Dynamic spillovers between clean energy stocks and fossil fuels: The role of climate policy uncertainty and geopolitical risk

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ABSTRACT

Clean energy stocks have emerged as a means for environmentally conscious investors to support and foster the growth of companies that are involved in the green energy sector. However, given the entrenched place that non-green energy still holds, investors must contend with the reality that these clean energy stocks may be connected to fossil fuels. Therefore, the study applies the TVP-VAR model to analyze the volatility spillovers among these markets. Our empirical analyses demonstrate that there is strong connectedness between clean energy stocks and fossil fuels. Notwithstanding, we observe that the spillovers among fossil fuels (crude oil, diesel, jet fuel etc.) are stronger than the intermarket spillovers between these energy commodities and the clean energy stock market. We then proceed to examine the effect of climate policy uncertainty and geopolitical risk on these spillovers. Using the causality-in-quantiles technique of Balcilar et al. (2016), we find that both climate policy uncertainty and geopolitical risk have a formidable impact on clean energy stock and fossil fuel intermarket spillovers. Moreover, using the Quantile-on-Quantile regression approach of Sim and Zhou (2015), we find that climate policy uncertainty and geopolitical risk have heterogeneous effects across the distribution of the clean energy stock and fossil fuel spillover nexus. These findings constitute important information for investors and policymakers.

Key words: Clean energy stocks, fossil fuels, climate policy uncertainty, geopolitical risk, non-parametric techniques.

Dedication

To my parents, James and Stella Mubaiwa, this thesis is affectionately dedicated.

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My supervisor, Professor Ismail O. Fasanya, your steadfast counsel is eternally appreciated.

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CHAPTER ONE

INTRODUCTION

1.1 Problem statement

Rising awareness among investors of the detrimental impact of the continued use of dirty energy sources on the environment has led to the emergence of green finance with the aim of encouraging sustainable energy generation and a low carbon economy. Along with this development, the Paris Climate Agreement has strengthened the resolve to progress to a clean economy, leading to the adoption of goals that include, among others, to prevent the increase in global temperatures from exceeding 2°C above pre-industrial levels (United Nations, 2016). Amid these changing perceptions about the environment, clean energy stocks are among several financial instruments that have gained prominence in recent years. These assets represent interests in companies involved in wind, hydro, solar and other renewable sources, as well as those companies concerned with energy efficiency. As Choi et al. (2022) note, the environmental, social and governance (ESG) issues brought to the fore by the Paris Climate Agreement have generated considerable interest in clean energy stocks.

In recognition of the increasing attention on these green financial assets from environmentally conscious investors, and in pursuit of a deeper understanding of their behavioural characteristics, several studies have sought to examine the connection between these assets and several commodities (see, inter alia, Ferrer et al., 2018; Umar et al., 2021; He et al., 2021; Chen et al., 2022). The interest behind such research has been, in part, driven by the fact that some fossil fuels like crude oil are substitutes for clean energy sources (Umar et al., 2021), a relation which is crucial for understanding the dynamics among energy commodities. Theoretically, this substitutability exposes investments in clean energy stocks to the interactions among incumbent fossil fuels and alternative energy markets. Moreover, given the dominance of fossil fuels, this situation is likely to persist until the world has made significant progress in the transition to the green economy.

In addition, disturbances like the global financial crisis (GFC) and the COVID-19 pandemic have raised questions about the extent of contagion among these markets during extreme events, leading to several studies looking at the volatility connectedness between clean energy stocks and fossil fuels before, during, and after the emergence of these disturbances (see, inter alia, Umar et al., 2021; Nguyen et al., 2021). Naturally, information on the extent and overall direction of spillovers among different markets is useful for environmentally conscious investors and even those who are agnostic on environmental issues and are only interested in risk and returns.

The clean energy stock and non-green energy commodity nexus is particularly complex because, while the energy sources which underlie clean energy stocks (solar, wind, hydro etc.) are substitutes for non-green energy commodities, essential commodities like crude oil can affect expected inflation and real interest rates (Miller & Ratti, 2009). Pertinently, this relation is further complicated by two issues. First, uncertainty connected to climate policies may have an impact on the decision-making of firms and investors alike. Specifically, climate policy uncertainty may diminish the incentive for investing in sustainable energy projects. Therefore, from a portfolio management perspective, it is imperative to understand the extent of the exposure of investments in clean energy stocks not only to other markets (fossil fuels) but to changes in climate policy uncertainty. Whereas the first consideration is purely concerned with regulation, the second, geopolitical risk, involves the supply of key inputs for production. A quintessential example is the political fallout from the war in Ukraine which resulted in disruptions in the supply of fossil fuels which were crucial for European energy security. Certainly, the immediate imperative was to seek out other sources of energy at home and abroad. This occurrence is instructive as it clearly demonstrates that potential and realized geopolitical risks may wreak havoc in energy commodity markets. Moreover, given the fact that clean energy (solar and wind, for example) tends to be locally produced, it is less vulnerable (at least in the short run) to the risk that an important input may be withheld or become unavailable. Notwithstanding these issues, to the best of our knowledge, no study has yet endeavored to fully examine the effect of geopolitical risk (GPR) and climate policy uncertainty (CPU) on the direction and strength of volatility spillovers among fossil fuels and clean energy stocks.

Considering the preceding discussion, the study undertakes to uncover not only the nature of the volatility spillovers among non-green energy commodities and clean energy stocks but also considers whether CPU and GPR have any predictive power to anticipate changes in these spillovers. Moreover, we assess a wider array of fossil fuel commodities in a single study while pursuing the primary objectives of the study.

Against this background, we seek to answer the following questions:

i. What is the direction and strength of volatility spillovers among fossil fuel markets and clean energy stocks?
ii. How does climate policy uncertainty affect the volatility connectedness among these markets?
iii. Does geopolitical risk have an impact on the clean energy stock - fossil fuel nexus?

1.2 Objectives of the study

To answer the preceding questions, the study's main objective is to analyze the impact of climate policy uncertainty and geopolitical risk on the connection between clean energy stocks and fossil fuels. The specific objectives are to:

i. Examine the volatility connectedness among clean energy stocks and fossil fuels.
ii. Analyze climate policy uncertainty's impact on the spillovers among these markets.
iii. Determine the effect of geopolitical risk on the strength of connectedness among clean energy stocks and fossil fuels.

1.3 Justification for the study

Several studies looking at intermarket spillovers have examined the connectedness among clean energy stocks and several commodities (see Ferrer et al., 2018; Coskun et al., 2023; Tiwari et al., 2021; Qi et al., 2022; Coskun & Taspinar, 2022; Chen et al., 2022; Deng et al., 2023; Chen et al., 2023; Lucey & Ren, 2023; Nguyen et al., 2021; He et al., 2021; Fu et al., 2022; Shahbaz et al., 2021). Overall, these studies have found evidence of strong connections among these markets and have been able to reveal the effects of extreme events on intermarket relations. However, to the best of our knowledge, no study has yet considered how uncertainty on climate policies and geopolitical risk may affect the interrelationships among these markets. This is a serious shortcoming because, as we will demonstrate, unclear or changing policies on climate change have considerable effects on firms and investors. Moreover, the risk that crucial inputs in production may suddenly fall out of the market is worthy of serious consideration. Therefore, the present study makes a significant contribution to the current body of literature by analyzing the effect of climate policy uncertainty and geopolitical risk on the spillovers among clean energy stocks and several (non-green) energy commodities.

As a first step, we assess the volatility spillovers among clean energy stocks and several fossil fuels using a time domain connectedness approach. Specifically, we apply the TVP-VAR technique of Antonakakis et al. (2020). This technique is robust to several weaknesses to which other measures of connectedness are susceptible. For example, the rolling window approach's loss of observations, results which are subject to random selection of the rolling window size and the Kalman filter generating process's effect on the resulting responsiveness to outliers (Bouri et al., 2020). In addition, we analyze the effect of CPU and GPR on the spillovers obtained from the TVP-VAR analysis by applying the non-parametric granger causality-in-quantiles technique of Balcilar et al. (2016). This technique allows us to detect time series dependency from CPU or GPR to the connectedness among our variables of interest. Moreover, the technique has some advantages; it is robust to various misspecification errors and can reveal dependence even in the presence of structural breaks (Balcilar et al., 2016).

Moreover, unlike previous literature on clean energy markets and commodities (see inter alia Shahbaz et al., 2021; Ding et al., 2022; Coskun et al., 2023), the present study provides an explicit exposition of the links that exist among these markets. With a few exceptions like assessing the effect of climate policy uncertainty on green stocks and commodities, the current body of literature has thoroughly assessed the associations among financial assets and commodities (see Coskun & Taspinar, 2022; Chen et al., 2023). However, despite the great length of research on this subject, no study, to the best of our knowledge, has paid much attention to building a framework that accounts for the spillovers observed among markets. We therefore undertake to fully account for the interlinkages among clean energy stocks and fossil fuel commodities like crude oil and natural gas.

1.4 Scope of the study

The study focuses on the impact of CPU and GPR on the spillovers among clean energy stocks and non-green energy commodities between December 2000 and August 2023. We focus on two types of fossil fuels: petroleum and natural gas.

1.5 Organisation of the study

The study has six chapters. The present chapter has described the specific gap in the literature as well as how we seek to fill this gap. Chapter two gives a detailed account of relevant methodological and empirical literature. Following this, in chapter three, we assess the U.S. energy landscape and then proceed to describe the analytical framework that accounts for the connections among our variables of interest. Chapter four gives a full exposition of the methodologies that enable the study to accomplish its objectives. Thereafter, chapter five discusses the results of the study. Lastly, chapter six concludes with some recommendations.

CHAPTER TWO

LITERATURE REVIEW

The present chapter provides a thorough methodological and empirical review of relevant literature on the associations among fossil fuels and clean energy stocks.

2.1 Methodological review

Among studies that have assessed the connection between financial markets (incl. green finance) and commodities, several have used wavelet analysis (see Nguyen et al., 2021; Zhu et al., 2022). This methodology can decompose economic time series into scale components and is thus useful in those cases where both the strength and direction of the associations among economic variables likely differ across time scales (Ramsey & Lampart, 1998; Gallegati, 2008). As Gallegati (2008) and Nguyen et al. (2021) highlight, from an investment management perspective, this analysis is especially serviceable. The time scales ensure that the results obtained are relevant given the variability in investors' horizons. Moreover, these studies applied the maximum overlap discrete wavelet transform (MODWT), which is chosen over the classical DWT on account of its advantages. For example, it can handle any sample size, it produces a more asymptotically efficient wavelet variance estimator and has improved resolution at longer time scales (Gallegati, 2008).

On the other hand, a few studies have instead used the quantile autoregressive distributed lag (QARDL) approach (see inter alia He et al., 2021; Fu et al., 2022). The methodology is an extension of the ARDL and was introduced by Cho et al. (2015). It allows for a fuller analysis of the short and long run dynamics of variables across different quantiles of the dependent variable. That is, it can capture any asymmetries in the relations among variables. Meanwhile, another stream of research on intermarket associations has instead depended on various causality tests such as those by Jeong et al. (2012) and Han et al. (2016). These are particularly useful in those cases where there is evidence of nonlinearity among the variables of interest. Despite its advantages, when used to assess intermarket connections, it has some shortcomings. Certainly, as Shahbaz et al. (2021) highlighted in their study on the connections among clean energy stocks and several other markets, the inability of these methodologies to assess both the time and frequency domains is disadvantageous.

Notwithstanding the advantages of these techniques, most studies on the subject have applied time and frequency domain spillover techniques to uncover the return and volatility connectedness among clean energy stocks and several commodities (see inter alia Ferrer et al., 2018; Tiwari et al., 2021; Umar et al., 2021; Chen et al., 2022). The utility of this type of analysis lies in its ability to finesse the issue of discretion in the selection of constraints imposed in the VAR environment. These connectedness measures largely arose out of Diebold and Yılmaz (2012, 2014)'s seminal work wherein they developed a method that generalized the VAR framework that uses a rolling-window dynamic analysis. The Diebold and Yılmaz (2012) was itself an improvement on a prior technique developed in Diebold and Yılmaz (2009). In this prior study, the methodology constructed relied on the Cholesky decomposition, which made it susceptible to the ordering of the variables. Moreover, more substantively, it was only capable of measuring spillovers among identical assets/commodities. Meanwhile, the Diebold and Yılmaz (2012) methodology uses a framework where the forecast error variance does not vary with the ordering of the variables.

More recently, these dynamic connectedness methodologies were improved by the TVP-VAR framework of Antonakakis et al. (2020) which has advantages over that of Diebold and Yılmaz (2012). Foremost of these is the fact that, unlike Diebold and Yılmaz (2012)'s framework, it is not susceptible to an arbitrarily assigned window size. Moreover, it is less susceptible to outliers in the data series. There was however room for further improvement. Certainly, the advancement made by Baruník and Křehlík (2018) to account for low, medium, and high frequencies greatly improved the previously time domain limited connectedness approaches of Diebold and Yılmaz (2012, 2014) and Antonakakis et al. (2020). This technique has several advantages, not least of which is its ability to reveal any differences in contribution of variables to a spillover network across frequency bands. This makes the technique especially applicable in a portfolio management setting. The high frequency entails those shocks in the network that result from short lived effects within the network. Meanwhile, the low frequency are those shocks in the system that arise from long lived effects.

Given that our foremost objective is to assess the impact of CPU and GPR on the spillovers among fossil fuels and clean energy stocks, we select the causality-in-quantiles technique of Balcilar et al. (2016) to detect time series dependency. Moreover, notwithstanding the utility of the Baruník and Křehlík (2018), favoring focus, we select the TVP-VAR methodology to assess the nature and extent of spillovers among clean energy stocks and fossil fuels in the time domain. To supplement the causality-in-quantiles test results, we make use of Sim and Zhou (2015)'s Quantile-on-Quantile regression technique.

