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Global Conventional and Clean Energy Spillovers, Uncertainty, and Local Markets: Evidence from Leading Oil-Exporting and Oil-Importing Countries

Mohd Ziaur Rehman*

Department of Finance, College of Business Administration, King Saud University, Riyadh 11587, Saudi Arabia.
*Email: zmuhammad@ksu.edu.sa

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ABSTRACT

This paper employs the Quantile VAR (QVAR) spillover approach to explore the spillover connectedness between global clean and dirty energy with local energy indices of the largest oil exporting and importing states, namely KSA, Canada, the US, Russia, China, and India. The study reports robust connectedness in the case of both clean and dirty energy; that is, 96.20% at the bearish quantile, 82.71% at the middle quantile, and 96.83% at the bullish quantile in the case of the clean energy index. Similarly, for dirty energy, we found 96.24% at the bearish quantile, 82.07% at the middle quantile, and 96.98% at the higher quantile. The GPRD and the energy sectors of Saudi Arabia, China, India, and the United States are net recipients of spillover effects, whereas the clean, dirty, global, and Canadian energy indices serve as net transmitters. OVX and Russian energy have a dual function, alternating between transmission and reception over quantiles. Moreover, in the median quantile of the clean energy framework, the Canadian and Russian energy sectors had the lowest net transmission rates (4.64% and 2.73%, respectively), whereas clean energy (44.34%) and global energy (43.5%) revealed the most significant spillover impacts. From an investor's viewpoint, the energy sectors in the US and India have the weakest spillover effects at the median quantile, hence adding minimally to systemic risk. Regulators should oversee clean and global energy markets as prelude to potential issues and implement green transition policies incrementally, given that disturbances in these markets affect the entire system, while the weakly transmitting Canadian and Russian energy sectors present less risk of contagion.

Keywords: Clean Energy, Dirty Energy, Oil Exporting Countries, Oil Importing Countries, Quantile VAR, Energy
JEL Classifications: C32, Q35, Q37, Q42, Q43

1. INTRODUCTION

The possibility of global connectivity across energy markets results from the increasing financialization of conventional stock markets. The massive rise in investment in the energy industry over the past few years has attracted intense attention from market practitioners and regulators (Ahmad, 2017; Naeem et al., 2023). Energy investments are becoming increasingly popular, and their size and worth are growing. According to a report from the US Energy Information Administration (EIA), fossil fuels account for a substantial portion of the world's energy supply. However, reliance on fossil fuels has heightened increased global concerns about resource depletion (Awodumi and Adewuyi, 2020; Umar et al., 2022). These concerns have spurred an extraordinary global interest in clean (renewable) energy as a potential substitute for fossil fuels (Song et al., 2019; Yousaf et al., 2022). There is increasing recognition that the availability of fossil fuels is shrinking, and clean energy has emerged as a replacement energy source and a remedy to the sustainability challenges for numerous regions. The International Renewable Energy Agency (IRENA) forecasts that by 2050, renewable energy will be able to supply a substantial part of the world's energy needs. Accordingly, a significant amount of funds is moving from the fossil fuel industry to clean energy, which inevitably strengthens the response of renewable energy stock returns to changes in the price of fossil fuels (Geng et al., 2021). In the opinion of Cai et al. (2019), "clean energy" or "renewable energy" can refer to a variety of energy sources other than conventional energy sources, such as solar energy, wind energy. In recent decades, fossil energy consumption has caused severe environmental pollution issues in numerous countries and has had devastating external impacts (He et al., 2020). After the 21st Conference of the Parties (COP21), Governments from all over the global arena established a path to tackle climate change over the next 10 years. The creation of a solid foundation for environmentally friendly investments can lead to low-risk investments (Ding et al., 2022). Therefore, the rapid growth of clean energy markets may have an impact on conventional energy commodities. Therefore, understanding the links of clean energy stock returns on the shifting patterns of dirty energy markets is of utmost importance (Yousaf et al., 2022).

Recently, there has been a rising curiosity in studying volatility across financial markets (Al-Hajieh, 2023). Energy price swings can spread readily to other markets, infecting them with financial risks and causing changes in the financial system (Fernández et al., 2018). An important topic that has been researched in recent years is the interaction between energy and financial market indices. Previous research has shown that the price of energy impacts stock indices, mostly through anticipated cash flows and investment decisions (Yang and Zhou, 2017). Studies on risk spillover among stock markets and commodity indices have generated interest owing to the ongoing integration of global financial markets and the growing monetarization of energy commodities. The link between the renewable and dirty energy markets has been the subject of numerous studies (Henriques and Sadorsky, 2008; Corbet et al., 2020). The performance of stock markets for renewable energy sources and the movement of markets for fossil fuels are theoretically connected. The primary channel is the well-documented direct link between stock returns for clean energy companies and those of fossil energy companies (Kumar et al., 2012). Prior research has demonstrated an economic substitution connection between renewable and dirty energy (Kassouri et al., 2021; Reboredo, 2015; Umar et al., 2022). Mokni (2020) argues that higher dirty energy prices make outlay in clean energy sectors more attractive, which boosts their financial results (Xia et al., 2019).

A body of academic research contends that variations in the price of fossil fuels have a significant impact on how well the stock markets for renewable energy perform (Song et al., 2019; Zhou and Geng, 2021), and that the prices of clean energy stocks and dirty fuel commodities move in tandem. Fossil energy demand increases when prices fall, reducing investment in and use of renewables while also depressing stock markets for renewable energy (Aslan et al., 2022). These studies support a viable replacement framework for fossil fuels and renewable energy sources. However, a different body of academic research challenges the idea that fossil fuels and renewable energy may be substituted for one another and highlights the viability of a decoupling thesis based on the idea that these two types of energy operate in distinct domain areas (Ahmad, 2017; Khan et al., 2017).

The widespread transmission of shocks through financial markets and assets, which increases unpredictability and systemic risk, is referred to in the literature as financial contagion. Investors are better able to diversify their portfolios and manage risk when they are aware of the uneven effects of uncertainty on stock markets. Policymakers can use this knowledge to design initiatives aimed at reducing the influence of oil prices on capital markets. The price movements of energy commodities are influenced by multiple factors, including uncertainties, interest rate differences, and wealth transfer systems between oil-importing and oil-selling countries. These influences cause movements in financial markets and in a variety of commercial segments (Ashraf and Goodell, 2022; Broadstock et al., 2016). The volatility of uncertainties has clearly had an impact on financial and economic systems as well as stock returns (Nath Sahu et al., 2014).

According to Antonakakis et al. (2018), uncertainties have a significant impact on option pricing, asset allocation, and hedging methods. This explains the depth of recent studies that examine the interactions and connections between different assets and factors related to risk and uncertainty. The impact of uncertainty is a significant contributor to the volatility and turbulence of commodity markets. Numerous studies focus primarily on how uncertainty in the economy affects financial and commodity markets (Tang et al., 2021; Wen et al., 2022). Consequently, investors panic due to unpredictability during acute uncertainty risk events can result in abnormal market volatility, which undermines the enduring viability of commodity markets (Tiwari et al., 2021). In this contemporary era, geopolitical instability and oil price shocks have emerged as leading sources of uncertainty (Lee et al., 2021). Uncertainty (geopolitical and oil), has become a key concern in both established and emerging economies (Song et al., 2022; Ghalayini, 2011). Oil volatility and geopolitical risk have drawn attention because of their substantial logical influence on macroeconomic variables (Song et al., 2022).

Additionally, geopolitical risk and oil volatility are the main variables influencing investors' investment decisions. Investors' anxiety has been substantially exacerbated by the mounting global danger. The literature has also emphasized how geopolitical risk affects market cycles and economic development. According to Caldara and Iacoviello (2022), geopolitical risk is the chance that wars, terrorist attacks, and struggles between regions disrupt the regular and peaceful development of global relations. Therefore, an empirical endeavor of uncertainty, energy, and the stock market is central to understanding these dynamics.

Few empirical studies have shown how changes in uncertainty affect stocks and commodities. Similarly, few studies have deliberated the link between geopolitics and oil volatility when assessing the interplay between energy and stock markets (Abbass et al., 2022). Increased uncertainty related to fossil commodities may unlock new opportunities for investing in the green energy sector, as well as creating new energy sources. To spread the risk linked with financial markets, participants are pushed to move their stakes in investment portfolios toward other types of assets. It is crucial to examine how resilient energy markets are to various uncertainties, to categorize their hedging capacities, and to design efficient policies to lessen the effects of disturbances on energy assets. It is pertinent to comprehend the effect of multiple uncertainties on the interplay between energy markets and stock markets, given the tremendous impact of energy markets on the stability of the international economy (Gupta et al., 2022).

