMVID_t + \beta_4' VXXLE_t + \beta_5' TEU_t + e_{i,t} \tag{9}$$

where  $Spillover_{i,t}$  alternatively represents the total directional connectedness to others (TO) and the total directional connectedness from others (FROM),  $Lockdown_{i,t}$  is logarithm of (1+lockdown index),  $NSI_t$  is the daily news economic sentiment,  $EMVID_t$  is the logarithm of (1+EMVID Index),  $TEU_t$  is the logarithm of Twitter-based economic uncertainty index and  $VXXLE_t$  denotes the logarithm of CBOE Energy Sector ETF Volatility Index. Some heterogeneity between countries is introduced through the time-invariant country fixed effects  $\alpha_i$ .

For the fixed effects panel regression and quantile regression, the sample period is chosen from 1 January 2020 through 5 November 2021, starting with the onset of the coronavirus and including the March period when the COVID-19 pandemic began spreading around the globe, and World Human Organization declared COVID-19 as Pandemic (11 March 2020).

## 4. Results

### 4.1. Average and dynamic connectedness measures

As it is given by Eq. (6), Total Connectedness Index (TCI) shows the influence one member of the network has on all the others on average with the implication that if this index increases then dependence between the network members and in turn the market risk increases. On the other hand, if TCI decreases then the dependence between the members decreases and hence in turn the market risk decreases. As it clear from Fig. 1, the dynamic connectedness of the MSCI energy index returns of 29 countries varies significantly over the time period from August, 2006 till November, 2020 which actually proves the necessity of the approach provided by TVP-VAR in this framework. The time dependent connectedness across the energy indices takes a minimum

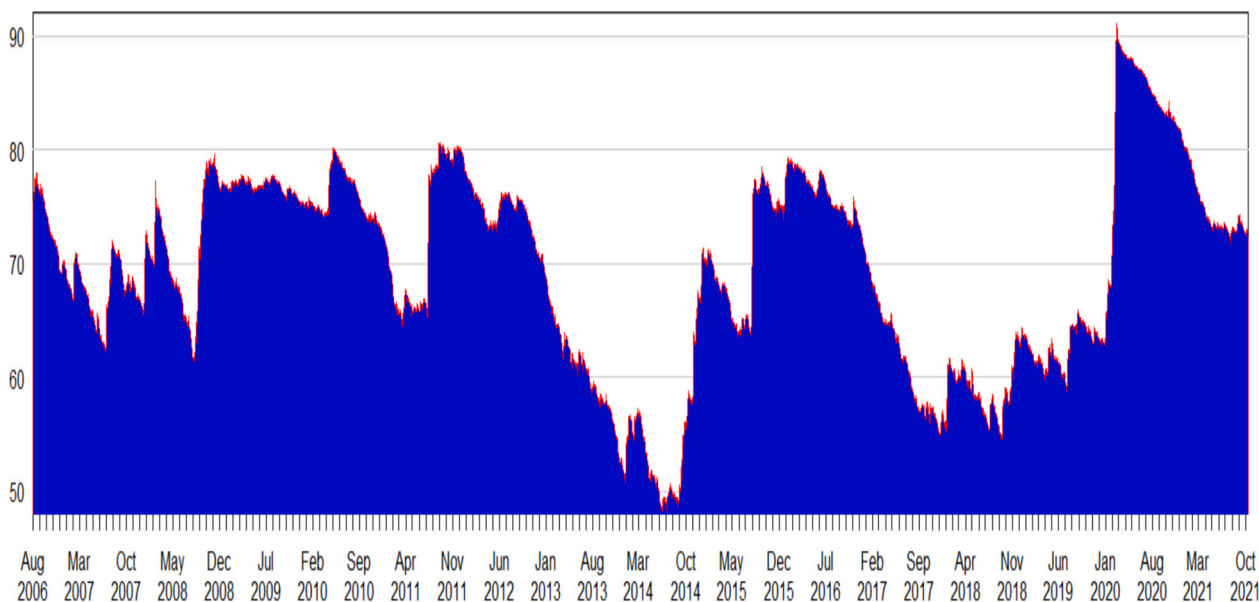


Fig. 1. Dynamic total connectedness. Results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

value of 48.22 on 30/07/2014 and in general we observe that the lowest values of TCI occur around June and July 2014. This period of lowest dependence across the countries corresponds to the 2014 plunge in import petroleum prices. Between June 2014 and January 2015, Bureau of Labor Statistics import crude petroleum index dropped 51.7 percent which is sharper than the dramatic drop at the end of 2008. Supporting this, a careful investigation of total connectedness figure also shows very low levels of interdependence towards the end of 2008.

Intuitively, we can state that the dependence between the countries diminishes with the decreasing petroleum prices which in turn results in lower market risk in the energy network of the countries. Another interesting observation from Fig. 1 is that in the last 14 years up to the March 2020, the connectedness level of around 80 stood like an artificial barrier such that many times the index reached the level of 80 but could not surpass 81. However, for the first time on 9 March 2020, the index jumps from 78.40 to 88.24 which exactly corresponds to the starting period of wide spread spillover of Covid-19 all over the world. With the increasing fears for the possibility of the second wave of infections, the index reaches a record high of 91.09 on 16 March 2020. Starting from this date, we observe a gradual decrease till the beginning of November 2021 but still they represent very high scores in the history. Clearly, after the onset of Covid-19 outbreak, because of the fast and feverish reaction towards the increasing uncertainty both at individual and country level, the overall risk in the energy markets indicated by the TCI level has attained its historical records in the last few months.

While Fig. 1 reveals the dynamic nature of the connectedness across the energy indices over time the period considered in this study, Table 3 presents the time averaged values of to, from, and net measures computed from  $\hat{\psi}_{ij,i}^s(F)$  given in the methodology section. The shocks from one component of the network to itself are represented by the numbers on the diagonal of Table 3 and the numbers on the upper and lower part of the diagonal show the spillovers among the energy indices. The column  $i$  in the table displays the impact that a shock in the energy index  $i$  has on the rest of the other indices (rows) which is described as the directional connectedness to others. The row  $j$  in the table shows the impact the rest of the variables have on the index  $j$  which is described as the total directional connectedness from others. It is also important to note that only the rows not the columns in this table sum up to unity (100%). First of all, from this table we observe that the own-variance shares of shocks for the emerging country energy

