

Tracing the Dynamic Impact of Energy Transitions on Equity Market Volatility in an Era of Financial Turbulence

Abstract

This study investigates the dynamic relationship between the shift towards clean energy and stock market fluctuations, covering the period from January 2004 to August 2021 by applying time-varying parameters vector autoregressions (TVP-VAR). The results reported strong spillovers between clean energy markets and stocks, while dirty ones demonstrated disconnected spillovers. Asymmetry in the spillovers detected dominance of negative (bad) spillovers due to various uncertain economic and financial circumstances. The most significant negative (bad) events tracked in time-varying attributes are the global financial crisis, European Debt Crisis, Shale Oil Crisis, Brexit, US interest rate agenda, and the COVID-19 pandemic. Meanwhile, negative asymmetries prevailed in time-varying analysis, echoing the pre-eminence of negative crisis periods. We identified clean energy markets and stocks as net spillover emitters and dirty energy markets as net recipients. These findings have profound implications for a range of stakeholders, including investors, policymakers, and market participants, offering valuable insights for portfolio diversification and risk management strategies amidst the ongoing energy paradigm shift.

Keywords

Renewable Energy Impact; Stock Market Volatility; Energy Sector Transition; Financial Crisis Influence; Risk Management; Economic Turbulence

1. Introduction

In recent years, and after decades of receiving limited attention, addressing climate change has mounted to the forefront of global priorities, compelling policymakers, governments, regulatory bodies, and environmentalists to take unprecedented actions. The increasing urgency of climate concerns has propelled the promotion of clean energy sources and a steadfast commitment to minimizing the use of environmentally damaging fossil fuels (Su et al., 2023; Wang et al., 2023). Across the globe, nations are intently pursuing environmental sustainability through a multitude of international and national initiatives. Leading this effort is the International Energy Agency (IEA, 2021), advocating the use of clean and renewable energy sources as a crucial step in the fight against the growing problems caused by climate change. Recent research explicitly stresses the abrupt, uncertain, and rapidly intensifying nature of climate changes. It primarily attributes these changes to the continued reliance on non-renewable energy resources (Umar et al., 2022; Tiwari et al., 2022). The persistent burning of fossil fuels not only complexes the planet's carbon footprint but also worsens the spectrum of environmental issues (Umar et al., 2022; Yousaf et al., 2022).

It is clear that renewable energy markets have the potential to reduce environmental risks as we face this growing ecological crisis. The crucial turn toward these markets, along with the parallel decline in reliance on unclean energy sources, marks a crucial turning point in the fight against environmental degradation on a global scale. Alternatively, the grasp of dirty energy markets—encompassing crude oil, heating oil, and natural gas—on the financial and economic systems remains unswerving (Dai et al., 2024; Elsayed et al., 2020; Yoon et al., 2019). These markets cannot be removed due to their entrenched role within the financial system and foreign currency operations, despite their considerable contribution to global warming and the threats to the ecosystem that go along with them. Nevertheless, a shift from unclean energy markets to cleaner substitutes may be facilitated by the tenacious efforts of

governments, policy makers, and regulatory bodies. Therefore, clean energy markets show promise as not just appealing investment opportunities, but also as environmentally and socially responsible investments that will fuel the green economy of the future.

Environmentalists and proponents of clean energy support clean energy markets as a way to reduce the risks that dirty energy sources pose to the environment on a global scale. In contrast, during periods of market volatility and economic uncertainty, the financial markets have a tendency to maintain the trade of traditional energy markets by taking use of their potency as diversifiers and risk mitigators (Naeem et al., 2021a). Investors are faced with the difficult decision of choosing between the clean and dirty energy markets as a result of these market dynamics. In fact, this conflict between environmental and financial goals makes choosing an investing strategy more difficult. Therefore, it is imperative to conduct a thorough analysis of the potential advantages of clean energy markets in solving environmental sustainability issues and lowering the consumption of harmful energy sources that endanger the global ecosystem.

In this perspective, it is crucial to understand that different stock markets, including those in America, Europe, Asia, and the Pacific, each boast distinctive qualities resulting from their diverse geographies and gross domestic products (GDPs). These distinctive qualities have attracted investors looking to reduce risk during economic turbulence and have provided a haven from market concerns. As a result, this study significantly adds to the body of literature by empirically examining the complex and asymmetric interaction between stock markets and energy markets (both clean and dirty). To achieve this, the study deploys the ground-breaking time-varying parameters vector autoregressions (TVP-VAR) methodology, which was first put forth by Primiceri (2005) and significantly improved by Antonakakis and Gabauer (2017). This methodology provides a robust analytical framework to address the rolling-window size problem and overcome the loss of observations during the estimation process.

Additionally, the asymmetry element of the TVP-VAR approach acts as a main compass while investigating the following questions: Do any asymmetries exist among clean energy, dirty energy, and stock markets? How is risk transmission observed among the considered markets, given that asymmetry is a common fluctuation indicator? Is there any discernible difference between the spillover network and its direction? If the answer is yes, how do these beneficial (positive) and detrimental (negative) spillovers manifest? These questions establish a strong basis for a thorough asymmetric analysis, enhancing the understanding of the scope and direction of spillovers, whether positive or negative. In turn, this information equips regulatory bodies and policy makers to make well-informed decisions, possibly revising their policies in light of the spillover network. Asymmetric analysis provides vital insights for stakeholders and policymakers, helping them to fully analyze risks and take the necessary action.

This study adds to the existing body of literature in several significant ways. First, it examines the asymmetric connectedness of the stock markets and energy markets (both clean and dirty) over a significant time period, spanning from 2004:M01 through 2021:M08. Second, the TVP-VAR methodology, which has gained popularity for being the best connectedness technique available, was applied. This methodology produces more accurate and reliable results because it acknowledges the fact that the data are time-varying and allows for structural changes in the relationships between variables over time. In comparison to other connectivity approaches, it stands out as a superior estimation method because of its robustness in managing non-linear relationships and resilience against outliers. Third, our study analyzes the asymmetric nature of the markets under consideration, categorizing spillovers according to their positive (beneficial) and negative (adverse) dominance across the time period. Fourth, we probe the dynamic nature of the energy markets (both clean and dirty) and stock markets to identify key events that have shaped the environment of intense risk spillovers. Additionally,

an asymmetric lens is used to evaluate the time-varying component in order to determine the contributions of both positive and negative spillovers to system-wide interconnectivity. Finally, we provide important insights for regulatory bodies, investors, and government agencies.

Analysis of the study findings shows that clean energy markets and equities are strongly interconnected; however, dirty energy markets are disconnected from the network. Notably, we find significant bidirectional spillovers between the markets for heating oil and crude oil. Natural gas stands out as a separate entity with noticeable detained spillovers, confirming both its high market integration inside the financial system and its function as a powerful market diversifier. By separating positive and negative spillovers in our analysis of daily returns, we are able to identify three separate clusters. Positive and negative spillovers inside markets and stocks for renewable energy, however, divide into two distinct clusters, with negative returns dominating. On the other hand, markets for dirty energy show a unique cluster of positive and negative returns. The predominance of negative returns highlights how vulnerable the markets are to external, internal, and economic factors.

Through our analysis, we shed light on the time dynamics of important events, such as the Global Financial Crisis, the European Debt Crisis, the Shale Oil Crisis, the Chinese stock market crash, the Brexit referendum, the rise in interest rates in the United States, and the COVID-19 pandemic. The dominance of negative spillovers, which act as the cornerstone of the overall network interconnectivity, is reaffirmed by our time-varying asymmetry analysis. Furthermore, the transmission of spillovers across global stock markets and clean energy markets is highlighted by our study of time-varying NET spillovers. In contrast, dirty energy markets are primarily in the negative or near zero, indicating their function as net recipients of risk spillovers from other markets. We provide useful recommendations for policymakers, regulatory agencies, and macroprudential authorities in light of these findings. Our

recommendations support investments in clean energy streams and advocate benefiting from the diversification potential offered by dirty energy markets.

The remainder of this study is organized as follows: Section 2 reviews previous empirical research, Section 3 describes the methodology utilized in the study, Section 4 discusses the empirical findings, and Section 5 concludes the study with policy implications.

2. Literature Review

There are abundant studies that unveil the financial markets' connectedness with different stocks and commodities (Liang et al., 2024; Chang et al., 2023; Gupta et al., 2023; Huang et al., 2021; Lee, & Olasehinde-Williams 2021; Tiwari et al., 2023). However, literature examining the asymmetric connectedness of energy markets (clean and dirty) and stock markets is negligible. This study's approach and contribution are unique in uncovering spillover dominance (positive/negative) during the crisis and normal periods, identifying potential diversification opportunities, and exploring current trends in the energy markets (clean and dirty) in specific stock markets. Prior literature, for instance, Raghutla et al. (2021), manifested the advantages of clean energy financing and found an indirect relationship between clean energy consumption and CO₂ emissions, substantiating the use of clean energy for the energy transition. Meanwhile, the authors also found a positive nexus between clean energy financing and economic growth, hence unveiling several policy implications for policymakers, governments, and environmentalists to encourage them to invest in clean energy avenues. Saeed et al. (2021) investigated the quantile connectivity between energy markets and identified heavy tails in clean energy equities, green bonds, and exchange-traded funds. Similarly, Liu et al. (2020) studied the relationship between clean energy and green bonds, discovering positive time-varying dependence in the tails of these two interconnected markets.