Unfortunately, several essential research voids still need to be filled. The connection between energy and the financial markets of oil-exporting and oil-importing nations is an ongoing trend that continues to spark intense discussion among academics, decision-makers, and investors worldwide. Although certain studies have focused on oil-exporting and oil-importing nations, to the best of our knowledge, no research has clarified the interplay between clean and dirty energy within the context of uncertainties in these economies. It would be of great interest to learn whether the clean energy market is linked to stock market indices differently from the dirty energy market in oil-exporting and oil-importing nations in the context of uncertainty.

This study addresses the following questions: Does the dynamic spillover connectedness among clean energy, dirty energy, global stock markets, and the energy, and stock indices of oil-exporting and oil-importing regions change over time under uncertainty? Do uncertainties, as measured by OVX and GPRD, affect not only clean and dirty energy, but also other energy and stock indices?

To do this, we employ Quantile VAR (QVAR) model to investigate the spillover connection within this system in the presence of global uncertainty measures (OVX and GPRD). The Quantile VAR framework is a potent tool for addressing information spillovers and the interconnectedness across the market conditions. The results demonstrate that market connectivity is deeper and stronger during extreme events and that energy and stock indices serve as both net transmitters and net recipients. This study enhances knowledge based on energy and stock indices in several ways. First, it explores the connections and spillovers among clean energy, dirty energy, global energy and stock markets, and energy-stock indices of oil-exporting and oil-importing countries. Second by integrating two separate measures of uncertainty oil market volatility (OVX) and geopolitical risk (GPRD) the research elucidates the interaction of various uncertainty sources with energy and equities markets across quantiles. Third, by utilizing the quantile VAR framework instead of mean-based connectedness methodologies, the research reveals a significant disparity between tail and median connectedness. The rest of the paper is organized as follows: Section 2 covers an extant review of the literature review, section 3 focuses on the data and methods, and section 4 presents the empirical results. Section 5 ends with the conclusion and policy implications.

2. LITERATURE REVIEW

Businesses, shareholders, and financial organizations are making major efforts to support the emission reduction drive, principally in the background of the Paris Climate Agreement and COP26. Studies reveal that the Paris Climate Agreement has increased investors' knowledge of the clean energy market (Fahmy, 2022a; Fahmy, 2022b). In light of this, a wide range of empirical literature has attempted to investigate the pricing connections between dirty and clean energy. The groundbreaking research by Henriques and Sadorsky (2008) represents an initial effort to investigate the causal connection between the markets for dirty and clean energy. This study identifies causal relationships among clean energy stocks, technology, and the crude oil market. The results reveal that the prices of clean energy stocks are affected by those of crude oil (dirty energy) and technology stocks. In this context, clean energy firms are gaining considerable interest from financial industry players as clean energy equities have become a new investment class.

According to Kumar et al. (2012), excessive oil price (dirty energy) volatility and environmental concerns are leading to an increase in investments in alternative energy stocks. With the aid of a copula framework, Reboredo (2015) investigates the systemic risk and dependency between the price of crude oil (dirty energy) and the value of clean energy assets. Subsequently, this study contends that investors favor clean energy investments over traditional ones because of the extreme volatility of oil prices during times of financial and economic collapse. Through the application of a quantile-based regression approach, Dawar et al. (2021) discover a significant effect of lagged WTI oil returns on clean energy stock returns, which fluctuates depending on the state of the market. Through a causality in quantile test, Hammoudeh et al. (2021) discover that oil returns drove the RS returns prior the COVID-19 pandemic. The study reveals that only at lower quantiles over identical periods, the volatility analysis reveals a strong bidirectional causal link between the instability of the dirty energy (oil) price and the volatility of the stocks of renewable energy sources, but it is not evident in highly volatile markets. Bouri et al. (2019) employ a mixed copula to investigate whether dirty energy (oil prices) could lower the risks of clean energy assets during a challenging phase, and discover that its impact is minimal.

Using the DS copula, Tiwari et al. (2021) explain the limited correlation between oil and clean energy assets during optimistic market periods. Zhang et al. (2020) investigate the effects of external dirty energy (oil prices) structural shocks on the renewable energy by employing wavelet-based quantile-on-quantile and Granger causality-in-quantile approaches. The study reports that the influence of oil shocks is unequal at higher quantiles across lengthy investment horizons and varies among quantiles. Dirty energy (oil price) shocks have significant short- and long-term influences on environmentally friendly energy. Quantile-based connectivity indicators utilized by Saeed et al. (2021) demonstrate that while return connectedness measurements change with time, they are less volatile in the tails. Additionally, there is a difference in return connectedness between extreme negative return periods and periods without extreme negative returns, which may indicate asymmetric behavior.

In parallel, another body of the extant literature reveals that the transmission mechanisms between the energy market and international stock markets continue to grow. Studies demonstrate that during the financial crisis, the dependency between energy and stock markets expanded dramatically (Wen et al., 2012;

Xie et al., 2021). Volatility transfer in stock markets and oil has been extensively investigated (Khalfaoui et al., 2015; Wang and Wu, 2018).

For several reasons, previous research tends to concentrate primarily on the energy market. First, although economic energy consumption patterns vary, crude oil remains a crucial resource for energy systems in all economies. Second, crude oil is intimately tied to stock markets as a strategic, limited resource and financial product (Xie et al., 2021). In addition, Lundgren et al. (2018) investigate how the stock market affects green energy behavior and contend that the effect of clean energy on the stock market is significant because there are numerous causal links between renewable energy and the stock market. Dutta (2017) investigates the volatility relationships between the dirty and clean energy. The findings emphasize that it is possible to predict the realized volatility of clean energy equities using the implied volatility of the crude oil market. In another study, Reboredo et al. (2017) investigate the co-movement between dirty and clean energy markets by employing the wavelet decomposition method. In the brief run, the underlying markets exhibit weak links, but over time, the relationship between them steadily strengthens.

A selected set of studies contrasted the effectiveness of clean and dirty energy businesses. In contrast to energy firms with the most severe environmental scores between 2000 and 2007, Arslam-Ayaydin and Thewissen (2016) demonstrate better presentation in the portfolio of energy companies with decent environmental functioning. In their analysis of the environmental protection agency's role under Donald Trump, Ramelli et al. (2018) show improved market performance for businesses most accountable for tackling climate change. In a more recent study, Wan et al. (2021) find that the COVID-19 epidemic had a favorable effect on clean energy firms' performance, while having a detrimental effect on dirty energy enterprises. Chen et al. (2022) identify a bilateral reliance connecting between "dirty" and "clean" energy markets that fluctuates across quantiles and becomes more pronounced at severe quantiles. The findings of Asl et al. (2021) offer no explanation for the relationship between the distributional tails of the oil and green equity markets, nor do they indicate how long they have existed. Ahmad (2017) offers evidence of an unfavorable link during crises, suggesting that falling oil prices encourage the expansion of the clean energy industry. Ahmad et al. (2018) analysis of the suitability of a specific tool to hedge green equity investments reveals that crude oil serves as a suitable instrument to protect green investments.

Investors in firms that produce green technology or renewable energy have focused on the issue of climate change because of widespread concern. When increasing the share of clean energy, it is necessary to encourage green investment, while dampening the opposite as a dirty investment (Zeqiraj et al., 2020; Al Mamun et al., 2018). This reduces the amount of energy with high carbon content in the overall energy mix. Additionally, supporters contend that the need for green investment as a market-based alternative to dirty investment is unquestionable (IPCC, 2014).

Shareholders are interested in the findings of causality studies because they offer insights into the potential future stock values of clean energy. Early indications from Steffen and Patt (2022) suggest that the conflict has altered public opinion regarding the gradual phasing of dirty energy and acceptance of clean energy sources. The recent events in 2020 and 2022 underscored the importance of examining how clean and dirty energy indices are related. According to current research, there is a chance for substantial co-movement. Given the causal relationship between clean and fossil energy, a thorough knowledge of the possible effects that disruptions in the former may have on the latter is necessary. Finally, in light of climate change, it is critical to understand the connection between clean and dirty energy activities to realize sustainable energy goals.

Another set of studies reveals an interdependence between energy prices and stock markets, making it vital to research how various energy sources affect stock markets. Studies have demonstrated a cointegration link between the pricing of multiple forms of energy (Hartley et al., 2008). Consequently, it is crucial to consider the potential transmission mechanisms between various energy market types when investigating the volatility spillover effects of energy and stock markets. Hartley et al. (2008) and Ramberg and Parsons (2012) claim connections between the uncertainty and different energy markets. As a result, both uncertainty spillovers and cross-market uncertainty propagation affect overall connectedness.

To comprehend the connections between uncertainties and different energy markets, it is pertinent to study the driving role of leading global uncertainties in the connectedness of the dirty and clean energy indices with selected energy and stock indices. Questions regarding the significance of the relationship between global financial indices and the dirty and clean energy markets have not been addressed in the literature. In general, market regulators and investors still lack adequate information on the connection between energy and financial indices under leading uncertainties, namely geopolitical risk and oil volatility. Clean energy may present fresh investment possibilities for market participants in response to the escalating challenges of energy security and climate variability.

