IJEEP

INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY

EJ EconJournals

ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2021, 11(4), 329-344.

EJ EconJournals

Examining Network Structures and Dynamics of World Energy Companies in Stock Markets: A Complex Network Approach

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Received: 12 February 2021 **Accepted:** 03 May 2021 **DOI:** https://doi.org/10.32479/ijeep.11287

ABSTRACT

The energy sector occupies a mainstay role in overall growth in the modern worldwide economy. Therefore, it is essential to examine network structures and dynamics of leading energy companies of the world through complex network methods. Because, complex network methods are significant tools of studying the static and dynamics properties of the stock market, which allows us to better comprehend the stock market. We use daily prices of 147 energy stocks belonging to 34 countries of the world from 2006-2019. In addition to the overall sample, we explore networks for two sub-periods to examine the topological evolution during global recession of 2008, and energy and European debt crisis of 2011. Our results show substantial clustering of energy companies based on their geographic position during overall sample period. However, the crisis periods lead to a break in Asian and European clusters and only one prominent cluster appears in all the periods belonging to North American energy companies. We also observe few top US and European based companies occupying important and great global influence positions in the networks. In addition, time-varying topological measures indicate contraction of networks during crisis time, and an expansion in the recovery periods. More implications are also discussed.

Keywords: Energy Companies, Complex Network, Threshold Network, Minimum Spanning Tree, Stock Market, Crisis
JEL Classifications: C18, E32, E44, G01, G14, G15, G19

1. INTRODUCTION

In today's world, countries rely heavily on the consumption of energy to increase their industrial production and to boost their economic growth. The EIA (US energy information administration) has projected a growth in the world energy consumption by 28% between 2015 and 2040[1]. Simultaneously, a constant growth in the overall energy consumption of 2.3% is observed in the year 2018, led by china with an overall energy consumption growth of 3.7%[2]. Previous work explores the relationship among the development and energy use of a country (Alam et al., 1998; Dias et al., 2006; Apergis and Payne, 2011; Lambert et al., 2014; Arto et al., 2016). They found strong correlations among energy use and living standards. Therefore, further understanding of worldwide energy companies, interaction, and evolution of network structures is of vital importance to investors and policy makers since stocks markets and energy companies to be specific have become much more integrated.

Although globalization and expansion of economic activities resulted in optimum allocation of economic resources in the financial markets, it simultaneously encourages a rapid spread of financial crises that can topple the world financial system. Such as, the 2008 financial crisis, that shook the world economic and financial system within no time. Many studies attempt to analyze the impacts of financial crisis 2008 on stock market networks. Gong et al. (2019) observed an increase in the network

1 Please see: https://www.eia.gov/todayinenergy/detail.php?id=32912
2 Please see: https://yearbook.enerdata.net/total-energy/world-consumption-statistics.html

connectedness of global stock markets during financial crisis of 2008. Similarly, a substantial increase in the average correlations during financial crisis time period of 2008 has been observed for US stock market (Qiu et al., 2018), Pakistan stock market (Memon and Yao, 2019), Chinese stock market (Ren and Zhou, 2014), South African stock market (Majapa and Gossel, 2016), and Korean stock market (Nobi et al., 2014). Therefore, market participants actively require better understanding of the correlations in complex financial market systems.

The world energy companies network can be regarded as a complex network. In the past, researchers occasionally use correlation analysis to develop stock market networks, by considering stocks as nodes of the networks and pairwise interaction among prices of stocks as their respective edges. The correlation based networks have emerged as a useful tool to define static and dynamic properties of the network (Nobi et al., 2014; Jo et al., 2018; Lee and Nobi, 2018; Li and Pi, 2018; Memon and Yao, 2019; Yao and Memon, 2019). Particularly, with Pearson cross-correlation network method, we can perceive topological properties of the threshold network (TN), produced by assigning a value of threshold (Lin et al., 1994; Boginski et al., 2005), the asset graph (AG) (Onnela et al., 2003; Onnela et al., 2003), the minimum spanning tree (MST) (Mantegna, 1999; Mantegna and Stanley, 2000), and the planar maximally filtered graph (PMFG) (Tumminello et al., 2005; Song et al., 2011). Clearly, Pearson correlation-based network methods have been extensively applied to numerous financial systems (Onnela et al., 2004; Kwapień et al., 2009; Coletti, 2016; Mai et al., 2018; Memon et al., 2019; Zięba et al., 2019; Memon et al., 2020), and is thus used in this paper.

Unlike most studies that primarily focuses on the network structure and evolution of either world stock markets indices (Lee and Nobi, 2018; Li and Pi, 2018; Sensoy and Tabak, 2014), or local stock markets (Memon and Yao, 2019; Yao and Memon, 2019; Nobi et al., 2014; Wiliński et al., 2013), this paper explores the state, network structure, and dynamics of well-known world energy companies. In the summary, this paper has made three main contributions. First, our study extends financial network literature by focusing on 147 most popular energy companies belonging to 34 countries of the world, using a dataset spanning over wide period of nearly 14 years. Secondly, previous research focuses solely on the econometric techniques for energy stocks. Therefore, we attempt to apply complex network methods to analyze network structures of energy companies of the world, for the 1st time. Additionally, our study is a comparative work that explore and compare network structures at two crucial time periods of Global financial crisis in the year 2008, and Oil prices spike in the year 2011. Thirdly, the results presented in our study and understanding of the correlation structure and dynamics of popular energy companies of the world is important for a wide range of market participants including: local investors, multinational corporations, and regulators or policy makers worldwide.

The paper is organized as follows. Section 2 provides a review of the relevant literature. Section 3 presents the data and methodology of constructing threshold networks, MST, and weighted network measures. Section 4 show results and discusses them. Finally, Section 5 concludes the paper.

2. LITERATURE REVIEW

The existing literature offers numerous stock market correlation-based networks to determine its possible structure. For example, (Tang et al., 2018) examined companies listed in two stock markets of China securities index 300 and Standard & Poor`s 500 between 2007 and 2015. In addition to the identification of stock connectedness in the MST network, their results also revealed similar topological properties for an emerging market of CSI300, and a mature well-developed stock market of S&P500. Kantar et al. (2012) analyzed topological properties of top 50 Turkish companies over the period of 2006 to 2010, and their results showed less influence of financial crisis 2008 on the Turkish market. In contrast, (Memon and Yao, 2019; Sensoy and Tabak, 2014; Coletti and Murgia, 2016) found contraction or shrinkage of the network structure during crises. Moreover, (Gałązka, 2011) investigated polish stock market network after applying MST method between January and December 2007. His results showed few hub companies in the network that can influence the price dynamics of other companies in the stock market.

Regarding network analysis for world oil market, (Jia et al., 2017) applied wavelength based complex network methods to study structural characteristics of 26 groups of oil prices in the world oil market between June 1999 and March 2011. In addition to identifying the global oil market integration, their results also showed prominent role of some regional markets due to the emergence of two big groups of regional markets in the network. Ji and Fan (2016) applied MST and confirmed integration among world crude oil market using weekly oil price data of 24 countries between 2000 and 2011. Li et al. (2019) studied spillover effects among oil and gas markets using complex network method. Their results revealed key correlation patterns and transmission relations by some network indicators.

A large set of methods has been used in exploring the relationship among stock markets and oil prices. Zhang and Liu (2018) applied dynamic copula and VAR-DAG models between 2000 and 2017 to examine oil stock contagion and its propagation in seven countries stock markets. Additionally, (Ahmadi et al., 2016) used structural vector autoregressive (SVAR) and found different responses to oil price shocks on the US stock market returns. Lin and Tsai (2019) found six structural breaks in the oil price due to major global events by applying structural change testing models and autoregressive distributed lag and error corrective model (ADRL-ECM). They directed investor attentions towards political and economic impacts on oil prices, combing with market fear gauge and the way it can affect oil prices. Wei and Guo (2017) studied the impact of oil price shocks on Chinese stock market between February 1996 and October 2015 by employing structural VAR model. They found that demand-oriented speculations related to oil prices have significant effects on china stock market. Moreno and Pereira da Silva (2016) used multifactor market models on Spanish stock market over the period of 2008-2015. Their results found significant positive and negative impacts of European Union ETS on stock market returns of Spanish companies in various phases. Using a GARCH based model, (Schaeffer et al., 2012) examined the impact on market value of oil companies that followed Dow Jones Sustainability Index (DJSI). Their empirical results show no change between volatility and linkage of oil companies with the oil price. While applying similar model, (Dutta et al., 2017) established a link between oil volatility index (OVX) and eleven Middle east and African stock markets. They found significant impact of OVX on the mean and volatility of majority Middle East and African stock returns.

Network analysis has also been introduced to analyze the relationship between renewable energy companies of the world. For instance, (Kazemilari et al., 2017) applied the MST to study 70 stocks of renewable energy companies over the time period of October 2010-March 2015. In addition to highlighting important nodes of the network, they also found significant role of these nodes for the development of renewable energy market. In addition, (Kazemilari et al., 2019) also investigated sectorial behavior pattern of 60 renewable energy companies listed in American stock market between July 2015 and January 2018. Their results showed association of stocks to their particular sector. Regarding energy markets, (Lautier and Raynaud, 2012) used 12 years data of daily futures returns to examine systematic risk in the energy derivative market. Their findings exhibited energy markets holding central position in the overall system. From literature, we can extract importance of the application of network-based methods due to its extensive use. It is also evident that there is a need to extract information of the important nodes, structural changes, and topological properties of energy companies of the world, due to the lack of literature in this domain.

