Journal of Economic Cooperation and Development, **47**, 1 (2026), 65-94

The Impact of Clean and Dirty Energies on Gulf Cooperation Council (GCC) Sectoral Indices: A Quantile Connectedness Model Analysis

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ABSTRACT

The world is increasingly relying on renewable energy sources such as wind and solar, reducing dependence on limited fossil fuels as nature's consumption continues to exceed renewability. This study uses the quantile connectivity approach to examine the impact of clean and dirty energy on different Gulf Cooperation Council (GCC) economic sectors using data from 2 January 2018 to 17 June 2022. The study revealed that the correlation between clean and dirty energy is 82.60%. The correlation between dirty energy and GCC sector indices is particularly strong in 2021. The clean and dirty energy indices are weak receivers at lower and higher quantiles in 2020 and 2021 and become weak transmitters in 2022. The transmission intensity of clean energy and dirty energy was high around 2022. GGSS becomes the weakest receiver of spillover shocks, followed by GCCI, GAE, and RCE, while GCCF, GCCE, GCCB, and GCCC become net transmitters. The study's findings document that clean and dirty energy indices are weak recipients and transmitters of spillover shock. It concludes that since the GCC's service sector has minimal connection to other industries, it offers the greatest diversification opportunity. Moreover, policymakers should prioritize energy efficiency and climate transparency to build resilient and sustainable economies.

ملخص

بات العالم معتمدا لحد كبير على مصادر الطاقة المتجددة مثل الرياح والطاقة الشمسية، في أفق التقليل من الاعتماد على الوقود الأحفوري المحدود من حيث توفره والذي ينزف الطبيعة ويضعف قابلية التجدد.

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تعتمد هذه الدراسة مقاربة الترابط الكمي لدراسة أثر الطاقة النظيفة والطاقة الملوثة على مختلف القطاعات الاقتصادية في بلدان مجلس التعاون الخليجي (GCC)، وذلك باستخدام بيانات تغطي الفترة الممتدة بين 2 يناير 2018 و 17 يونيو 2022. وكشفت الدراسة أن نسبة الارتباط بين الطاقة النظيفة والطاقة الملوثة تبلغ 82.60%. وبلغ معدل الارتباط بين الطاقة الملوثة ومؤشرات القطاعات الاقتصادية في دول مجلس التعاون الخليجي مستويات عالية جدا في 2021. وكانت مؤشرات الطاقة النظيفة والطاقة الملوثة مستقبلات ضعيفة في الكميات المنخفضة والعالية في عامي 2020 و2021، واصبحت ناقلات ضعيفة في 2022. وبلغت كثافة انتقال الطاقة النظيفة والطاقة الملوثة مستويات عالية في حدود عام 2022. أصبحت GGSS أضعف المستقبلات للآثار غير المباشرة، تليها GCCI و GAE و RCE، في حين أن GCCF و GCCE و GCCB و GCCC باتت من الناقلات المباشرة. وتبرز نتائج الدراسة أن مؤشرات الطاقة النظيفة والطاقة غير النظيفة هي مستقبلة وناقلة ضعيفة للتأثيرات غير المباشرة. وتخلص الدراسة إلى أنه نظرا لكون قطاع الخدمات في دول مجلس التعاون الخليجي له صلة ضعيفة بالصناعات الأخرى، فإنه يوفر أكبر فرصة للتنويع. كما يتعين على صانعي السياسات إعطاء الأولوية لكفاءة الطاقة وضمان الشفافية في قضايا المناخ لبناء اقتصادات مرنة ومستدامة.

RÉSUMÉ

Le monde s'appuie de plus en plus sur les sources d'énergie renouvelables telles que l'éolien et le solaire, ce qui réduit la dépendance vis-à-vis des combustibles fossiles limités, alors que la consommation de la nature continue de dépasser sa capacité de renouvellement. Cette étude utilise une approche quantitative pour examiner l'impact des énergies propres et sales sur différents secteurs économiques dans les pays du CCG, à partir de données recueillies entre le 2 janvier 2018 et le 17 juin 2022. L'étude a révélé que la corrélation entre les énergies propres et polluantes est de 82,60 %. La corrélation entre les énergies polluantes et les indices du secteur GCC est particulièrement forte en 2021. Les indices des énergies propres et polluantes sont des récepteurs faibles aux quantiles inférieurs et supérieurs en 2020 et 2021, et deviennent des émetteurs faibles en 2022. L'intensité de transmission de l'énergie propre et de l'énergie sale était élevée vers 2022. Le GGSS devient le récepteur le plus faible des chocs de contagion, suivi du GCCI, du GAE et du RCE, tandis que le GCCF, le GCCE, le GCCB et le GCCC deviennent des transmetteurs nets. Les conclusions de l'étude montrent que les indices d'énergie propre et sale sont de faibles récepteurs et transmetteurs des chocs de contagion. Elle conclut que, le secteur des services du CCG étant peu lié aux autres industries, il offre les meilleures opportunités de diversification. De plus, les décideurs politiques devraient donner la priorité à l'efficacité énergétique et à la transparence climatique afin de bâtir des économies résilientes et durables.

Keywords: Renewable energy, green economy, Quantile-VAR spillover.

JEL Classification: Q40, Q42, Q43, Q56, C32

1. Introduction

Leveraging environmentally friendly energy sources and systems, such as wind and solar, is on the rise, whilst witnessing a downward trend in reliance on fossil fuels, including oil, gas, and coal. This shift is evident in various global energy markets since natural resources are the source of renewable energy, which can be replenished indefinitely to make up for any used resources. A few examples of sustainable energy sources are wind, solar, hydropower, ocean, and thermal energy. Affordable production expenses, supportive laws and regulations, technological advances, and environmental considerations all aid in developing clean energy markets.