Further evidence of their study documented extreme upside and downside dependence between clean energy markets which transmitted risk to green bonds.

Similarly, Alkathery and Chaudhuri (2021) studied the co-movement of oil prices, renewable energy, energy equities, and CO₂ emissions and found volatility spillovers in extreme circumstances in the GCC markets. An augmented analysis of the study reported pronounced co-movement among the markets. Naeem and Karim (2021) documented substantial hedging capacity offered by green assets against virtual currencies. Hammoudeh et al. (2020) employed the time-varying Granger causality test to examine the relationships among clean energy markets, green bonds, and financial markets. Their findings revealed a shift in causality from US financial markets to green bonds. Ji et al. (2018) probed the information spillovers in the oil and gas markets using a unique empirical model and reported information transmission between them due to their varying behavior in different time horizons. Ferrer et al. (2021), utilizing the time-frequency connectedness of green markets and other assets in their returns and volatilities, found that extreme events bring higher connectedness to the markets. In their study of the spillover network between financial markets and commodities, Yoon et al. (2019) concluded that the US stock market plays a significant role in transmitting risk to other financial assets. In the meantime, when various other commodities and stocks are added to the dataset, the magnitude of spillovers decreases accordingly, stressing the diversification avenues of portfolios with stocks.

Umar et al. (2021) investigated the time-frequency connectedness of clean energy and fossil fuel markets. They found weak connections in the volatility of the clean energy and fossil fuel markets, whereas strong volatilities are reported between petroleum markets. Further evidence suggests that volatility spillovers persist in the short and long run. Naeem et al. (2021b) explored the asymmetric tail dependence for five energy markets and green bonds using the time-varying optimal copula (TVOC) technique. Multiple tail dependence regimes

are uncovered in the study for energy markets and green bonds, and in addition, various stressful periods shaped the tail dependence for extreme risk spillovers. Tiwari et al. (2021) investigated the risk transmission between carbon prices, green bonds, and renewable energy stocks. Shaikh (2021) studied the COVID-19 impact on the energy markets using multiple renewable markets of energy stocks, futures, ETFs, and implied volatilities. The authors reported the pronounced behavior of ETFs and stocks than S&P energy stocks.

Recently, Hong et al., (2022) assessed systemic risk in China's new energy stock markets, utilizing the VaR method and DCC model. The findings uncovered differing risks across energy sectors and emphasized the significance of grasping dynamic linkages for both regulators and investors. Li et al., (2023) analysed China's crude oil futures and green energy stock market. The price fluctuations in crude oil market is controlled by green energy stock. Contrary to expectations, the dominance was reinforced during COVID-19 crisis. Sokhanvar et al., (2023) investigated the Ukraine war's effect on commodity currencies due to energy price hikes. Findings reveal a significant positive impact on the Australian dollar, primarily driven by gas price shocks. Lee and Lee (2023) investigated causal relationships between U.S. monetary policy uncertainty, equity market volatility, and China's stock price index from 1994 to 2021. Findings showed that U.S. monetary policy uncertainty and equity market volatility influenced China's stock prices, underscoring the importance of flexible market strategies. Karkowska and Urjasz (2023) investigated volatility spillovers in clean and dirty energy markets amid geopolitical risk, using connectedness indices and structural breaks. It also examined green energy diversification benefits for hedging strategies. Findings suggested that while clean energy indices had lower risk, hedging costs in renewable energy assets were higher.

Mand et al., (2023) examined dynamic relationships between key clean and dirty energy assets, confirming a long-term relationship and causal influence of clean energy ETF on most

instruments. Wavelet-based tests on high-frequency data suggested clean energy as a potential distinct asset class and identified time scales for arbitrage opportunities and liquidity movements. These findings contributed to the limited literature on high-frequency dynamics in clean and dirty energy markets. Ghosh et al., (2023) analyzed the relationship between clean and dirty energy sources and energy metals during the COVID-19 pandemic, noting increased connectedness and asymmetry at different quantiles. Cobalt showed the least connection to energy markets, and a switch in net connectedness indexes occurred after January 2021. These findings had implications for investors and policymakers in energy and metal markets under various conditions. Sohag et al., (2023) applied three time-series methods to investigate the relationship between dirty and green investments from August 2014 to November 2021. Empirical results showed negative volatility spillovers from dirty to green investments, while dirty investment returns responded positively to green investments. These findings offered policy implications for investors' decision-making on risk hedging.

Wei et al., (2023) used TVP-VAR to reveal no time-varying connectedness of climate change and renewable energy stock markets during normal times. However, the connectedness approaches 30% during the global financial crisis and COVID-19 outbreak. More specifically, the relationship clusters in periods shorter than three months. Wang et al. (2023) further investigated the impacts of COVID-19 monetary policy changes on green Asian markets. They found that traditional monetary policy was not effective on financial markets. COVID-19 had weaker effect on green economic recovery in countries with high trade. Moreover, Mo et al., (2023) found similar results with high exposure of carbon prices on clean energy stocks during COVID-19 pandemic. They showed dynamic correlation and positive hedging ratios of carbon prices and clean energy market. El Khoury et al. (2023) studied the effect of the Russia-Ukraine war on the correlation and spillovers among clean energy, ESG, FinTech and gold using TVP-

VAR and DCC-GARCH. They concluded that gold and clean energy are net receivers before and during the Russia-Ukraine war in both developed and developing countries.

Bouri (2023) investigated spillovers of technology market, clean and dirty energy markets in the US. His results identified green energy as main net transmitter of volatility, and kurtosis; while solar energy as main net transmitter of skewness spillovers. Applying different methodology, Dutta et al. (2023) used Markov regime switching regression and asymmetric GARCH to study the impact of climate risk on returns and volatility of clean energy assets. Their findings revealed a positive correlation between climate risk and clean energy prices and a negative relationship with clean energy volatility. They determined better hedging efficacy of clean assets when compared with oil. On firms' level, van Benthem et al. (2022) applied a descriptive analysis on the effect of dirty climate risk on allocation of investments and how this affected firms decision making. The fastest firms' response to reduce emissions is through asset sales. They invited scholars and practitioners to include climate risk disclosures in their standardised financial reporting. Zhang and Kong (2022) found that clean energy increases total factor productivity on firm's level. Cheng et al. (2023) used difference-in-difference to analyze regulations of clean energy on firms' level. They verified that Green Finance Reform and Innovation Pilot Zones Policy China improved renewable energy utilization by facilitating funding restrictions and advancing digitalization.

The literature reviewed shows that while studies have attempted to reveal the interdependence of energy markets (clean and dirty) and stock markets, there is still fragmented evidence of the asymmetries in their connectedness. Following this, the current study uniquely contributes to the plethora of existing research studies by examining the asymmetric risk transmission between the energy markets (clean and dirty) and stock markets. Notably, the studies lack evidence employing the TVP-VAR approach for the markets under study to identify the contribution of spillovers from positive (good) and negative (bad) circumstances.

Hence, the current is novel in classifying the asymmetric distribution of spillovers generated from clean energy, dirty energy, and stock markets.

3. Methodology

3.1 Time-Varying Parameters Vector Autoregressions (TVP-VAR) Technique

In this study, we utilize the time-varying parameters vector autoregression (TVP-VAR) estimator, initially proposed by Primiceri (2005) and further developed by Antonakakis and Gabauer (2017). The primary advantage of the TVP-VAR approach is its ability to thoroughly examine whether disparities among the specified markets (clean energy, dirty energy, and stock markets) stem from shocks or a long change process. Additionally, the model offers distinct features for assessing potential structural breaks and ample rationale for understanding the underlying mechanisms of the variables. The model is presented as follows:

$$y_t = A(t)y_{t-1} + e_t \quad (1)$$

where y_t is a vector of the variables being modeled, $A(t)$ is a matrix of time-varying parameters, and e_t is a vector of error terms. The model assumes that the parameters of the matrix $A(t)$ change over time smoothly and predictably.

The study further applied the Generalized Impulse Response Function (GIRF) model that describes the dynamic connectedness between different variables in an econometric system. The model expands upon the traditional impulse response function (IRF) model by accounting for the direct and indirect effects of an exogenous shock on a specific variable. Mathematically, the GIRF model is expressed as:

$$GIRF(i, j, k) = \partial y(i, k) / \partial e(j, k) \quad (2)$$

where $GIRF(i, j, k)$ denotes the k -period generalized impulse response of variable $y(i)$ to an exogenous shock $e(j)$, i represents the variable of interest, j signifies the exogenous shock, and k is the period.

Subsequently, the study employs the Generalized Forecast Error Variance Decomposition (GFEVD) method to analyze the dynamic connectedness between various variables in an econometric system. The GFEVD is calculated as follows:

$$GFEVD(i, j, h) = \frac{Cov(e(i, t+h), e(j, t+h))}{Var(e(j, t+h))} \quad (3)$$

where $Cov(e(i, t+h), e(j, t+h))$ is the covariance between the forecast errors of variables i and j at horizon h , and $Var(e(j, t+h))$ is the forecast error variance of variable j at horizon h .

The GFEVD matrix allows researchers to understand how the forecast error of one variable influences the forecast errors of other variables in the system and how these effects evolve. It is important to note that the GFEVD method can only be applied in VAR models, as it relies on decomposing forecast errors.