2.2 Empirical review

In pursuit of a deeper understanding of the clean energy stock market's association with other markets, numerous studies have sought to analyze its connectedness with various commodities. These prior studies have however differed in their scope and methodologies employed. In one of the earlier studies, Ferrer et al. (2018) observed that clean energy stocks were net-transmitters of return and volatility spillovers in a system with crude oil and other financial assets for most of the period of assessment (2 January 2003 to 29 September 2017). Using the Baruník and Křehlík (2018) frequency framework, their results showed that return spillovers to and from clean energy stocks worked in opposite directions between higher and lower frequencies for large stretches of the period. Meanwhile, in the case of volatility spillovers, this effect was less pronounced. They also found that the intensity in the connectedness among markets had increased since the onset of the global financial crisis of 2007. In addition, Ding et al. (2022) examined the effect of attention on climate change on the connectedness among carbon, fossil fuel, and clean energy markets. Using the Google Search Volume Index (GSVI) as their proxy, they uncovered that attention on climate change had a significant effect on the spillovers among these markets. Moreover, they observed that this effect increased at the onset of the COVID-19 pandemic. Similarly, Coskun et al. (2023) analyzed the spillover connectedness among clean energy stocks, commodities, global stocks, and geopolitical oil price risk. They uncovered that the volatility spillovers intensified at the onset of various events like the Arab Spring and the COVID-19 pandemic. Interestingly, they found that gold was a net receiver of spillovers. An observation they attributed to the safe-haven status of gold as an asset. Furthermore, geopolitical oil price risk was the highest transmitter of volatility spillovers to the gold market.

Interestingly, there has been a stream of studies that have sought to examine clean energy stocks at the firm or subsector level (see inter alia Tiwari et al., 2021; Qi et al., 2022; Coskun & Taspinar, 2022; Chen et al., 2022; Deng et al., 2023). For example, Tiwari et al. (2021) examined the return connectedness among clean energy stocks (proxied by S&P Global Clean Energy Index, Solactive Global Wind, and Solactive Global Solar), green bonds, and CO2 emission prices. They observed that clean energy stocks (S&P Global Clean Energy Index) were the biggest transmitter of shocks to green bonds. Moreover, they uncovered that the clean energy indices were more susceptible to network spillovers than green bonds. From the dynamic total connectedness, they showed that connectedness reached its greatest extent during the COVID-19 period. Similarly, looking at the dynamic spillovers among clean energy stock markets and non-green energy commodities, Qi et al. (2022) found that clean energy stock indices (nuclear, photovoltaic, and wind) were the greatest transmitters and receivers in the system. This relation was maintained in both the short and long frequencies. Where these respectively entail the finest and coarsest intervals. However, there was only a marginal decrease in the level of connectedness between the two frequencies from the short to the long frequency.

Meanwhile, focusing on Turkey, Coskun and Taspinar (2022) uncovered that the connection between fossil fuel markets and Turkish energy stocks was strong and heavily affected by global financial, political, and extreme events. Interestingly, they observed that the volatility connectedness among these markets was stronger during the COVID-19 pandemic than during the global financial crisis. Using the Baruník and Křehlík (2018) approach, they also observed that volatility transmissions among the markets persisted in the long run. Similarly, Chen et al. (2022) examined the strength and direction of spillovers among sectoral clean energy stocks and non-ferrous metals. They found that spillovers in the time domain were mostly driven by short-term (high frequency) factors as opposed to long-term (low frequency) factors. They also observed that events such as the European debt crisis, the signing of the Paris Agreement and the COVID-19 pandemic all markedly increased the connectedness among clean energy markets and non-ferrous metals. Furthermore, in the time domain, the greatest spillover transmitters were the energy management and smart grid clean energy sub-sector stocks. Moreover, not only were non-ferrous metals the greatest receivers of spillovers, but they remained net-receivers in both the short and long frequency domain. Meanwhile, in a study focusing on China, Deng et al. (2023) used the Diebold and Yılmaz (2012) and Baruník and Křehlík (2018) techniques to assess the spillover dynamics among several clean energy sub-sectors and non-ferrous metals markets. They found that the connectivity among clean energy market sub-sectors was stronger than the connectivity between this market and non-ferrous metals. In addition, they observed that the connectedness among these markets changed significantly during the COVID-19 pandemic. During this period, the strength of the connectedness between clean energy markets and non-ferrous metals weakened, but intraconnectivity among the clean energy sub-sectors strengthened. Overall, Deng et al. (2023) show that net spillovers are transmitted from clean energy markets to non-ferrous markets.

Although differing somewhat from the present study, but in very much the same spirit, Chen et al. (2023) endeavored to examine the close connection between liquified natural gas and freight rates in a dynamic network. Theoretically, there is a direct causal effect from demand for liquified natural gas to freight rates instead of a substitution effect. Chen et al. (2023) noted that although the supply of liquified natural gas is set to expand, transportation capacities for freight routes are likely not to change significantly. With this observation in mind, they sought to assess the nature of connectedness among the futures prices, spots prices, and freight rates of liquified natural gas. They found that the spillovers received by transportation costs were greatest during periods where liquified natural gas prices were most volatile. This effect was most obvious at the onset of the COVID-19 pandemic and the war in Ukraine. It is also apparent from their results that the fluctuations explained by intermarket spillovers were relatively lower than those observed for other markets in previous literature. However, this is not to say that these intermarket spillovers are not consequential.

Moreover, there is also evidence to suggest that disturbances like the Russia-Ukraine conflict do not only intensify spillovers. For example, as Lucey and Ren (2023) observed, green energy markets took the role of spillover transmitter at the onset of the Russia-Ukraine war, an event which coincided with Europe's energy crisis. Their study used the asymmetric slope conditional autoregressive value at risk time varying autoregressive vector autoregressive (CAViaR TVP-VAR) to assess the tail risk spillovers among sustainability investments and non-green commodities. Their study found that non-green commodities, green bonds, and carbon assets were tail risk takers, while green equities were spillover transmitters. Surprisingly, they observed that the effect of the COVID-19 pandemic on the connection among these markets was mild, a finding that somewhat contradicts other studies. Equally confounding, Umar et al. (2021) found that there were weak volatility spillovers among fossil fuel markets and clean energy stocks, which may entail potential diversification benefits. Their results however corroborated with other studies that the interlinkages among these markets strengthened during crisis periods like the global financial crisis and COVID-19. Furthermore, they observed that the connectedness among petroleum markets was particularly strong.

Not all studies have relied on network analysis, however. For example, Nguyen et al. (2021) employed wavelet analysis in their study looking at the co-movement among clean energy stocks, commodities, and several other financial series. They found that the dynamics among these markets varied across frequency and time. Specifically, using the rolling window wavelet correlation approach, they observed that the correlation between clean energy stocks and commodities was especially positive during the global financial crisis. Moreover, the correlations between these two variables were revealed to be greatest in coarser time scales. Some studies such as He et al. (2021) and Fu et al. (2022) instead relied on QARDL. Using this technique, He et al. (2021) uncovered that, in the long run, there was a positive relationship between oil price fluctuations and clean energy stocks in the higher quantiles of clean energy stocks but observed that the effect of gold prices was negative across the same quantile range. Meanwhile, in the short run, the positive effect between oil price fluctuations and clean energy stocks was observed across all quantiles. Moreover, they showed that although this association was observed for both U.S. and Europe clean energy, there were some differences.

Similarly, Fu et al. (2022) assessed the dynamics of clean energy stocks and crude oil among other variables. They found that crude oil had a negative effect on clean energy stocks during normal and bullish market conditions. However, while the clean energy stock market was in a bearish condition, crude oil's effect was insignificant. Interestingly, Fu et al. (2022) proposed that this results from high oil prices compelling the government to subsidize demand for oil, which reduces the funds available for green projects. Unlike these preceding studies, Shahbaz et al. (2021) used causality-in-quantiles techniques to assess the connection among clean energy stock, the S&P 500, and commodities indices. As they explain, these techniques were chosen after having found evidence of nonlinearity among these markets using Broock et al. (1996)'s BDS test. As their results show, for both their proxies for clean energy stocks (the WilderHill Clean energy and the S&P Global clean energy indices), the S&P global stock index and oil prices had strong predictive power for the clean energy stock market. They however went further by using their two-way causality methodology and similarly found that non-causality between the clean energy stock market and the S&P 500 stock index as well as oil prices was rejected for the middle and extreme quantiles.

As the preceding literature shows, much work has been dedicated to assessing the possibility of contagion among clean energy markets and various commodities. However, the shortcoming of these previous studies, in our view, has been the failure to account for uncertainty on climate policy arising from unclear or changing regulation on environmental issues and geopolitical risk. Specifically, the question of how these phenomena affect the connectedness between non-green energy commodities and clean energy stocks has not been sufficiently addressed. Moreover, the present body of literature has not paid much attention to providing a full account of the theoretical link between these markets. This includes questions like "what interlinkages exist between these clean energy stocks and fossil fuels like crude oil and natural gas?", "on what grounds do we expect those connections?" and "through what channel does climate policy uncertainty/geopolitical risk affect the link between clean energy stocks and fossil fuels?". It is against this background that the present study undertakes to give an exposition of the analytical framework that accounts for the link between non-green commodities and clean energy stocks.

CHAPTER THREE

ENERGY LANDSCAPE AND ANALYTICAL FRAMEWORK

This chapter assesses the U.S. energy landscape. Specifically, we focus on present and historical consumption of primary energy. Following this, we develop a framework that accounts for the connectedness among non-green energy commodities and clean energy stocks.

3.1 U.S. Energy landscape

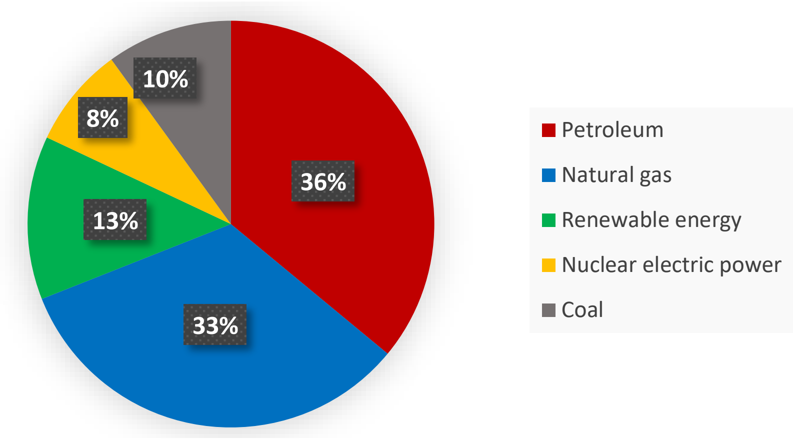
The present section briefly discusses U.S. energy consumption patterns as well as the shares of the various sources of energy. We select the U.S. as the subject of study on account that it is the most dynamic economy and possesses mature financial markets.

3.1.1 Present energy consumption

According to the U.S. Energy Information Administration (2023), the U.S. consumed a total of 100.41 quadrillion British Thermal Units (Btu) in 2022. This consumption was dependent on several primary energy sources whose shares varied over the years. They include petroleum, natural gas, nuclear energy, coal, and several renewable energy sources. These renewables include hydro-electric power, solar, wind, biothermal energy, and timber. As of 2022, petroleum has the greatest share in the energy mix with 36% of total primary consumption. Not far behind is natural gas at 33%. With renewable sources having a share of only 13%, the data shows that there is much work yet to be done for the advancement of renewable energy generation.

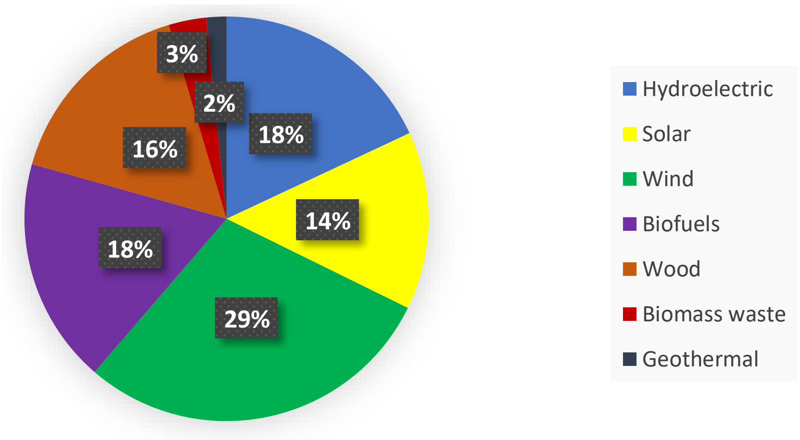
The renewables bracket in Figure 1 includes a wide range of energy sources as shown in Figure 2. From hydroelectric power to geothermal energy. It is here where we must distinguish between clean energy and renewable energy. While energy sources like timber are renewable, they cannot reasonably be considered as clean energy. In this study, we take clean energy to be those sources of energy whose byproducts have minimal or no detrimental effects on the environment. Prime examples are hydro, solar, and wind. However, an expanded definition includes energy saved using energy efficiency measures.