While the transition to clean energy across the globe highlights the benefits of renewable sources of energy, it also underscores the risks that arise from the continued use of fossil fuels in economic transactions. The topic of environmental risk and climate risk has become integral to the financial industry. Recognizing the potential risks posed by these factors, US federal bank regulatory agencies (2023) jointly issued a broad framework of principles for large financial institutions for safe and sound management of climate-related financial exposure. These principles encompass and emphasize several key areas for managing climate risk from a financial sector perspective: governance, policies, procedures, risk management frameworks, data and risk measurement systems, reporting structures, and scenario analysis. While addressing the fundamental aspects of climate risk, like physical and transition risks, these principles further elaborate on how climate risk can manifest in traditional micro-prudential risks such as credit, market, liquidity, operational, and legal risks.

Establishing the financial perspective in the context of climate-related risk classification leads to the classification of climate-related risks into physical and transition-related risks, each of which has its own implications for markets. The financial sector faces a wide range of risks stemming from a changing climate, broadly categorized as physical and transition risks. Physical risks associated with the shifting physical environment can be further divided into acute and chronic impacts. Acute risks relate to the immediate, direct consequences of extreme weather events, such as property damage and operational disruptions. Chronic risks, in contrast, are the longer-term, indirect effects on the economy, for instance, water scarcity impacting agricultural productivity or rising sea levels affecting coastal infrastructure. Transition risks arise from the socio-economic transformations necessary to adapt to a low-carbon future. These include shifting regulations, changing consumer preferences, and evolving technological landscapes. Quantifying the financial impact of both physical and transition risks requires incorporating climate projections and economic forecasts into stress testing and scenario analysis models.

Against the background of increasing danger, the global movement toward renewable sources of energy has become even more pressing and pertinent. The global transition toward renewable energy is increasing; institutions like the International Renewable Energy Agency (IRENA, 2020) predict that renewable energy will account for two-thirds of global energy consumption by 2050. This transformation not only prevents environmental damage but also promotes energy security, inspires innovation, and promotes economic growth. A green economy that is powered by renewable sources is increasingly considered to be the most effective path to sustainable development. This economy reduces the dependency on finite fossil fuels while creating opportunities for investment, employment, and diversification.

However, transitioning to a green economy is not simply a technological transition; it is also an economic challenge for society as a whole. Changing to more environmentally friendly energy systems also involves larger goals associated with the socio-economic sphere, including affordability, accessibility, and resilience. Governments, companies, and investors are increasingly involved in the carbonless agenda. From a scholarly perspective, the literature advocates that renewable energy adoption is of paramount importance in reducing emissions and improving energy efficiency; the transition itself is primarily driven by economic, political, and regulatory factors.

The fragility of this transition has been observed in actual world events. The pandemic COVID-19 and the subsequent global downturns demonstrated the fragility of the renewable energy market, and the uncertainty and policy shifts that occurred affected the course of investment and growth. Understanding the effects of energy market spillovers is therefore critical, especially in oil-dependent economies. Previous investigations have demonstrated the dependence of global energy markets; these investigations have demonstrated how oil price changes have an effect on financial and economic systems. However, new methods like quantile-based models of connectedness now allow researchers to deduce asymmetric and state-dependent spillover behavior. This behavior is more profoundly studied in regard to how clean and dirty energy waves travel.

This inspires us to a significant lack of critical research. While the importance of clean energy in combating climate change is recognized, the connection between these resources and the fossil fuel market is less well-known, specifically in oil-producing regions like the Gulf Cooperation Council (GCC). Many existing studies have focused on the dynamics of the energy market as a whole; these studies have typically disregarded the complex relationship between the renewable and fossil fuel markets in hydrocarbon-based economies. This represents an important omission, as understanding these connections is crucial to the successful management of risk, portfolio diversity, and energy transition planning.

Based on the identified gaps, the present study makes a unique contribution. This research addresses the lack of knowledge about (i) the connectedness of GCC sectoral indices over time, (ii) the way that clean and dirty energy interact with these sectors in different market conditions, and (iii) the way that the COVID-19 pandemic and the Ukraine conflict affect the spillover phenomenon. To the best of our knowledge, this is the first study to explore the relationship between clean and dirty energy indices and disaggregated sectoral indices in the GCC. By using quantile models that account for spillover effects, we discover the patterns of association between different market states. This provides new information about the stability and fragility of the GCC financial markets.

The remainder of the article is structured as follows: The next section contains the literature review, followed by the data and methodology. Empirical results and discussion are then presented, and finally, the conclusion summarizes the main findings, policy implications, Limitations, and Future Directions.

2. Literature Review

Clean and dirty energy approaches are fundamentally different methods of producing global energy. "Clean energy" is associated with renewable and low-carbon sources like solar, wind, hydropower, geothermal, and other environmentally friendly technologies. Conversely, "dirty energy" is associated with fossil fuel-based energy, including coal, oil, and natural gas. This energy is associated with high greenhouse gas emissions and environmental degradation (Dias et al., 2023; Tiwari, 2023). Understanding the financial connections between these two categories is crucial, as their interactions directly affect the energy markets, investment strategies, and climate policy in the context of climate change and economic transition.

Furthermore, the growing interconnectedness of the global financial system has significantly increased the importance of managing network connectivity risks. This increased emphasis is driven by factors such as globalization and liberalization, which have led to a more complex and interdependent financial landscape. The network connection can be described as market risk (caused by portfolio concentration and return connectivity), credit risk (caused by default connectivity), counterparty risk (caused by contractual commitments), and idiosyncratic risk. It is critical to ascertain how network connection affects macroeconomic factors and their overall implications on the business cycle. Current theoretical advancements (Baqaee & Farhi, 2019; Babus, 2016; Acemoglu et al., 2012) have stressed the importance and significance of network connections in both the financial and non-financial industries. Applications of understanding transmission mechanisms among markets may also be utilized to build global portfolios across boundaries. It is preferable to have lower connectedness among markets to achieve desirable portfolio risks. In this work, the association among markets is investigated from an international portfolio diversification standpoint.