Furthermore, the analysis is divided into three distinct components as follows:

- 1) The TO measure is calculated as the sum of the forecast error variance decompositions (GFEVD) for variable i and horizon h . The formula for TO is:

$$TO(i, h) = \sum_{j=1}^n GFEVD(i, j, h) \quad (4)$$

where $GFEVD(i, j, h)$ represents the proportion of the forecast error variance of variable i at horizon h attributable to the forecast error of variable j , and n refers to the number of variables in the system.

- 2) The FROM measure is computed as the sum of the forecast error variance decompositions (GFEVD) for a given variable i and a given horizon h , where the GFEVD is a tool used to decompose the forecast error variance of a variable into the contributions of the exogenous shocks in the system. The formula for FROM is:

$$FROM(i, h) = \sum_{j=1}^n GFEVD(j, i, h) \quad (5)$$

where $GFEVD(j, i, h)$ is the proportion of the forecast error variance of variable j at horizon h that is due to the forecast error of variable i , and n is the number of variables in the system.

- 3) The NET measure is computed as the difference between the total directional connectedness TO and FROM for a given variable i and a given horizon h . The formula for NET is:

$$NET(i, h) = TO(i, h) - FROM(i, h) \quad (6)$$

The NET measure ranges between -1 and 1, where -1 indicates that variable i is fully affected by other variables in the system and does not transmit any shocks to other variables, 1 indicates that variable i fully transmits shocks to other variables and is not affected by any other variable in the system, and 0 indicates that variable i transmits and receives shocks to other variables in a balanced way.

3.1.1 Spillover Asymmetry Measure (SAM)

Following Iqbal et al., (2021), the returns of clean energy, dirty energy, and stock markets were further disintegrated into positive (+) and negative (-) returns, which are termed asymmetric connectedness network arrangement. Hence, we derive the positive (r^+) and negative (r^-) returns series as follows:

$$r^+ = \begin{cases} r_t, & \text{if } r_t > 0 \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

$$r^- = \begin{cases} r_t, & \text{if } r_t < 0 \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

The disintegrated returns in equations (7) and (8) are summed up to showcase the net returns given as:

$$r_t = r^+ + r^- \quad (9)$$

Thus, we take the asymmetric returns spillovers of the energy markets (clean and dirty) and stock markets by following Baruník et al. (2017). The analysis is carried out with the amount of asymmetric spillover measure (SAM)¹ by using the H-step ahead forecast using the equation:

$$SAM = C^+ - C^- \quad (10)$$

Arguably, good spillovers dominate when SAM stays positive, while bad spillovers are shaped when SAM stays in the negative plot.

4. Empirical Results

4.1 Data and Preliminary Analysis

The study endeavors to investigate the asymmetric arrangement of clean energy, dirty energy, and stock markets from January 1, 2004, to August 31, 2021. The data have been extracted from Datastream for the selected markets. The study incorporates clean energy markets such as World Renewable Energy (RENX), S&P Global Clean Energy (SPGC), and Wilder Hill Clean Energy (WHCL). Dirty energy markets encompass Natural Gas (NGS), Heating Oil (HTO), and West Texas Intermediate (WTI) crude oil. Additionally, the stock markets examined in this research include MSCI America (AMER), MSCI Pacific (PACF), MSCI Europe (EURP), and MSCI Asia (ASIA). The descriptive statistics indicate that RENX yields

¹ For asymmetric spillovers, the contributions of r^+ (say C^+) and r^- (say C^-) must not be equal; else, the connectedness is symmetric.

the highest average return among clean energy markets, whereas WTI generates the maximum mean return among dirty energy markets. Out of stock markets, the average returns of AMER are superseded over other stock markets, whereas ASIA and PACF succumb to comparable results, and EURP reveals the least average returns. The variability of the average returns conquers our results of average values, where RENX shows the highest variability among clean energy markets. Surprisingly, NGS demonstrated the highest fluctuation in the average returns among dirty energy markets. Meanwhile, all stock markets exhibited parallel variability of the returns for the whole sample period. Slightly negatively skewed values of all markets reflect that they have undergone significant losses due to various economic and financial turbulent periods. The Jarque-Bera test indicates abnormal values for the energy markets (clean and dirty) and stock markets, symbolizing that their return series is not normally distributed.

[Table 1 about here]

Figure 1 illustrates the time series evolution for the energy markets (clean and dirty) and stock markets for the sample period under consideration. Various spikes in the return series reflect numerous uneven circumstances that intensify the spillovers of each market. WHCL and SPGC showed susceptibility to various shocks among clean energy markets, whereas RENX exhibited mild exposure to external shocks except for the European Debt Crisis (2010-2012) and COVID-19 outbreak. Dirty energy markets revealed highest vulnerability to the market ups and downs, as evident from their return series. Among stock markets, ASIA, EURP, and PACF revealed comparable risk exposure to external uncertainties, whereas AMER revealed susceptibility to economic shocks only during the global financial crisis (2007-2009) and COVID-19 pandemic (2019-2020). The major uneven events that occurred during the whole sample period are global financial crisis (2007-2009), European Debt Crisis (2010-2012), Shale

Oil Crisis (2014-2015), Brexit referendum (2016), US interest rate hike (2017-2018), and the outbreak of COVID-19 (2019-2020).

[Figure 1 about here]

Figure 2 illustrates the highest correlation between energy markets (clean and dirty) and stock markets is observed ASIA-PACF, WHCL-SPGC, WHCL-AMER, and WTI-HTO. Meanwhile, moderate correlations are reported between the markets of AMER-SPGC, EURP-SPGC, SPGC-RENX, and EURP-AMER. It is evident from the matrix that stock markets are mostly correlated with clean energy markets and a stronger intra-group correlation is documented as indicated by the correlations of ASIA-PACF and EURP-AMER. Contrarily, dirty energy markets are weakly correlated with clean energy markets and stocks markets. However, correlation is highest for intra-group markets, as revealed in the correlation of WTI-HTO. As a general trend, markets of a similar class show maximum correlation with few variations between clean energy markets and stock markets.

[Figure 2 about here]

4.2 Network Spillovers of Markets using TVP-VAR

This subsection presents networks of spillovers for energy markets (clean and dirty) and stock markets using the time-varying parameters vector autoregression (TVP-VAR) approach. Network connectedness is segregated into a system of daily returns (Figure 3a) and daily positive (negative) spillovers (Figure 3b). First, the study explains the findings in Figure 3a, where markets are arranged elliptically. Strong bi-directional spillovers are formed between PACF and ASIA stock markets, whereas moderate bi-directional spillovers are formed between AMER and EURP. Clean energy markets form spillovers with stock markets, whereas dirty energy markets remain disconnected from the network—however, HTO and WTI form intra-group spillovers. Nodes on the markets reflect their net transmission and reception of

spillovers, where red (white) indicates spillover transmission to (from) other markets. WHCL and SPGC transmit spillovers among clean energy markets, while RENX is the net recipient of spillovers. AMER and EURP transmit risk spillovers to ASIA, PACF, and clean energy markets among stock markets. This way, RENX, ASIA, and PACF are net recipients of risk spillovers. Interestingly, the disconnection of dirty energy markets and the sound in-class connectedness of HTO-WTI refers to their strong embeddedness in the market. Notably, NGS remained isolated from the network and is the net recipient of risk spillovers indicated from its node.

Empirically, the strong connectedness of similar markets conquers the findings of Caporin et al. (2021), who contend that markets share similar features and form a separate connectedness cluster. In addition, our findings contradict the study of Elsayed et al. (2020), who reported that clean energy markets are less connected with other financial markets. Regarding the net transmitting effect of AMER, our findings coincide with Mensi et al. (2021a) and Wang et al. (2020), who reported strong transmission of risk spillovers from US stocks to other asset classes. EURP also transmits risk spillovers to other stock and clean energy markets in line with Youssef et al. (2021), who reported sound risk transmission among stock markets during the COVID-19 pandemic. Concerning the spillovers among dirty energy markets, strong bi-directional spillovers are formed between WTI and HTO, symbolizing their sound interdependence as both represent commodities markets and their market integration in the financial system (Kang et al., 2017 and 2021). An evident disconnection of NGS from the overall system of connectedness reveals that the NGS market is a strong diversifier among other markets as it shows vivid indifference to the spillover network. Our findings indicate that NGS bears significant risk absorbance when markets undergo severe economic and financial turmoil. Thus, NGS can act as a diversifier among clean energy, dirty energy, and stock markets due to its distinct disconnection from the system and unassailable market integration.

Figure 3(b) demonstrates the asymmetric distribution of energy markets (clean and dirty) and stock markets' returns, where positive and negative returns are assimilated in separate clusters. Evidently, the positive (negative) returns of both clean energy and stock markets make two discernible groups. In the case of dirty energy markets, positive (negative) returns of HTO and WTI are paired similarly and positive and negative spillovers NGS are arranged bi-directionally with each other. Referring to the nodes of both positive (square) and negative (circle) spillovers, the node color indicates that negative (bad) spillovers are net transmitters, whereas positive (good) spillovers are net recipients of spillovers. The dominance of negative spillovers reflects frequent uneven economic and financial circumstances that shaped the overall spillover network. The negative externalities include Argentina's economic collapse, global financial crisis, European Debt Crisis, Shale Oil Crisis, Brexit referendum, spiked US interest rates, and COVID-19 pandemic. The supremacy of the negative spillovers for clean energy, dirty energy, and stock markets reiterates that these markets have undergone various crucial settings which ultimately dominated the negative spillovers. Hence, the daily positive and negative returns of all markets indicate the dominance of negative (bad) spillovers over positive (good) spillovers, which framed the connectedness of energy markets (clean and dirty) and stock markets.