Figure 1: U.S. primary energy consumption 2022



Source: U.S. Energy Information Administration

Figure 2: Breakdown of renewable energy



Source: U.S. Energy Information Administration

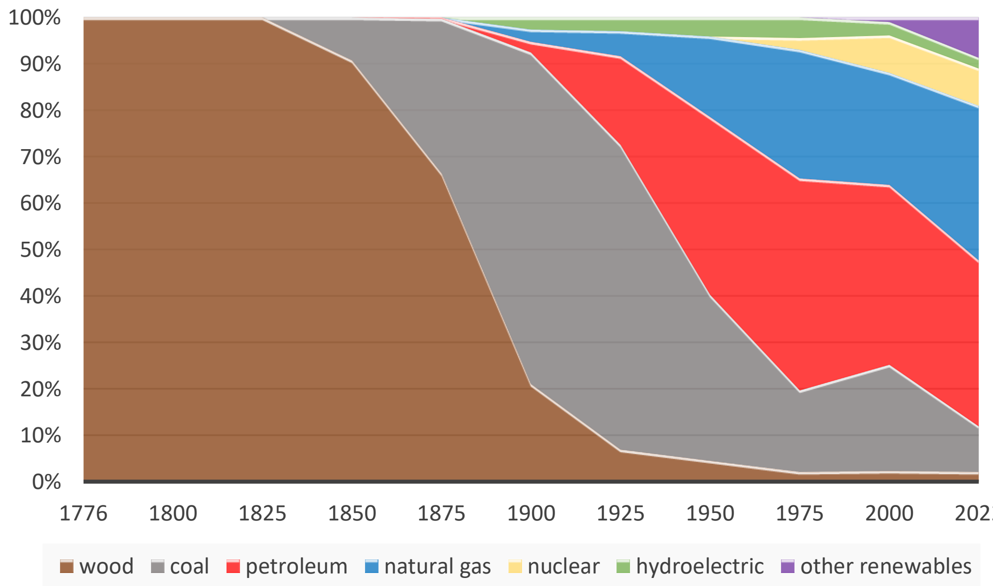
3.1.2 Historical perspective

We see in Figure 3 that timber and coal only lost their combined dominance around 1950. Since then, petroleum (crude oil, diesel, heating oil etc.) and natural gas have come to dominate U.S. energy consumption. Certainly, their combined share reached its zenith at 73.2% of total energy consumed in 1975. The predominance of these two fossil fuels, acquired between 1925 and 1950, may prove difficult to dislodge. Notwithstanding, it is apparent that hydro power is the

the forerunner among the clean energy sources. The other renewables have gained ground, moving from 1% to 8.7% of the total primary energy mix.

Interestingly, we observe that nuclear power's share of primary energy consumption has remained at around 8% between 2000 and 2022. Overall, we see a clean energy sector that is still trying to gain ground and whose ascendence may prove difficult given the clear dominance of fossil fuels. These fossil fuels (incl. petroleum, natural gas, and coal) account for approximately 78.8% of primary energy consumption. To prove equal to the task of transitioning to the green economy, great sums of capital investments in new infrastructure will be required.

Figure 3: U.S. primary energy source consumption 1776 - 2022



Source: U.S. Energy Information Administration

3.2 Analytical framework

The current section builds a framework that explains the interlinkages among non-green energy commodities, clean energy stocks, climate policy uncertainty, and geopolitical risk. We begin by looking at the underlying clean energy material and non-green commodity markets.

3.2.1 Microeconomic foundations of clean and dirty energy markets

To establish the link between clean energy stocks and fossil fuels, we take our starting point to be a firm that uses both clean energy materials (for wind, hydro, solar etc.) and non-green energy commodities (crude oil, for example) to generate energy for its production process. We do this to explain the demand for these materials/commodities which, along with the supply side, determines the prices of these materials/commodities. Moreover, it is important to stress that we take "the firm" to mean any company or organization that is involved in some aspect of energy generation and consumption. Its end-product may be the energy itself or equipment used to generate power for industrial, transportation or household needs. Thus, we can account for those firms involved in electric vehicle production and energy efficiency. Admittedly, this is a broad classification, but this is done to focus on the relationships that matter most to us. We assume the firm has the capacity to use both inputs in the production process. That is, clean energy materials (X_{CE}) and non-green commodities (X_{NG}) are substitutes. Furthermore, the productivity of each input reduces at the extremes of the ratio of the two inputs in the short run. This may not be as incredible as it seems if we imagine our single firm as the aggregation of firms that use clean energy materials and those that use dirty energy sources. The problem is primarily viewed as that of a simple cost-minimizing firm which chooses the optimal input ratio (X_{CE}/X_{NG}) . Given the substitutability between the inputs, the fluctuation in prices leads to changes in the ratio of inputs in the production process. This in turn causes pressure in the input factor markets, leading to changes in the prices of the inputs. For illustrative purposes, we adapt an example from Varian (1992):

$$\frac{w_{CE}}{w_{NG}} = \frac{\frac{\partial\, f(\mathbf{X})}{\partial\, X_{CE}}}{\frac{\partial\, f(\mathbf{X})}{\partial\, X_{NG}}}$$

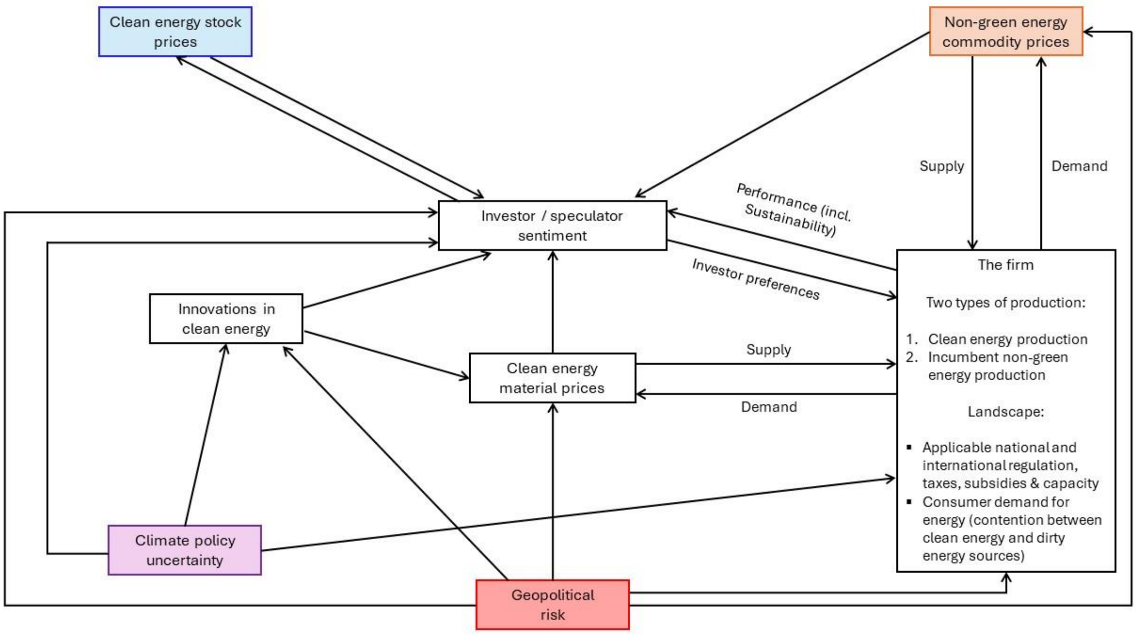
The left-hand side is the economic rate of substitution between clean energy materials (or inputs) (CE) and non-green commodities (NG). The right-hand side represents the marginal rate of technical substitution (MRTS) between the two inputs. If the equality does not hold, the firm adjusts the ratio of the inputs used until the MRTS equals the economic rate of substitution. However, we should note that the distinction between clean energy and non-green energy commodities, despite the heterogeneity among non-green energy commodities, is only a matter of our interest on clean energy. This means that although we have subsumed all non-green commodities under the variable X_{NG}, these commodities are themselves substitutes for each other in the production process (see for example Acaravci et al. 2012). This substitutability, however, does not hold in all instances.

In this framework, firms may invest in new capacity to produce with one input or another, increasing its relative proportion, which, given enough time, may then affect the relative prices of these inputs. Furthermore, in addition to changes in the relative prices of the inputs, (i) government regulation may limit the maximum quantity of an input that is permissible for a firm to use in its production process while (ii) consumers may have a strong preference for one input being used in the production process, and (iii) falling short of sustainability thresholds would limit the firm's ability to raise capital. However, these preceding considerations may be tempered by the fact that (iv) holding fast to incumbent production processes, which are geared toward dirty energy generation, require little, if any, capital investments. These facts would reasonably weigh on the decision-making of the firm's managers. For simplicity, we treat present and known regulation on taxes and limits to pollution as constraints faced by all firms.

The flexible microeconomic foundation thus developed allows for both incumbent dirty energy and clean energy firms, but we must now take a further step by putting clean energy firms at the center of our analysis. With this in mind, we take clean energy firms to be those energy producers who, of their own volition or through regulation, have restricted themselves to exclusively using clean energy sources for energy generation. However, this does not preclude spillovers between the two energy sources. This is because decreased demand for dirty energy sources, in favor of clean energy, would have the effect of generally reducing their prices. On the other hand, at least theoretically speaking, a fall in the prices of non-green energy commodities would make dirty energy producers more competitive. Moreover, any innovations in clean energy technologies, which reduce the prices of clean energy materials, would allow for decreases in clean energy prices.

We introduce geopolitical risk and climate policy uncertainty as *threats* to the system. As shown in Figure 4, these two phenomena may affect firms and the producers of clean energy materials/non-green energy commodities by sending signals that portend future outcomes. By "threats" we mean the risk that market conditions faced by firms and investors may change. This could be in a way that is fortuitous or ruinous. For example, clean energy producers may not enjoy the expected level of favor from regulation. In the case of geopolitical risk, the threat is more immediate and direct. That is, crucial inputs in the production process like crude oil may suddenly become unavailable or reduced in quantity by suppliers on the global stage. On account that the disturbances that cause these disruptions in financial and commodity markets may themselves birth other disturbances (prolonged warfare, protracted political impasses/trade wars); they can also act as threats. For example, the onset of the war in Ukraine increased the chance that energy commodities may be abruptly taken off the market. Therefore, in this way, even realized threats can give rise to other threats.

Figure 4: The framework



Note: Figure shows the associations among clean energy stocks, non-green energy commodities, climate policy uncertainty and geopolitical risk. These primary variables are shaded. Except where specified, the arrows represent signals. Source: Author's own compilation.

3.2.2 The market prices of clean energy stocks

Although the discussion taken up till now accounts for how (clean energy) firms behave in relation to non-green energy commodities and consumer preference for sustainable energy generation, it still does not account for the firm's stock. To make this leap, we appeal to investment theory. Specifically, we draw from the seminal work of Williams (1938) wherein he undertook an accounting of stock prices and stated that because no investor can be sure his estimate of the stock's fundamental value is correct, the current market price of stocks reflects today's opinion (or sentiment). Certainly, positive/negative news and the accompanying change in business outlook causes shifts in the demand curve for stocks. Where this demand curve is thought to come from a cumulative frequency of each stockholder's valuation of the price of a stock and the market price is the marginal valuation.

As Williams (1938)'s discussion clarifies, although fundamental value, which also entails the present value of dividends, is central to investors, there exists a separate group, given the moniker of speculators, for whom market sentiment, as well as how to anticipate it, instead of intrinsic value, is the foremost concern. This is incorporated in our framework. From Figure 4, we observe that investor sentiment is affected by climate policy uncertainty, geopolitical risk, the underlying business of the firm, any innovations in clean energy production, the prices of clean energy materials and non-green energy commodity prices. As the arrows in Figure 4 show, changes in climate policy uncertainty and geopolitical risk are taken as signals by investors/speculators. Furthermore, assuming there is no insider-information, stock market prices would respond to new information from official financial statements, company press releases and news media. That is, demand for companies' products or services over some period would be reflected in lower/higher sales and revenues. Certainly, clean energy stock prices may respond to news about changes in regulation and advancements in sustainable technologies, which would be consequential for investors. However, these prices may also react/overreact to more fleeting issues. This is less important for investors, whose horizon is long, but it is not a minor issue for speculators. This is because their horizon is exceedingly shorter than that of investors (Williams, 1938).

Although we have focused on investors who are currently holding or are prepared to buy energy companies' stocks if the market price falls below his/her valuation, this group is not limited to these individuals. That is, investors include those who are in possession of capital that could be deployed to fund energy generation projects. This includes institutional investors and other financial firms. Therefore, any firm seeking to expand will need to take the preferences of these potential investors into account if they are to be serious contenders for capital. This forms another channel through which investors may affect the prices of non-green energy commodities.

Moreover, as is apparent in Figure 4, clean energy stocks may themselves act as a proxy for innovation in clean energy technologies (a typical example is the development of two thin film solar modules by BP Solarex in 2000 that broke previous records) and movements in the prices of clean energy materials in addition to such things as market share and financial performance. This occurs because investors can observe movements in clean energy material prices and announcements of innovations in this industry. Given the nature of investor/speculator sentiment, clean energy stock prices may respond before these triumphs/failures are realized in terms of market share and financial performance.

Considering this, we may concisely describe the effect of climate policy uncertainty on clean energy stock prices in two statements. (i) Changes in climate policy uncertainty affect the expectations of investors and speculators with respect to business viability or profitability. Moreover, (ii) investors and speculators may feel strongly about ESG (on climate change) or are at least aware that other investors, speculators, and consumers have such preferences/beliefs. On the other hand, given the localized nature of clean energy (solar and wind, for example), the risk that crucial fossil fuels may not be supplied in sufficient quantities or simply withheld presents an opportunity for clean energy to fill the vacuum. These considerations constitute (new) information that is reflected in clean energy stock prices.

CHAPTER FOUR

METHODOLOGY

The present chapter describes the methodologies that are used in the study. That is, the TVP-VAR framework, the causality-in-quantiles technique, and the Quantile-on-Quantile regression approach. Each is explained in some detail.