Within the energy literature, two broad strands of research have developed. The first strand of research focuses on the relationship between environmental indicators and oil prices. It demonstrates how oil market fluctuations can have a significant effect on the performance of clean energy stocks (Sadorsky, 2012). Subsequent market-specific analyses confirm that shocks to oil prices shape returns in energy-related equities and clean-energy indices, with heterogeneous effects across markets and regimes (Managi & Okimoto, 2013; Inchauspe et al.,2015; Reboredo, 2015).

The second strand focuses on cross-market spillovers, asymmetry, and hedging properties between clean and dirty energy. Using nonlinear and tail-focused methods, studies document asymmetric and state-dependent connectedness, stronger comovements during stress, and only limited safe-haven potential from traditional energy toward clean-energy assets (Kocaarslan & Soytas, 2019; Saeed et al., 2021; Bouri et al.,2019). Time–

frequency analyses further show that connectedness intensifies around major crises, and that the direction and strength of spillovers vary across horizons (Umar et al., 2022). Despite these advances, most evidence is drawn from global indices or large developed/emerging markets, with minimal attention to sector-level transmission in Gulf Cooperation Council (GCC) equities. The few GCC-focused studies examine aggregate energy sectors or VaR/ES implications rather than sectoral spillovers with clean versus dirty energy benchmarks (Alkathery et al.,2022).

The empirical work further nuances this relationship. Alkathery and Chaudhuri (2021) and Jiang et al. (2021), there is a strong relationship between renewable energy and oil. Additionally, further evidence specifies a positive correlation between fossil fuel and clean energy indices, which indicates that these two energy sectors are alternatives to one another (Mokni, 2020). While some research (e.g., Nasreen et al., 2020) found a modest correlation between oil and renewable energy stocks, others (e.g., Maghyereh and Abdoh, 2021; Yahya et al., 2021) found an unstable association over time. The importance of the connection between clean energy and fossil fuels seems to be the common denominator amongst such works of literature, notwithstanding the degree of contradiction revealed in the findings.

Accordingly, Xi et al. (2022) attributed the observed variations to structural gaps within the oil market. Moreover, Kocaarslan and Soytas (2019) employed an NARDL model to reveal the asymmetric relationship between crude oil and renewable energy stock prices, explaining their diverse movements. According to Xia et al.'s (2019) research, renewable energy sources may effectively replace fossil fuel energy. Further, the findings of Bouri et al. (2019) show that during times of significant market volatility, crude oil serves as a safe-haven asset for clean energy enterprises. Besides, Dawar et al. (2021) have demonstrated that renewable energy equities are less reliant on changes in oil prices by using the quantile-based regression technique. However, they show that during bearish periods, the negative oil price returns have a significant influence on renewable energy returns.

Recent studies extend this line of inquiry with novel methodologies. Coskun (2023) studies the time varying connectedness between different subsector energy stocks and fossil fuels using the Diebold-Yılmaz framework, he demonstrates that oil has the highest degree of temporal variation in its connections to biofuels, while natural gas and coal have the greatest effect on energy storage industries- this is highlighted in specific cases and optimized hedge ratios over time. Zhang et al.(2025) utilize a quantile-based framework for connectedness that shows that extreme events in the market have a significant effect on return spills, with fossil fuels acting as a net receiver and clean energy as a net transmitter, and that climate policy and geopolitical uncertainties are responsible for these extreme connections.

Additionally, a 2023 study of dynamic spillover effects under multiple uncertainty regimes that include COVID-19 demonstrates that during the pandemic's duration, economic policy uncertainty increased the transmission of oil to clean energy, but also revealed a bidirectional relationship, which means that clean energy markets contributed to fluctuations in dirty energy markets.

Despite these advances, the literature has several blind spots. The literature on the association between clean and dirty energy markets has primarily focused on developed or global contexts; the majority of studies have examined the way oil prices are affected by renewable energy indices (Sadorsky, 2012; Henriques & Sadorsky, 2008). Other research has incorporated this into the dynamic and asymmetric nature of connectedness, examining the potential for volatility to be transferred from oil, gas, and renewable energy to other markets across different time periods and uncertainty scenarios (Ji et al., 2018; Reboredo, 2015; Umar et al., 2022). These investigations have consistently demonstrated that oil price changes have a destabilizing effect on renewable energy resources; however, the role of clean energy as a hedge is still modest and highly dependent on state laws.

Moreover, despite this progress, the majority of the literature on clean and dirty energy markets aggregates these markets as a single entity; it typically ignores the way in which their connection to the sectoral equity markets in specific regions like the Gulf Cooperation Council (GCC) will interact with the sectoral markets in general. The GCC economies are still heavily reliant on oil, but they have also made significant advances in the renewable energy sector as a part of their long-term diversification strategies (Al-Mulali et al., 2016). Existing empirical evidence on GCC markets has primarily focused on the impact of oil prices on macroeconomic performance or the aggregate stock market (Arouri and Rault, 2012), rather than on the interaction between renewable energy and stock prices. Additionally, investigations utilizing cutting-edge methods like spillover indices or quantile-based connectedness have typically focused on global markets, with limited consideration given to the GCC context (Kang et al., 2017).

A significant research gap remains to our knowledge, no published study has documented the degree to which clean and dirty energy indices are connected in a quantile-dependent manner, and no published study has documented the specifics of the GCC sectoral composition. This omission is significant because sectoral-level dynamics can expose different ways that energy shocks are transmitted that the aggregate analyses would have failed to recognize. By addressing this gap, "Exploring the Interconnectedness of Clean and Dirty Energies on GCC Sectoral Indices: A Quantile Connectedness Approach" provides a novel contribution, offering region-specific and sector-sensitive insights that are particularly relevant for policymakers, investors, and energy planners in oil-dependent economies undergoing energy transition.