Connectedness analysis can provide insights about the best asset allocation and risk diversification strategies. Few studies have examined how local stock markets and energy indices are connected with the dirty (clean) energy index, global energy index, and global stock index under selected global uncertainties in oil-exporting and oil-importing countries. Thus, the current study endeavors to lessen the literature deficit by examining the connectedness of the dirty (clean) energy index, global energy & global stock index and energy and stock indices of the largest oil-exporting countries (KSA, Canada, and Russia) and oil-importing countries (the US, China, and India) under selected global uncertainties (OVX and GPRD).

3. DATA AND METHODS

3.1. Empirical Methodology

Comprehension of risk transmission requires a grasp of the financial network structure. If a negative idiosyncratic shock spreads through interconnections with other parts of the financial system, it could jeopardize the stability of the entire system. The degree and quality of financial market links must be measured to guide policy responses to system-wide crises and to control risks. The intention of this study is to examine the interdependence framework that exists between the clean and dirty energy spillover and the local stock and energy indices of the major oil-exporting and importing countries, namely the United States, Canada, Saudi Arabia, Russia, China, and India. Through an examination of dynamic connectedness perspectives centered on the Quantile Vector Autoregressive (QVAR) model, this study aims to analyze interconnectivity issues and information transfers in stock and energy markets.

The quantile spillover context is unique and improved as compared to the remaining approach for multiple explanations. This separates the systematic and idiosyncratic portions of the error process. When using QVAR, the link between the endogenous variables is captured at any given quantile, as opposed to the traditional VAR approach, which simply calculates average connectedness. Over quantiles, the dynamic properties of the system change. By using the decomposition of QVAR variances to outperform mean-based connectedness estimations, the goal is to predict the tail behavior of the economy in the event of extreme financial and real shocks, thereby capturing the nature of connection under extreme circumstances.

3.2. Model Description (Quantile VAR (QVAR) Connectedness Approach)

We utilize the quantile-connectedness method projected by (Ando et al., 2022) to investigate the quantile propagation mechanism among given selected variables. To compute all connectivity measures, first we calculate the Quantile VAR *(p)*, which is as follows:

$$Y_t = \mu(\theta) + \sum_{j=1}^{p} .\Phi_{j(\theta)} Y_{t-j} + u_t(\theta)$$

Y_t and Y_{t-j} are K × 1 dimensional vectors of endogenous variables center on the first differences of significant variable-level indices. θ specifies the quantile of variables and oscillates between 0 and 1 [0, 1]. P indicates reflects the length of lag of the quantile VAR model. At the same time, $\mu(\theta)$ denotes the conditional mean vector with k × 1 dimension. $\Phi_{j(\theta)}$ signposts quantile VAR matrix of coefficients with k × k dimensions. Here, $u_t(\theta)$ denotes the error vector with k × 1 dimension and encompasses a k × k variance–covariance matrix of $\sum \theta$.

This paper employs the World theorem for converting QVAR (p) into the QVMA infinity:

$$Y_t = \mu(\theta) + \sum_{j=1}^{p} .\Phi_{j(\theta)} Y_{t-j} + u_t(\theta) = \mu(\theta) + \sum_{i=0}^{\infty} .\Psi_{i(\theta)} u_{t-i}$$

Then, the h-step forward "Generalized Forecast Error Variance Decomposition (GFEVD)" projected by (Koop et al., 1996; Pesaran and Shin, 1998) is taken to explore the spillover of a fluctuation or shocks in the j-variable on the i-variable and thus the ensuing equation is developed.

$$\psi_{ij}^{g}(h) = \frac{\sum_{.}\theta_{ii}^{-1} \sum_{h=0}^{h-1} .(e_i^{'} \Psi_h(\theta) \sum_{.}(\theta) e_j)^2}{\sum_{h=0}^{h-1} .(e_i^{'} \Psi_h(\theta) \sum_{.}(\tau) \Psi_h(\theta)' e_i)}$$

$$\tilde{\psi}_{ij}^{g}(h) = \frac{\tilde{\psi}_{ij}^{g}(h)}{\sum_{j=1}^{k} .\phi_{ij}^{g}(h)}$$

Here, e_i signifies a zero-vector with a one-value on the ith position. This standardization outcomes can be denoted in the following equalities:

$$(1) \sum_{j=1}^{k} .\tilde{\psi}_{ij}^{g}(h) = 1$$

$$(2) \sum_{i,j=1}^{k} .\tilde{\psi}_{ij}^{g}(h) = k$$

To inspect the influence of i-variables on all other j-variables, the total directional connectivity categorized as "TO" is estimated.

$$C_{i \to j}^{g}(h) = \sum_{j=1, i \neq j}^{k} .\tilde{\psi}_{ji}^{g}(h)$$

Similarly, to measure, the total directional connectedness from all the j-variables to the i-variable is stated below, signifying shocks received by the i-variable from other variables (i.e., stated as "from" connectedness).

$$C_{i \leftarrow j}^{g}(h) = \sum_{j=1, i \neq j}^{k} .\tilde{\psi}_{ij}^{g}(h)$$

Subsequently, the "NET" total directional connectedness, i.e., the subtraction between total directional connectedness "to" and "from," stated as:

$$C_i^{g}(h) = C_{i \to j}^{g}(h) - C_{i \leftarrow j}^{g}(h)$$

($C_i^g(h) < 0$) denotes final negative connectedness and displays that the i-variable is a receiver of volatility spillover inclined by other network variables. The final positive one ($C_i^g(h) > 0$) titles that the i-variable works as a spreader, prompting the entire variables in a network. The whole connectivity metric is changed total connectedness index (TCI) (Chatziantoniou and Gabauer, 2021) which ranges between (0, 1);

$$TCI(h) = \frac{\sum_{i,j=1, i \neq j}^{k} .\tilde{\psi}_{ij}^{g}(h)}{k-1}$$

The "total-connectedness-index" is generally more often employed as the substitution of systematic risk, and higher standards of the TCI are construed as the higher connectedness in the system.

3.3. Data and Preliminary Statistics

This study considers the spillover connectedness between clean (dirty) energy and global (energy and stock), local energy, and stock indices of the largest oil-exporting and oil-importing countries, namely KSA, Canada, the US, Russia, China, and India, in the setting of global uncertainties (OVX and GPRD). Table 1 presents the variables used in this study. The study covers the daily closing prices of the selected indices from January 7, 2013 to December 29, 2022. The study data were gathered from multiple sources. Figure 1 cover the time series plots of clean and dirty energy with selected variables. The effects of COVID-19 are evident in the energy sector, (dirty and clean). The global energy, global stock, Saudi Arabia, Canada, China, India, Russia, and US indices show a downward trend. Thus, the health crisis had a negative impact on energy indices from 2019 to 2020. Following the initial COVID-19 effect, the markets began to recover, as all these energy indices began to trend moderately upward after 2020, with a slight decrease in 2022 in the majority of cases due to the Russia-Ukraine war. This is consistent with the findings of Bhutto et al. (2022), who discovered that COVID-19 had detrimental effects on Pakistan's traditional and Islamic stock markets. Similar fluctuations may be seen in the uncertainty index (GPRD) and the pattern peaked in 2020 (coinciding with COVID-19).