indices which are indicated by the numbers on the diagonal are in general significantly higher than the ones for the developed countries. For example, while France and Italy have percentage levels of 15.6 and 16.4, Pakistan and Turkey have percentages of 57.6 and 47.1, respectively. Furthermore we can also investigate each country's to and from measures in detail from this table. For instance, if we look at the spillovers from Argentina to others we observe that the highest values are for USA (4.6%) and Brazil (4.4%). On the other hand, in terms of the spillovers from others to Argentina again USA (7.3%) and Brazil (5.6%) constitute the largest two. This may stem from the interconnectedness of the countries because of their geographical locations. Similarly, if we examine the energy index for France, we observe the highest spillovers from France to Italy (10.3%) and from France to Spain (9.4%). On the other hand, the spillovers from Italy to France (10%) and from Norway to France (6.4%) are ranked as the largest two. Again, we can state that geographical locations play an important role in terms of spillovers transfers. In terms of the aggregated average "to measures" which are given as a separate row at the bottom of the table, US, France, and Italy are ranked top three with values 5.0%, 4.9%, and 4.6%, respectively. On the other hand, in terms of the aggregated average "from measures", again France and Italy (2.9%) together with Australia, Norway, Spain, Norway, and USA (2.8%) constitute the largest top proportion of the countries. Finally, the last row in the table shows the time averaged net total directional connectedness. Given that a net positive (negative) value means that the energy index is a net transmitter (receiver) of the shocks and hence leading (being led by) the network. We observe that USA is the largest transmitter (2.2%) which is followed by France (1.9%), Italy (1.7%), Canada (1.5%), and Norway (1.3%). On the other hand, the table also reveals that Japan is the leading receiver (-1.7%) which is followed by Australia (-1.5%) and Taiwan and S. Korea (-1.2%).

While Table 3 provides the time averaged net total directional connectedness, it may also be the case the MSCI energy index changes from transmitter to receiver (or vice versa) throughout the time. Figs. 2 and 3 help us to observe this changing behavior (if any) in time. Note that in the figures positive values of the shaded area indicate the time period where the particular energy index is a net-transmitter, on the other hand negative values correspond to the time intervals in which the energy index is a net-receiver of the shocks. First, we observe that MSCI energy indices for Australia, China, Hungary, India, Indonesia, Japan, Korea, Malaysia, Pakistan, Taiwan, Thailand, and Turkey have

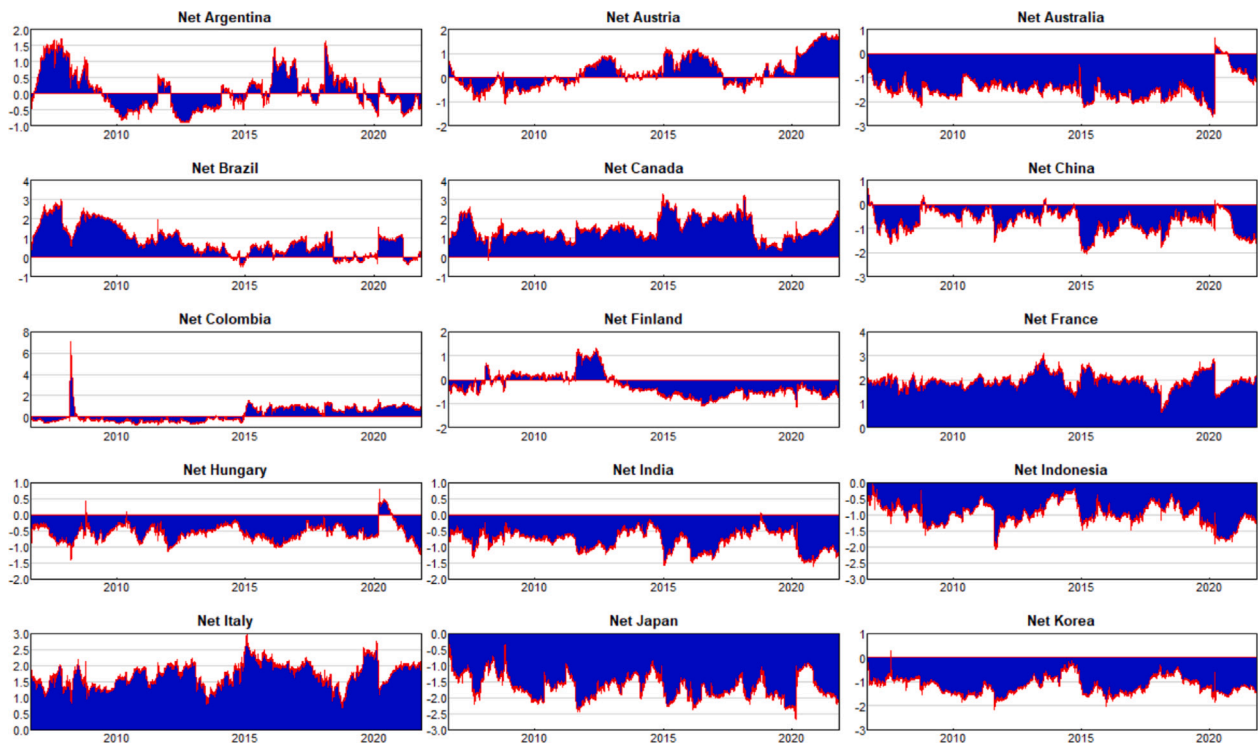


Fig. 2. Net total directional connectedness - 1. Results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

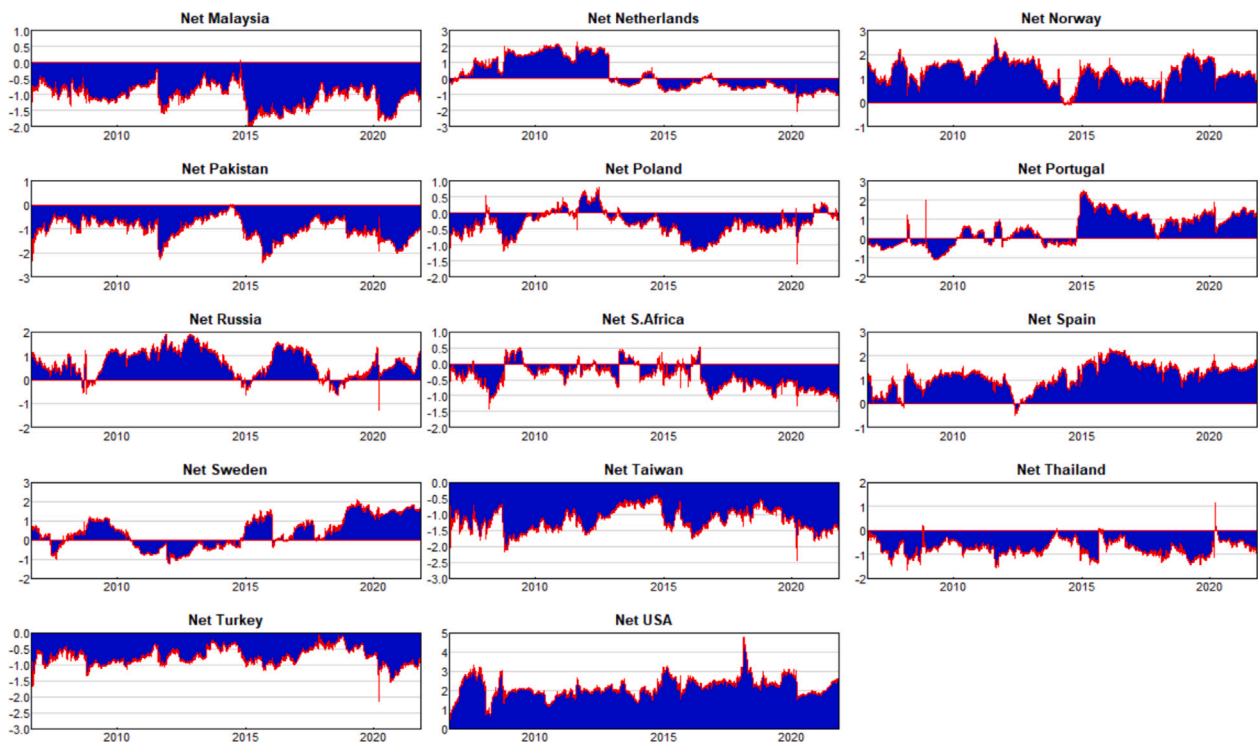


Fig. 3. Net total directional connectedness - 2. Results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