3. Data and Methodology

Using a quantile connectedness technique, we analyzed daily data from 2018-01-02 to 2022-06-17 to examine how clean and dirty energies influenced GCC sectoral indexes. Our main goal was to examine how the primary sectoral indices—the GCC Banking Sector, the GCC Commercial Sector, the GCC energy industry, the GCC finance sector, and the GCC investment sector respond to the spillovers from the Global Dirty and Clean Energy Indices (MSCI Global Alternative Energy Index (MSCIGAE), and Renewable and Clean Energy Index (RCE)) and vice versa. The applied data was obtained from the DataStream source. Moreover, owing to its user-friendly interface and relatively straightforward steps involved in loading data, writing code, managing datasets, creating graphs, and debugging and optimizing your code, R Studio Software was used to analyze the data. We chose these specific years because numerous studies have investigated the impact of the Global Financial Crisis; however, the influence of COVID-19 and the Russia-Ukraine war on these markets remains unexplored. This study, therefore, focuses on the latter two events. Moreover, understanding how these new events shape the markets is crucial for informed decision-making in the future.

3.1. Model Description

Diebold and Yilmaz's (2009) contributions remain a mainstay of study when it comes to comprehending the interconnectivity of the financial markets. They developed the generalized VAR-based empirical approach for connectivity and spillovers using unique techniques for compressing Forecast Error Variance Decompositions (FEVDs). They employ the conventional rolling windows technique to produce dynamic outcomes in their work. Although financial market interconnectedness may be measured using classical time-varying parameter vector autoregression (TVP-VAR), the authors argue that using Bayesian TVP-VAR (2019) yields more accurate results. With these methodological successes in mind, we use the quantile connectivity in the present study to expand the applicability of the literature. We use a novel econometric estimate technique to the quantile connectedness introduced by (Ando et al., 2022) and improved by (Chatziantoniou et al., 2021) to assess the connection between the clean, dirty indices, and major GCC sectoral indices. The quantile spillover paradigm is superior to existing methods for several reasons, including its uniqueness. The systematic and distinctive components of the error mechanism are distinguished. They are making use of a factor structure. The VAR residuals are handled as well. Third, the quantile spillover technique may be used to isolate the distinct disturbance that each system parameter experiences. Finally, one may use this methodology to look at the multivariate distribution's tails, which represent market swings.

The quantile vector autoregression (QVAR) is first calculated:

$$z_t = \pi(\tau) + \sum_{j=1}^{p} \varphi_j(\tau) z_{t-j} + \omega_t(\tau)$$

the d by Σ(τ). These zt and z_(t-1) endogenous summations are the first differenced-year renewable indices.$z_t \pi(\tau) + \sum_{j=1}^{p} \varphi_j(\tau) z_{t-j} + \omega_t(\tau) = \pi(\tau) + \sum_{i=0}^{\infty} \delta_i(\tau) \omega_{t-i}$ is used in this paper for changing QVAR(p) into QVMA (∞). The following formula was obtained by computing the H-step-ahead generalized Forecast Error Variance Decomposition (GFEVD), a technique for estimating the effects of a shock from variable j to variable i that was developed by Koop et al. (1996) and Pesaran & Shin (1998).

$$\varphi_{ij}^{k}(H) = \frac{\Sigma(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} (\varepsilon_i' \delta_h(\tau) \Sigma(\tau) \varepsilon_j)^2}{\sum_{h=0}^{H-1} (\varepsilon_i' \delta_h(\tau) \Sigma(\tau) \delta_h(\tau)' \varepsilon_i)}$$

$$\tilde{\varphi}_{ij}^{k}(H) = \frac{\varphi_{ij}^{k}(H)}{\sum_{j=1}^{k} (\theta_{ij}^{k}(H))}$$

To visualize and prove the next two equivalences, we employ a zero vector with a unity in the ith slot, denoted by ε_i.:

$$\sum_{j=1}^{k} \tilde{\varphi}_{ij}^{k}(H) = 1 \; and \sum_{ij=1}^{k} \tilde{\varphi}_{ij}^{k}(H) = k$$

To quantify the impact of the i variable on other j variables, we leverage this equation, which calculates its "total directional connection TO others.:

$$C_{i \dashrightarrow j}^{k}(H) = \sum_{j=1, i \neq j}^{k} \tilde{\varphi}_{ji}^{k}(H)$$

Additionally, the influence of factor j on variable i is taken into account while using the following equation to determine the total directional connectedness, which quantifies how much a variable is impacted by other variables.:

$$C_{i \dashleftarrow j}^{k}(H) = \sum_{j=1, i \neq j}^{k} \tilde{\varphi}_{ij}^{k}(H)$$

The net impact of variable 'i on the system tells us its "net directional connectedness," which reveals the difference between how strongly it influences other variables (TO others) and how significantly it's influenced by them (from others).

$$C_{i}^{k}(H) = C_{i \dashrightarrow j}^{k}(H) - C_{i \dashleftarrow j}^{k}(H)$$

Lastly, the following formula is used to calculate the total connectivity index (TCI) after accounting for relevant modifications.

$$TCI(H) = \frac{\sum_{ij=1,i\neq j}^{k} \tilde{\varphi}_{ij}^{k}(H)}{K-1}$$

The extent of network connectedness increases with increasing TCI.

4. Empirical Results and Discussion

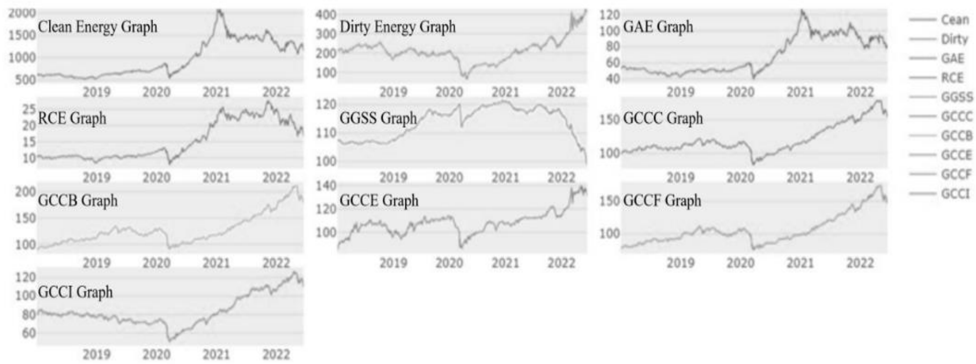
We use a time-varying parameter vector autoregression (TVP-VAR) model to calculate the degree of connectivity in the return series, as given by Equation 1. The net total directional connectedness (NET), total directional connectivity from others (FROM), Total connectedness index (TCI), and total directional connectedness to others (TO) are among the important metrics obtained from this study.