Table 1: Variables' definitions and sources

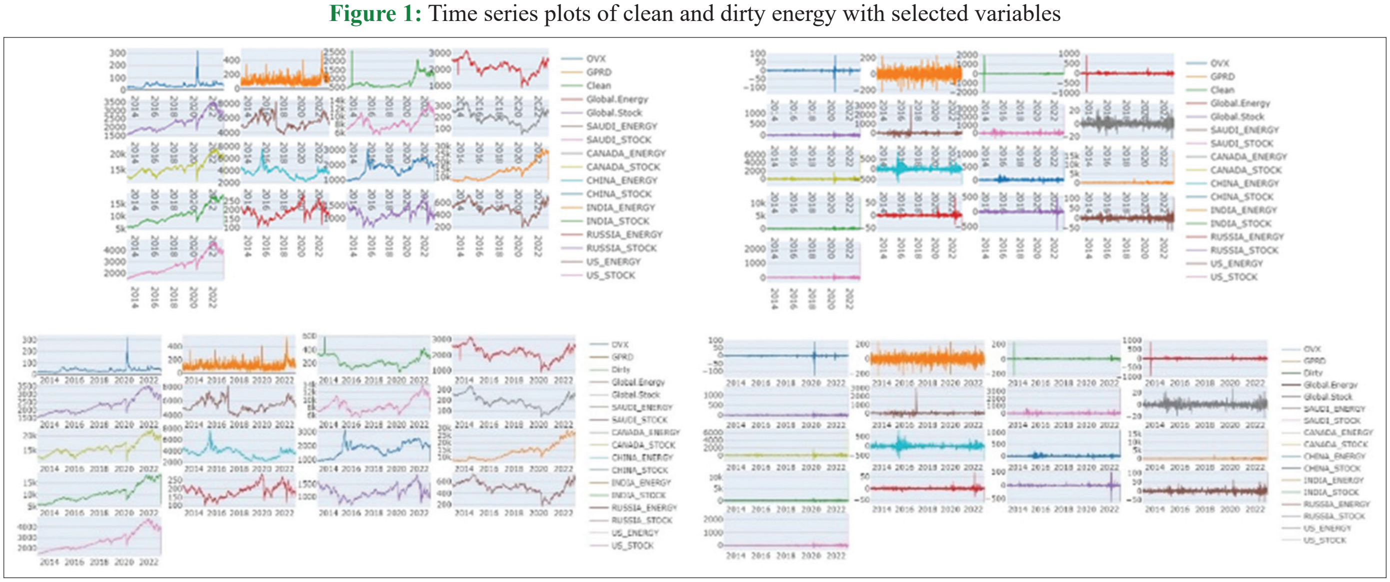
S. No	Variable	Abbreviation	Source
1	Crude Oil Volatility Index	OVX	Bloomberg terminal
2	Geopolitical Risk	GPRD	Bloomberg terminal
3	S&P GSCI Energy Spot	Dirty En	Bloomberg terminal
4	S&P Global Clean Energy	Clean En	Bloomberg terminal
5	S&P Global 1200 E	Gl.E	Bloomberg terminal
6	S&P Global 1200	Gl.S	Bloomberg terminal
7	SAUDI_ ENERGY	S_E	Bloomberg terminal
8	SAUDI_STOCK	S_S	Bloomberg terminal
9	CANADA_ENERGY	C_E	Bloomberg terminal
10	CANADA_STOCK	C_S	Bloomberg terminal
11	CHINA_ENERGY	CH_E	Bloomberg terminal
12	CHINA_STOCK	CH_S	Bloomberg terminal
13	INDIA_ENERGY	I_E	Bloomberg terminal
14	INDIA_STOCK	I_S	Bloomberg terminal
15	RUSSIA_ENERGY	R_E	Bloomberg terminal
16	RUSSIA_STOCK	R_S	Bloomberg terminal
17	US_ENERGY	US_E	Bloomberg terminal
18	US_STOCK	US_S	Bloomberg terminal

4. RESULTS AND DISCUSSIONS

Table 2 presents the descriptive statistics and unit root tests of the selected variables. Based on the statistics, we can deduce that the system's estimated returns have mixed average daily returns. The clean energy, global energy, Indian energy and US energy indices post minimal but positive returns, while, OVX, GPRD, dirty energy index and the Saudi and Canadian energy indices average approximately zero and the Chinese and Russian energy indices are marginally negative. However, the stock indices of Saudi Arabia, Canada, China, India, and Russia have negative average daily returns, except for the global and US stock market. Furthermore, the table shows a higher average variance in the clean energy index (4297.019) than in the dirty energy index (73.859), which may be due to the oil prices being more stable owing to the syndicated nature of OPEC than the nascent clean energy. The Elliot-Rothenberg-Stock unit root (ERS) test reveals that all the return series are stationary.

The key objective of this study is to investigate the nature of connectedness of clean (dirty) energy with a set of energy and stock indices. In line with this, the study examines how the connectedness of clean (dirty) energy changes under normal, bearish and bullish market conditions, assigning a profound cognizance to the conduct of shock transmissions between clean and dirty energy. Accordingly, Tables 3-5 present the connectedness of clean energy with global (energy and stock), local energy, and stock indices of the largest oil-exporting and oil-importing countries, namely, KSA, Canada, the US, Russia, China, and India at the lower, middle and upper quantiles. The results reveal strong connectedness in the case of the clean energy index, with a TCI of 96.20% at the lower quantile, 82.71% at the middle quantile, and 96.83% at the upper quantile. In the bear market (10th quantile) the contributions from (to) others range from 88.85% (78.71%) to 92.11% (117.14%), whereas in the normal markets (50th quantile), the contributions from (to) range from 67.86% (50.9%) to 84.63% (122.12%). In the

Figure 1: Time series plots of clean and dirty energy with selected variables



Source: Estimated by author utilizing data from Bloomberg terminal

Table 2: Descriptive statistics

Measures	OVX	GPRD	Clean En	Dirty En	Gl.E	Gl.S	S_E	S_S	C_E
Mean	0	0	0.002	0	0.004	0.003	0	−0.017	0
Variance	30.448	2149.447	4297.019	73.859	1811.182	1389.198	10906.52	15128.52	13.25
Skewness	−5.036***	−0.069	0.665***	0.529***	−0.244***	22.050***	10.955***	10.612***	0.537***
Ex.Kurtosis	255.110***	2.206***	828.300***	485.932***	214.977***	793.721***	327.783***	287.176***	5.567***
JB	5985914.944***	448.641***	63005198.700***	21684702.272***	4244096.902***	58032922.764***	9910820.970***	7614855.503***	2952.518***
ERS	−21.485***	−30.700***	−24.735***	−23.691***	−20.483***	−11.753***	−21.552***	−12.998***	−17.297***
Q (10)	154.974***	375.851***	330.941***	187.617***	89.740***	8.924	11.749**	14.599***	6.84
Q2 (10)	816.015***	258.659***	430.397***	438.050***	431.773***	0.009	0.677	0.055	194.966***
Measures	**C_S**	**CH_E**	**CH_S**	**I_E**	**I_S**	**R_E**	**R_S**	**US_E**	**US_S**
Mean	−0.002	−0.004	−0.004	0.005	−0.006	−0.002	−0.021	0.002	0.002
Variance	44662.23	7781.873	1535.558	184661.2	83455.57	18.298	1165.709	77.575	3797.25
Skewness	15.758***	0.815***	10.800***	31.028***	34.272***	1.064***	−2.235***	0.971***	26.522***
Ex.Kurtosis	493.301***	13.972***	291.395***	1261.430***	1443.188***	56.954***	129.332***	14.370***	1021.545***
JB	22438514.089***	18171.839***	7840492.072***	146479405.627***	191701104.875***	298299.939***	1537905.160***	19308.759***	96091436.091***
ERS	−13.419***	−18.496***	−14.260***	−9.087***	−8.497***	−6.662***	−5.874***	−11.364***	−10.311***
Q (10)	20.571***	19.019***	14.603***	2.902	2.246	49.557***	128.059***	9.514*	14.818***
Q2 (10)	0.28	623.095***	0.079	0.002	0.002	125.681***	138.447***	54.654***	0.004

*P<0.1, **P<0.05, and ***P<0.01 denote significance at 10%, 5%, and 1%, respectively

Table 3: Spillover connectedness quantile VAR (10th quantile) for the clean energy index

Variables	OVX	GPRD	Clean En.	Global.E	Global.S	S_E	S_S	C_E	C_S	CH_E	CH_S	I_E	I_S	R_E	R_S	US_E	US_S	FROM
OVX	11.15	5.76	6.78	7.13	5.43	5.4	5.4	5.4	4.87	5.22	5.16	5.34	5.15	5.55	5.36	5.39	5.52	88.85
GPRD	6.03	9.93	6.73	7.21	5.41	5.36	5.34	5.6	5.21	5.33	5.06	5.36	5.26	5.58	5.41	5.52	5.66	90.07
Clean En	6.14	5.26	10.98	7.3	6.57	5.07	5.24	5.78	5.3	5.31	4.84	5.29	5.06	5.45	5.24	4.97	6.21	89.02
Global. E.	6.02	5.35	7.16	10.32	6.3	5.06	5.21	7.16	5.22	5.12	4.74	5.07	5.07	5.55	5.49	5.18	5.97	89.68
Global. S.	6.38	5.22	7.45	7.85	8.94	4.92	5.29	5.71	4.98	4.95	4.64	5.09	5.12	5.45	5.45	4.89	7.67	91.06
S_E	6.32	5.72	6.98	6.97	5.28	9.78	5.97	5.61	4.96	5.24	5.11	5.5	5.16	5.65	5.22	5.24	5.3	90.22
S_S	6.53	5.57	6.62	7.07	5.43	6.27	9.19	5.76	5.01	5.33	4.77	5.25	5.39	5.66	5.36	5.2	5.59	90.81
C_E	6.41	5.31	6.9	8.43	5.57	5.33	5.31	9.33	5.41	5.28	4.94	5.15	5.13	5.55	5.34	5.09	5.51	90.67
C_S	6.44	5.35	7.29	7.56	6.47	5.28	5.09	6.58	7.89	5.12	4.7	4.97	5.17	5.24	5.32	5.1	6.42	92.11
CH_E	6.46	5.93	6.94	7.19	5.6	5.23	5.41	5.6	5.11	9.27	5.27	5.47	5.16	5.44	5.23	5.22	5.48	90.73
CH_S	6.13	5.52	6.96	7.1	5.64	5.24	5.26	5.46	5.04	7.09	8.36	5.36	5.14	5.39	5.36	5.43	5.53	91.64
I_E	6.43	5.63	6.88	7.04	5.47	5.1	5.41	5.57	5.15	5.39	5.09	8.8	6.45	5.49	5.34	5.35	5.4	91.2
I_E	6.43	5.69	6.97	6.98	5.9	5.12	5.3	5.41	5.11	5.38	4.88	5.77	9.06	5.65	5.45	5.21	5.68	90.94
R_E	5.92	5.46	6.83	7.35	5.56	5.36	5.16	5.74	5.03	5.03	4.76	5.24	5.16	9.28	7.62	5.09	5.4	90.72
R_S	5.88	5.41	6.76	7.27	5.63	5.27	5.17	5.66	4.99	5.02	4.76	5.27	5.12	7.88	9.42	5.02	5.47	90.58
US_E	6.39	5.98	6.83	7.05	5.4	5.35	5.22	5.88	4.97	5.34	5.23	5.31	5.03	5.46	5.3	9.84	5.42	90.16
US_S	6.32	5.42	7.23	7.63	7.95	4.92	5.33	5.63	4.88	5.06	4.77	5.01	5.11	5.3	5.28	4.98	9.16	90.84
TO	100.22	88.58	111.32	117.14	93.6	84.27	85.12	92.54	81.23	85.21	78.71	84.46	83.69	90.28	87.79	82.88	92.22	1539.28
Inc.Own	111.37	98.51	122.3	127.46	102.55	94.05	94.31	101.87	89.13	94.48	87.07	93.26	92.76	99.56	97.21	92.73	101.38	TCI
NET	11.37	−1.49	22.3	27.46	2.55	−5.95	−5.69	1.87	−10.87	−5.52	−12.93	−6.74	−7.24	−0.44	−2.79	−7.27	1.38	96.20
NPT	14	8	15	16	12	5	5	13	2	5	0	3	5	10	8	4	11	