[Figure 3 about here]

4.3 Time-Varying Spillovers

Using the TVP-VAR approach, this subsection sheds light on the time-varying attributes of clean energy, dirty energy, and stock markets over time. Figure 4(a) depicts the spillovers based on the returns system where significant ups and downs are observed, reflecting higher connectedness during crisis times and declining spillovers when markets return to normal periods. The initial jump in the plot signifies the aftermaths of Argentina's economic downfall

(2001-2003), which shows enhanced connectedness of the markets during 2004 consequent of the economic downturn of Argentina (Feldstein, 2002). Subsequently, the gradual decline in the spillovers reflects that markets are returning to stable periods, thus causing a fall in the systemwide connectedness. The upcoming enlarged spike in the plot signposts the Global Financial Crisis (2007-2009), where markets underwent global economic collapse, resulting in the surmounted connectedness of energy markets (clean and dirty) and stock markets. The next spike in the graph points toward European Debt Crisis (2010-2012) which increased the risk transmission among markets and framed intense spillovers. During EDC, the European economy experienced a challenging phase with balance sheet inaccuracies and current account imbalances (Blundell-Wignall, 2012).

Another spike in the graph during 2015-2016 indicates Shale Oil Crisis (SOC) and the Chinese stock market crash during 2016 in a single day (Womack, 2017). These crisis periods also elevated the spillover connectedness due to turbulence in the economic environment. In addition, the higher systemwide connectedness during 2016 reflects the Brexit referendum (Xiao et al., 2019) and spiked spillovers during 2017-2018 due to US interest rate hike (Elsayed et al., 2020). A final jump in the graph reflects the COVID-19 outbreak in March 2020, where markets were exposed to uncertainty generated by the global health pandemic, which ultimately raised the connectedness of the system in line with Mensi et al. (2021b).

Figure 4(b) indicates the asymmetric arrangement of energy markets (clean and dirty) and stock markets, where negative spillovers dominated the positive spillovers among daily returns of markets following the crisis periods, as reported in Figure 4(a). The asymmetry measure reveals that negative spillovers contributed to the overall connectedness of the system and spikes the spillovers. Meanwhile, the negative dominance reiterates that markets have suffered severe circumstances while undergoing the economic, financial, regulatory sanctions, global pandemics changes. Along these lines, the frequent disturbances coming in the way of markets

connectedness, negative spillovers reflected their dominance. In line with Iqbal et al. (2021), Naeem et al. (2021d), and Adekoya and Oliyide (2020), the contagion among markets shaped the overall connectedness of the system with the dominance of negative spillovers, which symbolizes the severe effects of external disturbances in framing the spillovers during harsh circumstances.

[Figure 4 about here]

4.4 Time-Varying NET Spillovers

Figure 5 demonstrates the time-varying NET spillover connectedness of energy markets (clean and dirty) and stock markets using the TVP-VAR technique. Notably, clean energy and stock markets reside in the graph's positive territories, denoting these markets as net transmitting spillovers. Conversely, the dirty energy markets are mainly positioned in the graph's negative territories, indicating their net risk reception from clean energy and stock markets. A closer look at the dirty energy spillovers reveals their adherence to zero during normal periods. However, during crisis periods, negative spillovers are dominated by dirty energy markets. The net transmitting effect of stocks is in agreement with the studies of Mensi et al. (2021a), Wang et al. (2020), and Youssef et al. (2021), who reported that stock markets of US, EURP, ASIA, and PACF transmit spillovers to other markets. Meanwhile, the net transmission from clean energy to other markets echoes the results of Sitara et al., (2023). Conversely, the adherence of dirty energy markets near zero and in the negative region substantiates their strong market integration in insensitivity to the externalities as they are closer to zero. However, the negative spillovers reflect their net risk reception from the systemwide connectedness, which denotes their diversification potential during uncertain circumstances. The net receiving of spillovers coincides with Yoon et al. (2019), where dirty energy markets receive risk spillovers from the rest of the markets. Following this, the study asserts that clean energy and stock markets

transmit net spillovers, whereas dirty energy markets receive shocks from clean energy markets and stocks.

[Figure 5 about here]

Our findings indicate that clean energy markets and stocks are closely connected, while dirty energy markets form bi-directional spillovers where NGS remains disconnected from the network. The asymmetric alignment of markets reflects the dominance of negative spillovers over the sample period, symbolizing various turbulent episodes, ultimately raising the spillover spikes. The time-varying trend also exhibits the exposure of markets to several economic, financial, regulatory, and health crises. In the end, time-varying NET spillovers showed that clean energy markets and stocks are net transmitting spillovers, whereas dirty energy markets are net recipients of risk shocks.

5. Conclusion and Policy Implications

The current study examines the asymmetric risk transmission between energy markets (clean and dirty) and stock markets from January 1, 2004, to August 31, 2021. We applied the novel approach of time-varying parameters vectors autoregression (TVP-VAR) for analysis purposes to identify the network connectedness of energy markets (clean and dirty) and stock markets along with spillover asymmetry measures for spotting the positive (good) and negative (bad) spillovers among the selected markets. In addition, the analysis was further extended by time-varying features of the markets, which addressed the asymmetric alignment of the markets in terms of segregating positive and negative spillovers. The time-varying NET spillovers were also analyzed to obtain the net transmitters and recipients of risk spillovers energy markets (clean and dirty) and stock markets.

Our step-by-step analysis revealed that clean energy markets and stocks are highly connected, while dirty energy markets are isolated from the network with strong bi-directional

spillovers between HTO and WTI due to their similar features. NGS showed remarkable quarantined spillovers, necessitating strong market integration in the financial system and reflecting its strong diversification potential among other markets. The positive and negative spillovers of daily returns formed three distinct clusters. In contrast, positive and negative spillovers of clean energy markets and stocks formed two clusters with distinct dominance of negative returns. Conversely, dirty energy markets' positive and negative returns were fashioned in a separate cluster. The dominance of negative returns over positive returns indicates extreme exposure of markets to harsh economic, financial, and external factors. Time-varying characteristics highlighted numerous unexpected events. Further, time-varying asymmetric analysis reiterated the dominance of negative spillovers, which shaped the overall network connectedness. Finally, time-varying NET spillovers revealed that clean energy markets and stock markets of various states are transmitting spillovers. In contrast, dirty energy markets mainly remained closer to zero or in the negative region, demonstrating its net reception of risk spillovers from other markets.

The findings of this study offer valuable insights for stakeholders and policymakers who are addressing environmental issues and seeking to transition towards clean energy markets to achieve sustainability. It is recommended that they utilize the study's results to enhance clean energy policies and reduce dependence on dirty energy sources. Governments should consider adjusting their strategies by prioritizing clean energy solutions that align with global sustainability objectives. Regarding asymmetric alignment, policymakers, and regulatory bodies are advised to revise their policies to minimize the negative effects of unfavorable situations, such as economic and financial crises, and develop contingency plans that allow financial markets to absorb shocks without disrupting overall operations.

Policymakers should prioritize implementing incentives and regulations supporting clean energy development and adoption, including tax breaks, subsidies, and grants for

renewable energy projects. By offering financial incentives, they can encourage individual and institutional investors to allocate resources towards clean energy technologies, fostering growth in renewable energy markets. Additionally, allocating resources to fund research and development in the clean energy sector can promote innovation, leading to the development of new, efficient technologies that reduce the cost of renewable energy production and increase its adoption. Raising awareness and promoting responsible investment practices are crucial in fostering a cleaner, greener future. Policymakers, regulators, and industry stakeholders should collaborate to develop educational initiatives informing investors, financial market participants, and the public about the long-term risks and opportunities in the energy sector and the importance of clean energy in addressing environmental issues. By implementing stringent environmental standards and regulations, policymakers can reduce the negative impacts of dirty energy industries and encourage a transition towards cleaner alternatives. Investing in educational campaigns highlighting renewable energy sources' benefits can further drive their adoption and contribute to sustainable economic growth.

Governments must invest in the necessary infrastructure, such as smart grids, electric vehicle charging stations, and energy storage facilities, to support the widespread adoption of clean energy technologies. In tandem, promoting corporate social responsibility (CSR) initiatives emphasizing clean energy adoption and environmental sustainability can incentivize companies to prioritize clean energy and incorporate sustainability goals into their business strategies. Regulators should closely monitor the impact of negative spillovers from uncertain economic and financial circumstances to ensure market stability and resilience. Encouraging financial market players, investors, and practitioners to incorporate clean energy assets into their portfolios can lead to more informed decision-making and promote responsible investment practices, further bolstering the transition to a clean energy future. Policymakers should better encourage international cooperation and information sharing to understand

asymmetric trends and spillovers among energy markets. Collaborating with other nations and participating in international agreements can enhance the exchange of knowledge, technology, and resources in the clean energy sector. By fostering a more coordinated approach to managing risks and harnessing opportunities in the global energy landscape, countries can work together to address common challenges and support the global transition towards a low-carbon economy. Building partnerships that advance global sustainability goals can accelerate innovation, drive down costs, and make renewable energy more accessible and affordable for all.