almost always been net receiver. However, it is also possible to detect that Australia and Hungary changed from net receiver to net transmitter especially after the Covid-19 outbreak. Among these countries, especially for India, Indonesia, Korea, Malaysia, Pakistan, Taiwan, and Turkey, we also observe that total net receiving percentages increase

with the onset of the infection. Figs. 2 and 3 also prove that MSCI energy indices for the countries Canada, France, Italy, Spain, and USA have almost always been net transmitter through the time. For the remaining countries, we witness an oscillating behavior between net transmitter and receiver.

**Table 3**  
Average connectedness table. Results are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition.

	ARG	AUS	AUT	BRA	CAN	CHN	COL	FIN	FRA	HUN	IND	IDN	ITA	JPN	KOR	MYS	NLD	NOR	PAK	POL	PRT	RUS	S.AF	SPA	SWE	TWN	THA	TUR	USA	From
ARG	34.4	0.9	2.5	5.6	5.7	1.4	3.1	2.2	4.2	1.3	0.7	0.8	4.0	0.7	0.6	0.5	2.3	3.6	0.4	1.6	2.2	3.3	1.7	3.8	2.4	0.6	1.3	0.8	7.3	2.3
AUS	2.8	19.6	3.2	4.2	7.0	2.8	3.3	2.1	5.1	1.4	1.1	1.1	4.8	2.3	1.4	0.8	2.6	5.0	0.6	1.6	3.2	3.1	1.9	4.2	3.3	0.9	1.8	0.8	8.1	2.8
AUT	2.1	1.1	22.7	3.1	4.4	1.4	2.5	3.2	7.3	1.7	0.9	0.7	6.8	1.1	0.6	0.5	3.3	5.7	0.3	2.2	4.6	3.6	2.0	6.3	3.9	0.4	1.2	1.2	5.1	2.7
BRA	4.4	1.0	2.8	26.7	6.5	1.6	4.3	2.0	4.8	1.6	1.1	0.7	4.6	0.6	0.7	0.6	2.7	4.2	0.4	1.8	3.1	4.5	2.0	3.8	2.9	0.6	1.5	1.3	7.2	2.5
CAN	4.0	1.1	3.3	5.6	20.8	1.2	4.0	2.4	5.8	1.3	0.7	0.5	5.3	0.9	0.6	0.4	2.7	4.9	0.3	1.4	3.5	3.8	2.1	4.6	3.3	0.5	1.3	0.8	12.8	2.7
CHN	2.7	2.9	2.5	4.6	4.9	20.8	3.2	1.8	4.5	1.6	2.0	2.1	4.4	2.2	2.4	1.2	2.3	4.2	0.6	1.8	2.9	3.9	2.2	3.8	2.8	1.8	3.0	0.9	6.1	2.7
COL	2.6	1.0	2.8	4.6	5.2	1.7	30.8	1.6	4.6	1.6	0.9	0.7	4.5	0.6	0.6	0.5	2.2	4.2	0.5	1.7	4.5	4.0	2.0	4.0	3.3	0.7	1.4	1.0	6.3	2.4
FIN	2.4	1.2	4.2	2.7	3.9	1.2	1.9	32.6	5.6	1.7	1.1	0.8	4.9	0.9	0.8	0.6	4.2	4.4	0.4	2.1	2.9	3.1	1.7	4.3	3.4	0.6	1.2	1.3	4.0	2.3
FRA	2.4	1.1	5.0	3.4	4.8	1.5	2.7	3.0	15.6	1.8	1.0	0.6	9.9	0.9	0.6	0.4	4.1	6.4	0.2	2.0	5.0	4.2	2.2	8.0	4.4	0.6	1.2	1.1	5.8	2.9
HUN	1.9	1.2	2.6	2.8	2.4	1.8	2.2	2.1	4.1	38.9	1.3	1.0	4.1	0.9	0.7	1.0	2.3	3.2	0.8	4.3	2.5	3.4	1.6	3.6	2.4	0.8	2.0	1.2	2.8	2.1
IND	1.8	1.6	1.6	2.6	2.1	3.7	1.6	1.7	3.1	1.7	43.1	2.0	2.8	1.0	1.4	1.6	2.0	2.4	0.7	2.5	1.7	2.9	1.9	2.3	1.8	1.4	3.0	1.7	2.4	2.0
IDN	2.3	1.8	1.7	2.8	2.9	3.8	2.0	1.5	2.7	1.3	1.9	43.1	2.4	1.3	1.2	1.6	1.9	2.7	0.9	1.6	1.6	3.1	1.6	2.0	1.5	1.2	3.3	0.9	3.5	2.0
ITA	2.4	1.0	4.9	3.3	4.5	1.4	2.9	2.8	10.3	1.8	0.9	0.6	16.4	0.9	0.5	0.4	4.1	6.2	0.3	2.2	5.1	4.1	1.9	8.2	4.4	0.5	1.3	1.1	5.5	2.9
JPN	3.1	2.7	3.3	3.7	6.2	2.5	3.1	2.1	5.3	1.5	0.8	1.1	4.9	21.4	1.3	0.8	2.7	4.5	0.6	1.5	3.0	3.3	1.8	4.2	3.5	0.9	1.7	0.9	7.6	2.7
KOR	1.8	2.5	2.1	3.0	3.2	3.9	1.9	1.8	3.2	1.0	1.3	1.1	3.0	1.9	38.3	1.2	2.2	3.0	0.5	1.9	2.0	3.1	1.8	2.7	2.2	2.3	1.9	1.1	4.1	2.1
MYS	1.6	1.6	1.5	2.4	2.8	2.6	1.9	1.3	2.6	1.3	1.9	1.8	2.5	1.3	1.5	47.5	1.5	2.2	0.9	1.1	1.9	2.4	1.9	2.1	1.9	1.5	2.0	1.2	3.5	1.8
NLD	2.0	0.9	3.1	2.8	3.5	1.3	1.9	3.5	6.2	1.5	1.1	0.8	6.0	0.7	0.6	0.6	33.0	5.3	0.3	1.8	3.2	3.2	1.8	4.9	3.4	0.5	1.0	1.2	4.1	2.3
NOR	2.5	1.4	4.4	3.6	5.2	1.7	3.0	2.8	7.3	1.6	0.9	0.9	6.7	1.0	0.8	0.4	4.0	17.6	0.4	1.9	4.6	4.8	2.6	5.5	5.2	0.5	1.5	1.1	6.1	2.8
PAK	1.4	1.3	1.5	2.2	2.5	1.4	2.2	0.9	1.8	1.2	1.1	1.2	1.9	1.0	0.9	1.1	1.0	2.1	57.6	1.0	1.6	2.0	1.5	1.7	1.7	0.7	1.6	1.0	2.9	1.5
POL	1.9	1.0	2.9	2.8	2.7	1.8	2.1	2.4	4.1	3.8	1.8	1.0	4.2	0.6	0.9	0.7	2.6	3.3	0.4	35.9	2.5	4.0	2.7	3.7	2.5	0.8	1.7	1.8	3.2	2.2
PRT	1.7	1.0	4.2	2.9	4.1	1.2	4.1	2.1	6.7	1.4	0.7	0.5	6.6	0.7	0.5	0.4	2.7	5.4	0.3	1.7	28.1	3.4	2.0	6.4	3.9	0.5	1.2	0.9	4.7	2.5
RUS	2.8	1.1	3.4	4.5	4.5	2.2	3.5	2.3	5.7	2.0	1.3	1.2	5.4	0.9	0.9	0.7	2.9	5.9	0.5	2.8	3.5	21.7	2.7	4.4	3.8	0.8	1.8	1.8	5.0	2.7
S.AF	2.3	1.3	2.7	3.2	4.5	2.2	2.5	1.8	4.4	1.4	1.3	1.1	3.8	1.1	1.1	0.9	2.4	4.5	0.7	2.4	2.7	4.0	33.8	3.2	2.6	0.9	1.4	1.2	4.5	2.3
SPA	2.5	1.1	5.1	3.2	4.4	1.3	2.8	2.7	9.4	1.8	0.8	0.5	9.1	0.8	0.6	0.4	3.7	5.7	0.3	2.1	5.4	3.8	1.9	18.5	4.1	0.4	1.2	1.0	5.3	2.8
SWE	2.0	1.2	3.9	3.0	4.2	1.4	2.8	2.7	6.2	1.5	0.8	0.6	5.9	0.9	0.7	0.6	3.2	6.4	0.4	1.8	4.3	3.8	1.9	5.0	27.2	0.5	1.2	1.0	4.8	2.5
TWN	1.7	1.8	1.9	2.7	2.6	3.8	2.1	1.5	3.0	1.5	1.7	1.3	2.7	1.5	2.7	1.5	1.6	2.4	0.6	1.8	1.8	2.7	1.8	2.5	1.9	41.7	2.4	1.0	3.7	2.0
THA	2.6	2.0	2.0	3.6	3.8	4.2	2.7	1.6	3.2	1.8	2.2	2.6	3.4	1.8	1.5	1.3	2.0	3.5	0.8	1.8	2.2	3.4	1.9	2.8	2.4	1.6	31.7	0.9	4.6	2.4
TUR	1.3	0.9	2.3	3.0	3.2	1.5	1.7	2.2	3.4	1.5	1.6	0.8	3.1	0.8	0.9	0.8	2.3	2.7	0.6	2.6	2.0	3.9	1.8	2.4	2.0	0.9	1.2	47.1	2.6	1.8
USA	4.6	1.0	3.4	5.7	11.8	1.3	4.4	2.2	6.3	1.3	0.7	0.5	5.8	0.8	0.6	0.4	2.9	5.0	0.3	1.6	3.6	3.6	1.9	5.0	3.5	0.5	1.3	0.8	19.1	2.8
to	2.3	1.3	2.9	3.4	4.2	2.0	2.6	2.1	4.9	1.5	1.2	1.0	4.6	1.0	1.0	0.8	2.6	4.1	0.5	1.9	3.0	3.4	1.9	4.0	2.9	0.8	1.6	1.1	5.0	69.5
Net	0.1	-1.4	0.3	0.8	1.5	-0.7	0.3	-0.3	1.9	-0.6	-0.8	-1.0	1.7	-1.7	-1.2	-1.0	0.2	1.3	-1.0	-0.3	0.5	0.7	-0.4	1.2	0.4	-1.2	-0.8	-0.8	2.2	