3. DATA AND METHODOLOGY

3.1. Data

Over the past, the stock markets throughout the world have experienced several crises, including the global financial crisis 2008, and oil price shocks combined with European debt crisis of 2011, etc. Therefore, the time period we have chosen for the network analysis of energy companies starts from January 03, 2006 to June 28, 2019, covering all such events. Additionally, there are several energy companies in the world. Our study attempts at gathering the data of well-known energy companies of the world. Table A1 highlights websites for popular energy companies of the world. To sum up, we evaluate daily closing prices of 147 well known energy stocks from 34 countries over the time period 2006 to 2019. We construct network of N=147 using correlation distances among closing stock prices obtained from http://finance.yahoo.com. Table 1 lists 147 energy companies, acting as nodes in the network (differentiated with a unique ID), and categorized by their respective sector and country.

3.2. Methodology of Network Construction

We describe the daily energy stock returns i to be $r_i(t)=\ln P_i(t)-\ln P_i(t-1)$, where $P_i(t)$ is the price of i stock at time t and $t-1$, respectively. The interrelations between two stocks i and j are formed through correlation coefficient C_{ij}, and is defined as:

$$C_{ij} = \frac{r_i r_j - r_i \langle r_j \rangle}{\sqrt{\left(r_i^2 - r_i^2\right)\left(r_j^2 - r_j^{\,2}\right)}} \quad (1)$$

Where r_i and r_j symbolize return time series of stock i and j, and $\langle r_i \rangle$ represents its mean value over the time period under investigation. In our study, there are N=147 energy stocks of the network, the correlation matrix C highlights summary of complex system among the 147 (147-1)/2 pair of stock components. Additionally, the elements of correlation matrix C_{ij} ranges from −1 to 1, where a positive value of $C_{ij}>0$ indicates the two stocks fluctuate in a positively correlated manner, and a negative value $C_{ij}<0$ represents the two stocks fluctuate in an anticorrelated way. However, if $C_{ij}\approx 0$ means two stocks are uncorrelated, and if $C_{ij}\approx 1$ represents two stocks are perfectly correlated. From here, we can easily form a threshold network θ, by providing a specific value θ, $(-1 \leq \theta \leq 1)$, from cross-correlation coefficients. Such as, if $C_{ij} > \theta$ between two stocks, an undirected edge is drawn. Clearly, at certain threshold θ, one can obtain various set of links (Lee and Nobi, 2018).

Thereafter, we convert correlation matrix C_{ij} into distance matric d_{ij} among stocks i and j. It is defined as (Mantegna, 1999):

$$d_{ij} = \sqrt{2\left(1 - C_{ij}\right)} \quad (2)$$

Where distance matrix d_{ij} deviates from 0 to 2 between stocks i and j, and the minimum spanning tree (MST), represented as T, can be computed by applying (Kruskal, 1956) algorithm, as follows:

$$T = \sum\nolimits_{(i,j)\epsilon T} d_{ij} \quad (3)$$

3.3. Network Topology Measures

Our study applies numerous network measures to examine network static properties and dynamics at various partitions. Node degree refers to the direct connections and linkages a certain node has in the overall network. It is calculated as follows:

$$k_i = \sum_{j=1}^{N} a_{ij} \quad (4)$$

Where k_i is the degree of node i, N is the size of the network, and a_{ij} is the number of links among stocks i and j. Further, to detect the modularity of threshold network at different intervals, we apply following definition (Newman, 2006):

$$Q = \frac{1}{4m} \sum\nolimits_{ij} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta c_i, c_j \quad (5)$$

In the above formula 5, A_{ij} represents values of adjacency matrix containing 0 and 1, $K_i K_j/2m$ symbolizes the required number of edges among nodes i and j, $m = \frac{1}{2}\sum_{ij} A_{ij}$ signifies total number of links in the network, the Kronecker delta symbol δ_{ij}, and c_i, c_j represents community consists of nodes i and j.

Table 1: 147 energy stocks from 34 countries of the world are included in our data sample. In the table, we mention unique ID of the stock, stock ticker, company name, sector & Industry code, and their respective country and continent name

ID	Stock Ticker[3]	Company Name	Sector	Industry	Country	Continent
Z1	ACE.MI	Acea SpA	Utilities	Utilities	Italy	Europe
Z2	AEP	American Electric Power Company	Utilities	Utilities	United States	North America
Z3	AOI.TO	Africa Oil Corp.	Energy	Oil & Gas E&P	Canada	North America
Z4	APA	Apache Corp	Energy	Oil & Gas E&P	United States	North America
Z5	APC	Anadarko Petroleum Corp	Energy	Oil & Gas Integrated	United States	North America
Z6	BEP	Brookfield Renewable Partners	Utilities	Utilities	Canada	North America
Z7	BHGE	Baker Hughes	Energy	Oil & Gas Equipment & Services	United States	North America
Z8	BIR.TO	Birchcliff Energy Ltd	Energy	Oil & Gas E&P	Canada	North America
Z9	600578.SS	Beijing Jingneng Power Co Ltd	Utilities	Utilities	China	Asia
Z10	BPCL.NS	Bharat Petroleum Corp	Energy	Oil & Gas Refining & Marketing	India	Asia
Z11	BP.L	BP p.l.c.	Energy	Oil & Gas Integrated	UK	Europe
Z12	CEO	CNOOC Limited	Energy	Oil & Gas E&P	China	Asia
Z13	CFW.TO	Calfrac Well Services Ltd	Energy	Oil & Gas Equipment & Services	Canada	North America
Z14	CHK	Chesapeake Energy Corporation	Energy	Oil & Gas E&P	United States	North America
Z15	CIG	Companhia Energetica de Minas Gerais	Utilities	Utilities	Brazil	South America
Z16	CMS	CMS Energy Corporation	Utilities	Utilities	United States	North America
Z17	CNA.L	Centrica plc	Utilities	Utilities	UK	Europe
Z18	CNE.L	Cairn Energy	Energy	Oil & Gas E&P	UK	Europe
Z19	CNQ	Canadian Natural Resources Ltd	Energy	Oil & Gas E&P	Canada	North America
Z20	COG	Cabot Oil & Gas Corporation	Energy	Oil & Gas E&P	United States	North America
Z21	COP	ConocoPhillips	Energy	Oil & Gas E&P	United States	North America
Z22	COPEC.SN	Empresas COPEC SA	Industrials	Conglomerates	Chile	South America
Z23	2883.HK	China Oilfield Services Limited	Energy	Oil & Gas Equipment & Services	China	Asia
Z24	CPE	Callon Petroleum Company	Energy	Oil & Gas E&P	United States	North America
Z25	CPL	CPFL Energia	Utilities	Utilities	Brazil	South America
Z26	CVN.AX	Carnarvon Petroleum Limited	Energy	Oil & Gas E&P	Australia	Oceania
Z27	CVX	Chevron Corporation	Energy	Oil & Gas Integrated	United States	North America
Z28	D	Dominion Energy	Utilities	Utilities	United States	North America
Z29	DCC.L	DCC PLC	Energy	Oil & Gas Refining & Marketing	Ireland	Europe
Z30	DNO.OL	DNO ASA	Energy	Oil & Gas E&P	Norway	Europe
Z31	DO	Diamond Offshore Drilling	Energy	Oil & Gas Drilling	United States	North America
Z32	DUK	Duke Energy Corporation	Utilities	Utilities	United States	North America
Z33	DVN	Devon Energy Corporation	Energy	Oil & Gas E&P	United States	North America
Z34	E	Eni S.p.A.	Energy	Oil & Gas Integrated	Italy	Europe
Z35	EBK.DE	EnBW Energie Baden-Wurttemberg	Utilities	Utilities	Germany	Europe
Z36	ECA	Encana Corporation	Energy	Oil & Gas E&P	Canada	North America
Z37	EDF.PA	Électricité de France	Utilities	Utilities	France	Europe
Z38	EIX	Edison International	Utilities	Utilities	United States	North America
Z39	ENB	Enbridge Inc.	Energy	Oil & Gas	Canada	North America
Z40	ENEL.MI	Enel SpA	Utilities	Utilities	Italy	Europe
Z41	ENGI.PA	ENGIE	Utilities	Utilities	France	Europe
Z42	ENG.MC	Enagás	Utilities	Utilities	Spain	Europe
Z43	EOAN.DE	E.ON SE	Utilities	Utilities	Germany	Europe
Z44	EOG	EOG Resources Inc	Energy	Oil & Gas E&P	United States	North America
Z45	EPD	Enterprise Products Partners L.P.	Energy	Oil & Gas	United States	North America
Z46	EQNR	Equinor ASA	Energy	Oil & Gas Integrated	Norway	Europe
Z47	EQT	EQT Corporation	Energy	Oil & Gas E&P	United States	North America
Z48	EXC	Exelon Corporation	Utilities	Utilities	United States	North America
Z49	5017.T	Fuji Oil Company	Energy	Oil & Gas E&P	Japan	Asia
Z50	6505.TW	Formosa Petrochemical Corp	Energy	Oil & Gas Refining & Marketing	Taiwan	Asia
Z51	078930.KS	GS Caltex Corporation	Industrials	Conglomerates	South Korea	Asia
Z52	010950.KS	S-Oil Corp	Energy	Oil & Gas Refining & Marketing	South Korea	Asia
Z53	HAL	Halliburton Company	Energy	Oil & Gas Equipment & Services	United States	North America
Z54	HES	Hess Corporation	Energy	Oil & Gas E&P	United States	North America
Z55	HFC	HollyFrontier Corporation	Energy	Oil & Gas Refining & Marketing	United States	North America
Z56	HINDPETRO.NS	Hindustan Petroleum	Energy	Oil & Gas Refining & Marketing	India	Asia
Z57	HP	Helmerich & Payne	Energy	Oil & Gas Drilling	United States	North America

(Contd...)