4.1 Time-varying connectedness framework

To analyze the connectedness among fossil fuels and clean energy stocks, we employ Antonakakis et al. (2020)'s TVP-VAR framework. The technique improves the standard connectedness framework of Diebold and Yılmaz (2012, 2014) by allowing the variances to evolve across time. The TVP-VAR model is specified as below:

$$y_t = A_t z_{t-1} + \mu_t \ ; \ \mu_t \,|\Omega_{t-1} \sim N(0, \tau_t) \tag{1}$$

$$vec(A_t) = vec(A_{t-1}) + \gamma_t; \gamma_t |\, \Omega_{t-1} \sim N(0, \varepsilon_t) \tag{2}$$

Where y_t, z_{t-1}, and μ_t are $mx1$ vectors. Meanwhile, A_t and τ_t are mxm dimensional vectors. Moreover, $vec(A_{t-1})$ and γ_t are vectors of the form m^2x1. Lastly, ε_t is a m^2xm^2 dimensional vector. Antonakakis et al. (2020) use generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) to estimate dynamic connectedness. This is done by transforming the TVP-VAR to its vector moving average (VMA) form as shown below:

$$y_t = \sum_{j=0}^{\infty} B_{jt} \mu_{t-j} \tag{3}$$

Where B_{jt} is an mxm vector. The GIRFs characterize the reactions of all variables j after a shock in variable i. In lieu of a structural model, the differences between the H-step ahead forecast are computed. This is done twice. That is, where the variable experiences a shock and where it does not. We then designate as j the forecast horizon and ϑ_j is an $mx1$ vector which is equal to 1 in the jth position and 0 elsewhere. The GIRF, which is denoted by $\alpha_{ij,t}(H)$, is then specified as follows:

$$GIRF_t\left(H, \delta_{j,t}, \Omega_{t-1}\right) = E(y_{t+H} \mid \vartheta_j = \delta_{j,t}, \Omega_{t-1}) - E\left(y_{t+J} \mid \Omega_{t-1}\right) \tag{4}$$

$$\alpha_{ij,t}(H) = \frac{B_{H,t} \sum_t \vartheta_j}{\sqrt{\sum_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{\sum_{jj,t}}} \qquad \delta_{j,t} = \sqrt{\sum\nolimits_{jj,t}} \tag{5}$$

$$\alpha_{ij,t}(H) = \sum\nolimits_{jj,t}^{-\frac{1}{2}} B_{H,t} \sum\nolimits_t \vartheta_{j,t} \tag{6}$$

Furthermore, we compute the GFEVD ($\tilde{\rho}_{ij,t}\,(H)$) that entails the pairwise directional spillovers from j to i. That is, its influence on this variable in terms of forecast error variance share.

$$\tilde{\rho}_{ij,t}\,(H) = \frac{\sum_{t=1}^{H-1} \alpha_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \alpha_{ij,t}^2} \tag{7}$$

Where $\sum_{j=1}^{m} \tilde{\rho}_{ij,t}\,(H) = 1$ and $\sum_{i,j=1}^{m} \tilde{\rho}_{ij,t}\,(H) = m$. The denominator of Equation (7) characterizes the cumulative effect of all shocks while the numerator shows the cumulative effect of the shock in variable *i.* After, the total spillover index is derived through the GFEVD.

$$C_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\rho}_{ij,t}\,(H)}{\sum_{i,j=1}^{m} \tilde{\rho}_{ij,t}\,(H)} * 100 = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\rho}_{ij,t}\,(H)}{m} * 100 \tag{8}$$

Equation (8) captures how shocks in one variable spill over to other variables. Furthermore, we measure the total directional spillovers transmitted by variable *i* through Equation (9).

$$C_{i\rightarrow j,t}(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\rho}_{ji,t}\,(H)}{\sum_{i,j=1}^{m} \tilde{\rho}_{ji,t}\,(H)} * 100 \tag{9}$$

Meanwhile, the total directional spillovers received from other variables *j* by variable *i* are measured by Equation (10).

$$C_{i\leftarrow j,t}(H) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\rho}_{ij,t}\,(H)}{\sum_{i,j=1}^{m} \tilde{\rho}_{ij,t}\,(H)} * 100 \tag{10}$$

The difference between Equations (9) and (10) is the net total connectedness. If positive (negative), it means variable *i* is an overall net transmitter (receiver) of spillovers in the system. This is shown in Equation (11).

$$C_{i,t} = C_{i\rightarrow j,t}(H) - C_{i\leftarrow j,t}(H) \tag{11}$$

Meanwhile, the net pairwise directional connectedness (NPDC) is obtained in Equation (12). If the NPDC is positive, it means variable *i* dominates variable *j*. However, if it is negative, it means variable *i* is dominated by variable *j*.

$$NPDC_{ij}(H) = \left(\tilde{\rho}_{jit}\,(H) - \tilde{\rho}_{ijt}\,(H)\right) * 100 \tag{12}$$

4.2 Nonlinear causality-in-quantile technique

Recalling that our second and third objectives are to analyze the effect of CPU and GPR on the connectedness between fossil fuels and clean energy stocks, we apply the nonlinear causality methodology of Balcilar et al. (2016). This technique builds on the work of Jeong et al. (2012) and Nishiyama et al. (2011). The variable c_t (CPU or GPR) is designated as the predictor which does not cause the predicted variable a_t (in our case, intermarket spillovers) in the φth quantile considering $\{a_{t-1}, \dots, a_{t-w}, c_{t-1}, \dots, c_{t-w}\}$ if:

$$K_{\varphi}(a_t | a_{t-1}, \dots, a_{t-w}, c_{t-1}, \dots, c_{t-w}) = K_{\varphi}(a_t | a_{t-1}, \dots, a_{t-w}) \tag{13}$$

Where $K_{\varphi}(a_t | \cdot)$ is the φth quantile of a_t. While c_t causes a_t in the φth quantile if:

$$K_{\varphi}(a_t | a_{t-1}, \dots, a_{t-w}, c_{t-1}, \dots, c_{t-w}) \neq K_{\varphi}(a_t | a_{t-1}, \dots, a_{t-w}) \tag{14}$$

Where $U_t = (A_t, C_t)$ is the historical values of both the variables. Causality across quantiles is tested as follows:

$$H_0 = P\{F_{a_t | U_{t-1}}\{K_{\varphi}(A_t) | U_{t-1}\} = \varphi\} = 1 \tag{15}$$

$$H_1 = P\{F_{a_t | U_{t-1}}\{K_{\varphi}(A_t) | U_{t-1}\} = \varphi\} < 1 \tag{16}$$

Appealing to Nishiyama et al. (2011)'s nonlinear granger causality framework, Balcilar et al. (2016) develop second moment causality by expressing the following:

$$a_t = f(A_{t-1}) + \beta(C_{t-1})\mu_t \tag{17}$$

Where $f(\cdot)$ and $\beta(\cdot)$ are stationarity functions and μ_t is the white noise process. In the case where $\beta(\cdot)$ is a nonlinear function, the specification in Equation (17) can determine the predictive power from $C_{t-1}\ to\ a_t^2$. Thus, Equations (15) and (16) are re-formulated in Equations (18) and (19) to account for variance.

$$H_0 = P\left\{F_{a_t^2 | U_{t-1}}\{K_{\varphi}(A_t | U_{t-1})\} = \varphi\right\} = 1 \tag{18}$$

$$H_1 = P\left\{F_{a_t^2|U_{t-1}}\{K_\varphi(A_t|U_{t-1})\} = \varphi\right\} < 1, \tag{19}$$

Causality in higher order moments is explained by Balcilar et al. (2016) using the following model:

$$a_t = f(A_{t-1}, C_{t-1}) + \mu_t, \tag{20}$$

Therefore, the generalized quantile causality, which accounts for higher order moments, is given by:

$$H_0 = P\{F_{a_t^n|U_{t-1}}\{K_\varphi(A_t|U_{t-1})\} = \varphi\} = 1, \quad for\ n = 1,2,..,N, \tag{21}$$

$$H_1 = P\{F_{a_t^n|U_{t-1}}\{K_\varphi(A_t|U_{t-1})\} = \varphi\} < 1, \quad for\ n = 1,2,\dots,N. \tag{22}$$

Using Equation (21), we can create test statistics of the null for each n. In general, we can then test causality from c_t to a_t across quantiles (φ). Considering this, we test for the existence of causality from US CPU and GPR to intermarket spillovers. The bandwidth is selected using the SJ method.

4.3 Quantile-on-Quantile regression

To better understand the causality from CPU or GPR to the clean energy stock - fossil fuel nexus, we appeal to the Quantile-on-Quantile (QQ) regression technique of Sim and Zhou (2015). This technique enables us to examine the effects of different quantiles of one variable (say CPU) on different quantiles of another variable (intermarket spillovers). Considering this, we can unravel the connection between two variables in a way that other techniques, like the usual OLS, cannot. The QQ extends the usual Quantile regression (QR) method as follows:

$$CFS_t = \beta^{\theta}(CPU_t) + u_t^{\theta} \tag{23}$$

Where CFS_t represents intermarket spillovers between clean energy stocks and fossil fuels at time t and CPU_t represents climate policy uncertainty at time t. θ represents the quantiles of the conditional distribution of CFS. The QR approach in Equation (23) enables us to regress different quantiles of CFS on CPU. To develop the QQ, Sim and Zhou (2015) begin by specifying the first Taylor expansion around a quantile CPU^{τ}:

$$\beta^{\theta}(CPU_t) \approx \beta^{\theta}(CPU^{\tau}) + \beta^{\theta\,\prime}(CPU^{\tau})(CPU_t - CPU^{\tau}) \tag{24}$$

In Equation (24), $\beta^{\theta}(\cdot)$ is an unknown function of the usual quantile regression and the τth quantile of CPU is denoted by CPU^{τ}. $\beta^{\theta\,\prime}$ represents a partial derivative of $\beta^{\theta}(CPU^{\tau})$. Respectively, $\beta^{\theta}(CPU^{\tau})$ and $\beta^{\theta\prime}(CPU^{\tau})$ are respecified as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$ in Equation (25).

$$\beta^{\theta}(\theta, \tau) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(CPU_t - CPU^{\tau}) \tag{25}$$

Equation (25) is then substituted into Equation (23) to derive Equation (26). On account that indexes τ and θ are present in Equation (26), we are able to examine dependence across the quantiles of both CFS and CPU.

$$CFS_t = \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(CPU_t - CPU^{\tau}) + \mu_t^{\theta} \tag{26}$$

CPU_t *and* CPU^{τ} are replaced with $\widehat{CPU}_t$ *and* $\widehat{CPU}^{\tau}$, their empirical counterparts. We then obtain estimates of the parameters b_0 and b_1 through the following minimization problem:

$$\min_{b0,b1} \sum_{k=0}^{n} \rho_{\theta}\left[CFS_t - b_0 - b_1(\widehat{CPU}_t - \widehat{CPU}^{\tau})\right] K\left(\frac{F_n(\widehat{CPU}_t) - \tau}{h}\right) \tag{27}$$

Where:

$$F_n\left(\widehat{CPU}_t\right) = \frac{1}{n}\sum_{k=1}^{n}\left(\widehat{CPU}_k < \widehat{CPU}_t\right) \tag{28}$$

ρ_θ represents the quantile loss function. Observations are weighted in proximity of $\widehat{CPU}^\tau$ using the gaussian kernel denoted by $K(\cdot)$. We do this for the purpose of examining the local impact of CPU's τth quantile. Following Sim and Zhou (2015), we choose 0.05 as our bandwidth.

CHAPTER FIVE

EMPIRICAL DISCUSSION

This chapter examines the volatility spillovers among fossil fuels and clean energy stocks. Thereafter, we assess the effect of climate policy uncertainty and geopolitical risk on intermarket spillovers. Preceding this, we analyze the characteristics of the time-series data.

5.1 The data

To accomplish the objectives of this study, we select the WilderHill (ECO) index as our measure of the clean energy stock market. This series is sourced from BLOOMBERG. The ECO index includes solar, wind, electric vehicles, energy efficiency, smarter grids, and green hydrogen, among others. Furthermore, it is a modified equal-weight index. Among the various clean energy indices used in the literature, it is the most favored. Its foremost advantage is that it has the earliest date for which data is available when compared to the S&P Global Clean Energy Index (SPGTCED) and the European Renewable Energy Price Index (ERIXP). Pertinently, it is composed of stocks that are publicly traded in the United States. Certainly, several studies we have discussed in chapter two have based their analyses on the ECO index (see inter alia Ferrer et al. 2018; He et al., 2021; Choi et al., 2023). In addition, the fossil fuel spot prices are obtained from the United States Energy Information Administration (EIA). These data include WTI crude oil, Brent crude oil, New York Harbor gasoline, U.S. Gulf Coast gasoline, Los Angeles Diesel, New York Harbor Heating oil, Propane, Gulf Coast Jet fuel and Henry Hub Natural gas. Except for crude oil (both WTI and Brent), which is priced in USD per Barrel, the petroleum fuels are priced in USD per Gallon. Natural gas is priced in USD per million Btu. The study also employs the U.S. climate policy uncertainty (US CPU) and geopolitical risk (GPR) indices to consider their effect on the intermarket spillovers among the fossil fuels and clean energy stocks. While the US CPU index was created by Gavriilidis (2021), the GPR index was constructed by Caldara and Iacoviello (2022). These indices are obtained from www.policyuncertainty.com. Monthly data covering the period between 12/2000 and 08/2023 is selected as the subject of our analysis. This period is chosen on careful consideration of the beginning date of the ECO index, the end date of the US CPU index, and the frequency of the US CPU and GPR indices.

5.2 Preliminary analysis

We derive returns (r_t) by differencing the natural log of the price level (P_t) and multiplying it by 100. This is done for all the variables.

$$r_t = (\Delta ln P_t) \times 100$$

The results in Table 1 show that, except for the ECO index and Propane, all the series have positive average returns. We also find that, excepting GPR, the rest of the return series have a greater minimum value than maximum value when considered in absolute terms. While Heating oil has the lowest standard deviation (9.1310), US CPU has the highest standard deviation (37.5667). In addition to having, respectively, the highest and second highest standard deviations, we also observe that the US CPU and GPR indices each have the greatest distance between their minimum and maximum return values. This is an indication that climate policy uncertainty and geopolitical risk have fluctuated greatly.