Figure 1 demonstrates the effects of COVID-19 on alternative (Clean) energy, conventional energy, and the GCC sector as a whole. All indices (clean, dirty, GAE, RCE, GGSS, GCCC, GCCB, GCE, GCCF, GCCI) had a declining return during the 2019/2020 season. This substantiates that health-related uncertainties had a negative impact on both energy and sectoral metrics during the early stages of COVID-19. After the initial shock, the markets regained popularity, and by 2021, all indices had peaked. However, volatility has primarily been driven by the conflict between Russia and Ukraine since 2022. These general patterns of crisis-related connectedness are in agreement with the connectedness literature that demonstrates that spillovers are more intense during large-scale events (e.g., Diebold & Yılmaz,2015, on spillover behavior). Moreover, these findings replicate Khan's. (2022), who documented that COVID-19 adversely affected both conventional and Islamic stock markets in Pakistan.

Unit root tests and descriptive data are included in Table 1 for the global energy index and the GCC sectoral index. All selected indices appear to have positive average daily returns, except the GCC Service sector. Moreover, as per the data. Notably, the GCC financial and commercial sectors have the lowest average returns, averaging 0.07 and 0.09, while the clean and dirty energy worldwide indexes have the greatest average returns, with 0.693 and 0.255, respectively.

Among them, the clean energy index has the largest total standard deviation (681.379), followed by the dirty energy index (36.623). This demonstrates the greater variation and tail risk associated with the renewable-energy index relative to other sectoral indices in the Gulf, a finding that is in line with previous research that documents a higher degree of variation and tail risk in clean-energy assets (see Reboredo, 2015; Song et al., 2019). The Jarque–Bera (JB) normalcy test reveals the series's non-normal distribution. The Elliot-Rothenberg-Stock unit root (ERS) test further demonstrates statistical significance within the sample period, which suggests that our data does not possess the issue of the Unit root here.

Figure 1: Implications of COVID-19 on renewable, dirty energy, and GCC sectoral indices' returns



Source: Author's calculation

Note (s): Clean =S&P Global Clean Energy Index, Dirty = S&P Global Dirty Energy Index, GAE=MSCI Global Alternative Energy index. RCE= Renewable and Clean Energy NTR index, GGSS= Gulf Cooperation Council Service Sector Index, GCCC=Gulf Cooperation Council Commercial Index, GCCB= Gulf Cooperation Council Banking Index, GCCE=Gulf Cooperation Council Energy Index, GCCF= Gulf Cooperation Council Financial Index, GCCI=Gulf Cooperation Council Industrial index

Table 1: Descriptive Statistics

	Clean	**Dirty**	**GAE**	**RCE**	**GCSS**	**GCCC**	**GCCB**	**GCCE**	**GCCF**	**GCCI**
Mean	0.693	0.255	0.033	0.008	-0.011	0.07	0.115	0.059	0.09	0.039
Variance	681.379	36.623	2.551	0.138	0.101	1.749	2.613	1.563	1.739	0.99
JB	5116.243***	4857**	4666**	977.1**	3166.***	39144.***	31107.***	14713.662***	33545.220***	16403.881***
ERS	-11.189***	-.80***	-11.2**	-11.9***	-7.97***	-7.231***	-5.719***	-11.718***	-5.844***	-10.517***
Q(10)	27.562***	12.05**	8.52	6.947	57.13***	9.082	12.441**	5.458	12.630**	10.171*
Q2(10)	85.847***	187***	29***	59.7***	175.6***	11.183**	10.371*	46.851***	10.843**	10.894**

Note (s): Level of significance: ***p < 0.01; **p < 0.05 *p<0.10, Clean =S&P Global Clean Energy Index, Dirty = S&P Global Dirty Energy Index, GAE=MSCI Global Alternative Energy index. RCE= Renewable and Clean Energy NTR index, GGSS= Gulf Cooperation Council Service Sector Index, GCCC=Gulf Cooperation Council Commercial Index, GCCB= Gulf Cooperation Council Banking Index, GCCE=Gulf Cooperation Council Energy Index, GCCF= Gulf Cooperation Council Financial Index, GCCI=Gulf Cooperation Council Industrial Index

Table 2: Average Connectedness

	Clean	Dirty	GAE	RCE	GGSS	GCCC	GCCB	GCCE	GCCF	GCCI	FROM
clean	23.19	4.81	18.65	16.58	3.87	6.7	6.35	7.63	6.17	6.06	76.81
Dirty	4.88	33.62	4.97	9.4	2.65	8.38	7.76	11.1	7.68	9.55	66.38
GAE	20.28	4.11	21.56	15.48	4.09	6.87	6.18	9.15	5.99	6.28	78.44
RCE	17.59	3.73	14.72	26.9	2.67	6.84	6.65	6.94	6.65	7.3	73.1
GGSS	8.02	7.08	7.2	7.73	33.78	7.03	7.24	8.63	6.87	6.44	66.22
GCCC	4.03	5.42	4.07	5.21	1.24	19.03	17.73	11.68	17.98	13.62	80.97
GCCB	3.39	4.42	3.43	4.45	1.42	18.15	20.91	10.8	20.9	12.15	79.09
GCCE	2.99	5.1	3.19	3.78	1.37	15.52	13.59	30.66	13.68	10.13	69.34
GCCF	3.51	4.55	3.48	4.69	1.42	17.96	20.43	10.87	20.55	12.55	79.45
GCCI	3.53	5.06	3.45	4.74	1.18	16.16	13.22	12.33	13.87	26.45	73.55
TO	68.22	44.28	63.16	72.07	19.91	103.61	99.15	89.12	99.78	84.06	743.36
Inc.Own	91.41	77.9	84.72	98.97	53.69	122.63	120.06	119.78	120.33	110.51	cTCI/TCI
NET	-8.59	-22.1	-15.28	-1.03	-46.31	22.63	20.06	19.78	20.33	10.51	82.60/74.34
NPT	4.00	1.00	2.00	3.00	0.00	8.00	7.00	6.00	9.00	5.00	-