[3]Company Identification or stock ticker on the website of http://finance.yahoo.com.

Table 1: ***(Continued)***

ID	Stock Ticker[3]	Company Name	Sector	Industry	Country	Continent
Z58	600346.SS	Hengli Petrochemical Co Ltd	Materials	Chemical	China	Asia
Z59	HSE.TO	Husky Energy Inc.	Energy	Oil & Gas Integrated	Canada	North America
Z60	IMO	Imperial Oil Limited	Energy	Oil & Gas Integrated	Canada	North America
Z61	INT	World Fuel Services Corporation	Energy	Oil & Gas Refining & Marketing	United States	North America
Z62	IOC.NS	Indian Oil Corporation	Energy	Oil & Gas Refining & Marketing	India	Asia
Z63	IRPC.BK	IRPC Public Company	Energy	Oil & Gas Refining & Marketing	Thailand	Asia
Z64	ISRL	Isramco	Energy	Oil & Gas E&P	United States	North America
Z65	JKX.L	JKX Oil & Gas	Energy	Oil & Gas E&P	UK	Europe
Z66	5020.T	JXTG Holdings	Energy	Oil & Gas Refining & Marketing	Japan	Asia
Z67	KEY.TO	Keyera Corp.	Energy	Oil & Gas Midstream	Canada	North America
Z68	036460.KS	Korea Gas Corp	Utilities	Utilities	South Korea	Asia
Z69	LNG	Cheniere Energy	Energy	Oil & Gas Midstream	United States	North America
Z70	LUKOY	PJSC LUKOIL	Energy	Oil & Gas Integrated	Russia	Europe
Z71	LUPE.ST	Lundin Petroleum AB	Energy	Oil & Gas E&P	Sweden	Europe
Z72	M05.SI	MTQ Corporation	Energy	Oil & Gas Equipment & Services	Singapore	Asia
Z73	MARI	Mari Petroleum Company	Energy	Oil & Gas E&P	Pakistan	Asia
Z74	MEL.AX	Metgasco Limited	Energy	Oil & Gas E&P	Australia	Oceania
Z75	MRO	Marathon Oil Corporation	Energy	Oil & Gas E&P	United States	North America
Z76	MUR	Murphy Oil Corporation	Energy	Oil & Gas E&P	United States	North America
Z77	MXC	Mexco Energy Corporation	Energy	Oil & Gas E&P	United States	North America
Z78	NBL	Noble Energy	Energy	Oil & Gas E&P	United States	North America
Z79	NBR	Nabors Industries	Energy	Oil & Gas Drilling	United States	North America
Z80	NDX1.DE	Nordex SE	Industrials	Diversified Industrials	Germany	Europe
Z81	NE	Noble Corporation plc	Energy	Oil & Gas Drilling	UK	Europe
Z82	NEE	NextEra Energy	Utilities	Utilities	United States	North America
Z83	NESTE.HE	Neste Oyj	Energy	Oil & Gas Refining & Marketing	Finland	Europe
Z84	NGG	National Grid plc	Utilities	Utilities	UK	Europe
Z85	NI	NiSource Inc.	Utilities	Utilities	United States	North America
Z86	NOV	National Oilwell Varco	Energy	Oil & Gas Equipment & Services	United States	North America
Z87	NS	NuStar Energy L.P.	Energy	Oil & Gas Midstream	United States	North America
Z88	NVA.TO	NuVista Energy Ltd.	Energy	Oil & Gas E&P	Canada	North America
Z89	OGDC	Oil & Gas Development Company	Energy	Oil & Gas E&P	Pakistan	Asia
Z90	OGZPY	Public Joint Stock Company Gazprom	Energy	Oil & Gas Integrated	Russia	Europe
Z91	OKE	ONEOK	Energy	Oil & Gas Midstream	United States	North America
Z92	OMV.VI	OMV Aktiengesellschaft	Energy	Oil & Gas Integrated	Austria	Europe
Z93	ONGC.NS	Oil and Natural Gas Corporation Limited	Energy	Oil & Gas Integrated	India	Asia
Z94	ORG.AX	Origin Energy Limited	Energy	Oil & Gas Integrated	Australia	Oceania
Z95	9532.T	Osaka Gas Co Ltd	Utilities	Utilities	Japan	Asia
Z96	OXY	Occidental Petroleum Corporation	Energy	Oil & Gas E&P	United States	North America
Z97	PAA	Plains All American Pipeline	Energy	Oil & Gas Midstream	United States	North America
Z98	PBR	Petroleo Brasileiro S.A. - Petrobras	Energy	Oil & Gas Integrated	Brazil	South America
Z99	PDCE	PDC Energy	Energy	Oil & Gas E&P	United States	North America
Z100	PEY.TO	Peyto Exploration & Development Corp.	Energy	Oil & Gas E&P	Canada	North America
Z101	PFC.L	Petrofac	Basic Materials	Oil & Gas Equipment & Services	Jersey	Europe
Z102	PGAS.JK	PT Perusahaan Gas Negara Tbk	Utilities	Utilities	Indonesia	Asia
Z103	PMO.L	Premier Oil	Energy	Oil & Gas E&P	UK	Europe
Z104	PNN.L	Pennon Group	Utilities	Utilities	UK	Europe
Z105	PTR	PetroChina Company Limited	Energy	Oil & Gas Integrated	China	Asia
Z106	PTT.BK	PTT Public Company Limited	Energy	Oil & Gas Integrated	Thailand	Asia
Z107	PXD	Pioneer Natural Resources Company	Energy	Oil & Gas E&P	United States	North America
Z108	RDS-B	Royal Dutch Shell plc	Energy	Oil & Gas Integrated	Netherlands	Europe
Z109	RELIANCE.NS	Reliance Industries	Energy	Oil & Gas Refining & Marketing	India	Asia
Z110	REP.MC	Repsol	Energy	Oil & Gas Integrated	Spain	Europe
Z111	RIG	Transocean Ltd.	Energy	Oil & Gas Drilling	Switzerland	Europe
Z112	RUI.PA	Rubis	Utilities	Utilities	France	Europe
Z113	RWE.DE	RWE Aktiengesellschaft	Utilities	Utilities	Germany	Europe
Z114	SDRL	Seadrill Limited	Energy	Oil & Gas Drilling	Bermuda	North America
Z115	SGRE.MC	Siemens Gamesa Renewable Energy	Industrials	Diversified Industrials	Spain	Europe

(Contd...)

Table 1: *(Continued)*

ID	Stock Ticker[3]	Company Name	Sector	Industry	Country	Continent
Z116	SGTZY	Surgutneftegas Public Joint Stock Company	Energy	Oil & Gas Integrated	Russia	Europe
Z117	SLB	Schlumberger Limited	Energy	Oil & Gas Equipment & Services	United States	North America
Z118	SNP	China Petroleum&Chemical Corporation/Sinopec	Energy	Oil & Gas Integrated	China	Asia
Z119	SO	The Southern Company	Utilities	Utilities	United States	North America
Z120	9908.TW	Great Taipei Gas Co Ltd	Utilities	Utilities	Taiwan	Asia
Z121	SOIL.V	Saturn Oil & Gas Inc.	Energy	Oil & Gas E&P	Canada	North America
Z122	SPM.MI	Saipem S.p.A.	Energy	Oil & Gas Equipment & Services	Italy	Europe
Z123	SPWR	SunPower Corporation	Technology	Solar	United States	North America
Z124	SRE	Sempra Energy	Utilities	Utilities	United States	North America
Z125	SRG.MI	Snam	Utilities	Utilities	Italy	Europe
Z126	SSL	Sasol Limited	Energy	Oil & Gas Integrated	South Africa	Africa
Z127	STO.AX	Santos Limited	Energy	Oil & Gas E&P	Australia	Oceania
Z128	SU	Suncor Energy	Energy	Oil & Gas Integrated	Canada	North America
Z129	600248.SS	Shaanxi Yanchang Petroleum Chemical Engineering	Energy	Oil & Gas Integrated	China	Asia
Z130	TLW.L	Tullow Oil plc	Energy	Oil & Gas E&P	UK	Europe
Z131	TOP.BK	Thai Oil Public Company Limited	Energy	Oil & Gas Refining & Marketing	Thailand	Asia
Z132	TOT	TOTAL S.A.	Energy	Oil & Gas Integrated	France	Europe
Z133	TRP	TC Energy Corporation	Energy	Oil & Gas Midstream	Canada	North America
Z134	TS	Tenaris	Energy	Oil & Gas Equipment & Services	Luxembourg	Europe
Z135	TUPRS.IS	Turkiye Petrol Rafinerileri	Energy	Oil & Gas Refining & Marketing	Turkey	Asia
Z136	UGP	Ultrapar Participacoes	Energy	Oil & Gas Refining & Marketing	Brazil	South America
Z137	UKOG.L	UK Oil & Gas	Energy	Oil & Gas E&P	UK	Europe
Z138	VLO	Valero Energy Corporation	Energy	Oil & Gas Refining & Marketing	United States	North America
Z139	VWS.CO	Vestas Wind Systems	Industrials	Diversified Industrials	Denmark	Europe
Z140	WLL	Whiting Petroleum Corporation	Energy	Oil & Gas E&P	United States	North America
Z141	WOPEY	Woodside Petroleum	Energy	Oil & Gas E&P	Australia	Oceania
Z142	WOR.AX	WorleyParsons Limited	Energy	Oil & Gas Equipment & Services	Australia	Oceania
Z143	XEC	Cimarex Energy Co.	Energy	Oil & Gas E&P	United States	North America
Z144	XOM	Exxon Mobil Corporation	Energy	Oil & Gas Integrated	United States	North America
Z145	600188.SS	Yanzhou Coal Mining Co Ltd	Basic Materials	Coal	China	Asia
Z146	YPF	Sociedad Anónima	Energy	Oil & Gas Integrated	Argentina	South America
Z147	YUMA	Yuma Energy	Energy	Oil & Gas E&P	United States	North America