It is possible to observe the time averaged “to” and “from” measures between the pairs of countries both at individual and aggregated levels from Table 3 but it may not be possible to clearly visualize the “net” relationships between the countries. Hence to highlight how transmission of shocks works within the energy sector, in Fig. 4, we depict the network analysis of returns connectedness for each country’s MSCI energy indices. In particular, Fig. 4 shows time average of the net directional pairwise spillovers from one country to another. While each edge between two nodes denotes the net pairwise spillovers between two countries, the arrow’s direction indicates which country received shocks from which country on average. For instance, an arrow from Country A to Country B means that, on average, Country A is a net transmitter of shocks to Country B. The thickness of edge between two countries reflects the strength of the connectedness between countries so that thicker edges denote a stronger net pairwise connectedness. Similarly, each node’s size represents the overall magnitude of net total directional connectedness for each country, implying that a larger node size has a significant role as sender/receiver of shocks within the energy industry. Each node’s color helps to identify whether a country is a net transmitter or a net receiver of spillovers. We highlight with red (green) if a country is a net transmitter (receiver) of the shocks within the system.

From Fig. 4, it becomes crystal clear that USA, France, Italy, Canada, Norway, and Spain are the largest shock transmitters to the energy network of the countries. On the other hand, Japan, Australia, Taiwan, Korea, and Malaysia can be ranked as the highest information receivers from the network. At this point, it is also important to note that for 23 countries out of 29, the net transmitting (receiving) characteristic of the MSCI energy index coincides with the net oil exporter (importer) position of the country. In particular, we observe that the oil exporter countries in our data set i.e. Argentina, Brazil, Canada, Colombia, Norway, Russia, and USA are also the net transmitter in the energy network. On the other side, the oil importer countries Australia, China, Finland, Hungary, India, Japan, Korea, Malaysia, Pakistan, Poland, S.Africa, Taiwan, Thailand, and Turkey are found to be the net receiver of the energy shocks. All of the exception countries i.e. Austria,

France, Italy, Netherlands, Portugal, and Sweden are shown to be the transmitters in the model although they are oil importing countries. This can be explained by the fact these countries are also producing significant amount of clean energy. Hence green energy resources may be playing a substantial role in the net shock transmission property of these countries. Fig. 4 also provides a better understanding of the “net” relationships among the countries by putting a threshold on the edge values. We impose a 90% bound on the edge values in the sense that we first sort the net values from smallest to largest and then we determine the cutoff point which corresponds to top 10% of the values. In our case, the threshold level is found to be 0.08. Hence, we only observe the edge values greater than 0.08 on this figure. We further distinguish between these edges by coloring the ones of strength greater than 0.12 as blue and others as orange.