The outcomes rely on the quantile VAR specification with a lag length of order one (SIC) and a and a 10-step-ahead forecast. The acronym TCI stands for total connectivity index. "FROM others" indicates the total amount of spillover that an index receives from all other indices. The total spillovers that a particular index transmits to all other indexes are displayed in "TO others." "NET" is the distinction between "TO others" and FROM others. "A value that is positive implies a net transmitter of information spillovers, whereas a value that is negative demonstrates a net receiver of shock spillovers. "Inc. own" refers to the portion that includes own

Table 4: Spillover connectedness quantile VAR (50th quantile) for the clean energy index

Variables	OVX	GPRD	Clean En	Gl.E	Gl.S	S_E	S_S	C_E	C_S	CH_E	CH_S	I_E	I_S	R_E	R_S	US_E	US_S	FROM
OVX	32.14	3.13	6.75	6.52	5.67	3.49	3.88	4.63	3.77	3.31	2.87	3.14	3.5	4.44	4.48	3.33	4.92	67.86
GPRD	4.15	23.94	7.25	7.29	5.3	4.51	4.37	4.83	4.25	4	3.71	3.56	4.17	4.79	4.91	3.94	5.02	76.06
Clean En	4.39	3.22	26.37	8.32	8.27	3.24	3.99	4.67	4.43	3.5	3.16	3.35	4	4.55	4.49	3.14	6.91	73.63
Gl.E	4.71	3.14	8.16	21.38	8.23	3.23	3.79	10.36	4.68	3.16	2.64	2.95	3.47	5.3	4.88	3.2	6.73	78.62
Gl_.S	5.23	2.91	9.21	9.06	19.07	3.24	3.7	4.89	4.57	3.11	2.61	2.99	3.98	4.3	4.54	2.92	13.69	80.93
S_E	4.58	3.11	6.13	6.4	4.69	28.61	7.95	4.13	3.37	3.28	3.26	4.08	3.52	4.5	4.65	3.37	4.39	71.39
S_S	4.74	3.47	7.66	6.75	5.65	7.02	22.66	5.07	3.95	3.68	3.18	3.56	4.14	4.78	4.85	3.84	5.04	77.34
C_E	4.82	3.14	7.71	12.22	6.73	3.41	4.27	20.23	5.5	3.6	2.79	3.12	3.74	4.84	4.7	3.63	5.56	79.77
C_S	5.22	3.26	7.96	8.58	10.2	3.17	3.82	7.63	15.37	3.38	2.82	3.14	4.06	4.28	4.63	3.63	8.84	84.63
CH_E	4.4	3.82	7.16	6.5	5.78	3.91	4.18	4.5	3.83	25.16	4.66	4.13	4.27	4.55	4.28	3.81	5.08	74.84
CH_S	4.2	3.58	7.19	6.52	6.23	3.75	4.1	4.48	3.71	12.62	17.25	4	4.26	4.54	4.48	3.75	5.32	82.75
I_E	4.5	3.36	7.26	6.59	6.13	3.74	4.37	4.75	3.83	4.08	3.4	18.68	10.65	4.67	4.43	3.92	5.63	81.32
I_S	4.9	3.43	8.45	6.5	6.86	3.96	4.36	4.85	4.04	4.1	3.25	5.08	21.26	4.72	4.76	3.72	5.75	78.74
R_E	4.61	3.21	6.23	7.74	6.09	3.68	3.98	5.31	3.97	3.53	3.08	3.36	4.12	19.82	12.69	3.41	5.16	80.18
R_S	4.4	3.1	6.1	7.54	6.21	3.52	3.91	4.81	4.03	3.41	2.93	3.12	4.25	13.91	20.49	3.16	5.11	79.51
US_E	4.7	3.78	6.87	7.08	5.38	4.36	4.45	4.8	4.34	4.03	3.64	3.87	4.11	4.69	4.52	24.73	4.64	75.27
US_S	5.35	3.22	7.86	8.53	14.77	3.31	3.75	4.72	4.25	3.39	2.9	3.16	3.86	4.05	4.27	3.11	19.49	80.51
TO	74.91	52.87	117.96	122.12	112.19	61.54	68.88	84.41	66.52	66.19	50.9	56.62	70.1	82.91	81.57	55.87	97.8	1323.36
Inc.Own	107.05	76.81	144.34	143.5	131.26	90.15	91.53	104.64	81.89	91.34	68.16	75.31	91.36	102.73	102.05	80.6	117.29	TCI
NET	7.05	−23.19	44.34	43.5	31.26	−9.85	−8.47	4.64	−18.11	−8.66	−31.84	−24.69	−8.64	2.73	2.05	−19.4	17.29	82.71
NPT	12	0	15	16	14	5	7	11	7	3	1	4	6	10	10	3	12	

The outcomes rely on the quantile VAR specification with a lag length of order one (SIC) and a and a 10-step-ahead forecast. The acronym TCI stands for total connectivity index. “FROM others“ indicates the total amount of spillover that an index receives from all other indices. The total spillovers that a particular index transmits to all other indexes are displayed in “TO others.“ “NET“ is the distinction between “TO others“ and FROM others. “A value that is positive implies a net transmitter of information spillovers, whereas a value that is negative demonstrates a net receiver of shock spillovers. “Inc. own“ refers to the portion that includes own

Table 5: Spillover connectedness quantile VAR (90th quantile) for the clean energy index