The influence strength (IS) of a particular node is the summation of the associations or correlations of the node with all other connected nodes (Kim et al., 2002), it is calculated as:

$$S_i = \sum_{j \int \Gamma_i} \rho_{ij} \tag{6}$$

Where ρ_{ij} is Pearson correlation coefficient between two stocks i and j, and Γ_i signifies set of nodes directly connected to node i. To examine the shortest distance from a node to other nodes in the MST networks, we use closeness centrality measure that is applied to observe the power associated with the node (Tabak et al., 2010). Given a node i in a network containing N nodes, it is calculated as follows:

$$C(i) = \frac{1}{d_i} = \frac{N-1}{\sum_{j=1}^{N} d_{ij}} \tag{7}$$

Where d_{ij} is the distance between two stocks i and j. Further, to analyze the mediator roles of energy stocks in the MST network, we apply betweenness centrality measure. For a node i the betweenness centrality is given as (Freeman, 1977):

$$B(i) = \sum_{k \neq i \neq h} \frac{\sigma_{kh}(i)}{\sigma_{kh}} \tag{8}$$

Where $\sigma_{kh}(i)$ represents shortest routes among nodes k and h that pass-through node i, and σ_{kh} characterizes total number of shortest paths among k and h.

To examine dynamic properties of the MST network, we divide our sample period 2006-2019 into T windows t=1,2,…, T, having a width L to approximately 1 year. Furthermore, normalized tree length (NTL) and average path length (APL) is used to assess the time-varying length of MST networks. The formula for calculating NTL denoted as L(t) is as follows (Yao and Memon, 2019):

$$L(t) = \frac{1}{(N-1)} \sum_{(i,j) \in T^t} d_{ij} \tag{9}$$

The average path length (APL) is described as the mean distance among two stocks in a network, as follows:

$$L(t) = \frac{1}{\frac{1}{2} N(N-1)} \sum_{i \geq j} d_{ij} \tag{10}$$

4. RESULTS

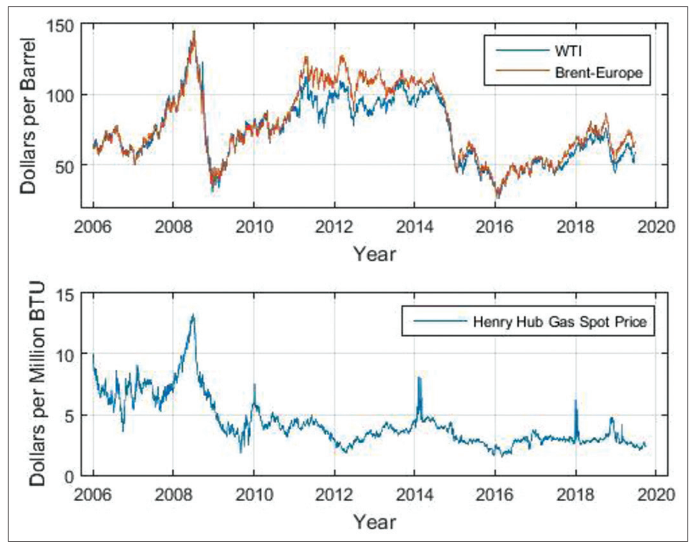
4.1. Statistical Analysis

Table 2 mentions summary of correlation matrices that have been obtained by splitting our data into different T windows of length L, and the overall sample period. We immediately observe highest correlation of 0.341, and standard deviation of σ=0.243 among energy stocks during the year 2008, the time when global financial crisis struck stock markets of the world. An increase in the average correlation of 0.332 is also encountered in the year 2011, during energy and European debt crisis period. Further, Figure 1 presents time varying history of oil and gas prices from 2006 to 2019, in-line with the sample period of our study. Since, oil price is considered a core determinant of economic growth (Dagher and El Hariri, 2013), and higher oil prices leads to economic recessions (Hamilton, 1983; Pönkä and Zheng, 2019). Therefore, it is crucial to observe the state and network structures of world energy companies during the time periods of 2008 and 2011, respectively. From Figure 1, we instantly observe a spike in the oil price during crisis time period of 2008. The Arab spring and ambiguity over Libyan oil output spread fears in the energy markets specifically resulted in sharp increase in the crude oil prices, causing 2011 energy crisis. The high average cross correlations among the energy stocks of the world represents strong interaction among stocks during crisis time. Additionally, the average cross correlation during entire sample period from 2006 to 2019 for the world energy companies remain at 0.240. Moreover, higher positive skewness of 1.214 is observed during the year 2017, possibly reflecting strong interaction among energy companies of the world.

Table 2: Descriptive statistics of Pearson CC {C_{ij}; $i<j$}

Year	{C_{ij}; $i<j$}					
	Mean	Maximum	Minimum	σ_r	Skew	Kurt
2006	0.189	0.864	−0.211	0.192	1.109	3.832
2007	0.198	0.904	−0.249	0.192	0.681	2.850
2008	0.341	0.945	−0.237	0.243	0.330	2.225
2009	0.288	0.996	−0.228	0.242	0.354	2.141
2010	0.275	0.918	−0.226	0.211	0.359	2.283
2011	0.332	0.921	−0.196	0.238	0.165	1.981
2012	0.211	0.843	−0.251	0.182	0.596	2.913
2013	0.153	0.814	−0.212	0.148	0.972	3.920
2014	0.172	0.846	−0.211	0.195	1.004	3.531
2015	0.245	0.906	−0.187	0.198	0.742	2.799
2016	0.232	0.888	−0.176	0.211	0.717	2.605
2017	0.113	0.812	−0.314	0.174	1.214	4.198
2018	0.170	0.899	−0.252	0.196	1.007	3.399
2019	0.171	0.889	−0.342	0.207	0.666	2.861
(2006-2019)	0.240	0.949	−0.061	0.193	0.782	2.779

Figure 1: Oil and gas prices history



Sources: EIA and Fred

4.2. Correlation Threshold Networks in the World Energy Companies

Given a network of 147 energy stocks of the world, and 147 (147−1)/2 total number of edges in the correlation matrix, we define threshold θ a value, such as: ($-1 \leq \theta \leq 1$) to chop the edges. For different correlation thresholds θ, any edges whose correlations are higher than the threshold are filtered. Therefore, we obtain high amount of edges at lower θ levels. Based on our correlation matrices, we examine energy companies' threshold network through edge filtering procedure with a step of 0.1. Figure 2 presents amount and percentage of retaining edges during various interval levels of thresholds for the two subsample periods of 2008 and 2011, and overall sample period. We can see the amount and percentage of retaining edges of the threshold network declines, with an increase in the threshold level. Additionally, we observe higher number of edges in the threshold network for energy companies during subsample periods, in comparison with the overall sample period, verifying our pervious findings of high correlations during crisis period.

Figure 2: Amount and percentage of retaining edges at various threshold levels for the world energy stock networks