References

- Adekoya, O. B., & Oliyide, J. A. (2020). How COVID-19 drives connectedness among commodity and financial markets: evidence from TVP-VAR and causality-in-quantiles techniques. *Resources Policy*, 70, 101898.
- Alkathery, M. A., & Chaudhuri, K. (2021). Co-movement between oil price, CO2 emission, renewable energy and energy equities: Evidence from GCC countries. *Journal of Environmental Management*, 297, 113350.
- Antonakakis, N., & Gabauer, D. (2017). Refined measures of dynamic connectedness based on TVP-VAR.
- Baruník, J., Kočenda, E., & Vácha, L. (2017). Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance*, 77, 39-56.
- Blundell-Wignall, A. (2012). Solving the financial and sovereign debt crisis in Europe. *OECD Journal: Financial Market Trends*, 2011(2), 201-224.
- Bouri, E. (2023) Spillovers in the joint system of conditional higher-order moments: US evidence from green energy, brown energy, and technology stocks, *Renewable Energy*, 210, 507-523.
- Caporin, M., Naeem, M. A., Arif, M., Hasan, M., Vo, X. V., & Shahzad, S. J. H. (2021). Asymmetric and time-frequency spillovers among commodities using high-frequency data. *Resources Policy*, 70, 101958.
- Chang, H. W., Chang, T., & Lee, C. C. (2023). Return and volatility connectedness among the BRICS stock and oil markets. *Resources Policy*, 86, 104241.
- Cheng, Z., Kai, Z., & Zhu, S. (2023). Does green finance regulation improve renewable energy utilization? Evidence from energy consumption efficiency, *Renewable Energy*, 208, 63-75,
- Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1), 57-66.
- Dutta, A., Bouri, E., Rothovius, T., & Salah Uddin, G. (2023). Climate risk and green investments: New evidence, *Energy*, 265, 126376,
- El Khoury, R., Nasrallah, N., Hussainey, K., & Assaf, R. (2023). Spillover analysis across FinTech, ESG, and renewable energy indices before and during the Russia–Ukraine war: International evidence. *Journal of International Financial Management & Accounting*, 34, 279-317.
- Elsayed, A. H., Nasreen, S., & Tiwari, A. K. (2020). Time-varying co-movements between energy market and global financial markets: Implication for portfolio diversification and hedging strategies. *Energy Economics*, 90, 104847. <https://doi.org/10.1016/j.eneco.2020.104847>
- Feldstein, M. (2002). Argentina's Fall-Lessons from the Latest Financial Crisis. *Foreign Aff.*, 81, 8.

Ferrer, R., Shahzad, S. J. H., & Soriano, P. (2021). Are green bonds a different asset class? Evidence from time-frequency connectedness analysis. *Journal of Cleaner Production*, 125988.

Gupta, R., Lee, C. C., Nielsen, J., & Pierdzioch, C. (2023). *Stock Market Bubbles and the Realized Volatility of Oil Price Returns* (No. 202325).

Hammoudeh, S., Ajmi, A. N., & Mokni, K. (2020). Relationship between green bonds and financial and environmental variables: A novel time-varying causality. *Energy Economics*, 92, 104941.

Huang, B. N., Lee, C. C., Chang, Y. F., & Lee, C. C. (2021). Dynamic linkage between oil prices and exchange rates: new global evidence. *Empirical Economics*, 61, 719-742.

International Energy Transitions (2021). Retrieved from: <https://www.iea.org/news/pathway-to-critical-and-formidable-goal-of-net-zero-emissions-by-2050-is-narrow-but-brings-huge-benefits>

Iqbal, N., Naeem, M. A., & Suleman, M. T. (2021). Quantifying the asymmetric spillovers in sustainable investments. *Journal of International Financial Markets, Institutions and Money*, 101480.

Ji, Q., Liu, B. Y., Zhao, W. L., & Fan, Y. (2020). Modelling dynamic dependence and risk spillover between all oil price shocks and stock market returns in the BRICS. *International Review of Financial Analysis*, 68, 101238.

Kang, S. H., McIver, R., & Yoon, S. M. (2017). Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets. *Energy Economics*, 62, 19-32.

Kang, S., Hernandez, J. A., Sadorsky, P., & McIver, R. (2021). Frequency spillovers, connectedness, and the hedging effectiveness of oil and gold for US sector ETFs. *Energy Economics*, 99, 105278.

Lee, C. C., & Lee, C. C. (2023). International spillovers of US monetary uncertainty and equity market volatility to China's stock markets. *Journal of Asian Economics*, 84, 101575.

Lee, C. C., & Olasehinde-Williams, G. (2021). Gasoline demand elasticities in the world's energy gluttons: a time-varying coefficient approach. *Environmental Science and Pollution Research*, 28, 64830-64847.

Li, J., Umar, M., & Huo, J. (2023). The spillover effect between Chinese crude oil futures market and Chinese green energy stock market. *Energy Economics*, 119, 106568,

Liu, N., Liu, C., Da, B., Zhang, T., & Guan, F. (2021). Dependence and risk spillovers between green bonds and clean energy markets. *Journal of Cleaner Production*, 279, 123595.

Mensi, W., Nekhili, R., Vo, X. V., Suleman, T., & Kang, S. H. (2021a). Asymmetric volatility connectedness among U.S. stock sectors. *North American Journal of Economics and Finance*, 56, 101327.

Mensi, W., Naeem, M. A., Vo, X. V., & Kang, S. H. (2021b). Dynamic and frequency spillovers between green bonds, oil and G7 stock markets: Implications for risk management. *Economic Analysis and Policy*.

- Mo, B., Li, Z. & Meng, J. (2022). The dynamics of carbon on green energy equity investment: quantile-on-quantile and quantile coherency approaches. *Environ Sci Pollut Res*, 29, 5912–5922.
- Naeem, M. A., Nguyen, T. T. H., Nepal, R., Ngo, Q. T., & Taghizadeh-Hesary, F. (2021a). Asymmetric relationship between green bonds and commodities: Evidence from extreme quantile approach. *Finance Research Letters*, 101983.
- Naeem, M. A., Bouri, E., Costa, M. D., Naifar, N., & Shahzad, S. J. H. (2021b). Energy markets and green bonds: A tail dependence analysis with time-varying optimal copulas and portfolio implications. *Resources Policy*, 74, 102418.
- Naeem, M. A., Mbarki, I., Alharthi, M., Omri, A., & Shahzad, S. J. H. (2021c). Did COVID-19 impact the connectedness between green bonds and other financial markets? Evidence from time-frequency domain with portfolio implications. *Frontiers in Environmental Science*, doi: 10.3389/fenvs.2021.657533
- Naeem, M. A., Rabbani, M. R., Karim, S., & Billah, S. M. (2021d). Religion vs ethics: hedge and safe haven properties of Sukuk and green bonds for stock markets pre-and during COVID-19. *International Journal of Islamic and Middle Eastern Finance and Management*.
- Naeem, M. A., & Karim, S. (2021). Tail dependence between bitcoin and green financial assets. *Economics Letters*, 110068.
- Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, 72(3), 821-852
- Raghutla, C., Shahbaz, M., Chittedi, K. R., & Jiao, Z. (2021). Financing clean energy projects: New empirical evidence from major investment countries. *Renewable Energy*, 169, 231-241.
- Saeed, T., Bouri, E., & Alsulami, H. (2021). Extreme return connectedness and its determinants between clean/green and dirty energy investments. *Energy Economics*, 96, 105017.
- Shahzad, S. J. H., Bouri, E., Kristoufek, L., & Saeed, T. (2021). Impact of the COVID-19 outbreak on the US equity sectors: Evidence from quantile return spillovers. *Financial Innovation*, 7(1), 1-23.
- Shaikh, I. (2021). Impact of COVID-19 pandemic on the energy markets. *Economic Change and Restructuring*, 1-52.
- Dai, Z., Zhang, X., Liang, C., 2024. Efficient predictability of oil price: The role of VIX-based panic index shadow line difference. *Energy Econ.* 129, 107234. <https://doi.org/10.1016/j.eneco.2023.107234>
- Liang, C., Wang, L., Duong, D., 2024. More attention and better volatility forecast accuracy: How does war attention affect stock volatility predictability? *J. Econ. Behav. Organ.* 218, 1–19. <https://doi.org/10.1016/j.jebo.2023.12.009>
- Su, C.-W., Pang, L.-D., Qin, M., Lobont, O.-R., Umar, M., 2023. The spillover effects among fossil fuel, renewables and carbon markets: Evidence under the dual dilemma of climate change and energy crises. *Energy* 274. <https://doi.org/10.1016/j.energy.2023.127304>