Variables	OVX	GPRD	Clean En	Gl.E	Gl.S	S_E	S_S	C_E	C_S	CH_E	CH_S	I_E	I_S	R_E	R_S	US_E	US_S	FROM
OVX	10.3	5.15	6.33	7.28	6.04	4.94	5.66	5.52	5.42	5.59	5.34	4.87	5.36	5.68	5.15	5.33	6.03	89.7
GPRD	5.46	9.92	6.5	7.13	6.02	5.02	5.6	5.8	5.31	5.5	5.3	4.85	5.13	5.82	5.51	5.41	5.7	90.08
Clean En	5.18	4.78	9.58	8.05	6.76	4.61	5.45	5.86	5.36	5.59	5.1	4.77	5.53	5.98	5.64	5.35	6.4	90.42
Gl_.E	5.1	4.78	6.62	10.29	6.77	4.67	5.59	6.89	5.32	5.34	5.06	4.75	5.54	6.05	5.55	5.23	6.45	89.71
Gl.S	5.2	4.9	6.88	8.02	9.05	4.59	5.45	5.88	5.33	5.36	5.24	4.75	5.5	5.59	5.33	5.29	7.63	90.95
S_E	5.5	5	6.55	7.46	6.05	8.68	6.19	5.75	5.15	5.42	5.29	5	5.4	6.01	5.43	5.36	5.74	91.32
S_S	5.33	4.99	6.49	7.61	5.92	5.53	8.64	5.94	5.49	5.39	5.38	4.81	5.6	5.91	5.58	5.28	6.1	91.36
C_E	5.17	4.98	6.42	8.83	6.24	4.78	5.46	8.86	5.44	5.47	5.07	4.8	5.53	6.08	5.69	5.1	6.07	91.14
C_S	5.47	4.93	6.86	8.14	7	4.58	5.46	6.46	7.55	5.31	5	4.75	5.37	5.7	5.53	5.16	6.74	92.45
CH_E	5.18	5.14	6.74	7.47	6.09	4.73	5.67	5.73	5.34	8.95	5.64	4.87	5.5	5.91	5.56	5.32	6.16	91.05
CH_S	5.3	5.23	6.87	7.41	6.22	4.68	5.45	5.51	5.3	6.87	7.98	5.03	5.49	5.72	5.55	5.28	6.12	92.02
I_E	5.43	5.05	6.41	7.66	6.15	4.8	5.75	5.94	5.36	5.5	5.42	7.2	6.5	5.7	5.52	5.42	6.2	92.8
I_S	5.37	5.05	6.61	7.59	6.38	4.85	5.64	5.81	5.36	5.34	5.37	5.06	8.47	5.79	5.59	5.5	6.21	91.53
R_E	4.96	5.09	6.4	7.82	6.14	4.73	5.46	5.93	5.42	5.38	5.11	4.81	5.5	9.2	7.2	4.99	5.84	90.8
R_S	5.02	5.03	6.57	7.7	6.13	4.86	5.46	6.02	5.41	5.33	5.2	4.72	5.63	7.7	8.44	5.02	5.77	91.56
US_E	5.48	4.97	6.63	7.66	6.27	4.99	5.51	5.84	5.37	5.35	5.39	4.93	5.32	5.83	5.41	8.91	6.15	91.09
US_S	5.41	4.9	6.76	8.02	7.92	4.6	5.36	5.87	5.34	5.45	5.16	4.73	5.45	5.7	5.37	5.27	8.69	91.31
TO	84.56	79.98	105.65	123.82	102.1	76.95	89.19	94.76	85.74	88.2	84.06	77.5	88.35	95.18	89.6	84.32	99.3	1549.27
Inc.Own	94.86	89.9	115.23	134.12	111.15	85.63	97.83	103.62	93.3	97.15	92.04	84.7	96.82	104.38	98.04	93.23	107.99	TCI
NET	−5.14	−10.1	15.23	34.12	11.15	−14.37	−2.17	3.62	−6.7	−2.85	−7.96	−15.3	−3.18	4.38	−1.96	−6.77	7.99	96.83
NPT	6	1	15	16	14	1	8	11	7	6	5	1	7	12	9	4	13	

The outcomes rely on the quantile VAR specification with a lag length of order one (SIC) and a and a 10-step-ahead forecast. The acronym TCI stands for total connectivity index. “FROM others” indicates the total amount of spillover that an index receives from all other indices. The total spillovers that a particular index transmits to all other indexes are displayed in “TO others.” “NET” is the distinction between “TO others” and FROM others. “A value that is positive implies a net transmitter of information spillovers, whereas a value that is negative demonstrates a net receiver of shock spillovers. “Inc. own” refers to the portion that includes own bullish markets (90th quantile), the contributions from (to) others lie between 89.7% (76.95%) and 92.8% (123.82%).

At the lower quantile, the global energy index exerts the greatest influence on others (117.14), whereas the OVX index is least impacted by others (88.85). The results are comparable at the middle and higher quantiles, with the OVX index (67.86 and 89.7, respectively) determined to be the least affected index and the Global Energy Index (122.12 and 123.82, respectively) having the greatest impact on other indices.

Additionally, the Tables 3-5 display the net volatility spillover estimations, which provide a description of the net spillover position of each market in the system. A market's ability to transmit shocks to other markets in the network system is indicated by a net positive spillover value, whereas a market's ability to receive shocks from other markets in the system is confirmed by a negative net spillover estimation. The GPRD, Saudi_Energy, Saudi_Stock, Canada_Stock, China_Energy, China_Stock, India_Energy, India_Stock, Russia_Energy, Russia_Stock, and US_Energy indices are the principal receivers of directional spillovers and are easily influenced by external aspects (−1.49, −5.95, −5.69, −10.87, −5.52, −12.93, −6.74, −7.24, −0.44, −2.79, and −7.27, respectively) at the lower quantile.

Likewise, the results are similar in the middle quantile, except for the Russian energy and stock indices which switch to net transmitters (2.73 and 2.05, respectively); in the upper quantile, only the Russian energy index retains this transmitting role. In contrast, OVX, clean energy, Global Energy, Global stock, Canadian energy, and US Stock indices are reported to be net transmitters (11.37, 22.3, 27.46, 2.55, 1.87, and 1.38, respectively) at the lower quantile. Similarly, the net transmitter indices remain the same for the middle and upper quantiles with the exception of OVX which becomes a net recipient at the upper quantile. Moreover, the energy sectors of Canada and Russia demonstrate the least net spillovers across all three quantiles, suggesting a relatively balance state in which they both transmit and absorb shocks in around similar proportions.

With regard to the uncertainty indices, at the lower quantile (Table 3) the highest (lowest)connection of GPRD is with US_ Energy (Global stock) at 5.98 (5.22). The highest (lowest) connection of OVX is Saudi_ Stock (Russian_stock) at 6.53 (5.88). At the middle quantile (Table 4) the highest (lowest)connection of GPRD is with China_ Energy (Global stock) at 3.82 (2.91). The highest (lowest)connection of OVX is with US_ Stock (GPRD) at 5.35 (4.15). At the higher quantile (Table 5) the highest (lowest) connection of GPRD is with China_ Stock (Clean Energy and Global Energy) at 5.23 (4.78). The highest (lowest)connection of OVX is Saudi energy (Russian Energy) at 5.50 (4.96). The results are heterogeneous for the most and least affected by uncertainties, requiring sophisticated diversification methods for foreign investors.

Tables 6-8 examine the dynamic interrelationship of the dirty energy index with global (energy and stock) indices, as well as local energy and stock indices from the main oil-exporting and oil-importing nations, specifically KSA, Canada, the US, Russia, China, and India, across low, medium, and high quantiles. In the case of the dirty energy index, we discovered strong connectedness, specifically, 96.24% at the lower quantile, 82.07% at the middle quantile, and 96.98% at the upper quantile. In the bear market (10th quantile), the contributions from (to) others range between 88.86% (78.76%) and 91.66% (110.8%), whereas in the normal markets (50th quantile), the contributions from (to) range from 66.95% (51.82%) to 83.73% (112%). In the rising markets (90th quantile), the contributions from (to) others lie between 89.63% (77.74%) and 92.81% (119.99%). At the lower quantile, the dirty energy index has the greatest influence on others (110.8%), while the OVX index is least impacted by others (88.86%). The results are somewhat comparable at the middle and higher quantiles, with the OVX index (66.95% and 89.63%, respectively) determined to be the least affected index. Global energy index at the middle (112%) and higher (119.99%) quantiles has the greatest impact on the other indices.

In addition, the GPRD, Saudi_Energy, Saudi_Stock, Canada_ Stock, China_Energy, China_Stock, India_Energy, India_Stock, Russia_Stock, and US_Energy indices are the largest directional connectedness receivers of spillovers and are easily influenced by external factors (−0.65, −6.78, −6.98, −7.07, −7.22, −12.9, −8.48, −4.19, −3.37, and −8.93, respectively) at the lower quantile. Likewise, in the middle and upper quantiles, the results are similar, except for the Russian stock index, which is not the recipient of spillovers from other indices. In contrast, OVX, Dirty energy, Global Energy, Global Stock, Canada Energy, Russia_Energy, and US Stock are net transmitters of spillovers (13.75, 21.01, 20.82, 2.35, 4.63, 1.8, and 2.2, respectively) at the lower quantile. Similarly, the transmitter indices remain the same for the middle and upper quantiles, with the exception of the OVX index, which transforms into a net recipient (−3.83) at the upper quantile.

With regard to the uncertainty indices, at the 10th quantile (Table 6) the highest (lowest) connection of GPRD is with OVX (Global energy) at 5.94 (5.3). The highest (lowest)connection of OVX is global Stock (Russian stock) of 6.7 (6.02). At the middle quantile (Table 7) the highest (lowest)connection of GPRD is with China_ Energy (Global stock) at 3.86 (2.85). The highest (lowest) connection of OVX is with the Dirty Index (GPRD) at 6.77 (4.32). At the 90th quantile (Table 8) the highest (lowest)connection of GPRD is with China_ Stock (Global Stock) at 5.06 (4.69). The highest (lowest)connection of OVX is GPRD (Russian stock) at 5.63 (5.06). The results show heterogenous results for the most and least affected by uncertainties, requiring sophisticated diversification methods for foreign investors.