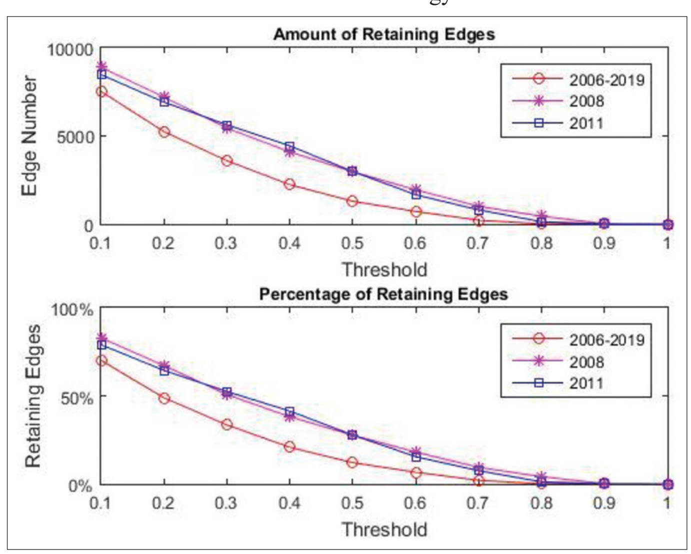
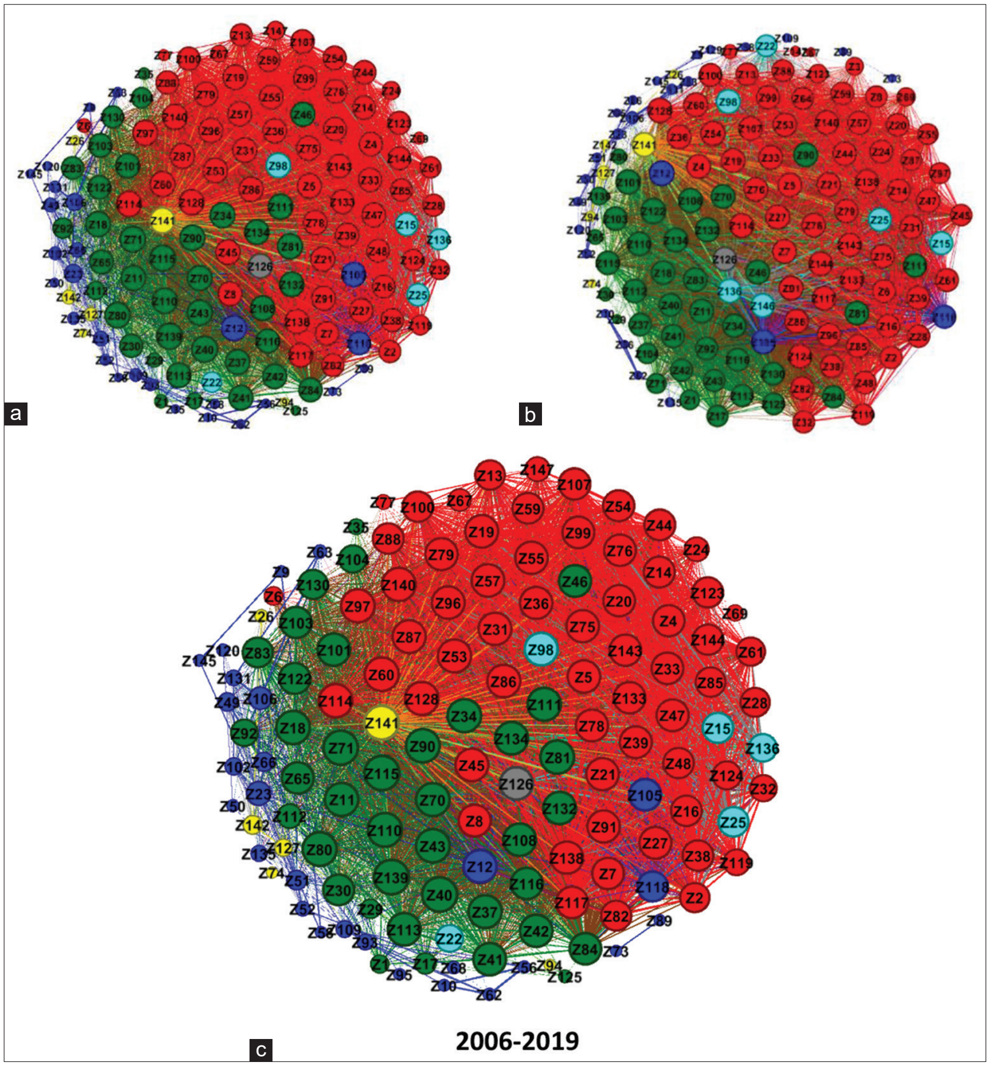


Figure 3 presents three different networks at $\theta > 0.3$ of 2008, 2011, and overall sample periods. All nodes are sized based on their degree of centrality, and colored by its geographical distribution of continent of the company. We observe dense networks at correlation threshold level of 0.3, where two thresholds networks of 2008, and 2011 are calculated to be extreme denser in comparison with the network of

Figure 3: Comparison threshold network at $\theta>0.3$ of 2008, 2011 and overall sample period. Color coding: Asian companies in blue, South American companies in cyan, European companies in green, African companies in grey, North American companies in red, and Oceania in yellow. Nodes are ranked based on degree of centrality measure



overall sample period. By highlighting top stocks of the threshold network, we can easily observe details of the overall networks. The top stocks[4] with largest values of the degree of connections at $\theta > 0.3$ during 2008 are: Z_{40} (Enel S.p.A. 115), Z_{139} (Vetas wind systems 115), and Z_{115} (Siemens Gamesa renewable energy 114). We observed that all of the top nodes belong to European continent that carry important role in the network. Comparing it with 2011 network at $\theta > 0.3$, the Italian top energy company holds principle position in the network, out of four companies in total, and these are: Z_{122} (Saipem S.P.A. 118), Z_{12} (CNOOC 113), Z_{101} (Petrofac 113), and Z_{128} (Suncor energy 113). However, the degree of connections of important nodes of the overall sample network at $\theta > 0.3$ is much lower. These key nodes are calculated to be Italian based company Z_{34} (Eni S.p.A. 99), and France based company Z_{132} (Total S.A. 97).

Figure 4 shows three different networks at a higher $\theta > 0.7$ of 2008, 2011, and overall sample periods. All nodes are sized based on betweenness centrality, and colored by its geographical distribution of the continent of the company. Immediately, we observe the break of whole network into small components, along with the subsequent decline in the network density at a higher threshold level. In terms of degree of connectivity, two top most important stocks are US based, namely: Z_{27} (Chevron Corporation) connecting directly with 53 and 46 companies during crisis time of 2008 and 2011, and Z_{21} (ConocoPhillips 23) for the overall sample period. Therefore, the influence of US based energy companies is visible during crisis periods and overall sample period at higher threshold level of 0.7. Additionally, the stocks during crisis periods of 2008 and 2011 are clustered together, behaving like a herd or flock. With regard to betweenness centrality, the stocks[5] that represents highest short routes are: Z_{98} (Petrobras 152.111) during the year 2008, Z_{34} (Eni S.p.A. 468.141) during the year 2011, and Z_{81} (Noble Plc 62.729) during overall sample period.

Moreover, Table 3 presents topology of correlation threshold networks at different intervals with bins of 0.1. We also built

4 The number besides company name represents degree of connections of the company.

5 The number besides company name indicates betweenness centrality score of the company.

Figure 4: Comparison threshold network at $\theta > 0.7$ of 2008, 2011 and overall sample period. Nodes are ranked based on betweenness centrality measure

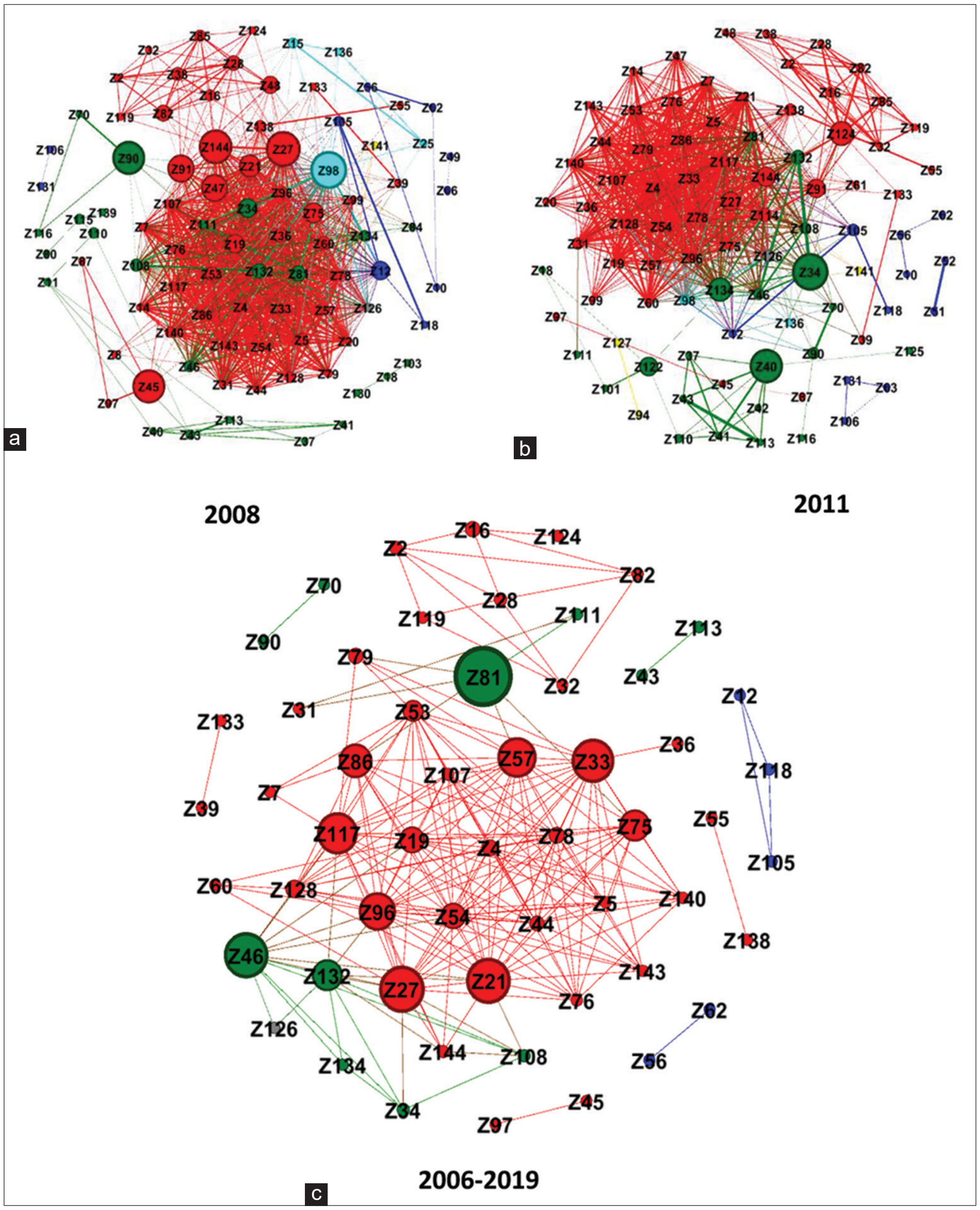


Table 3: For the world energy stocks network, the number of nodes N, the average degree $\langle d_{ij} \rangle$, the graph density, and the modularity are presented for different θ levels from θ>0.1 to θ>0.9 in a step of 0.1, along with θ<0 to highlight negative correlation values during 2008, 2011 and overall study period