- Umar, M., Farid, S., Naeem, M.A., 2022. Time-frequency connectedness among clean-energy stocks and fossil fuel markets: Comparison between financial, oil and pandemic crisis. *Energy* 240. <https://doi.org/10.1016/j.energy.2021.122702>
- Wang, T., Umar, M., Li, M., Shan, S., 2023. Green finance and clean taxes are the ways to curb carbon emissions: An OECD experience. *Energy Econ.* 124. <https://doi.org/10.1016/j.eneco.2023.106842>
- Yousaf, I., Nekhili, R., Umar, M., 2022. Extreme connectedness between renewable energy tokens and fossil fuel markets. *Energy Econ.* 114. <https://doi.org/10.1016/j.eneco.2022.106305>
- Taghizadeh-Hesary, F., Yoshino, N., & Phoumin, H. (2021). Analyzing the Characteristics of Green Bond Markets to Facilitate Green Finance in the Post-COVID-19 World. *Sustainability*, 13(10), 5719.
- Tiwari, A. K., Abakah, E. J. A., Gabauer, D., & Dwumfour, R. A. (2022). Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: Implications for hedging and investments strategies. *Global Finance Journal*, 51, 100692.
- Tiwari, A. K., Trabelsi, N., Abakah, E. J. A., Nasreen, S., & Lee, C. C. (2023). An empirical analysis of the dynamic relationship between clean and dirty energy markets. *Energy Economics*, 106766.
- Umar, M., Farid, S., Naeem, M.A., 2022. Time-frequency connectedness among clean-energy stocks and fossil fuel markets: Comparison between financial, oil and pandemic crisis. *Energy* 240. <https://doi.org/10.1016/j.energy.2021.122702>
- Uddin, G. S., Rahman, M. L., Hedström, A., & Ahmed, A. (2019). Cross-quantilogram-based correlation and dependence between renewable energy stock and other asset classes. *Energy Economics*, 80, 743-759.
- van Benthem, A. A., Crooks, E., Giglio, S., Schwob, E., & Stroebel, J. (2022). The effect of climate risks on the interactions between financial markets and energy companies. *Nature Energy*, 7(8), 690-69
- Wang, J., Chen, X., Li, X., Yu, J., & Zhong, R. (2020). The market reaction to green bond issuance: Evidence from China. *Pacific-Basin Finance Journal*, 60, 101294.
- Wang, J., Cui, M. & Chang, L. (2023). Evaluating economic recovery by measuring the COVID-19 spillover impact on business practices: evidence from Asian markets intermediaries. *Economic Change and Restructuring*, 56, 1629–1650.
- Wang, T., Umar, M., Li, M., Shan, S., 2023. Green finance and clean taxes are the ways to curb carbon emissions: An OECD experience. *Energy Econ.* 124. <https://doi.org/10.1016/j.eneco.2023.106842>
- Yousaf, I., Nekhili, R., Umar, M., 2022. Extreme connectedness between renewable energy tokens and fossil fuel markets. *Energy Econ.* 114. <https://doi.org/10.1016/j.eneco.2022.106305>
- Wei, Y., Zhang, J., Bai, L., Wang, Y. (2023). Connectedness among El Niño-Southern Oscillation, carbon emission allowance, crude oil and renewable energy stock markets: Time- and frequency-domain evidence based on TVP-VAR model. *Renewable Energy*, 202, 289-309.

Womack, B. (2017). International Crises and China's Rise: Comparing the 2008 Global Financial Crisis and the 2017 Global Political Crisis. *The Chinese Journal of International Politics*, 10(4), 383-401.

Xiao, B., Yang, Y., Peng, X., & Fang, L. (2019). Measuring the connectedness of European electricity markets using the network topology of variance decompositions. *Physica A: Statistical Mechanics and its Applications*, 535, 122279.

Yoon, S. M., Al Mamun, M., Uddin, G. S., & Kang, S. H. (2019). Network connectedness and net spillover between financial and commodity markets. *The North American Journal of Economics and Finance*, 48, 801-818.

Youssef, M., Mokni, K., & Ajmi, A. N. (2021). Dynamic connectedness between stock markets in the presence of the COVID-19 pandemic: does economic policy uncertainty matter?. *Financial Innovation*, 7(1), 1-27.

Zhang, D., & Kong, Q. (2022). Green energy transition and sustainable development of energy firms: An assessment of renewable energy policy, *Energy Economics*, 111, 106060

Dai, Z., Zhang, X., Liang, C., 2024. Efficient predictability of oil price: The role of VIX-based panic index shadow line difference. *Energy Econ.* 129, 107234. <https://doi.org/10.1016/j.eneco.2023.107234>

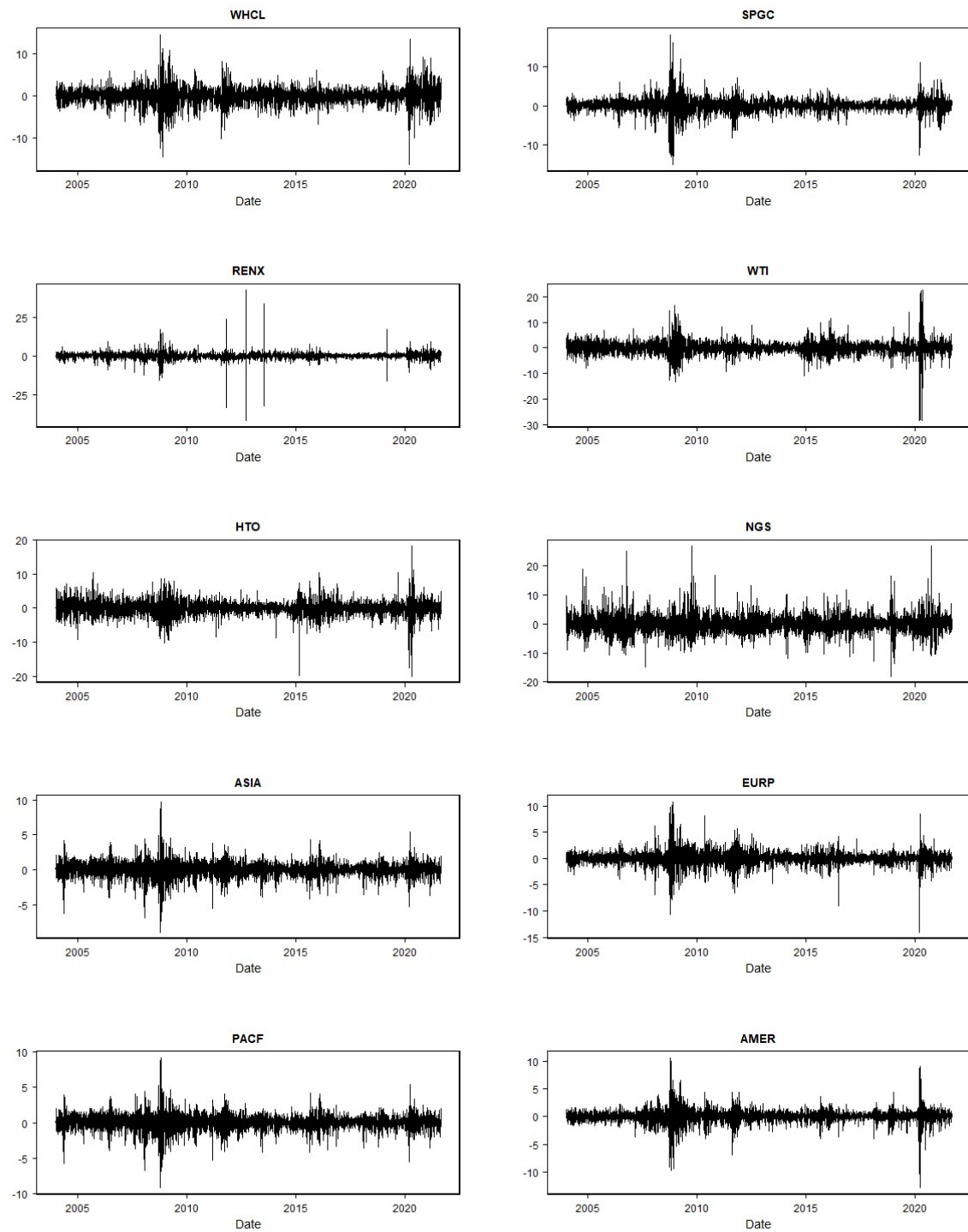
Liang, C., Luo, Q., Li, Y., Huynh, L.D.T., 2023. Global financial stress index and long-term volatility forecast for international stock markets. *J. Int. Financ. Mark. Inst. Money* 88, 101825. <https://doi.org/10.1016/j.intfin.2023.101825>

Table 1: Descriptive statistics

Group	Markets	Symbol	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Clean Energy	Wilder Hill Clean Energy	WHCL	0.003	14.520	-16.239	2.087	-0.453	9.172	7472.059
	S&P Global Clean Energy	SPGC	0.006	18.093	-14.973	1.809	-0.610	16.406	34796.700
	World Renewable Energy	RENX	0.029	42.217	-41.627	2.316	-0.443	82.772	1222211.000
Dirty Energy	Crude Oil WTI	WTI	0.026	22.394	-28.221	2.569	-0.144	20.341	57766.040
	Heating Oil	HTO	0.018	18.196	-19.996	2.144	-0.261	10.563	11037.360
	Natural Gas	NGS	-0.008	26.771	-18.055	3.160	0.668	8.649	6471.275
Stock Markets	MSCI Asia	ASIA	0.018	9.688	-8.839	1.104	-0.346	9.492	8186.130
	MSCI Europe	EURP	0.012	10.778	-14.023	1.329	-0.471	13.981	23329.020
	MSCI Pacific	PACF	0.018	9.220	-9.247	1.117	-0.426	9.765	8928.311
	MSCI America	AMER	0.030	10.626	-12.846	1.183	-0.700	18.507	46555.590

Note: *** indicates significance at 1%

Figure 1: Time evolution of return series for clean energy, dirty energy and stock markets



Note: This figure shows the time evolution of sampled markets from 1/1/2004 to 31/8/2021.