#### 4.2. What drives the net directional spillovers across countries?

Tables 4 and 5 summarize the panel regression results where standard errors of the estimated coefficients are computed based on a robust procedure. A closer examination of the results in Tables 4–5 presents a number of interesting results. The coefficients of the lockdown variable are positive and statistically significant, indicating that lockdown measures increase both the total directional connectedness “to others” and “from others”. However, the coefficients of the lockdown variable are higher in case of the total directional connectedness to others (TO). Put differently, countries that implement more stringent lockdown measures transmit the financial stress in the overall network by increasing their effects on the other countries. There may be several possible explanations for this result. Firstly, implementing the containment measures leads to a better balance between limiting the transmission of infections and supporting economic activity rather than an immediate reopening (where infections may rise sharply) or a very slow reopening (which may be costly in terms of activity). Relevantly, Acemoglu et al. (2020) investigate the optimal containment policy in a multi-group SIR model and show that optimal policies differentially targeting risk/age

**Table 4**  
Fixed effects panel regression results: FROM.

VARIABLES	Dependent variable: FROM				
	(1)	(2)	(3)	(4)	(5)
Lockdown	0.129*** (0.0029)	0.0782*** (0.0028)	0.0502*** (0.0029)	0.0406*** (0.0029)	0.0497*** (0.0029)
NSI		-0.751*** (0.0085)	-0.647*** (0.0088)	-0.537*** (0.0105)	-0.400*** (0.0153)
EMVID			0.0889*** (0.0039)	0.0354*** (0.0045)	0.0392*** (0.0044)
VXXLE				0.222*** (0.0121)	0.153*** (0.0136)
TEU					0.0691*** (0.0059)
Constant	2.337*** (0.00974)	2.369*** (0.00918)	2.236*** (0.0112)	1.605*** (0.0372)	1.493*** (0.0379)
Observations	14,005	14,005	14,005	14,005	14,005
Adj. R <sup>2</sup>	0.689	0.797	0.808	0.814	0.816
Fixed effects	Yes	Yes	Yes	Yes	Yes
Prob(F-statistic)	0.00	0.00	0.00	0.00	0.00

Note: Entries correspond to the coefficients of panel fixed effect regression results. The parenthesis represent robust standard errors. The \*, \*\*, \*\*\* denote the significance level of 10%, 5%, 1%, respectively.

**Table 5**  
Fixed effects panel regression results: TO.

VARIABLES	Dependent variable: TO				
	(1)	(2)	(3)	(4)	(5)
Lockdown	0.139*** (0.0047)	0.0893*** (0.0046)	0.0648*** (0.0052)	0.0560*** (0.0053)	0.0669*** (0.0052)
NSI		-0.734*** (0.0158)	-0.643*** (0.0165)	-0.542*** (0.0207)	-0.381*** (0.0282)
EMVID			0.0779*** (0.0069)	0.0290*** (0.0078)	0.0336*** (0.0078)
VXXLE				0.203*** (0.0259)	0.121*** (0.0271)
TEU					0.0820*** (0.0094)
Constant	2.307*** (0.0153)	2.338*** (0.0149)	2.222*** (0.0180)	1.645*** (0.0786)	1.513*** (0.0803)
Observations	14,005	14,005	14,005	14,005	14,005
Adj. R <sup>2</sup>	0.925	0.936	0.937	0.937	0.938
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Prob(F-statistic)	0.00	0.00	0.00	0.00	0.00

Note: Entries correspond to the coefficients of panel fixed effect regression results. The parenthesis represent robust standard errors. The \*, \*\*, \*\*\* denote the significance level of 10%, 5%, 1%, respectively.

groups significantly outperform optimal uniform policies (which treat all groups symmetrically), especially when combined with measures that reduce interactions between groups and effectively test and isolate those infected, thereby minimizing both economic losses and COVID-related deaths. Secondly, the increased level of COVID mask-wearing could improve this trade-off notably, allowing for faster reopening for the same rate of new cases because of the elevated infection awareness among residents. This is in line with the findings of Zaremba et al. (2020), who find that COVID-19-related public information campaigns may motivate investors to restructure their portfolio positions and exert a positive and significant effect on the liquidity of stock markets.

Regarding the control variables, NSI negatively and significantly influences the “TO” and “FROM” directional connectedness across

**Table 6**  
Individual country regression results - FROM.

Country	Lockdown	NSI	EMVID	VXXLE	TEU	R <sup>2</sup>
Argentina	0.131***	-0.707***	0.0401**	0.561***	-0.138***	0.864
Australia	-0.0189***	-0.218***	0.0166***	0.0315***	0.0497***	0.864
Austria	0.0859***	-0.196***	0.0130***	0.0423**	0.0167***	0.935
Brazil	0.110***	-0.299***	0.00717	0.0804*	0.145***	0.861
Canada	0.0684***	-0.154***	0.0101**	0.124***	0.0328***	0.932
China	-0.0245***	-0.369***	0.0279***	0.156***	0.0572***	0.830
Colombia	0.0563***	-0.173***	0.0280***	0.167***	0.0120	0.908
Finland	0.107***	-0.532***	0.0174	0.221***	0.126***	0.733
France	0.0252***	-0.151***	0.00959***	0.0602***	0.0145***	0.925
Hungary	0.113***	-0.581***	0.0723***	0.247***	0.0231	0.881
India	0.109***	-0.924***	0.118***	0.415***	0.0708***	0.933
Indonesia	-0.0748***	-1.360***	0.0627***	0.0988**	0.221***	0.928
Italy	0.0320***	-0.166***	0.00447*	0.0527***	0.0101***	0.918
Japan	0.0232***	-0.246***	0.0156***	0.0908***	0.0269***	0.840
Korea	0.0143	-0.805***	0.0278**	0.0812**	0.200***	0.900
Malaysia	0.0113	-1.287***	0.0881***	0.173***	0.226***	0.900
Netherlands	-0.347**	0.247**	0.0201	0.831***	-0.128***	0.651
Norway	0.0379***	-0.196***	0.00689**	0.0255*	0.0356***	0.909
Pakistan	0.201***	-0.0757	0.119***	-0.309***	0.529***	0.733
Poland	0.0947***	-0.426***	0.0781***	0.274***	-0.112***	0.823
Portugal	0.0396***	-0.0827***	0.00831**	0.0630***	0.0353***	0.898
Russia	0.0583***	-0.126***	0.0410***	0.0789***	0.0460***	0.895
South Africa	0.0999***	-0.466***	0.0750***	0.256***	0.0863***	0.879
Spain	0.0405***	-0.190***	0.0118***	0.0621***	0.0209***	0.949
Sweden	0.0560***	-0.243***	0.00430	0.0766***	0.0170***	0.958
Taiwan	-0.0318***	-0.637***	0.0781***	0.308***	0.00206	0.716
Thailand	0.0197***	-0.311***	0.0556***	0.212***	0.0563***	0.834
Turkey	0.115***	-1.034***	0.0729***	0.409***	-0.118***	0.911
USA	0.0494***	-0.148***	0.00607**	0.0912***	0.0198***	0.940

Note: Entries correspond to the coefficients of OLS regression. The \*, \*\*, \*\*\* denote the significance level of 10%, 5%, 1%, respectively, based on robust standard errors.