Note (s): Level of significance: ***p < 0.01; **p < 0.05 *p<0.10, Clean =S&P Global Clean Energy Index, Dirty = S&P Global Dirty Energy Index, GAE=MSCI Global Alternative Energy index. RCE= Renewable and Clean Energy NTR index, GGSS= Gulf Cooperation Council Service Sector Index, GCCC=Gulf Cooperation Council Commercial Index, GCCB= Gulf Cooperation Council Banking Index, GCCE=Gulf Cooperation Council Energy Index, GCCF= Gulf Cooperation Council Financial Index, GCCI=Gulf Cooperation Council Industrial Index

Source: Author’s calculations

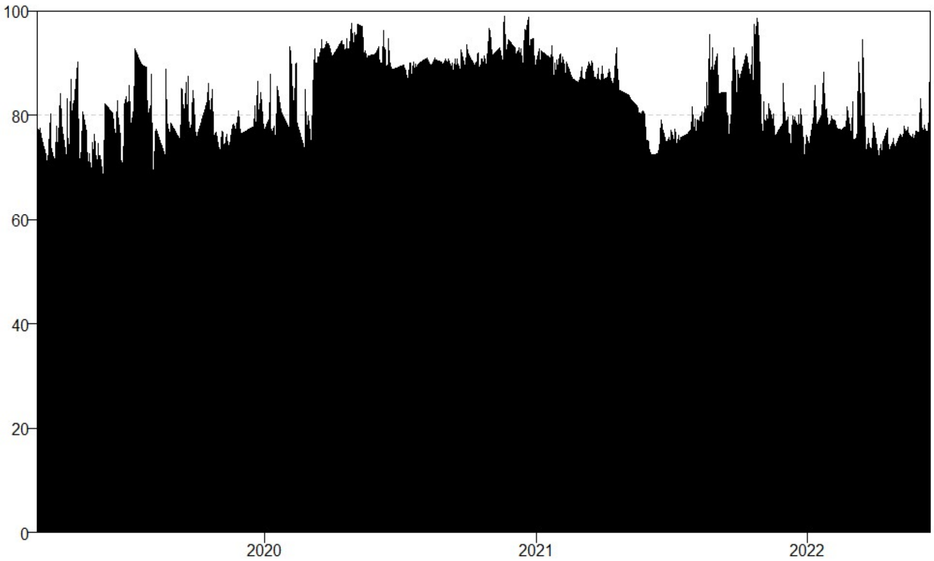
Furthermore, Table 2's average connectedness illustrates that the GCCC index (103.61) has the most influence on other indices, while the GCC service sector (GGSS) index (66.22) is the least affected by others. Overall, Strong connectivity (82.60%) between these indices is demonstrated by the data, which supports Singh et al.'s (2021) findings. In the context of North American and European economies, their research shows a significant and more noticeable return spillover connection in global energy markets. Moreover, it is discovered that the Clean, Dirty, GAE, RCE, and GGSS indices are most affected by outside factors, and have the highest directional connectedness receivers of spillovers (-8.59, -22.10, -15.28, -1.03, and -46.31, respectively). In contrast, GCCC, GCCB, GCCE, GCCF, and GCCI were discovered as net spillover transmitters. (22.63, 20.06, 19.78, 20.33, and 10.51, respectively). While the GCCC sector has the highest level of connectivity (22.63%), the RCE sector has the lowest level of connectivity (1.03%) with other global energy and GCC sectoral indices, subsequently followed by the clean energy index at 8.59%.

Furthermore, the primary goals of this research are to track the evolution of regional sectoral indices' interconnection and how clean and dirty energy indices affect these sectors. Accordingly, the sectoral breakdown reveals important heterogeneity. The GGSS index was least impacted by the Dirty Energy Index (7.08) and most related to the spillovers from the clean index (8.02). Next, the RCE (5.21) spillovers have the highest connection with the GCCC index, while the clean index (4.03) has the lowest. The RCE index's spillovers resulted in the highest degree of connectedness for the GCCB and GCCF indices (4.45 and 4.69, respectively). However, the strongest linkage with the dirty energy index is seen in the GCCE and GCCI indices (5.10 and 5.06, respectively).

Similarly, except for GGSS, which was least impacted by the dirty energy index (7.08), the least amount of connectivity for these indices—GCCC, GCCB, GCCE, and GCCF—came from the clean energy index (4.03, 3.39, 2.99, 3.51). Our results show that the GCCC, GCCB, and GCCE sectors are somewhat less significantly impacted by the clean energy index (clean). This is consistent with the findings of Alkathery et al. (2022), who find that the volatility of the GCC daily returns is not significantly influenced by the output of renewable energy, the price of crude oil, or the price of CO_2 emissions. This sector-level differentiation is in line with empirical evidence that connection patterns differ between subsectors, and that energy subsectors have a disparate distribution of receiving and transmitted shocks across horizons and regimes (Ferrer et al., 2018; Hao et al., 2018).

Similarly, Alkathery and Chaudhuri's (2021) study, which used three different multivariate GARCH models, somewhat supports our analysis's findings that dirty energy has the greatest influence on GGSS. Evidence of volatility spillover and co-movement between the GCC energy stock markets, worldwide clean energy production, crude oil prices, and CO2 emission prices is found in their research. This illustrates the interdependence and connectivity of price variations among different markets. Similarly, for every pairwise directional connectedness metric in the GCC sectorial indices, we find that the GCC Financial sector and the GCC Banking sector have the highest connectivity (20.90). The significant contribution of the banking and financial indices (high net transmitters: -20.90) also mirrors the general financial-connectedness literature that identifies financial institutions as the central portion of a shock's propagation (Reboredo, 2015; Balsalobre-Lorente et al., 2023).