Comparing the Total Connectedness Index (TCI) reported in Tables 3-8 reveals that connectedness is comparatively higher at the lower and upper quantiles, indicating that the markets are more connected at the extreme positive and negative market settings. Thus, our quantile VAR model results, demonstrate a moderate connectedness at the middle quantile but substantial connectivity at the lower and upper quantiles. Our results corroborate studies that report that connections between markets are higher in stressful or volatile market conditions than they are during regular market

Table 6: Spillover connectedness quantile VAR (10th quantile) for the dirty energy index

Variables	OVX	GPRD	Dirty En	Gl.E	Gl.S	S_E	S_S	C_E	C_S	CH_E	CH_S	I_E	I_S	R_E	R_S	US_E	US_S	FROM
OVX	11.14	5.94	6.6	6.67	5.34	5.41	5.28	5.54	5.02	5.24	5.18	5.37	5.52	5.65	5.42	5.26	5.4	88.86
GPRD	6.34	9.92	6.8	6.52	5.87	5.23	5.22	5.71	5.45	5.18	5.05	5.13	5.4	5.69	5.42	5.27	5.78	90.08
Dirty En	6.66	5.6	10.21	7.46	5.52	5.34	5.44	6.46	5.23	4.96	4.87	5	5.21	5.81	5.4	5.28	5.55	89.79
Gl.E	6.28	5.3	7.7	10.03	6.07	5.14	5.19	7.25	5.5	4.92	4.85	4.98	5.01	5.61	5.33	4.93	5.89	89.97
Gl.S	6.7	5.34	6.74	7.43	9.06	5.01	5.21	5.74	5.33	4.97	4.71	5.01	5.37	5.4	5.29	4.93	7.76	90.94
S_E	6.4	5.77	6.91	6.47	5.45	9.75	6.06	5.9	5.17	5.12	4.84	5.31	5.37	5.64	5.44	5.07	5.33	90.25
S_S	6.6	5.75	7.03	6.72	5.35	6.13	9.03	6.03	5.22	5.09	4.95	5.09	5.41	5.58	5.36	5.29	5.36	90.97
C_E	6.28	5.62	7.62	8.06	5.72	4.99	5.29	9.4	5.5	5.03	4.67	5.06	5.13	5.57	5.36	5.11	5.6	90.6
C_S	6.58	5.39	6.79	7.13	6.53	5.11	5.04	6.69	8.41	5.01	4.72	4.95	5.21	5.47	5.33	5.07	6.57	91.59
CH_E	6.46	5.87	6.78	6.58	5.67	5.06	5.2	5.75	5.15	9.43	5.34	5.57	5.44	5.66	5.28	5.18	5.57	90.57
CH_S	6.1	5.6	6.86	6.64	5.78	5.05	5.22	5.72	5.22	7.17	8.34	5.39	5.45	5.39	5.32	5.16	5.6	91.66
I_E	6.5	5.56	6.81	6.72	5.49	5.18	5.37	5.63	5.42	5.21	5.09	8.39	6.56	5.94	5.26	5.04	5.84	91.61
I_S	6.38	5.46	6.85	6.66	5.9	5.26	5.22	5.57	5.39	5.24	4.92	5.64	9.35	5.87	5.34	5.05	5.89	90.65
R_E	6.15	5.33	6.78	6.95	5.5	5.12	5.06	5.88	5.24	5.08	4.75	5.2	5.46	9.55	7.41	4.91	5.63	90.45
R_S	6.02	5.53	6.74	6.99	5.7	5.16	4.99	5.78	5.16	4.96	4.7	5.15	5.43	7.86	9.3	4.87	5.65	90.7
US_E	6.61	5.92	7.09	6.61	5.41	5.32	5.02	5.91	5.31	5.18	5.19	5.3	5.16	5.73	5.19	9.55	5.5	90.45
US_S	6.56	5.43	6.68	7.18	7.99	4.96	5.17	5.67	5.22	5	4.93	4.97	5.31	5.38	5.19	5.09	9.26	90.74
TO	102.61	89.42	110.8	110.79	93.29	83.48	83.99	95.23	84.52	83.34	78.76	83.13	86.45	92.25	87.33	81.53	92.94	1539.86
Inc.Own	113.75	99.35	121.01	120.82	102.35	93.22	93.02	104.63	92.93	92.78	87.1	91.52	95.81	101.8	96.63	91.07	102.2	TCI
NET	13.75	−0.65	21.01	20.82	2.35	−6.78	−6.98	4.63	−7.07	−7.22	−12.9	−8.48	−4.19	1.8	−3.37	−8.93	2.2	96.24
NPT	15	8	15	15	12	3	3	13	8	2	1	4	7	10	7	2	11	

The outcomes rely on the quantile VAR specification with a lag length of order one (SIC) and a and a 10-step-ahead forecast. The acronym TCI stands for total connectivity index. "FROM others" indicates the total amount of spillover that an index receives from all other indices. The total spillovers that a particular index transmits to all other indexes are displayed in "TO others." "NET" is the distinction between "TO others" and FROM others. "A value that is positive implies a net transmitter of information spillovers, whereas a value that is negative demonstrates a net receiver of shock spillovers. "Inc. own" refers to the portion that includes own

Table 7: Spillover connectedness quantile VAR (50th quantile) for the dirty energy index

Variables	OVX	GPRD	Dirty En	Gl.E	Gl.S	S_E	S_S	C_E	C_S	CH_E	CH_S	I_E	I_S	R_E	R_S	US_E	US_S	FROM
OVX	33.05	3.11	5.55	5.73	5.76	3.75	3.79	4.68	3.89	3.45	3.24	3.26	3.56	4.43	4.57	3.11	5.06	66.95
GPRD	4.32	24.47	5.66	6.58	5.41	4.72	4.88	4.67	4.17	4.3	3.73	3.92	4.31	4.96	5.02	3.78	5.13	75.53
Dirty En	6.77	3.36	22.41	10.81	5.33	3.9	4.08	7.59	4.12	3.58	3.04	3.23	3.6	5.16	4.89	3.32	4.81	77.59
Gl.E	4.73	3	9.46	21.36	8.08	3.35	3.85	10.2	4.61	3.13	2.55	2.82	3.42	5.08	4.81	2.94	6.6	78.64
Gl.S	5.56	2.85	4.32	8.36	20.46	3.59	3.87	5.42	4.94	3.44	2.82	3.15	4.08	4.46	4.85	2.93	14.89	79.54
S_E	4.74	3.02	4.47	5.27	4.6	30.44	8.58	4.08	3.36	3.55	3.17	3.94	3.69	4.74	4.67	3.23	4.43	69.56
S_S	4.85	3.3	5.48	6.4	5.88	7.61	24.27	5.16	3.9	3.72	3.1	3.8	4.24	4.53	4.65	3.64	5.48	75.73
C_E	5.02	3.08	7.61	11.23	6.83	3.65	4.31	20.22	5.54	3.74	2.83	3.27	3.92	4.97	4.75	3.39	5.63	79.78
C_S	5.47	3.21	4.75	7.89	10.61	3.48	3.74	8.18	16.27	3.61	2.88	3.43	4.36	4.37	4.8	3.61	9.33	83.73
CH_E	4.99	3.86	5.08	5.57	5.91	4	4.47	4.84	4.1	25.67	4.87	4.27	4.33	4.73	4.51	3.77	5.02	74.33
CH_S	4.58	3.62	4.5	5.29	6.41	4.22	4.23	4.59	3.81	13.33	18.13	4.25	4.36	4.99	4.66	3.66	5.36	81.87
I_E	4.65	3.53	4.91	5.52	5.77	3.97	4.45	4.99	4.28	4.43	3.42	19.94	10.76	4.97	5.24	3.61	5.54	80.06
I_S	5.07	3.42	5.06	5.89	7.03	4.03	4.56	5.03	4.19	4.3	3.48	5.46	22.48	5	5.22	3.65	6.11	77.52
R_E	4.79	3.04	5.27	6.8	5.92	3.78	4.05	5.44	3.96	3.63	3.16	3.35	4.15	20.64	13.43	3.48	5.12	79.36
R_S	4.73	2.97	5.12	6.54	6.19	3.66	3.93	5.04	3.86	3.48	3.04	3.12	4.2	14.59	21.13	3.23	5.17	78.87
US_E	4.78	3.74	5.35	6.41	5.31	4.8	4.7	4.94	4.32	4.15	3.62	4.06	4.28	4.87	4.8	24.94	4.93	75.06
US_S	5.52	3.04	4.36	7.69	15.3	3.57	3.89	5.28	4.55	3.59	2.86	3.22	4.36	4.18	4.45	3.14	21.01	78.99
TO	80.58	52.16	86.96	112	110.33	66.09	71.38	90.13	67.59	69.43	51.82	58.55	71.61	86.05	85.34	54.49	98.62	1313.11
Inc.Own	113.62	76.63	109.37	133.36	130.79	96.53	95.65	110.35	83.87	95.1	69.95	78.48	94.09	106.68	106.47	79.43	119.63	TCI
NET	13.62	−23.37	9.37	33.36	30.79	−3.47	−4.35	10.35	−16.13	−4.9	−30.05	−21.52	−5.91	6.68	6.47	−20.57	19.63	82.07
NPT	14	0	12	16	15	7	7	11	6	4	1	3	6	10	9	2	13	