Recalling that a skewness value of zero and kurtosis value of 3 would indicate normality, from Table 1 we find evidence of non-normality among the series. Excepting GPR, which is left skewed, the rest of the series are right skewed. We also observe that all the series are leptokurtic given that the kurtosis values of all the series exceed 3. As a supplementary measure of normality, these results are confirmed by the observation that all the Jarque-Bera (JB) test statistics are significantly much greater than 0. This is strong evidence against the assumption of normality among all the series. Moreover, given the importance of ensuring stationarity prior to performing econometric analyses, we provide unit root test results in Table 2. We employ the Augmented Dickey-Fuller and Phillips-Perron unit root tests. Expectedly, given the nature of returns, we find that all the variables are integrated of order 0. That is, they are stationary without differencing.

Table 1: Descriptive statistics

Variable	Mean	Median	Min.	Max.	Std. Dev.	Skewness	Kurtosis	Jacque-Bera	Obs.
ECO WilderHill	-0.342	0.140	-38.657	36.931	10.256	-0.367	4.096	19.721***	272
WTI crude oil	0.387	1.579	-56.813	54.562	10.461	-0.943	10.978	761.630***	272
Brent crude oil	0.445	1.947	-55.479	46.905	10.576	-1.132	9.375	518.588***	272
NY gasoline	0.500	1.172	-57.284	39.017	11.068	-1.043	6.928	224.149***	272
GC gasoline	0.513	1.549	-56.361	41.881	12.064	-0.953	6.808	205.537***	272
Diesel	0.433	1.971	-43.460	26.042	9.858	-0.736	4.710	57.691***	272
Heating oil	0.418	1.078	-31.814	28.375	9.131	-0.477	4.266	28.471***	272
Propane	-0.049	1.101	-38.125	29.272	11.126	-0.563	3.734	20.445***	272
Jet fuel	0.457	1.566	-45.959	35.973	10.213	-1.063	6.666	203.502***	272
US CPU	0.309	-0.385	-170.138	123.268	37.567	-0.234	4.183	18.343***	272
GPR	0.309	-0.575	-60.009	205.130	22.641	2.831	26.940	6858.826***	272

Source: Author's computation.

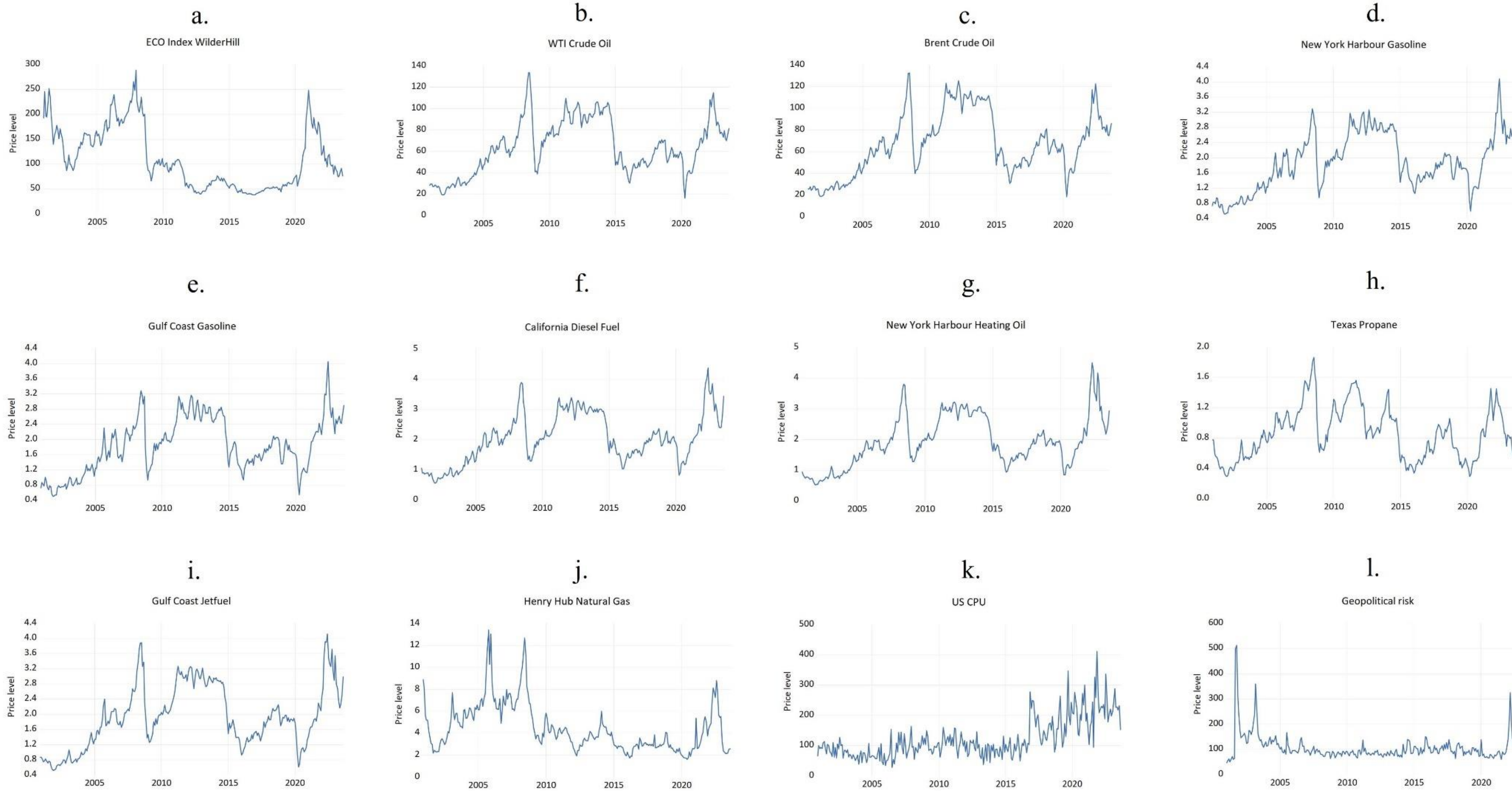
Table 2: Unit root tests

Variable	Augmented Dickey Fuller (ADF) test	Phillips Perron (PP) test	Order of integration
ECO WilderHill	-15.605***	-15.636***	I(0)
WTI crude oil	-12.359***	-11.860***	I(0)
Brent crude oil	-12.540***	-12.081***	I(0)
NY gasoline	-12.488***	-12.186***	I(0)
GC gasoline	-12.255***	-12.752***	I(0)
Diesel	-12.827***	-12.519***	I(0)
Heating oil	-12.346***	-12.238***	I(0)
Propane	-12.656***	-12.532***	I(0)
Jet fuel	-12.641***	-12.395***	I(0)
Natural gas	-11.116***	-94.553***	I(0)
US CPU	-12.173***	-23.033***	I(0)
GPR	-15.605***	-15.636***	I(0)

Note: The null hypothesis is that of a unit root. Source: Author's computation.

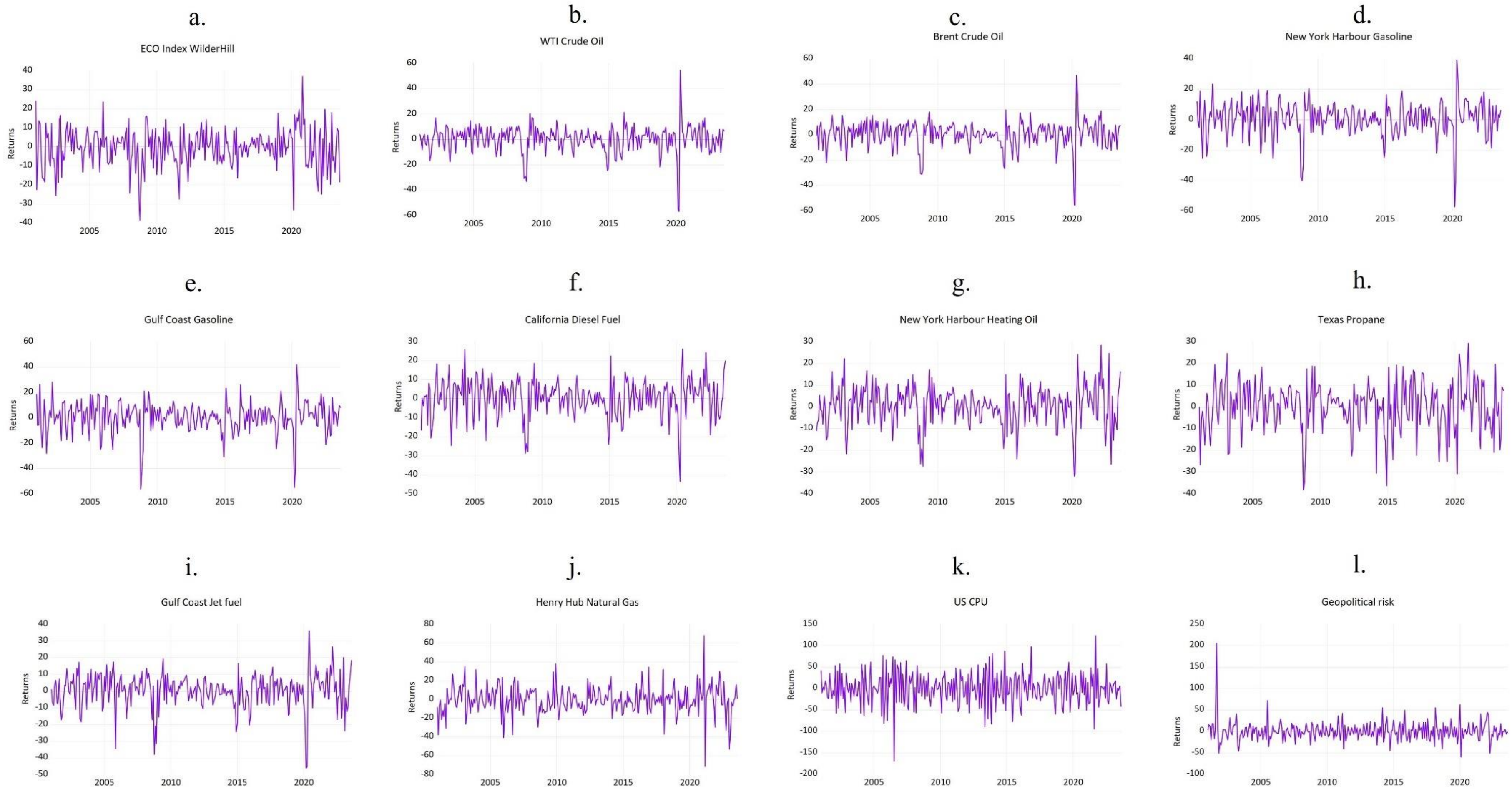
To better understand the evolutions of the series, we turn to Figures 5 and 6. From an analysis of Figure 5, we see that the price levels of the ECO index and the fossil fuels have two prominent peaks around the 2007/2008 and another around 2022. The earlier peak coincides with the period immediately before the global financial market crash. Meanwhile, the later peak coincides with the Russia-Ukraine war. We also see that the fossil fuel prices fell sharply amid the global financial crisis and around March 2020. This is corroborated by the wide swings in returns around these periods as shown in Figure 6. Certainly, following lockdowns and travel restrictions, the WTI crude oil price turned negative on 20 April 2020. As Chen et al. (2023) point out, while the COVID-19 pandemic and the ensuing lockdown caused a reduction in demand for commodities, at the same time, storage costs were high. Therefore, with limited demand, transportation costs rose. This was the case for many fossil fuels over the COVID-19 period.

Figure 5: Series price levels



Note: Figure shows series price levels between 12/2000 and 08/2023. Source: Author's compilation.

Figure 6: Series returns



Note: Figure shows series returns between 12/2000 and 08/2023. Source: Author's compilation.

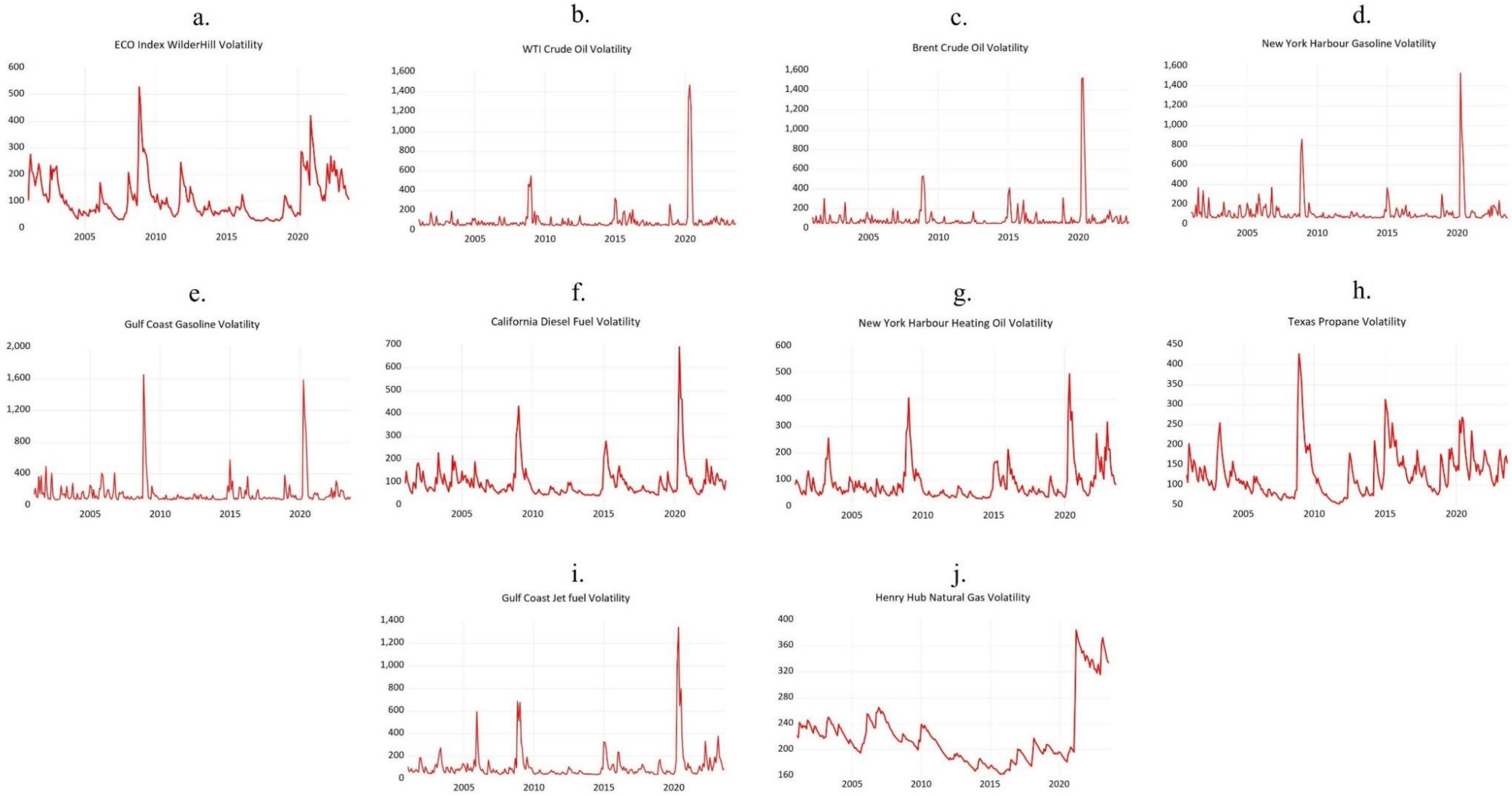
While the prices of the fossil fuels plummeted around 2015/16 from weak demand, the ECO index did not experience the same decline during this period. Admittedly, the ECO index was already at a relative nadir during the 2015/16 period. Interestingly, we observe that both clean energy stocks and the fossil fuels rise sharply in the period after the start of the Russia-Ukraine war. While the rise in the prices of fossil fuels can be attributed to the disruption in the supply of energy commodities amid the political fallout from the conflict, things are a little more complex for clean energy stocks. Drawing on the discussion in section 3.2 (Analytical framework), we propose that as chaos spread among the fossil fuel markets, clean energy alternatives were well-placed to replace some of these non-green commodities (at least according to market sentiment).