θ	2006-2019				2008				2011			
	N	$\langle d_{ij} \rangle$	Density	Modularity	N	$\langle d_{ij} \rangle$	Density	Modularity	N	$\langle d_{ij} \rangle$	Density	Modularity
>0.1	144	104.5	0.731	0.083	146	121.8082	0.84	0.094	147	115.2925	0.79	0.055
>0.2	140	74.871	0.539	0.088	143	100.7552	0.71	0.103	143	96.6713	0.681	0.056
>0.3	128	56.1718	0.442	0.109	140	77.7285	0.559	0.112	140	80.4	0.578	0.058
>0.4	114	39.1578	0.347	0.135	134	61.04477	0.459	0.114	132	67.2272	0.513	0.071
>0.5	103	25.1456	0.247	0.142	127	46.7559	0.371	0.129	123	48.42276	0.397	0.109
>0.6	75	19.0666	0.258	0.191	113	34.37168	0.307	0.144	108	30.7407	0.287	0.143
>0.7	56	7.8928	0.144	0.303	89	22.7191	0.258	0.16	88	18.2954	0.21	0.201
>0.8	19	1.15789	0.064	0.86	65	13.72307	0.214	0.159	47	5.5319	0.12	0.314
>0.9	2	1	1	0	21	1.619047	0.081	0.688	6	1	0.2	0.667
<0	128	5.4218	0.043	−0.057	147	9.1156	0.062	−0.043	147	9.95918	0.068	−0.031

networks and explore the topology of negative values of correlation threshold at $\theta > 0$, that shows high number of nodes and increased density for crisis periods of 2008 and 2011 among world energy companies. Additionally, we observe high modularity of 0.688, and 0.667 at top most threshold level of $\theta > 9$ for the crisis periods of 2008 and 2011, and 0.86 at higher threshold $\theta > 8$ for overall sample period, respectively. This implies strong bond among stocks while containing communities within a threshold network. Similarly, few recent studies have reported high modularity among stocks during crisis time (Memon and Yao, 2019; Lee and Nobi, 2018).

4.3. Minimum Spanning Tree (MST)

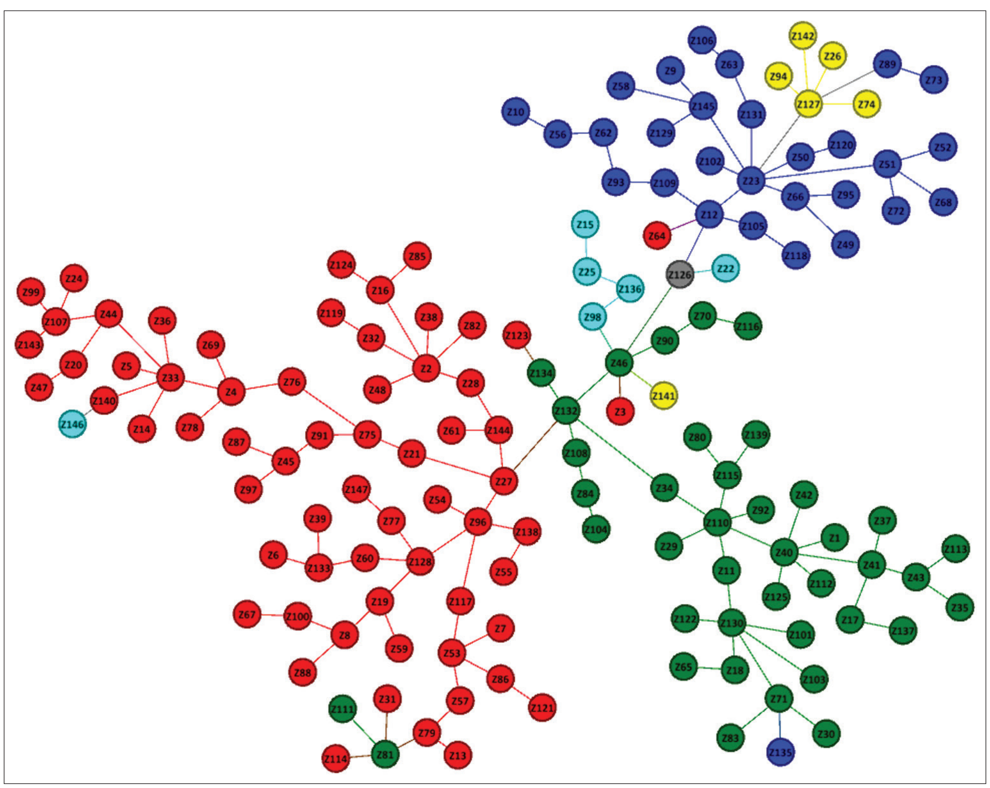
In this section, we present three MSTs of 147 energy companies of the world, based on the separation of our data into two subsamples for crisis periods of 2008, and 2011, while comparing it with overall data sample network to examine network evolving connectivity and influence of stocks. In the MSTs, all nodes are colored based on their geographical distribution of continents.

The overall energy stock market network across the whole period of study is presented in Figure 5. We immediately observe substantial clustering based on geographic positioning of energy companies. The results show three prominent clusters: the north American energy companies (red) in the left, the European energy companies (green) in the bottom right, and the Asian energy companies (blue) in the top right. Several studies have reported homogenous clustering in the MST networks of stock markets (Majapa and Gossel, 2016; Yao and Memon, 2019; Coletti and Murgia, 2016). In addition, Table 4 presents top energy stocks based on their degree of connections. The Asian energy giant, the China oilfield services company (Z_{23}) holds central or hub position in the overall MST with 8 degree of connections. Other key nodes in the MST network with six degree of connections include 2 US, 1 Australian, and 4 European energy companies. The acquisition of central or key positions in the overall MST network is not unusual, given the fact that it has been acquired by top energy companies of the world. Moreover, the results show high average degree of connection for European energy companies of 2.15, followed by Asian energy companies score of 1.965, and north American energy companies score of 1.938 in the overall MST network. This represents high influence and importance of European energy companies in the overall MST network.

Table 4: List of the top stocks with the highest degree of connections in MST of World energy stocks. As is shown, the top energy stocks are diverse in the country of origin which includes 1 China stock, 2 US stocks, 1 Italy stock, 1 Norway stock, 1 Spain stock, 1 Australia stock and 1 UK stock

Degree	Node ID	Company Name	Industry	Country
8	Z23	China Oilfield Services Limited	Oil & Gas Equipment & Services	China
6	Z2	American Electric Power Company	Utilities	United States
6	Z33	Devon Energy Corporation	Oil & Gas E&P	United States
6	Z40	Enel SpA	Utilities	Italy
6	Z46	Equinor ASA	Oil & Gas Integrated	Norway
6	Z110	Repsol	Oil & Gas Integrated	Spain
6	Z127	Santos Limited	Oil & Gas E&P	Australia
6	Z130	Tullow Oil plc	Oil & Gas E&P	UK

Figure 5: MST of 147 world energy companies during entire period of study from January 2006 to June 2019. Color coding: Asian companies in blue, South American companies in cyan, European companies in green, African companies in grey, North American companies in red, and Oceania in yellow



Additionally, the European energy companies also dominate with high average betweenness centrality score of 665.325, followed by North American companies betweenness score of 558.554, representing strong intermediary role by European and North American energy companies in the overall MST network.

The crisis period MST 2008 of 147 world energy companies is presented in Figure 6, and shows different structure of MST, where Asian energy companies (blue) are detached and connected with companies from three different continents. However, energy companies belonging to Europe or North American region are still intact and clustered together. In addition, Table 5 shows appearance of two hub nodes of US based Occidental petroleum (Z_{96}), and German based utilities company E.ON SE (Z_{43}), connecting directly with 10 and 8 nodes in the MST. Additionally, MST structure during the period of global financial crisis 2008 comprises, 49.66% of nodes' (i.e. 73 stocks) degrees are equal to one, around 25% (37 stocks) of nodes' degrees equal to two, almost 15% (22 stocks) of nodes' degrees equal to three, 4% (6 stocks) of nodes' degrees equal to four, and 4.76% (7 stocks) of nodes' carry degrees of five and six. The companies with number of links >6 is around 1.36% from the total number of vertices in the network.