Figure 2: Correlation matrix

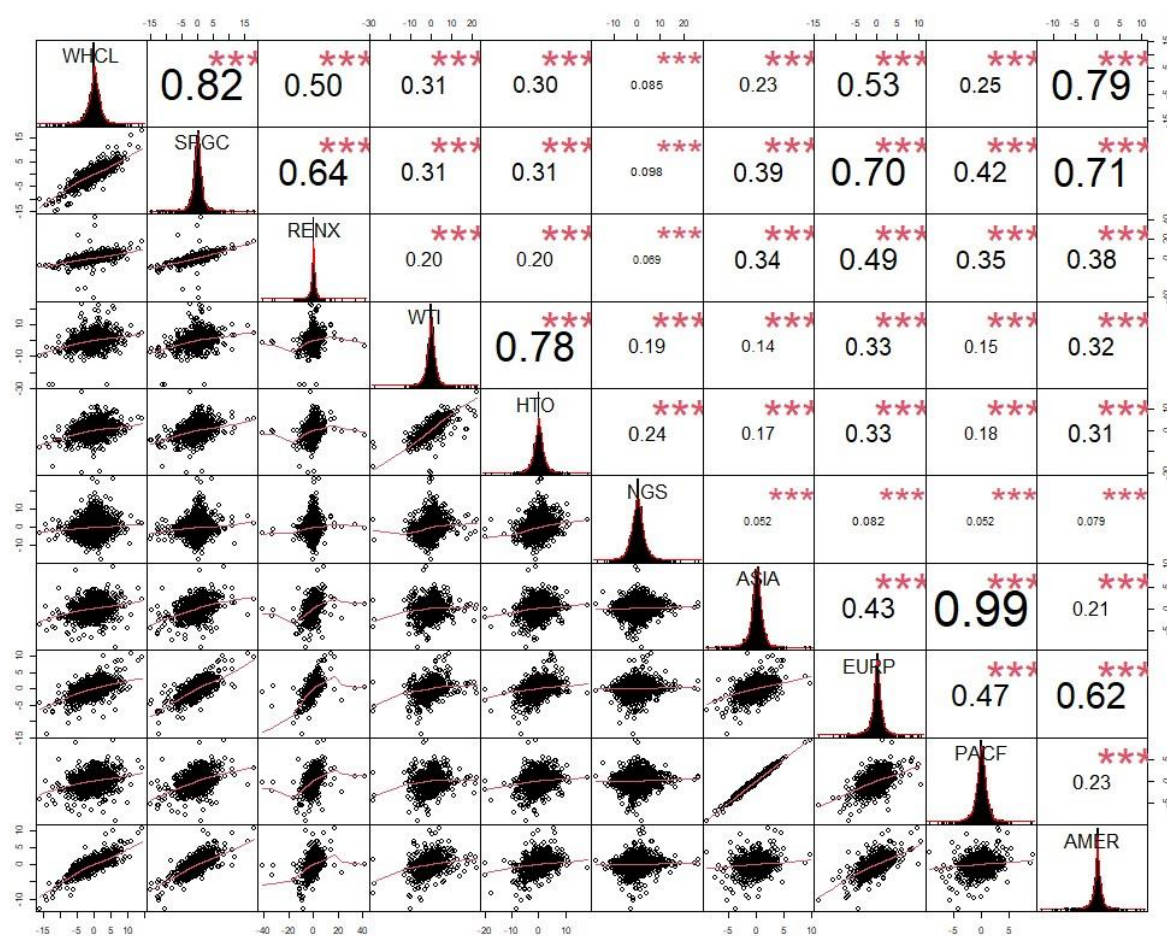
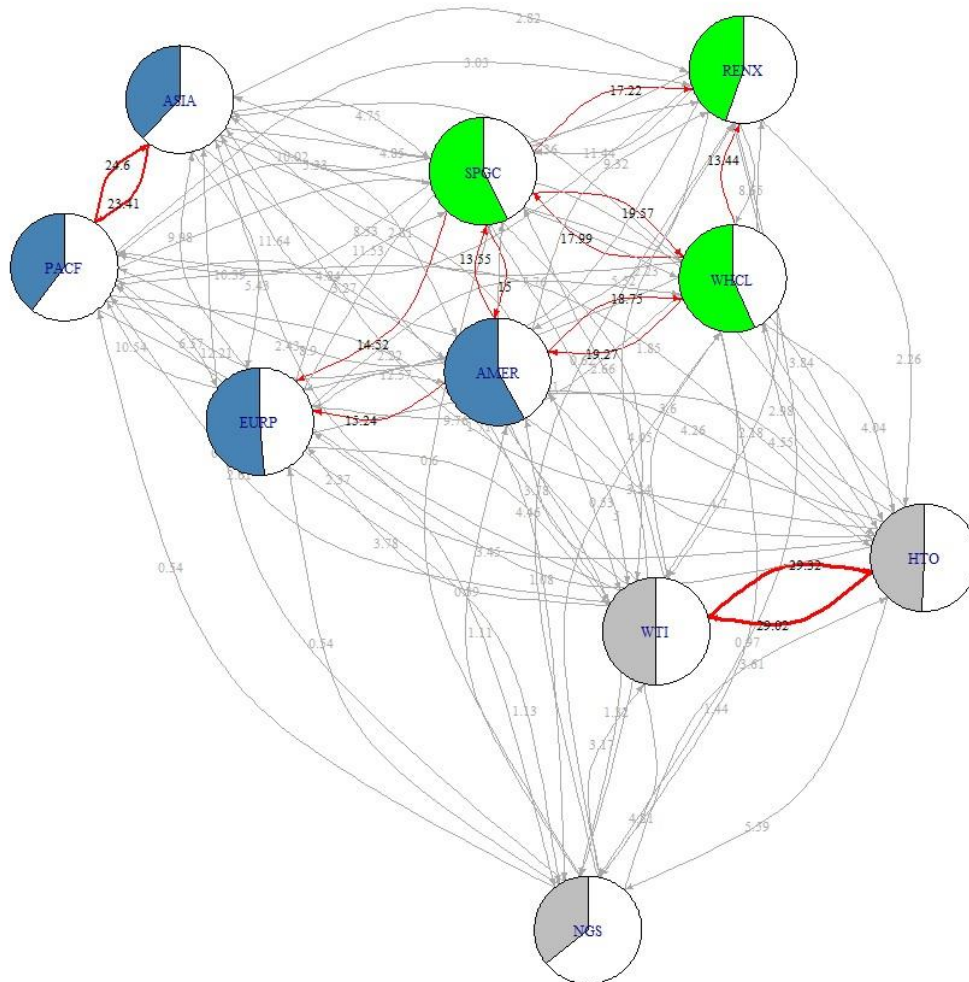
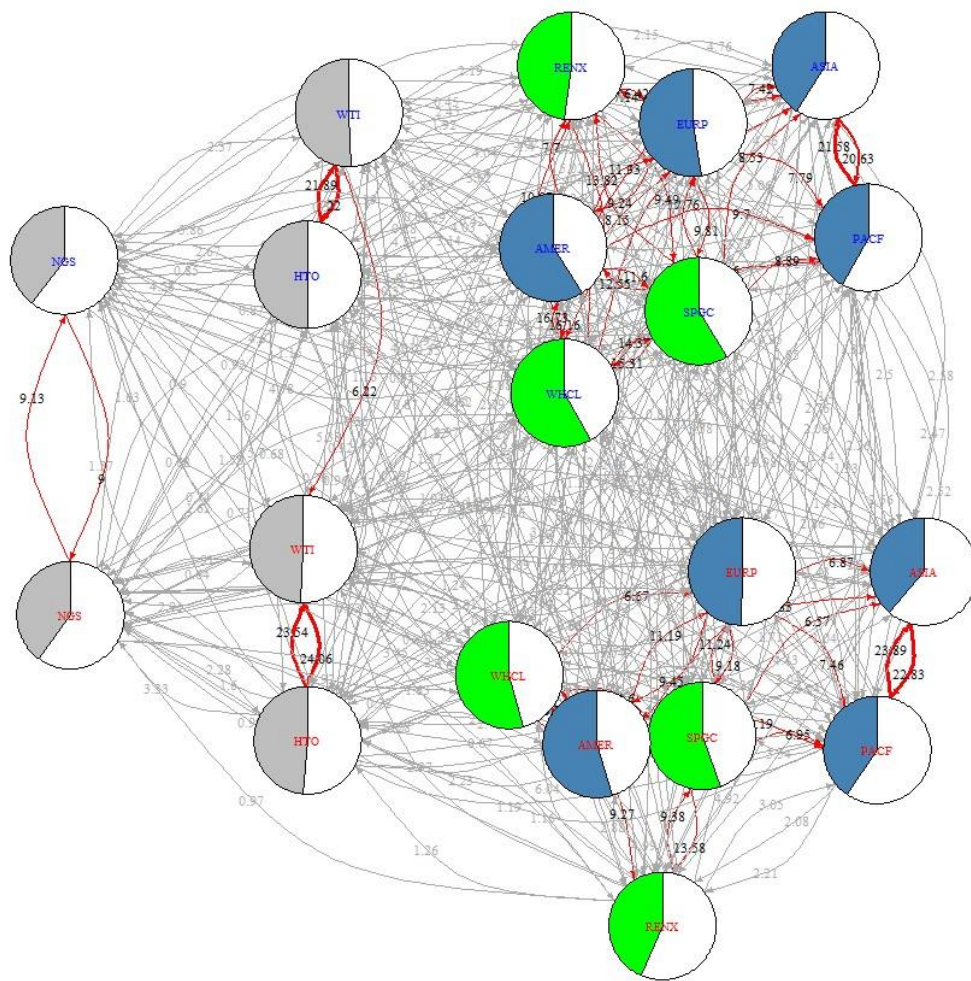