As we shift our attention to the US CPU and GPR indices, we immediately observe that these series are starkly different from the ECO index and fossil fuels. For example, looking at the US CPU index in Figure 5 (k), we observe several peaks that coincide with notable events. The earliest of these is the June 2006 statement by the then U.S. president George W. Bush. Another is the Environmental Protection Agency (EPA) emissions legislation in December 2007. Interestingly, we also see that the UN Climate Change Conference in December 2009 causes a sizable rise in the index. Another peak coincides with the rejection of the Keystone XL pipeline in November 2015. Given our previous discussion on regulation being constraints, it may happen that firms may try to circumvent such constraints, which may lead to punitive measures being exacted on the firm. For example, the US CPU index rises around January 2017 when Volkswagen AG pled guilty to the EPA for cheating emissions tests. On the political front, we observe that U.S. disengagement from the Paris Climate Accord in June 2017 led to a rise in the US CPU index. Furthermore, we see a great peak in the US CPU index that coincides with the UN Climate Action Summit in September 2019.

More recently, we observe three large spikes in the index. The earlier spike coincides with the Trump administration's rejection of a new emission rule in April 2020. Meanwhile, the second coincides with the enactment of the EPA new greenhouse gas emission standards in December 2020. However, we observe that the US CPU index reached its greatest extent around November 2021, a period that coincides with, among other events, the US Climate Action Plan. Furthermore, for the GPR index as shown in Figure 5 (l), we see three large peaks. The first and the largest is the 9/11 terror attacks in 2001 which was then subsequently followed by war in Iraq. The least of these and the most recent spike was the war in Ukraine.

Although the prices and returns presented in Figures 5 and 6 provide important information for understanding the evolutions of these variables, it is market volatility that is at the center of our concern. Following Ferrer et al. (2018), we generate volatility series from the variables using a univariate conditional volatility model. In this endeavor, we appeal to the standard GARCH (1,1) process. The graphs of these volatility series are presented in Figure 7. Expectedly, we see several large spikes in volatility across the series. This ranges from the 9/11 attacks, the Iraq war, the GFC, the 2015/16 period, COVID-19, and the war in Ukraine. Strikingly, we see that the evolution of natural gas' volatility differs greatly from petroleum. Specifically, unlike most of the other fossil fuels, natural gas' volatility reaches its greatest extent at the onset of the Russia-Ukraine war.

Figure 7: Series volatility



Note: Figure shows series volatility between 12/2000 and 08/2023. Generated using a univariate conditional volatility model. The vertical axis indicates the relative magnitude of a variable's volatility over the entire period. Source: Author's compilation.

5.3 TVP-VAR analysis

As our starting point, we analyze the volatility spillovers among fossil fuels and clean energy stocks using the TVP-VAR of Antonakakis et al. (2020). The next section focuses on static connectedness and is then followed by a section on the dynamic spillovers among fossil fuels and clean energy stocks between 12/2000 and 08/2023. As a preliminary step, we perform the necessary unit root tests on the volatility series. These results are in the appendix.

5.3.1 Average connectedness

To uncover the nature of connectedness among fossil fuels and clean energy stocks, we begin with the average spillovers among them. Table 3 shows that the static Total Connectedness Index (TCI) is 74.4%. This shows that the network of variables can explain the greater part of their volatility evolutions. Despite this high total connectedness, we can observe that clean energy stocks have a relatively weaker connectedness with the fossil fuels. By this we mean that the volatility connectedness among fossil fuels, specifically petroleum (crude oil, diesel etc.), is stronger. As shown in Table 3, the forecast error variance contribution of clean energy stocks to others is 40.4%. while the spillovers it receives sum up to 64%. This is markedly lower than those among petroleum. Certainly, WTI crude oil, Brent crude oil, NY gasoline, GC gasoline, diesel, heating oil, and jet fuel transmit spillovers well above 80%. Similarly, all the petroleum fuels (incl. propane) receive spillovers above 76%. However, there are some exceptions. For example, propane only transmits 49.7% to the system. Interestingly, despite its sizable contribution to the U.S. primary energy mix, natural gas's share of forecast error variance to other variables is only 1.4% while it receives 34.9%. This clearly demonstrates the dominance of the petroleum market. Expectedly, we observe that clean energy stocks, propane, and natural gas are net receivers. Indeed, clean energy stocks and propane are dominated (that is, they receive more than they transmit) by 7 and 8 other assets/commodities, respectively. Worse yet, natural gas is dominated by all the other assets/commodities.

The observation that the clean energy stock market is a net-receiver of shocks from almost all the fossil fuels may be an indication that despite the present push towards renewable energy, the entrenched place of dirty energy sources ensures that they may not be dislodged soon. That is, the events in the fossil fuel market still dominate those in the clean energy market. Moreover, the lower degree of connectedness between this asset class and its non-green alternatives in comparison to the spillovers among the fossil fuels provides evidence that these markets are not yet fully in competition. We may conclude that there is only a partial connection because of the deep roots of non-green energy commodities and the lack of ubiquitous green alternatives to compete with some fossil fuels.

Table 3: Static connectedness

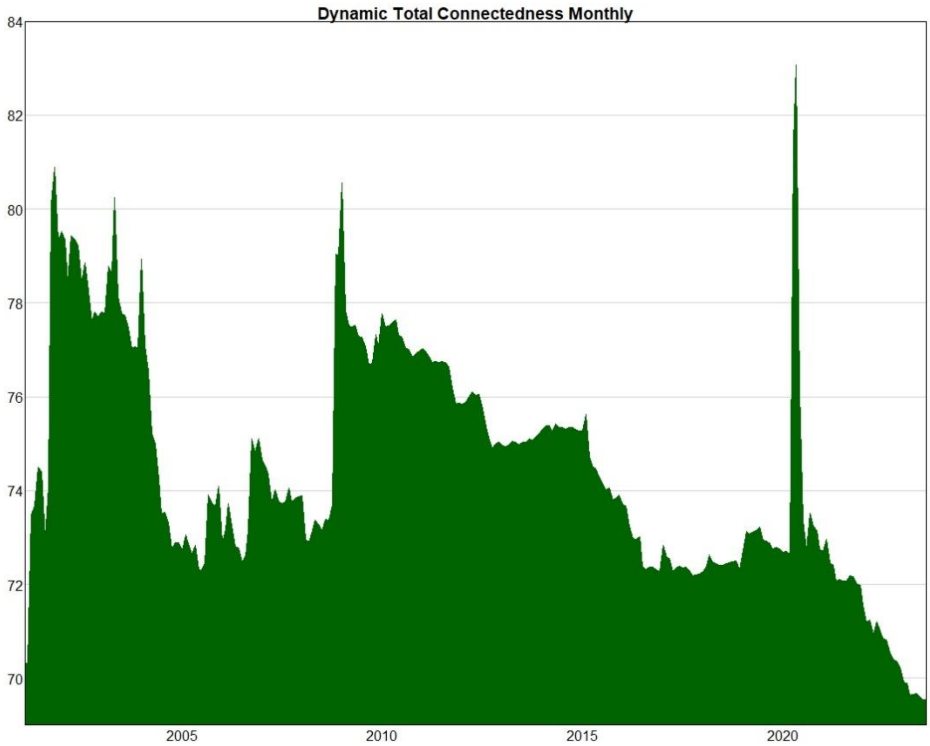
	ECO	WTI	BRNT	NGLN	GGLN	DSL	HOI	PRP	JETF	NATG	FROM
ECO	**36**	6.9	7.4	6.2	7.6	9.3	11.1	4.5	10.6	0.4	64
WTI	3.1	**19.3**	18	13.5	11.4	9.7	9	4.4	11.5	0	80.7
BRNT	2.9	17.1	**18.8**	13.9	11.9	10	9.1	4.6	11.7	0.1	81.2
NGLN	3.9	13	14.4	**19.3**	17	9	7.8	5.4	10.4	0	80.7
GGLN	5.1	11.4	13	17	**20.4**	8.5	7.4	5.8	11.4	0	79.6
DSL	4.2	11	12.4	11.9	10.8	**16.9**	12.2	7.5	12.9	0	83.1
HOI	5.7	10.7	11.8	9.7	9.1	13.5	**18**	7.6	13.6	0.1	82
PRP	6.7	8.3	9	9.3	11	10.3	11.3	**23.9**	9.6	0.5	76.1
JETF	4.3	11.4	12.5	11.7	12.4	12.1	11.9	5.7	**17.9**	0.1	82.1
NATG	4.5	4	3.9	3.4	2.5	4.1	4.1	4.2	4.1	**65.1**	34.9
TO	40.4	93.8	102.6	96.7	93.8	86.5	83.9	49.7	95.8	1.4	744.5
NET	-23.7	13.2	21.4	16	14.2	3.4	1.9	-26.5	13.7	-33.5	TCI
NPDC	7	4	0	1	2	5	6	8	3	9	**74.4**

Note: NPDC represents net pairwise directional connectedness, which shows how many other variables dominate a particular variable. Source: Author's computation.

5.3.2 Dynamic connectedness

We now appeal to dynamic analysis to assess intermarket connectedness across time. From Figure 8, we see that total connectedness reached its greatest extent during the COVID-19 pandemic. This corroborates Tiwari et al. (2021)'s finding that connectedness among green financial markets was greatest during this period. Although the rise in connectedness did not last long, it occurred during a period of chaos in commodity markets caused by swift quarantine measures put in place in response to the pandemic. Beyond this, we see two other prominent jumps in connectedness. The more recent of these two, the global financial crisis, is also followed by a period of relatively strong spillovers among energy commodities and clean energy stocks. These results also are consistent with those of Coskun and Taspinar (2022) who found that the connectedness between fossil fuels and Turkish energy stocks was stronger during COVID-19 than during the GFC. The other period, which coincides with the 9/11 terrorist attacks and the Iraq war, shows a formidable level of connectedness.