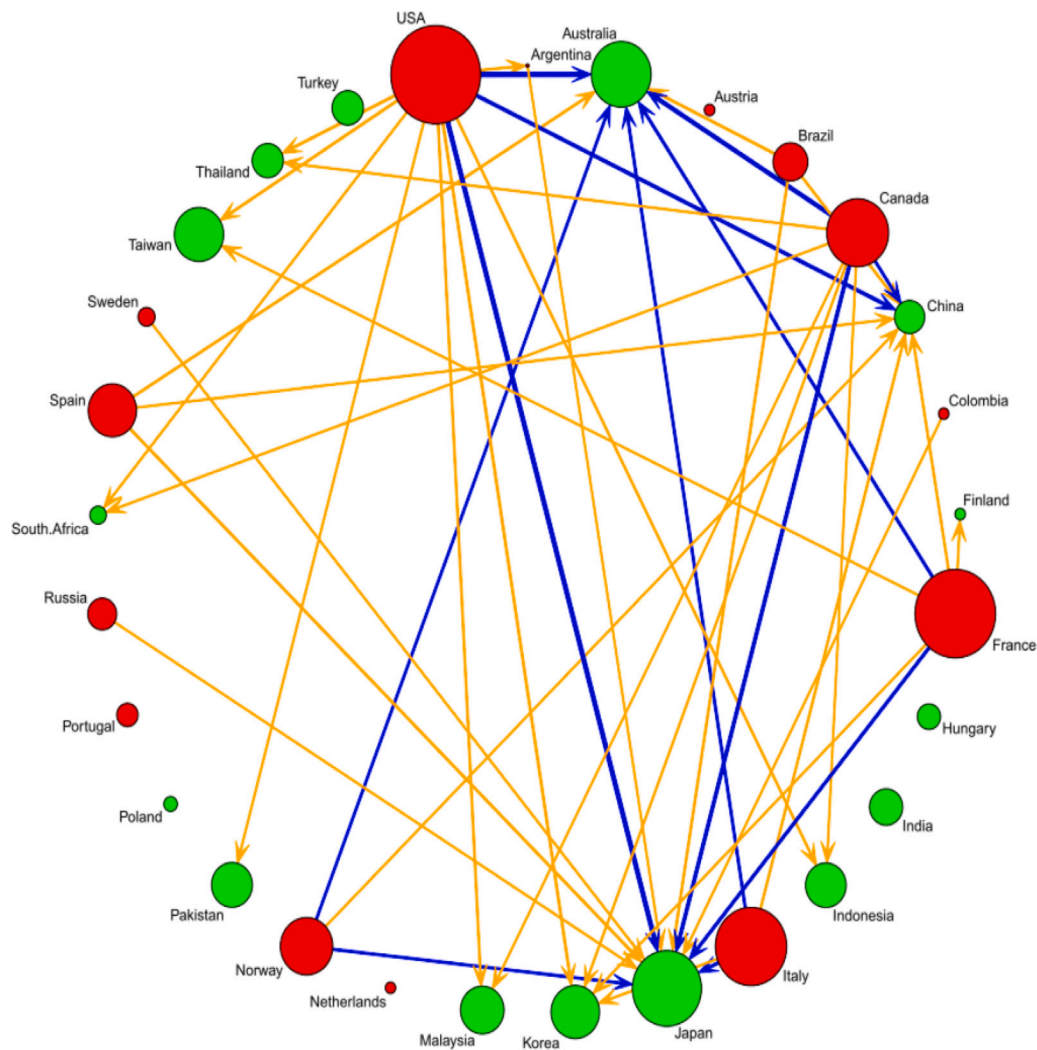
**Table 7**  
Individual country regression results - TO.

Country	Lockdown	NSI	EMVID	VXXLE	TEU	R <sup>2</sup>
Argentina	0.158***	-1.385***	-0.0774***	0.924***	-0.111***	0.860
Australia	0.238***	-1.051***	0.113***	0.733***	0.121**	0.821
Austria	0.456***	0.551***	0.0259*	-0.00222	-0.116***	0.921
Brazil	0.150***	-0.956***	0.0295	0.0853	0.514***	0.720
Canada	0.138***	-0.145	-0.0535*	0.533***	-0.329***	0.471
China	0.00591	-1.773***	0.00318	-0.445***	0.510***	0.865
Colombia	0.0848***	0.376***	0.0672***	0.313***	0.140***	0.738
Finland	0.136***	-1.202***	-0.0235	0.0384	0.165***	0.712
France	-0.139***	0.788***	0.0699***	-0.0669	0.0510***	0.644
Hungary	0.183***	-1.564***	0.0899***	0.106	0.361***	0.890
India	-0.0387***	-0.446***	0.0297*	0.700***	0.0913***	0.839
Indonesia	-0.0795***	-0.693***	0.0133	0.501***	-0.00277	0.888
Italy	-0.0437***	0.662***	0.0462***	-0.223***	0.0372*	0.679
Japan	0.144***	-1.267***	0.0768**	-0.0589	0.195***	0.706
Korea	-0.0208	-0.434***	-0.00716	0.426***	0.110***	0.743
Malaysia	0.00154	-0.390***	0.0270*	0.361***	0.0701***	0.786
Netherlands	-0.303***	0.401***	0.0906***	0.412***	-0.146***	0.661
Norway	-0.0266**	0.316***	0.00837	-0.380***	0.247***	0.421
Pakistan	0.0609***	-0.618***	0.0178	-0.0924	0.381***	0.824
Poland	0.251***	0.0177	0.137***	-0.273**	-0.199***	0.660
Portugal	0.00703	0.920***	0.0354**	0.118	-0.0310	0.657
Russia	0.0734**	-0.0566	0.147***	-0.675***	0.0817*	0.110
South Africa	0.0699***	-0.469***	0.0741***	0.0277	0.207***	0.793
Spain	-0.0474***	-0.0817*	0.0258*	0.337***	-0.0584***	0.367
Sweden	0.111***	-0.153***	0.0407***	0.0567	-0.113***	0.586
Taiwan	-0.0310***	-1.090***	0.0147	0.0264	0.0231	0.747
Thailand	-0.0354	-0.287***	0.0667***	0.765***	0.0969***	0.795
Turkey	0.0862***	-1.311***	0.0461**	0.158**	-0.205***	0.719
USA	-0.202***	-0.400***	-0.0360**	0.0481	-0.152***	0.706

Note: Entries correspond to the coefficients of OLS regression. The \*, \*\*, \*\*\* denote the significance level of 10%, 5%, 1%, respectively, based on robust standard errors.