Figure 2: Dynamic total connectedness



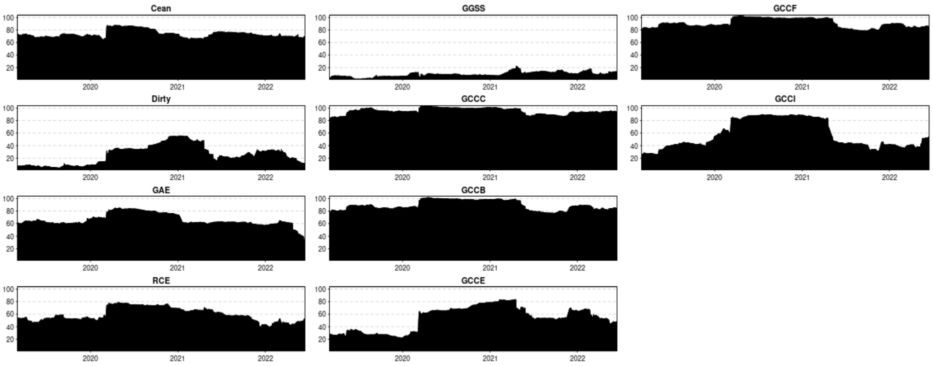
Source: Author’s calculations

The clean/dirty energy indices (Clean, Dirty, GAE, RCE) and the GCC sectorial indices (GGSS, GCCC, GCCB, GCCE, GCCF, GCCI) are represented by the total connectedness index (TCI) in Fig. 4. Our analysis demonstrates that during our observations, the TCI fluctuates. There is variation in the TCI from 77% to 98%. The World Health Organization declared the COVID-19 pandemic in 2020–2021, which coincided with the total connectivity index (TCI), a measure of interconnection within a system, reaching its maximum point. Interestingly, the TCI started to rise again in the early phases of the Russia-Ukraine conflict in 2022, following an initial dip following the pandemic's peak. Our examination of connection trends throughout the COVID-19 pandemic and the Russia-Ukraine war is consistent with Lorente et al. (2023). According to their analysis, TCI increased first during the first 100 days of the conflict and then started to fall during the second COVID-19 wave.

To understand the temporal evolution of directional return spillovers between the Sectoral and energy indices, this study computes the total directional connectivity in more detail. Figure 3 illustrates how each energy or sectoral index is dynamically connected in all directions TO others, while Figure 4 shows how each energy or sectoral index is dynamically connected in all directions FROM others. These graphs demonstrate how total directional connectivity changed over time in the different GCC sectors and energy markets.

All four indices (Clean, Dirty, GAE, and RCE) in the examined energy markets, as shown in Fig. 3, have demonstrated a decrease in connectedness before2020, after 2020, however, there has been a noticeable spike in market spillover on other markets for Clean, Global Alternative Energy Index, and Renewable & Clean Energy Index, a timeframe that aligns with the COVID-19 era. During the entirety of the study period, the Dirty Energy Index does, however, exhibit slight connectedness and spillovers on other markets. Moreover, in the GCC sectoral indices GCC commercial, Banking, and financial sectors show a strong spillover tendency to other markets. Conversely, the GSS service, energy, and investment sector displayed minimal connectivity before 2020, then a sudden spike in connectivity during the Covid-19 period, i.e., during 2020. Though there are occasional variances, overall TDC patterns point to a pattern of persistent interdependencies across sectoral and energy markets, independent of the period being examined. Taking the COVID-19 era as an example, there was a spike in connectivity in all given indices during that period. Similarly, in the 2022 period, there was a boom in connectivity in most of the indices due to Russia Russia-Ukrainian war.

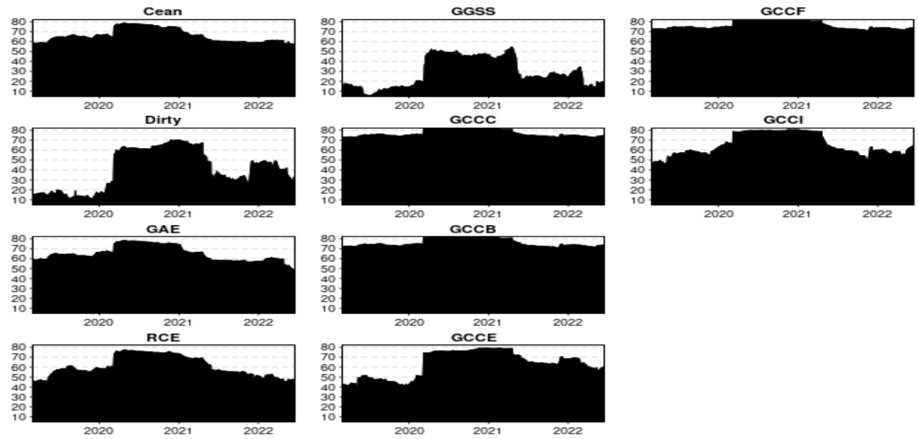
Figure 3: Dynamic total connectedness (To Others)



Source: Author's calculations

Note (s): Clean =S&P Global Clean Energy Index, Dirty = S&P Global Dirty Energy Index, GAE=MSCI Global Alternative Energy Index. RCE= Renewable and Clean Energy NTR index, GGSS= Gulf Cooperation Council Service Sector Index, GCCC=Gulf Cooperation Council Commercial Index, GCCB= Gulf Cooperation Council Banking Index, GCCE=Gulf Cooperation Council Energy Index, GCCF= Gulf Cooperation Council Financial Index, GCCI=Gulf Cooperation Council Industrial Index