Similar to the MST structure of 2008, Figure 7 shows broken cluster and sparse Asian energy companies in MST map. Additionally, we observe split of European energy companies that has been detached and connected with North American companies in two groups. Therefore, there is only 1 dominant cluster of North American companies (red) in the MST map of 2011. Moreover, Table 6 presents two star-like hub nodes of US based Apache corp. (Z_4), and Italian based Saipem S.p.A. (Z_{122}), directly connecting with 11 and 10 nodes in the MST network. While comparing the

Table 5: List of the top stocks with highest degree of connections in the MST of World energy stocks over the year 2008. As is shown, Occidental Petroleum stock from US is the most connected stock in the MST with a degree of 10. The rest of stocks having degree >5 are composed of 1 Germany stock, 1 UK stock, and 1 US stock

Degree	Node ID	Company Name	Industry	Country
10	Z96	Occidental Petroleum Corporation	Oil & Gas E&P	United States
8	Z43	E.ON SE	Utilities	Germany
6	Z18	Cairn Energy	Oil & Gas E&P	UK
6	Z33	Devon Energy Corporation	Oil & Gas E&P	United States

Table 6: List of the top stocks with highest degree of connections in the MST of World energy stocks over the year 2011. As is shown, Apache stock from US is the most connected stock in the MST with a degree of 11. The rest of stocks having degree >5 are composed of 2 Italy stocks, 2 US stocks, 1 Canada stock, and 1 Australia stock

Degree	Node ID	Company Name	Industry	Country
11	Z4	Apache Corp	Oil & Gas E&P	United States
10	Z122	Saipem S.p.A.	Oil & Gas Equipment & Services	Italy
7	Z40	Enel SpA	Utilities	Italy
7	Z124	Sempra Energy	Utilities	United States
7	Z128	Suncor Energy	Oil & Gas Integrated	Canada
6	Z33	Devon Energy Corporation	Oil & Gas E&P	United States
6	Z127	Santos Limited	Oil & Gas E&P	Australia

Figure 6: MST of 147 world energy companies during global recession Year of 2008

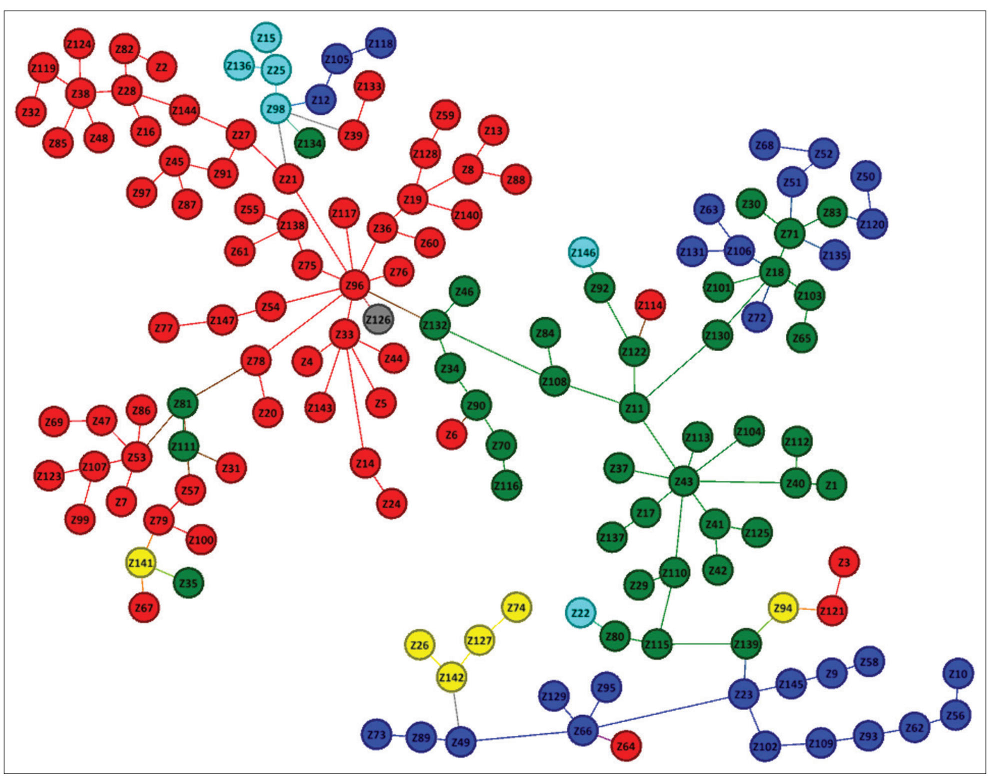
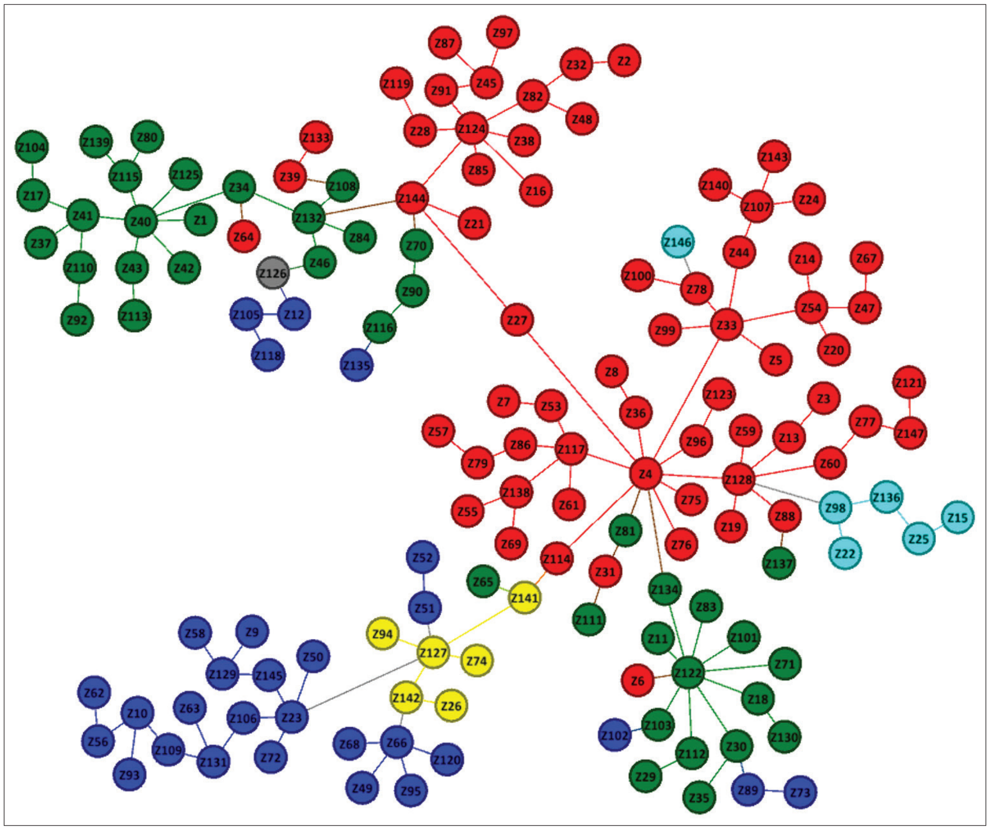


Figure 7: MST of 147 world energy stocks during oil price hikes in the Year 2011



two crisis period MSTs, companies with number of connections >6 is about 3.40% (5 stocks) for 2011, and 1.36% (2 stocks) for 2008 from total number of vertices in the network. To sum up, the crisis period structures confirm formation of low clusters, sparse nodes, and appearance of star-like hub nodes in the MST map.

4.4. Centrality Structures of Minimum Spanning Trees

We apply centrality measures on three MSTs to examine dominance of energy companies of the world. After calculating three prominent centrality tests of each and every node, Table 7 ranks top five nodes based on their individual score. Considering overall MST, three top US energy companies namely: Devon energy (Z_{33}), American electric power (Z_2), and Occidental Petroleum (Z_{96}) appear to be most influential stocks in the network, followed by European top energy companies. Despite having lower degree of connections of six, in comparison with eight degree of connections of Asian based China Oilfield Services (Z_{23}) in the overall MST network, these companies have more power to influence the entire MST network. The betweenness and closeness centrality test nominate France based Total S.A. (Z_{132}) energy company taking intermediary or bridge role in the overall MST network. During crisis periods of 2008 and 2011, US top energy companies namely: Occidental petroleum (Z_{96}), Apache Corporation (Z_4), along with France based Total S.A. (Z_{132}) appears on the top position among all stocks in the MSTs. Finally, the centrality structures of MSTs reveal few top US and European based companies occupying important and great global influence positions in the MST networks. Therefore, the rise and fall of these few nodes will impact the stability structure of entire energy companies' network. In addition, there is always a chance of rapid spread of systematic risk towards the entire network structure of world energy companies, as external shock can transmit easily and quickly.

4.5. Dynamic Structure of Energy Stocks Networks

The distance d_{ij} specifies the correlation among stocks, i.e. the higher the distance the smaller the correlation among two stocks and vice versa. Figure 8 presents dynamic mean distance $\langle d_{ij} \rangle$, and total distance $d_{total} = \sum_{i,j} d_{ij}$ of the overall distance matrix, and MST, by taking into account varied edge numbers. It can be calculated as follows:

$$\langle d_{ij} \rangle = \frac{1}{N(N-1)/2} \sum_{i,j} d_{ij} \qquad (11)$$

$$\langle d_{ij} \rangle = \frac{1}{N-1} \sum_{i,j} d_{ij} \qquad (12)$$

Our results suggest similar pattern of four figures, which means MST presents a backbone of the original network, and the parallel trend stays robust over time. Similarly, the distances present a sharp decline during crisis periods of 2008 and 2011, hinting towards tight correlations among energy stocks. But soon after crisis period of 2011, a gradual increase and stability among energy market is also observed.