countries with a more sizeable effect in the latter. Since higher values of the NSI indicate more positive economic sentiment, it is likely that economic recovery implies higher energy demand, which boosts the energy companies' revenues for a given country, limiting the its





**Fig. 4.** Network analysis of returns connectedness for MSCI country energy indices with a 90% threshold which corresponds to 2.33 on the edge values. (Notes: Each edge between two nodes denotes the net pairwise spillovers between two countries and the arrow's direction indicates which country received shocks from which country on average. The thickness of edge between two countries reflects the strength of the connectedness between countries. Each node's size represents the overall magnitude of net total directional connectedness. Red (green) node indicates whether a country is a net transmitter (receiver) of the shocks within the system. Edges which have strength greater than 3 are shown in blues others that have strength greater than 2.33 are shown in purple.) (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

influence on the other countries. As shown in Tables 4–5, columns (3)–(4)–(5) present that the coefficients associated with COVID-induced uncertainty are positive and significant, which means that the COVID-19 has increased the level of directional connectedness MSCI energy indices through enormous downward shock to global energy demand. Put differently, the energy sector is severely affected because of the infectious disease uncertainty, which has resulted in a slowdown in transport, trade, and economic activity across the globe. Hence, our results also support the findings of Le et al. (2020), Corbet et al. (2020), Werth et al. (2020) and Bouri et al. (2021). Similar to the COVID-induced uncertainty, the Twitter-based economic uncertainty index increases the directional connectedness in the overall network by affecting economic activity through postponing of investment and consumption's decisions until the economics agents feel more confident about the economy.

It is expected that the coefficient of the CBOE Energy Sector ETF Volatility Index is positive and statistically significant, leading to a propagation of shocks across countries. However, the response of directional connectedness to global volatility shocks may differ between periods of extreme negative returns, suggesting an asymmetric behavior. Drilling down a little deeper, in Tables 6–7, we present the

results of individual country regressions where the dependent variable alternatively represents the total directional connectedness to others (TO) and the total directional connectedness from others (FROM). An inspection of Tables 6–7 shows that, in general, emerging market high-yielders tend to be more sensitive to global volatility shocks. For instance, Argentina, Brazil, Colombia, India, Indonesia and Turkey appear particularly exposed positively to energy sector ETF volatility because of their relatively high exposure to a viral outbreak, significant external imbalances, and relatively high exposure to distressed sectors, currency mismatch risk, and limited reserve buffers.

Finally, Fig. 5 shows the effect of the COVID-induced uncertainty on TCI over different quantiles. Notably, the positive and significant slope coefficient estimates of EMVID on different quantiles (except for 0.9) confirm that the COVID-induced uncertainty increases the connectedness among MSCI Energy indices, which implies a shock in one country's MSCI Energy index will influence the MSCI Energy indices of the other countries relatively higher. The effect reaches its maximum around 0.3 percentile and then decreases at upper quantiles. The reason might be that once the uncertainty about COVID-19 has risen above a certain level, the financial markets have already incorporated this information into prices, and its impact on the connectedness of the

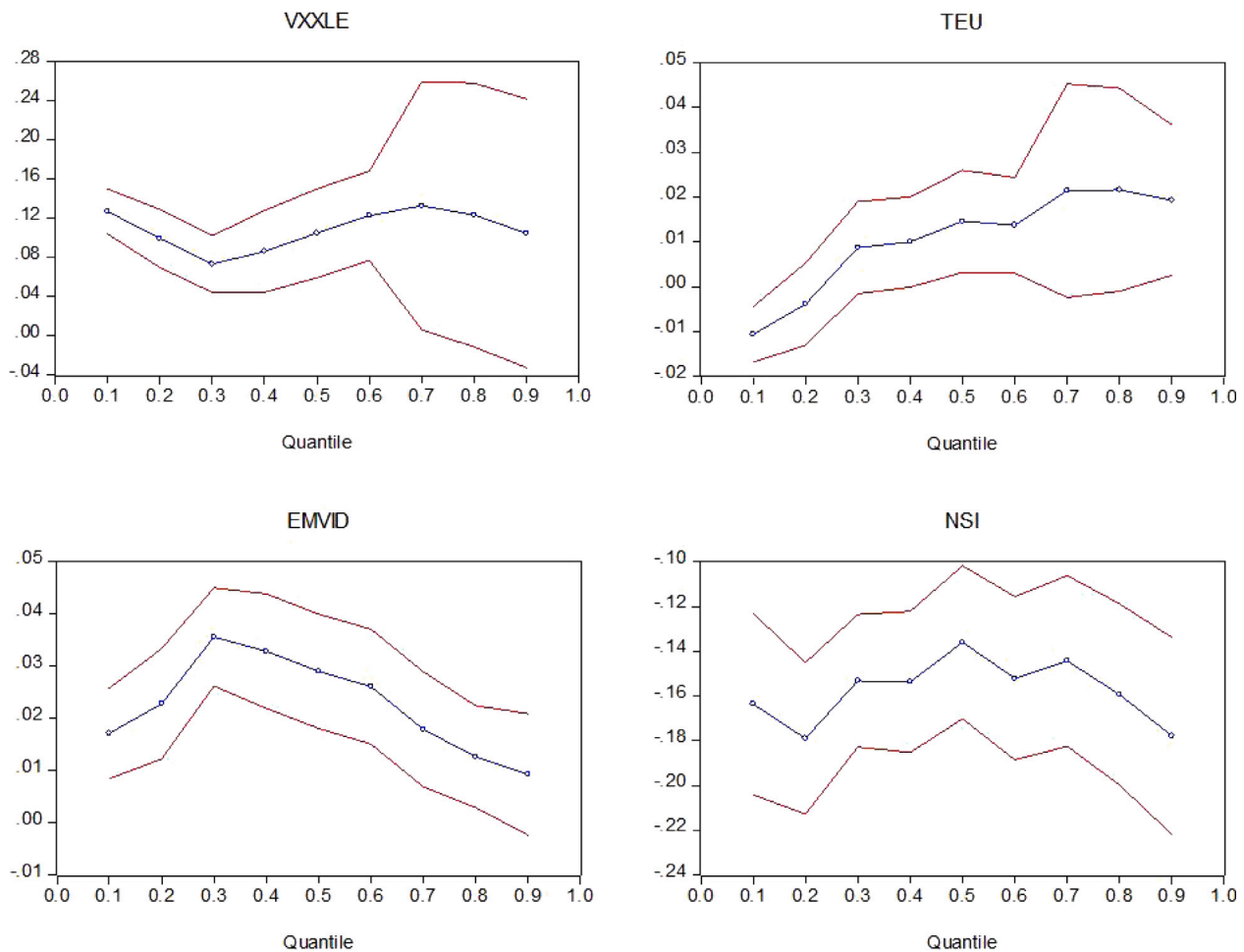


Fig. 5. Quantile regression results. (Notes: This graph shows the parameter estimates of the Eq. (7) at various quantiles with 95% confidence intervals using quantile regression approach of Koenker and Bassett (1978).)

system declines at higher quantiles. On the other hand, the NSI has a negative effect at all quantiles, suggesting that improving economic conditions leads to decrease return spillovers and thus the level of the total connectedness in the system. The VXXLE significantly impacts the TCI at the lower and upper quantiles, whereas the TEU has no effect almost in all quantiles.