Figure 3: Network diagram of return, positive and negative spillover using TVP-VAR

a) System of daily returns



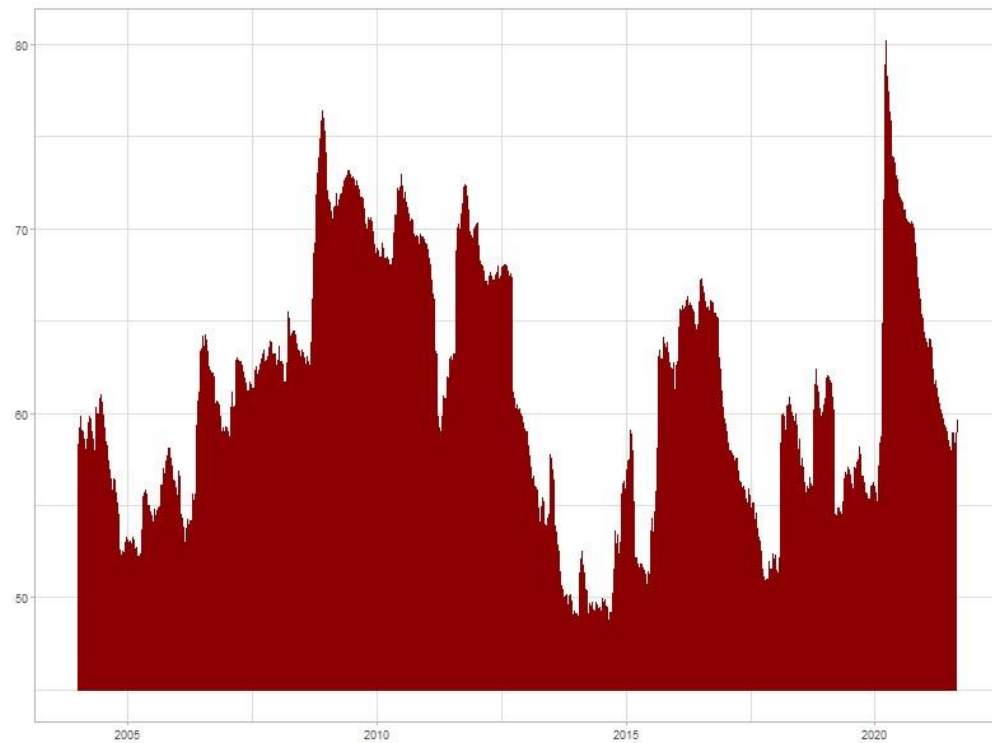
b) System of daily positive and negative returns



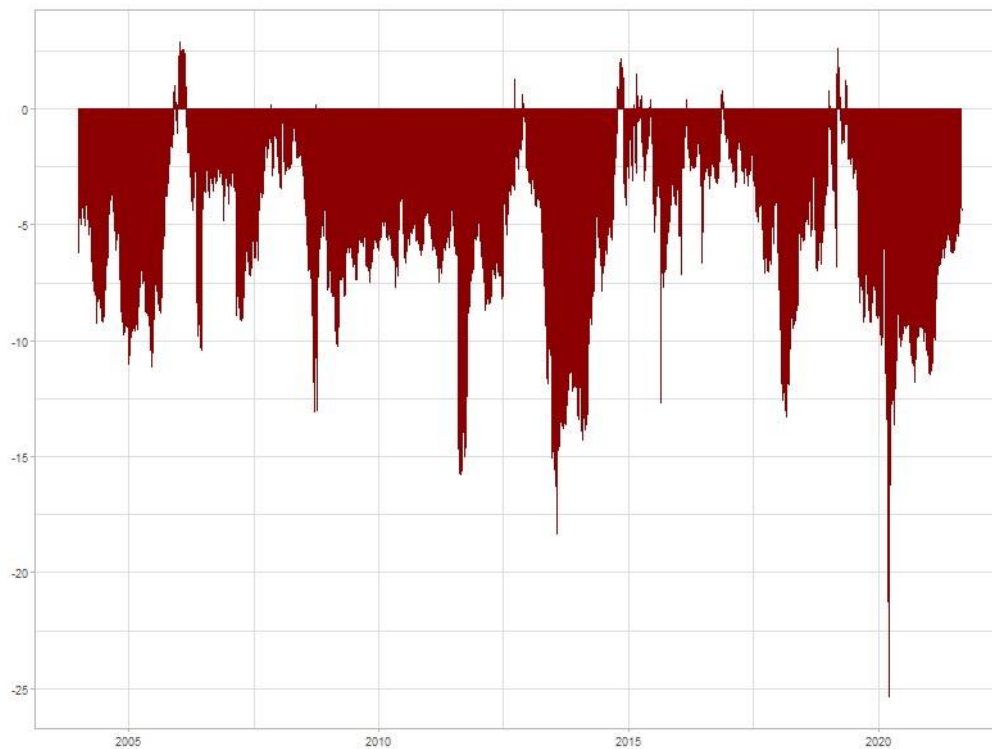
Note: The network graph illustrates the degree of pairwise weighted directional connectedness of a system that consists of the daily returns and daily positive and negative returns of the of clean energy (green), dirty energy (blue) and stock markets (yellow). Total connectedness is measured using the TVP-VAR connectedness framework. The border colour indicates the origin of connectedness. Red implies a contribution from the variable under consideration to the other variables of the system. The size of edges (indicated by the figure on the edge) shows the magnitude of pair-wise directional spillover. In Panel (b), the squares indicate positive returns, while the circles show negative returns. Lag=1 (SIC criteria); forecast horizon=10 days. The sample period is from 1/1/2004 to 31/8/2021.

Figure 4. Time-varying spillover based on TVP-VAR

(a) Spillover based on the system of returns

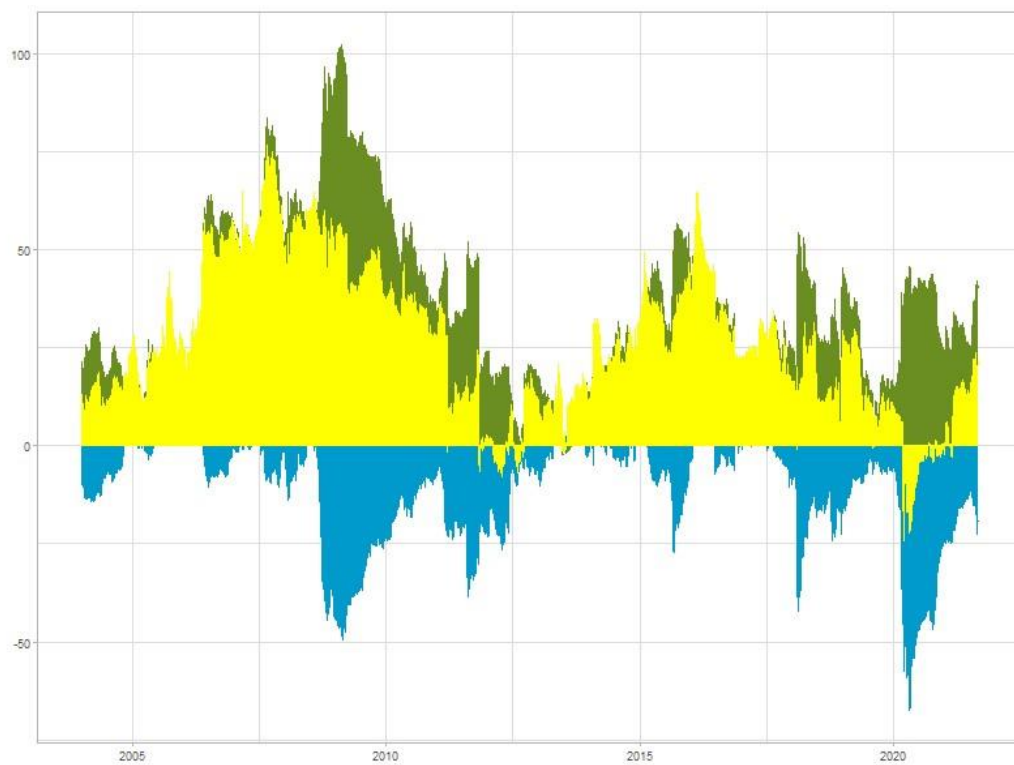


(b) Spillover based on the system of asymmetry measure (SAM)



Notes: The total spillover and spillover asymmetry measure has $h = 10$ trading days. In Panel (b), negative values imply higher negative spillover, and vice versa.

Figure 5. Time-varying NET spillover based on TVP-VAR



Notes: The NET spillover $h = 10$ trading days with lag = 1 (SIC criteria).

Green Color: Clean Energy, **Blue Color:** Energy; **Yellow Color:** Stock