Figure 9 shows dynamic results of NTL and average path length in the minimum spanning tree network of length T=14. The dynamic APL represents fluctuation pattern and information escalation for the world energy stocks. Additionally, the NTL curve shows

Table 7: For the world energy stocks network, we present top five stocks based on centrality measures of influence strength (S_i), betweenness centrality (B_i), and closeness centrality (C_i), for 2008, 2011, and overall study period

Rank	Influence Strength			Betweenness Centrality			Closeness Centrality		
	Node ID	Company	S_i	Node ID	Company	B_i	Node ID	Company	C_i
Section 1: MST 2006-2019									
1	Z33	Devon Energy	4.492	Z132	TOTAL S.A.	7031	Z132	TOTAL S.A.	0.204
2	Z2	American Electric Power	4.358	Z27	Chevron Corporation	6539	Z27	Chevron Corporation	0.199
3	Z132	Total S.A.	3.946	Z46	Equinor ASA	4896	Z46	Equinor ASA	0.189
4	Z96	Occidental Petroleum	3.693	Z12	CNOOC Limited	3946	Z34	Eni S.p.A.	0.182
5	Z46	Equinor ASA	3.599	Z126	Sasol Limited	3919	Z96	Occidental Petroleum Corporation	0.177
Section 2: MST 2008									
1	Z96	Occidental Petroleum	8.799	Z96	Occidental Petroleum Corporation	7296	Z132	TOTAL S.A.	0.1886
2	Z43	E.ON SE	5.824	Z11	BP p.l.c.	6244	Z96	Occidental Petroleum Corporation	0.1884
3	Z33	Devon Energy Corporation	5.423	Z132	TOTAL S.A.	5736	Z108	Royal Dutch Shell plc	0.1855
4	Z53	Halliburton Company	4.388	Z108	Royal Dutch Shell plc	5345	Z11	BP p.l.c.	0.1816
5	Z38	Edison International	4.074	Z43	E.ON SE	4683	Z43	E.ON SE	0.1684
Section 2: MST 2011									
1	Z4	Apache Corp	9.101	Z4	Apache Corp	8596	Z4	Apache Corp	0.2441
2	Z122	Saipem S.p.A.	6.299	Z144	Exxon Mobil	5187	Z27	Chevron Corporation	0.2250
3	Z124	Sempra Energy	5.592	Z27	Chevron Corporation	4653	Z114	Seadrill Limited	0.2131
4	Z128	Suncor Energy	5.279	Z114	Seadrill Limited	3393	Z144	Exxon Mobil	0.2080
5	Z40	Enel SpA	5.138	Z141	Woodside Petroleum	3331	Z134	Tenaris	0.2053

Figure 8: Dynamic evolution of mean and total distances of overall network, and MST for world energy stocks over time in the study period. We used time windows and length of T=14

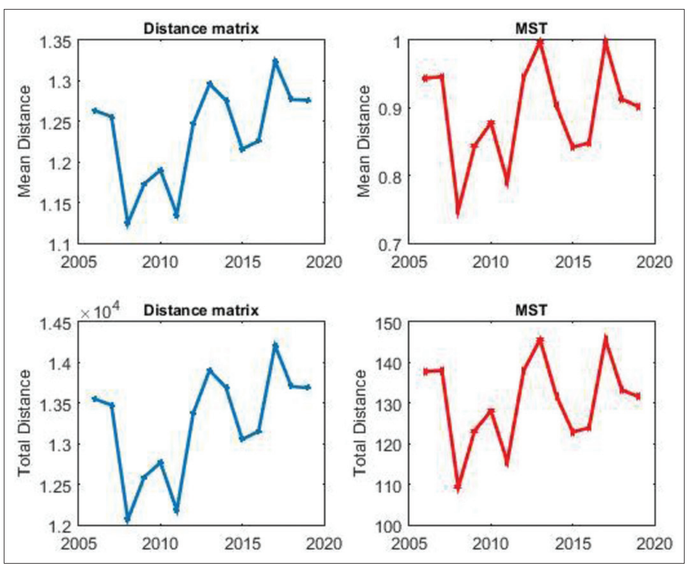
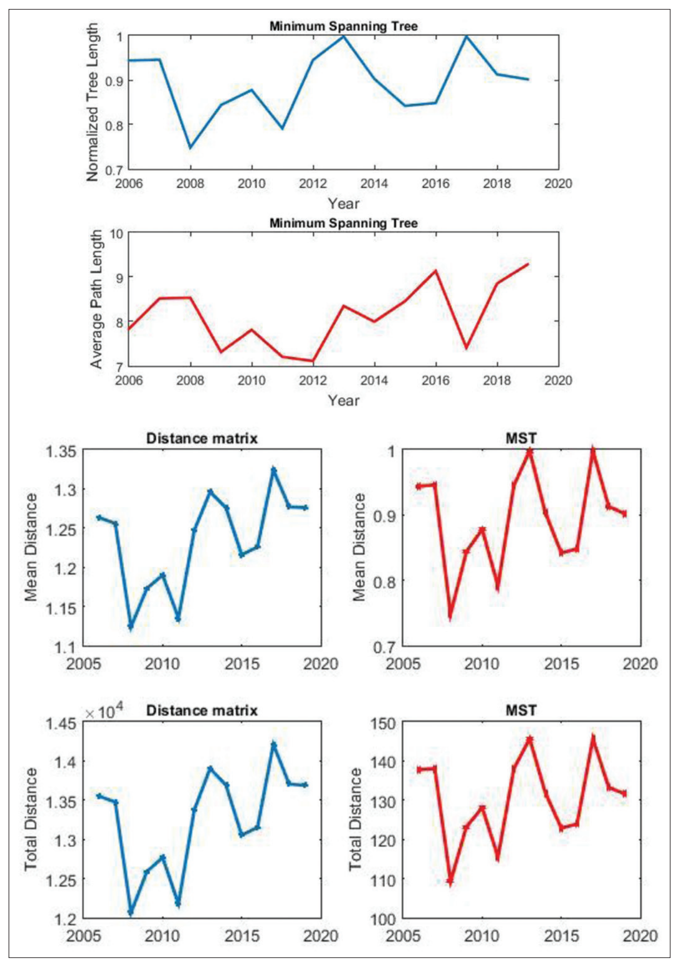


Figure 9: Dynamic evolution of normalized tree length (NTL), and average path length (APL) of MST. We used time windows and length of T=14



extreme network contraction during time periods of global recession 2008, and oil price hikes coupled with european debt crisis of 2011 for the world energy stocks. Additionally, the results show a valley, possibly due to high correlation among stocks during crisis periods. Previous studies in literature point towards correlation move to one during crisis, which is a sign of instability for the stock markets (Yao and Memon, 2019; Papenbrock and Schwendner, 2015). We also observed high expansion of the MST network for the year 2017, which was robust year for stocks and energy market. The global energy market exceeded $1.4 trillion during the year 2016, representing a massive increase of 7%

compared to earlier year. Simultaneously, a constant expansion after crisis periods of global recession 2008, oil price shocks, and european debt crisis is being observed showing economic recovery after crisis periods.

5. CONCLUSION

In this paper, we investigated network structures and dynamics of popular 147 energy stocks from 34 countries through properties and models of complex network theory. We used data spreaded approximately 14 years, from January 03, 2006 to June 28, 2019. Additionally, this study compares network structures of two sub-sample periods including: Global financial crisis 2008, energy and european debt crisis period of 2011, and overall sample period. We present time varying statistical analysis of correlation coefficients, correlation threshold networks, the clustering structure of MSTs, the centrality measures of MSTs, and importance of nodes and identification. We also examine time evolving distance matrices, and dynamic topological properties of MSTs.

Our results show strong correlations and interaction among energy companies of the world during crisis periods of 2008 and 2011. From the correlation threshold network, we examined a decline in the amount and percentage of retaining edges with an increase in the threshold level. Additionally, we observed higher influence and stability of US based energy companies during crisis periods. For the MST networks, we found three prominent clusters belonging to North American, European, and Asian energy companies in the overall MST map. During crisis periods, only one cluster of North American companies remains intact, and rest of the two clusters are detached. The Asian energy giant China oilfield service appear to be hub node in the overall MST. However, the importance and influence of European and North American energy companies is highly visible in the overall MST network. During sub-sample crisis periods, we observed star-like hub nodes of Occidental petroleum, E.ON SE for 2008, and Apache Corporation, and Saipem S.P.A. for 2011. The centrality measurement results stated the influence of few top US and European energy companies in MSTs. In addition, there is always a chance of rapid spread of systematic rick towards entire energy companies' structure. Moreover, time varying topological measures highlighted substantial decline in the tree length during crisis time periods and economic recovery after crisis period.

We have built energy companies network structures based on correlation coefficients. Perhaps, our future work will explore additional methods of constructing energy companies network such as: partial correlation method (Wang et al., 2018), and tail dependence networks (Wen et al., 2019). In addition, the results and implications of our study will provide guidance for a wide audience including: individual investors, multinational organization, policy makers and government agencies.

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APPENDIX A

Table A1: Websites for well-known energy companies of the world

S. No	Website
1	https://top250.platts.com/Top250Rankings
2	https://www.thomsonreuters.com/en/products-services/energy/top-100.html
3	https://www.worldatlas.com/articles/biggest-oil-companies-in-the-world.html
4	https://en.wikipedia.org/wiki/List_of_largest_oil_and_gas_companies_by_revenue
5	https://www.value.today/world-top-companies/energy
6	https://www.offshore-technology.com/features/largest-oil-and-gas-companies-in-2018/
7	https://www.investopedia.com/articles/investing/022516/worlds-top-10-utility-companies.asp
8	https://www.power-technology.com/features/top-10-power-companies-in-the-world/