## 5. Conclusion

The detailed analysis of the global energy markets connectedness has been of significant importance for the economic agents, especially during the COVID-19 period. We study connectedness among equity energy indices of 29 countries around the world and how this connectedness is influenced by uncertainty, economic sentiment, and COVID-19. Economic sentiment is measured as News Sentiment Index of Buckman et al. (2020), the severity of COVID-19 is measured from Google Mobility Reports and The Oxford COVID-19 Governance response tracker, and three measures of uncertainty are considered: Twitter-based economic uncertainty index of Baker et al. (2020a), Infectious Disease Equity Market Volatility Tracker by Baker et al. (2020b) and the CBOE Energy Sector ETF Volatility Index (VXXLE).

Our findings have several practical implications. First, identifying the potential spillover drivers of the energy market across countries provides crucial insights for portfolio diversification. For instance, portfolio managers might invest in country pairs that are unlikely to spill over to each other to diversify their portfolio risks during elevated uncertainty periods. Note that these strategies need to be constantly

monitored, as our empirical evidence shows that the spillover patterns within the energy market are time-varying. Second, considering that energy prices have a significant pass-through to the domestic inflation rate in many countries via global supply chains and international trade channels, monitoring the connectedness of energy markets provides valuable insights for policymakers to formulate better policy responses for price stabilization. Third, policymakers might effectively monitor the connectedness of energy markets to reduce the risk of potential contagion between different sectors since energy companies are highly sensitive to abnormal fluctuations in energy prices. First, we construct a directional connectedness index based on the MSCI energy index of each country, which is a time-varying measure of how much shocks one country transmits to other countries and how much shocks one country receives from other countries and discuss which countries are net receivers and which ones are net transmitters. It is found that, on average, oil exporter countries are net shock transmitters, the oil-importing countries are net shock receivers. Next, we study which variables can explain connectedness among energy markets. We find that connectedness (both TO and FROM) is high during periods of high uncertainty and low economic sentiment. One of our key findings is that connectedness was higher during periods when more strict lockdown measures were implemented. Altogether, our results imply that connectedness among energy markets is higher during periods with higher uncertainty and serious problems, i.e., during crisis periods when diversification benefits are most important.

Furthermore, this study provides valuable insights not only for the oil-importing and exporting countries but also for the other capital

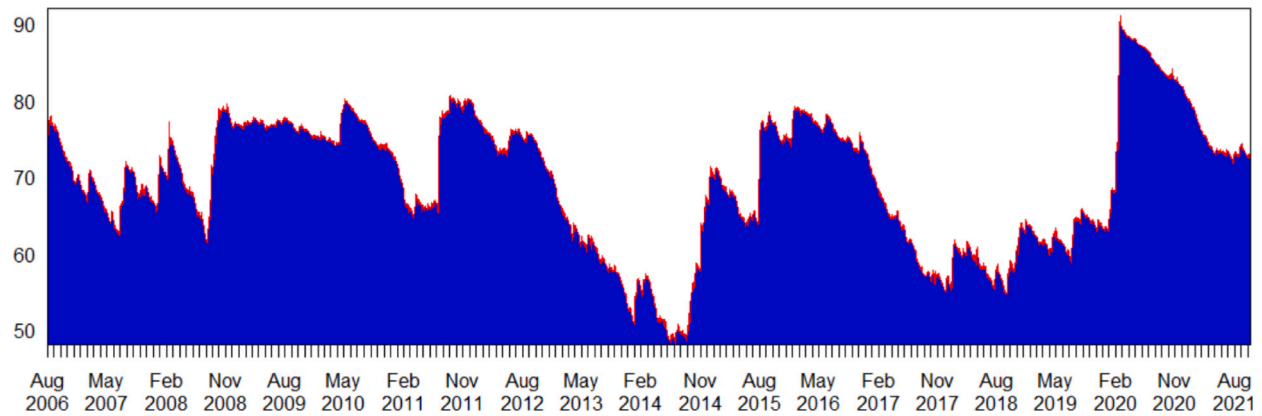


Fig. A.1. Total connectedness index of MSCI energy indices for alternative forecast horizon  $F = 5$ .

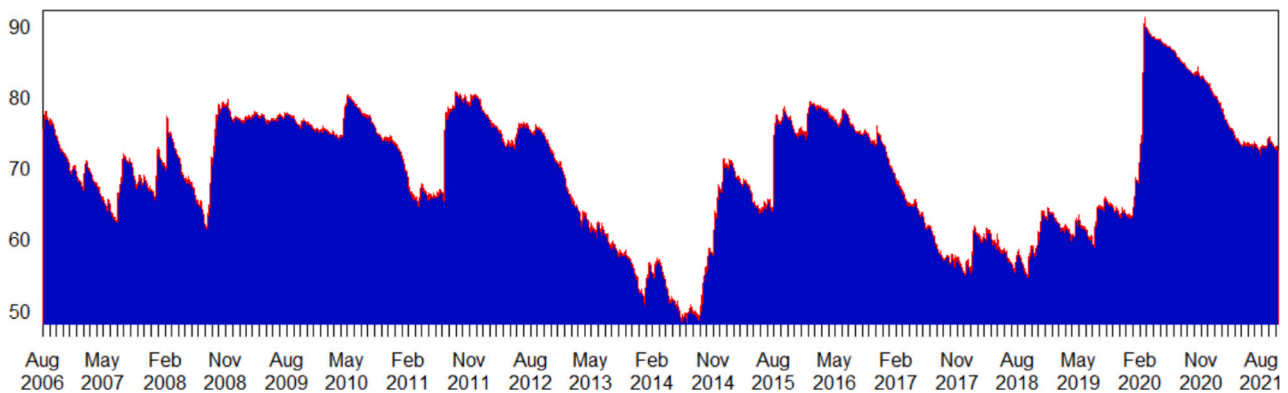


Fig. A.2. Total connectedness index of MSCI energy indices for alternative forecast horizon  $F = 15$ .

market participants from the perspective of lockdown and COVID-induced uncertainty measures. Hence, our results can be extended to other crucial areas of dependence across the countries.

#### CRedit authorship contribution statement

**Erdinc Akyildirim:** Conceptualization, Methodology, Formal analysis. **Oguzhan Cepni:** Conceptualization, Methodology, Data curation, Formal analysis. **Peter Molnár:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Gazi Salah Uddin:** Writing – original draft, Writing – review & editing.

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#### Appendix A

See Figs. A.1 and A.2

#### Appendix B. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.eneco.2022.105900>.

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