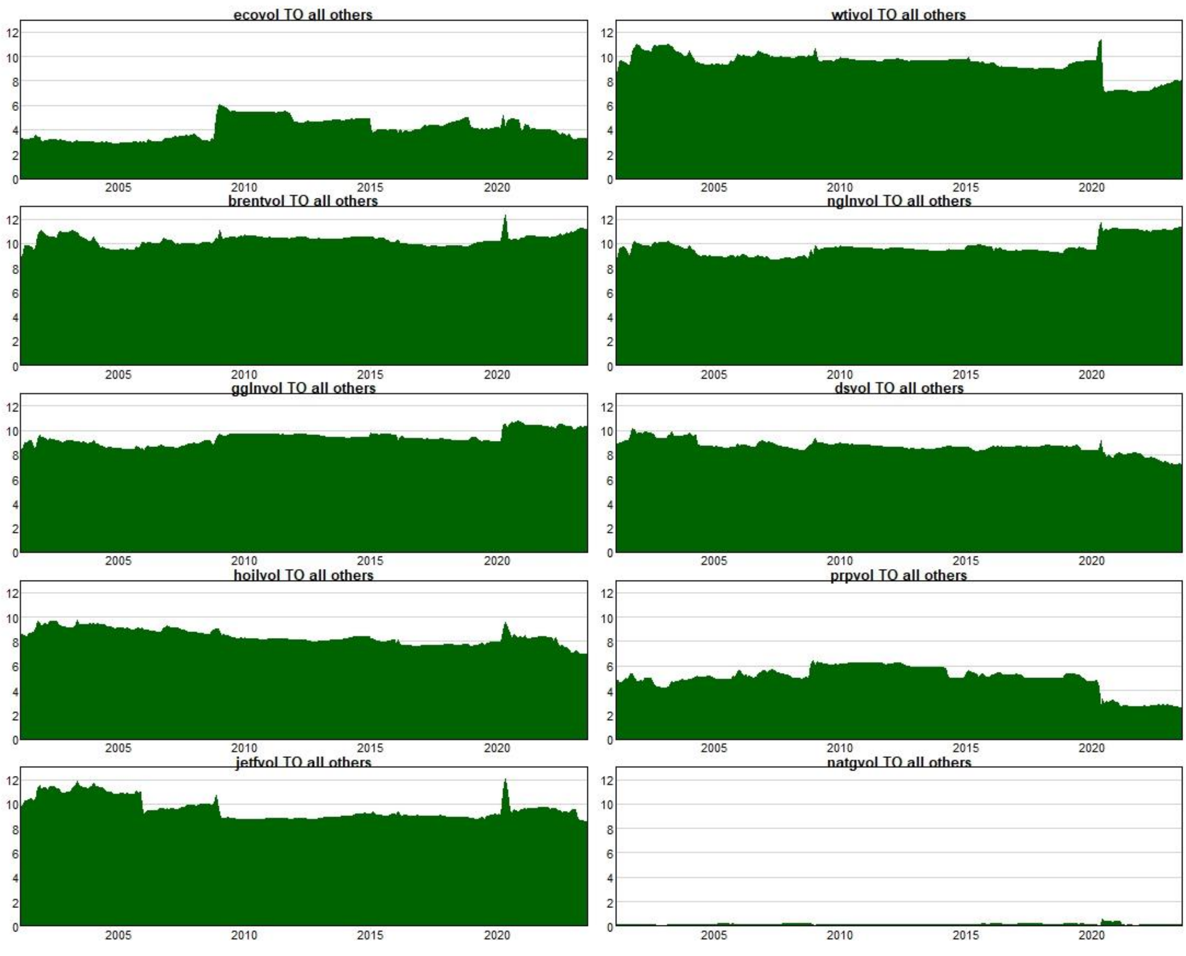
Figure 8: Dynamic Total Connectedness



Note: The shaded area represents joint connectedness. The results are generated by a TVP-VAR model and a 10-step ahead forecast. Source: Author's computation.

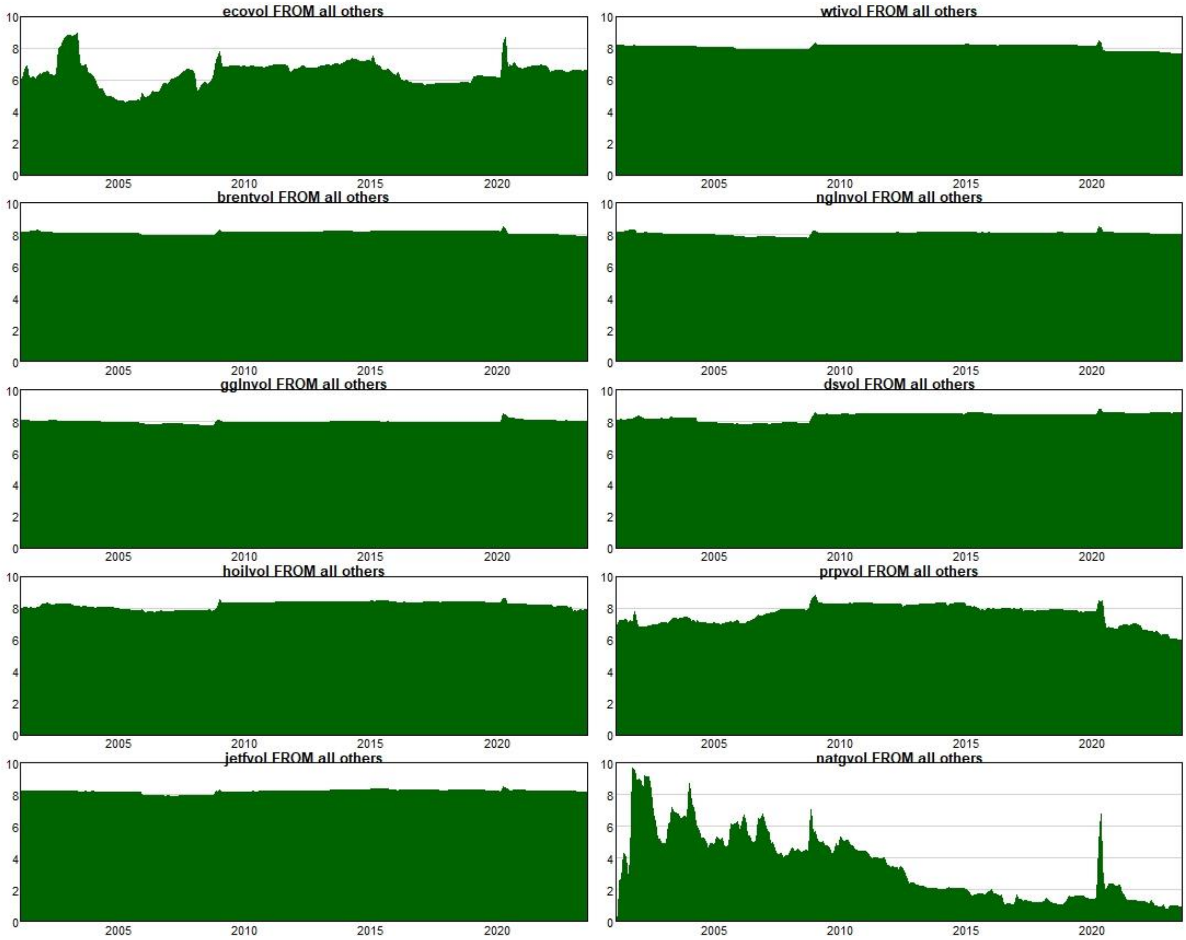
To better understand the transmitter/receiver roles of each of the variables in our network, we look to the Figures 9 and 10. We find that the relatively lower spillovers transmitted by clean energy stocks and propane we found in the static analysis in section 5.3.1 are uniformly observed across the entire sample period. Similarly, natural gas's 1.4% average spillovers transmitted translate into virtually no spillovers from this energy commodity across the entire period. Conversely, the spillovers natural gas receives are more concentrated in periods that are closest to the 9/11 terrorist attacks and the war in Iraq, with a comparatively small spike during the COVID-19 pandemic. Adding context to Table 3, Figures 9 and 10 further demonstrate the dominance of petroleum over the whole period. Consistent with what we observed in Figure 5, WTI and Brent crude oil have had very similar spillover evolutions across the period. There is however a divergence after the COVID-19 pandemic as we see in Figure 11. That is, while Brent crude maintains its net transmitter role, WTI crude takes the role of net receiver around March 2020. It is also apparent that while clean energy stocks, propane and natural gas are consistent net receivers of spillovers, diesel's role varies. In the earlier (later) half of the sample period, diesel is a net transmitter (receiver) of spillovers. Lastly, from the pairwise connectedness in Figure 12, we see that clean energy stocks are net transmitters to propane and natural gas. This is consistent with the results presented in Table 3, where clean energy stocks are dominated by 7 other variables.

Figure 9: Spillovers TO others



Note: Green shaded area represents spillovers TO other variables. Based on a 10-step ahead forecast. Source: Author's computation

Figure 10: Spillovers FROM others

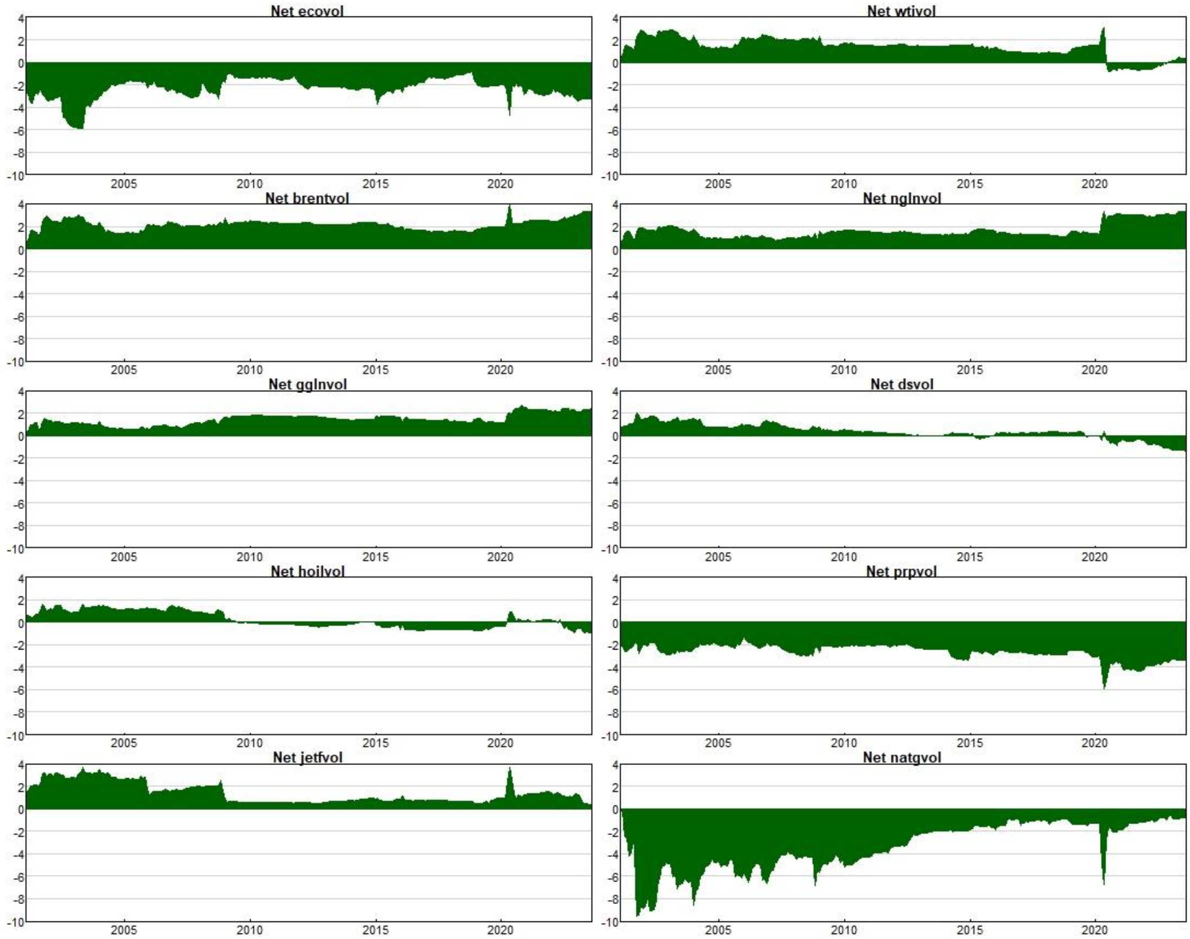


Note: Green shaded area represents spillovers FROM other variables. Based on a 10-step ahead forecast.

Source: Author's computation.

The results in Table 3 as well as Figures 8 and 9 contrast with those of Qi et al. (2022) as they observed greater spillovers to and from the clean energy stock market in relation to fossil fuels. However, it is important to note that Qi et al. (2022) focused on the Chinese economy and the variables in their study differ somewhat from ours. Specifically, we use a composite clean energy stock index whereas they disaggregated the sector into photovoltaic, wind and nuclear. Moreover, the fossil fuels that were considered in their study, except for coal, are less extensive than the present study.

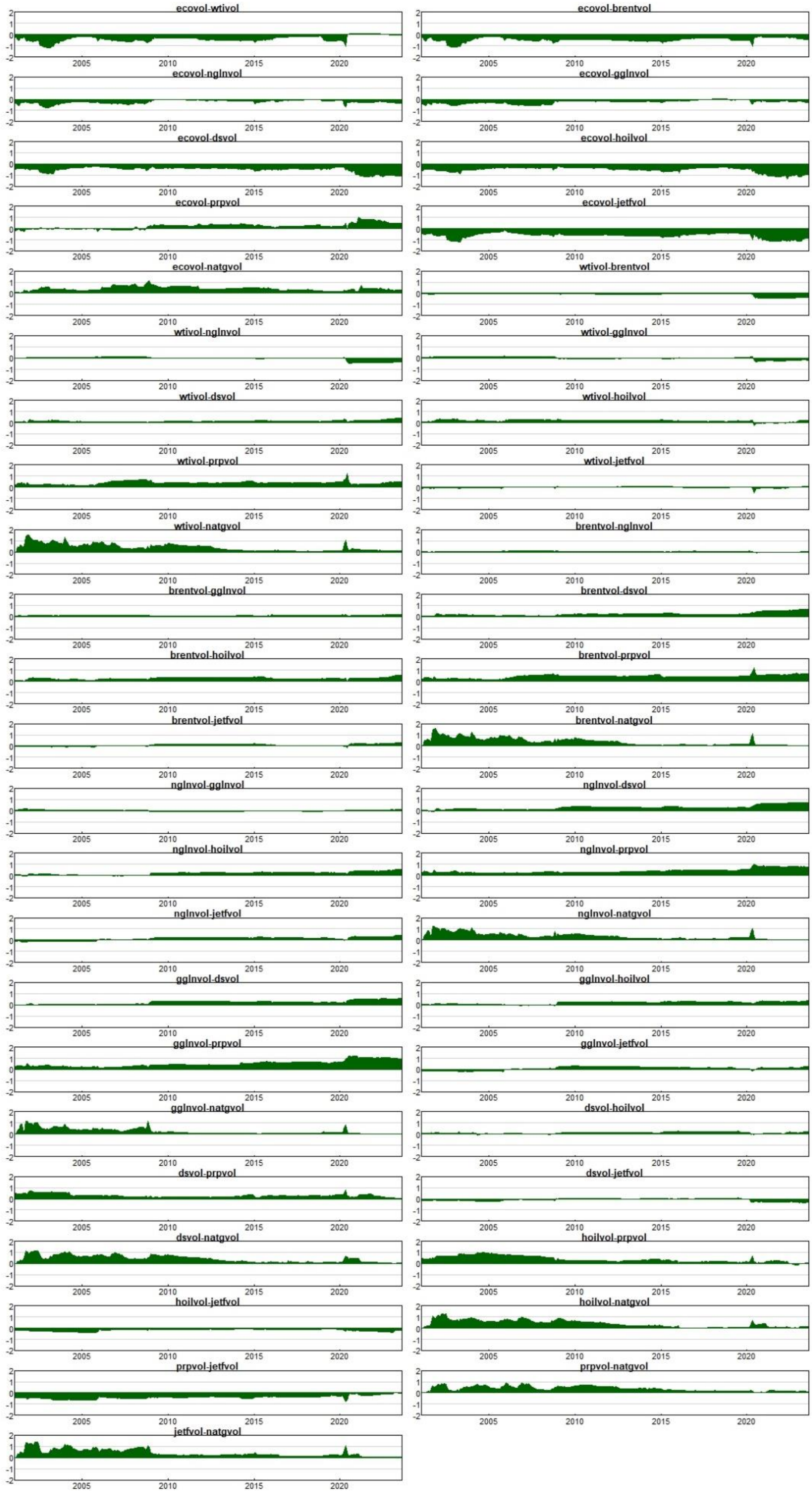
Figure 11: Dynamic Net Connectedness



Note: Green shaded area represents net connectedness. Based on a 10-step ahead forecast. Source: Author's computation.