The outcomes rely on the quantile VAR specification with a lag length of order one (SIC) and a and a 10-step-ahead forecast. The acronym TCI stands for total connectivity index. "FROM others" indicates the total amount of spillover that an index receives from all other indices. The total spillovers that a particular index transmits to all other indexes are displayed in "TO others." "NET" is the distinction between "TO others" and FROM others. "A value that is positive implies a net transmitter of information spillovers, whereas a value that is negative demonstrates a net receiver of shock spillovers. "Inc. own" refers to the portion that includes own

Table 8: Spillover connectedness quantile VAR (90th quantile) for the dirty energy index

Variables	OVX	GPRD	Dirty En	Gl_E	Gl_S	S_E	S_S	C_E	C_S	CH_E	CH_S	I_E	I_S	R_E	R_S	US_E	US_S	FROM
OVX	10.37	4.96	6.61	7.09	6.01	4.98	5.49	5.68	5.28	5.34	5.17	5.1	5.39	5.74	5.62	5.36	5.83	89.63
GPRD	5.63	9.45	6.77	7.14	6.05	4.94	5.46	5.69	5.24	5.35	5.24	4.99	5.38	5.91	5.5	5.32	5.93	90.55
Dirty En	5.54	4.86	9.64	7.87	6.13	5.11	5.63	6.4	5.33	5.39	5.08	4.98	5.55	5.82	5.59	5.27	5.82	90.36
Gl.E	5.27	4.73	7.03	10.09	6.75	4.85	5.5	6.71	5.27	5.23	5.23	4.82	5.38	6.15	5.67	5.04	6.3	89.91
Gl.S	5.28	4.69	6.39	7.86	9.03	4.79	5.43	5.79	5.52	5.28	5.17	4.98	5.55	5.76	5.56	5.25	7.67	90.97
S_E	5.43	4.86	6.67	7.07	6.14	8.49	6.31	5.61	5.34	5.36	5.41	5.09	5.58	5.89	5.59	5.36	5.79	91.51
S_S	5.31	4.72	6.6	7.48	6.42	5.44	8.71	5.92	5.28	5.36	5.17	4.91	5.44	6	5.83	5.26	6.12	91.29
C_E	5.3	4.85	7.22	8.42	6.44	4.99	5.62	8.48	5.36	5.07	5.26	4.92	5.36	6.03	5.61	5.1	5.97	91.52
C_S	5.53	4.84	6.77	7.82	7.01	4.72	5.57	6.42	7.44	5.34	5.05	4.93	5.44	5.76	5.52	5.14	6.7	92.56
CH_E	5.38	4.93	6.61	7.29	6.25	4.86	5.72	5.76	5.24	8.43	5.56	5.17	5.5	6.03	5.78	5.32	6.18	91.57
CH_S	5.29	5.06	6.57	7.13	6.49	4.94	5.58	5.66	5.45	6.69	7.68	5.04	5.45	5.93	5.67	5.24	6.11	92.32
I_E	5.38	4.91	6.68	7.41	6.07	4.85	5.49	5.98	5.32	5.63	5.23	7.19	6.66	5.99	5.76	5.33	6.1	92.81
I_S	5.37	4.92	6.75	7.48	6.28	4.99	5.73	5.75	5.51	5.38	5.19	5.29	8.63	5.79	5.62	5.22	6.1	91.37
R_E	5.13	4.87	6.68	7.4	6.28	4.91	5.48	5.83	5.18	5.3	5	4.86	5.56	8.96	7.28	5.11	6.16	91.04
R_S	5.06	4.85	6.7	7.4	6.45	5.02	5.64	5.86	5.29	5.35	5.05	4.79	5.68	7.44	8.23	5.12	6.06	91.77
US_E	5.45	4.85	6.73	7.44	5.93	5.13	5.68	5.74	5.31	5.28	5.29	5.01	5.58	5.91	5.75	8.91	6.02	91.09
US_S	5.46	4.83	6.49	7.69	7.73	4.8	5.57	5.89	5.42	5.26	5.24	4.95	5.45	5.86	5.53	5.14	8.66	91.34
TO	85.8	77.74	107.28	119.99	102.43	79.35	89.9	94.69	85.35	86.62	83.35	79.81	88.94	96.02	91.88	83.58	98.87	1551.61
Inc.Own	96.17	87.2	116.91	130.08	111.46	87.84	98.61	103.17	92.79	95.04	91.04	87.01	97.57	104.98	100.11	92.49	107.53	TCI
NET	−3.83	−12.8	16.91	30.08	11.46	−12.16	−1.39	3.17	−7.21	−4.96	−8.96	−12.99	−2.43	4.98	0.11	−7.51	7.53	96.98
NPT	7	0	15	16	14	1	9	11	6	5	4	2	8	12	9	4	13	

The outcomes rely on the quantile VAR specification with a lag length of order one (SIC) and a and a 10-step-ahead forecast. The acronym TCI stands for total connectivity index. "FROM others" indicates the total amount of spillover that an index receives from all other indices. The total spillovers that a particular index transmits to all other indexes are displayed in "TO others." "NET" is the distinction between "TO others" and FROM others. "A value that is positive implies a net transmitter of information spillovers, whereas a value that is negative demonstrates a net receiver of shock spillovers. "Inc. own" refers to the portion that includes own

times (Ang and Bekaert, 2002; Betz et al., 2016). Moreover, the spectrum of contributions to others was broader within the clean energy framework compared to the dirty energy framework, signifying a more extensive distribution of transmission roles among markets when clean energy is factored in, while the contributions from others remained largely consistent across both systems. The significance of global energy is considerable, continually serving as a pivotal factor across all quantiles, as demonstrated by the findings presented in the tables.

5. CONCLUSION

The financialization of the commodities markets and expansion of equity markets have strengthened the relationship between global equities and the energy industry. The benefits of diversification have diminished owing to the complexity of hedging brought about by shifts in global asset markets. Therefore, investigating the connections across energy-related assets is necessary, as seen by the increased attention paid to environmentally friendly securities. In fact, returns for the energy asset class have shown a significant level of co movement owing to the growing connectivity among these assets. This presents investors with difficulties in portfolio diversification, emphasizing the significance of resolving this problem. Although energy markets have become viable alternatives to a global range of investment portfolios, the benefits of hedging decline as correlation between the energy and stock markets increases. The study aims to identify whether non-renewable (dirty) and clean energy indices act as net transmitters or net recipients of spillovers by examining their connectedness with a broad set of heterogeneous energy and stock market indices. Examining how clean and dirty energy are related to stock markets is important, as it could help risk executives during a severe energy crisis. Given the concerns raised about energy security and the speeding up of climate and environmental action, it is critical to examine how clean and dirty energy indices are connected with the equity markets in oil-exporting and oil-importing nations.

For asset allocation and portfolio risk management, it is essential to comprehend the patterns of volatility spillovers among energy assets, and local energy and stock indices of the largest oil-exporting and oil-importing countries, namely KSA, Canada, the US, Russia, China, and India. This study reveals that, in comparison to the dirty energy index, the clean energy index is a stronger net transmitter to financial markets, specially under normal market circumstances, where its net spillovers (44.34%) significantly surpass those of dirty energy (9.37%), although the disparity greatly diminishes during extreme bearish and bullish phases. This trend could indicate the increasing direct connections between the clean energy industry and equity markets.

Nonetheless, the contributions of distinct markets vary between the median and extreme quantiles, with both net transmitters and net receivers of shocks being recognized. Although total interconnectedness is slightly elevated in the dirty energy system at the extreme quantiles, the clean energy index serves as a significantly more potent net transmitter than the dirty energy index in normal market circumstances. At the median quantile of the clean energy framework, the Canadian and Russian energy sectors exhibit the lowest net transmission rates (4.64% and 2.73%, respectively), while clean energy (44.34%) and global energy (43.5%) demonstrate the highest. The almost identical positions of the Canadian and Russian energy industries offer investors a largely neutral energy exposure.

Thus, the findings of this study assist to better grasp whether clean or dirty energy connectedness is more crucial from a risk spillover standpoint. Consequently, it is essential to fully comprehend the interplay among stock markets, energy markets and the changes in geopolitical and oil risks. Our research may also help clarify the decoupling and substitution hypotheses (Ferrer et al., 2018; Xia et al., 2019) regarding the association between clean and the dirty energy market. It not only offers a more thorough understanding of the connectedness of the clean and dirty energy indices with a range of stock and energy indices but also provides relevant insights for global policy formulation.

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