Figure 4: Dynamic total connectedness (From Others)



Source: Author's calculations

Note (s): Level of significance: ***p < 0.01; **p < 0.05 *p<0.10, Clean =S&P Global Clean Energy Index, Dirty = S&P Global Dirty Energy Index, GAE=MSCI Global Alternative Energy index. RCE= Renewable and Clean Energy NTR index, GGSS= Gulf Cooperation Council Service Sector Index, GCCC=Gulf Cooperation Council Commercial Index, GCCB= Gulf Cooperation Council Banking Index, GCCE=Gulf Cooperation Council Energy Index, GCCF= Gulf Cooperation Council Financial Index, GCCI=Gulf Cooperation Council Industrial Index

Figure 4 demonstrates the striking similarity of the directional influence patterns, with transmitting (TO) and receiving (FROM) impacts adhering to comparable tendencies. The energy markets displayed a diminishing tendency before 2020, followed by a heightened level of connection during the 2020 and 2022 timeframe, coinciding with COVID-19 and the Russian-Ukrainian war. This can be seen through the 'FROM' directional connection spillovers and how other markets impact specific energy markets during this period. Similar findings can be seen in the case of GCC sectoral markets, which indicates a comparable impact of the economic crisis on both energy and sectoral markets. Furthermore, the peak period in Figure 4 is comparable to that in Figure 3, suggesting that severe economic shocks amplify directional "TO" spillovers and directional "FROM" spillovers. This finding holds for the sectoral indices that were sampled as well.

Overall, the evidence suggests that both health crises and geopolitical conflicts increase the connectivity of the energy sector and the GCC as a whole, which increases the overall vulnerability of the system. The close correspondence between the TO and FROM patterns suggests that shocks have an enhancing effect on both the sending and receiving dynamics; this double effect of spillovers under stress resembles the larger connectedness and spillover literature (Diebold & Yılmaz; Ji et al., 2018; Reboredo, 2015). Extreme events, such as the COVID-19 pandemic and the Russia-Ukraine conflict, not only increase volatility but also alter the pattern of connectedness, causing some sectors to be more powerful transmitters and others to be larger recipients.

5. Conclusion

Among the most difficult tasks in financial analysis is investment analysis, which aims to give accurate information by considering all the dynamics of both the present and past market conditions. In this regard, we provide an investment mechanism. Investors in the stock market should take heed of our findings. This research utilizes a quantile connectedness approach to explore the impact of clean and dirty energies on various economic sectors within the Gulf Cooperation Council (GCC). Specifically, using the data from 2018-01-02 to 2022-06-17, we looked at the composite indexes for GCC's commercial, Banking, Financial, investment, service, and energy sectors in terms of their connectedness with global clean and dirty energy indices.

The study found a robust, i.e., 82.60% connectedness among clean, dirty energies, and GCC sectoral indices, especially during 2021. Clean and dirty energies indices appeared weak recipients at lower and higher quantiles during 2020 and 2021, while turning into weak transmitters during 2022. Overall, Strong connectivity between these indices is demonstrated by the data, which supports Singh et al. (2021) findings. Their research shows a significant and more noticeable return spillover connection in global energy indices in North American and European economies. Besides, it is discovered that the Clean, Dirty, GAE, RCE, and GGSS indices are most affected by outside factors, and the net recipient of spillovers (-8.59, -22.10, -15.28, -1.03, and -46.31, respectively). In contrast, GCCC, GCCB, GCCE, GCCF, and GCCI indexes are net spillover transmitters. (22.63, 20.06, 19.78, 20.33, and 10.51, respectively). While the GCCC sector has the highest level of connectivity (22.63%), the RCE sector has the lowest level of connectivity (1.03%) among various energy and GCC sectoral indexes, followed by the clean energy index at 8.59%.

The transmitting intensity was high before and after 2022 for clean and dirty energies, respectively. Moreover, the GCC service sector (GGSS) was found to be the least connected to other energy and sectoral indices. Thus, portfolio managers ought to consider investing in low-volatility sectors, such as the GGSS sector, which the analysis found to be the least connected. By doing so, overall returns can be raised, and portfolio risk can be decreased. Moreover, it is recommended that portfolio managers implement a dynamic asset allocation approach that considers the evolving dynamics of both the clean and dirty energy markets. This could entail modifying portfolio weights, considering predictions, and movements in the market. The risk of unfavorable changes in the price of clean and dirty energy should be reduced by portfolio managers by employing hedging techniques. Derivative instruments like futures and options contracts can be used for this.

For Policymakers, it is recommended that policymakers prioritize the implementation of energy efficiency measures and investments in renewable energy sources to enhance the GCC economies' resilience to changes in energy prices. By doing this, economies will become less reliant on fossil fuels and more resilient to outside shocks. Further, the risks and opportunities associated with climate change should be disclosed transparently and openly by policymakers. As a result, investors will be able to deploy funds to sustainable companies and make well-informed investment decisions. Finally, a thorough regulatory framework for the clean and dirty energy markets should be developed by regulators in the GCC region. The creation of sustainable energy solutions, fair competition, and transparency ought to be the goals of this framework. Tax incentives, subsidies, and expedited regulatory procedures are some ways that policymakers could encourage investments in sustainable energy.

5.1. Limitation and Future Direction

The present study utilized an empirical methodology to examine the mechanisms of spillover transmission from global clean and dirty energy indices to the primary sectoral indices, like commercial, Banking, Financial, investment, service, and energy sectors, of the Gulf Cooperation Council (GCC), with a four-year data time frame. While we only look at the effects of global Clean and Dirty energy indices, we only consider the local indices of the GCC region. Future research should include more nations and a longer data period of investigation to overcome these constraints. This will facilitate the long-term analysis of the effects of global energy spillovers on regional financial markets. Moreover, we solely consider the conflict between Russia and Ukraine and the COVID-19 pandemic. Future studies ought to cover a wider range of national and local problems, including geopolitical ones like the Israel-Palestine Conflict.

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