In contrast to Figure 12 where we observe that the ECO index (clean energy stocks) is a net receiver of volatility spillovers from WTI crude during the GFC, Ferrer et al. (2018) found that the ECO index was a net transmitter during this period. However, we submit that this seeming contradiction may be on account that the present study uses WTI spot prices whereas Ferrer et al. (2018) used WTI futures prices. Similarly, using fossil fuel futures prices, Umar et al. (2021) concluded that there was weak volatility connectedness among these commodities and clean energy stocks. This is contrary to section 5.3.1 and Figure 8, where we find that the network explains the greater part of the volatility evolutions among these markets.

Figure 12: Net Pairwise Pairwise Connectedness

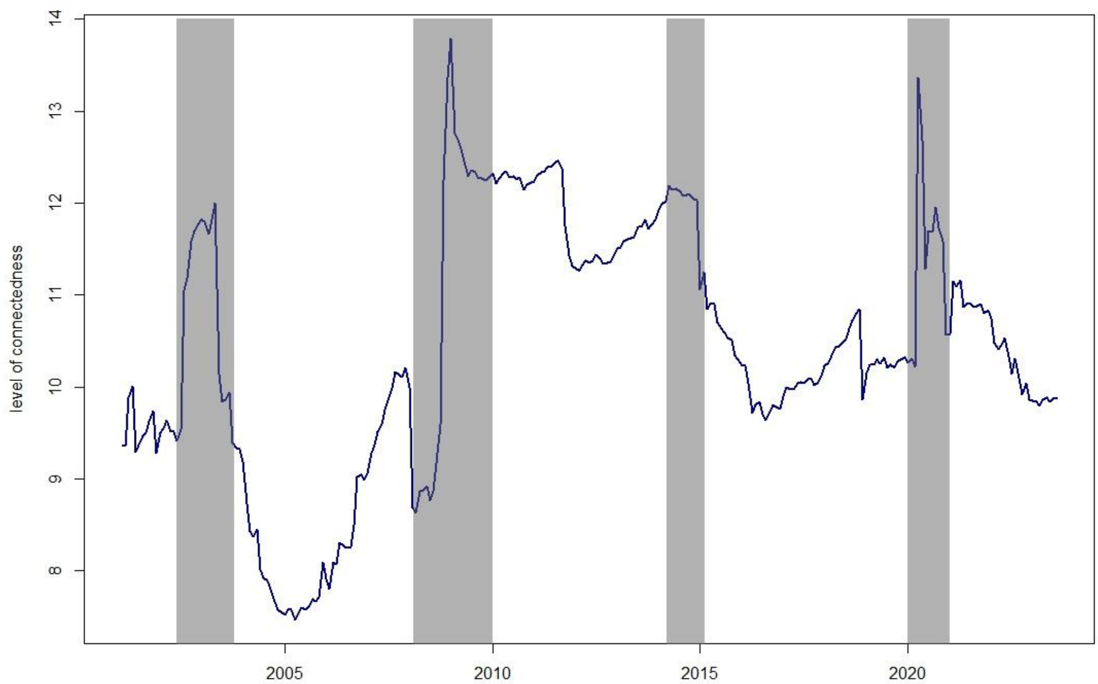


Note: Figure shows net pairwise spillovers from the net result of TO minus FROM spillovers. Based on a 10-step ahead forecast. Source: Author's computation.

5.4 The Role of US Climate policy uncertainty & Geopolitical risk

In this section, we proceed to assess the impact of climate policy uncertainty and geopolitical risk on intermarket spillovers. Recalling that the concern of the present study has centered on the connection between fossil fuels and clean energy stocks, we focus on clean energy stock - fossil fuel intermarket spillovers. By this we mean the summation of the ECO "TO" spillovers and the ECO "FROM" spillovers. The series thus obtained is shown in Figure 13.

Figure 13: Total spillovers between ECO index and Fossil Fuels



Note: The figure shows the summation of the ECO "TO" spillovers and ECO "FROM" spillovers. Based on a 10-step ahead forecast. Source: Author's computation.

In Figure 13, we see that there are four notable peaks in volatility connectedness. These periods are highlighted in grey. The first coincides with the war in Iraq, the second with the onset of the global financial crisis, the third with the period before the commodity price crash around 2015/16 and the fourth with the COVID-19 pandemic. Interestingly, the peak around the Iraq war begins its ascent before the initiation of the conflict in March 2003. Certainly, the premature rise in connectedness is consistent with key moments preceding the conflict. Among these is the passing of a resolution permitting the use of military force against Iraq by the U.S. Congress in 2002. Although we still observe the same general evolution for the clean energy stock - fossil fuel intermarket spillovers (CFIS) as we found for the total spillovers among all the variables, there are some differences. The most obvious is that the peak around the COVID-19 period is now much less prominent than the one observed during the GFC. This is not surprising given the way these intermarket spillovers have been calculated. The consequence of this is that the ECO index is given greater weight as the "TO" spillovers of the fossil fuels, at least those not directed at the ECO index, are not included. Before proceeding with further analyses, we assess the stationarity properties of the intermarket spillovers. The series is stationary after differencing. These results are relegated to the appendix in Table A2.

As a precondition for analyzing the effects of US CPU and GPR on these spillovers, we perform the BDS test of Broock et al. (1996) to test for nonlinearity in the CFIS time-series data. If the null of linearity does not hold, linear models will be weak to produce reliable results. Certainly, as is evident in Table 4, the null of linearity in the series is rejected. We are therefore justified in appealing to the causality-in-quantiles technique.

Table 4: BDS test results

Variable	2	3	4	5	6
CFIS	0.040***	0.078***	0.105***	0.118***	0.121***

*Note: Table reports BDS statistics. *** represents significance at 1%. Numbers 2 to 6 represent dimensions. Source: Author's computation.*

From Figure 14, we see that both US CPU and GPR have a significant impact across the quantiles of the intermarket spillovers. Specifically, except for the highest quantile, US CPU is particularly potent across the entire spectrum of quantiles. Meanwhile, GPR is significant across most quantiles except for the two highest quantiles. This is evidence that these phenomena have a non-trivial effect on clean energy stock and fossil fuel intermarket connectedness.

Table 5: Causality-in-quantiles test statistics

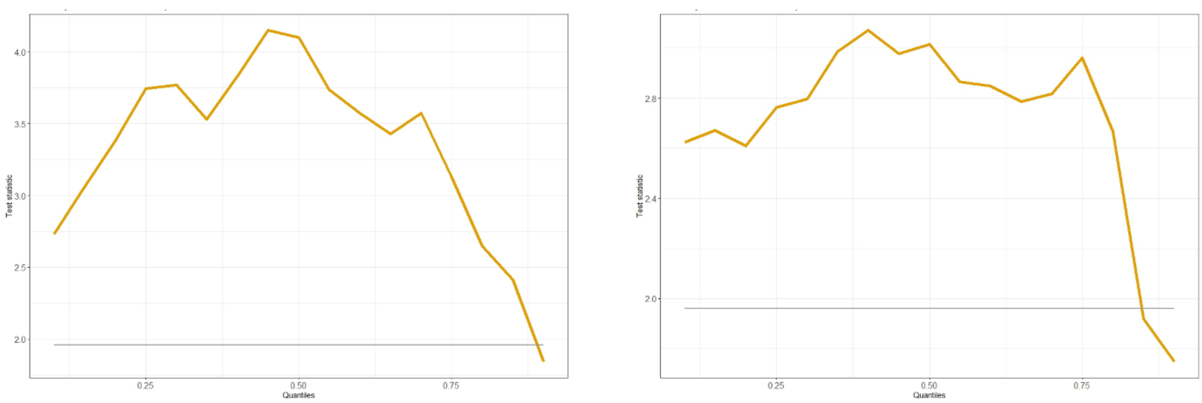
Quantile	US CPU	GPR
0.1	2.730*	2.623*
0.15	3.058*	2.672*
0.2	3.377*	2.610*
0.25	3.744*	2.763*
0.3	3.769*	2.796*
0.35	3.530*	2.986*
0.4	3.829*	3.071*
0.45	4.147*	2.979*
0.5	4.098*	3.016*
0.55	3.734*	2.866*
0.6	3.572*	2.849*
0.65	3.428*	2.786*
0.7	3.573*	2.817*
0.75	3.129*	2.960*
0.8	2.649*	2.669*
0.85	2.413*	1.918
0.9	1.846	1.748

*Note: Table reports test statistics across the quantiles of the ECO total spillovers. * entails significance at 10%. Source: Author's computation.*

Figure 14: Causality-in-quantiles

a. CFIS & US CPU

b. CFIS & GPR

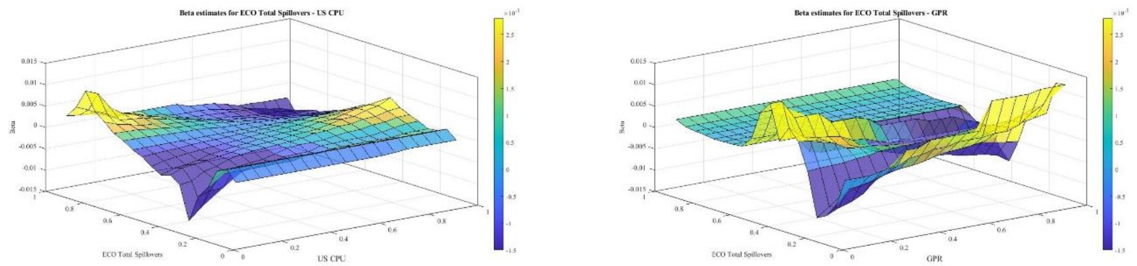


Note: The dependent variable is clean energy stock - fossil fuel intermarket spillovers (CFIS). US CPU/GPR is the independent variable. Bandwidth is selected using SJ. Source: Author's computation.

Although the causality-in-quantiles results showed us that US CPU and GPR had a significant causal impact on the clean energy stock - fossil fuel intermarket spillovers, we do not know much else. Therefore, we employ the Quantile-on-Quantile regression technique to better understand the nature of this causal impact. On account that we have made modifications to both the intermarket spillovers and the US CPU and GPR indices, care should be taken while interpreting the results in Figure 15.

Figure 15: Quantile-on-quantile regression

a. US CPU b. GPR



Note: Figure shows the relationship between two variables across each of their distributions. ECO total spillovers are the dependent variable. US CPU/GPR is the independent variable. Source: Author's computation.

Immediately we see a very complex relationship between CFIS and US CPU as well as CFIS and GPR. Given that the intermarket spillovers have been differenced and the US CPU and GPR indices have been transformed into returns, the lower (upper) quantiles of both the dependent and independent variables are generally negative (positive) values. That is, the differenced CFIS series is to be taken as fluctuations in the intermarket spillovers among clean energy stocks and fossil fuels. Likewise, the US CPU and GPR values represent percentage changes in the series.

In Figure 15 (a), we observe that when the intermarket spillovers are in their low quantiles and US CPU is in its higher quantiles, US CPU has a positive effect on the intermarket spillovers. This positive effect is also evident when the intermarket spillovers are in their highest quantiles and US CPU is in its lowest quantiles. Conversely, we find a negative relationship when both the intermarket spillovers and US CPU are in the low or high quantiles. This means that when intermarket spillovers and US CPU are both experiencing negative or positive changes, US CPU will generally reduce the level of connectedness among clean energy stocks and fossil fuels. Meanwhile, when intermarket spillovers are already experiencing high positive changes, negative shifts in US CPU will increase these spillovers. So too, if this connectedness is already falling, high positive changes in US CPU will increase the intermarket spillovers.

Meanwhile, in Figure 15 (b), we see a markedly different quantile association between intermarket spillovers and GPR. When intermarket spillovers are in their lowest quantiles and GPR is in its highest quantiles, GPR has a positive impact on intermarket spillovers. Moreover, a positive effect is also observed around the median quantiles of the intermarket spillovers when GPR is in its lower quantiles. Strikingly, we see a negative effect when both indices are in their lowest quantiles. Unlike the complex relationship we observe when intermarket spillovers are in the lower quantiles (0.05 to 0.5), there is a uniformly positive effect from GPR when intermarket spillovers are in their upper quantiles (0.5 to 0.95). However, it is worth noting that this impact is of much lower magnitude. These results entail that the association between intermarket spillovers and GPR depends on whether one or both is rising/falling.

Overall, it is evident from the preceding discussion that the effects of climate policy uncertainty and geopolitical risk on the clean energy stock - fossil fuel spillover nexus are not only significant, but they are also heterogeneous. That is, for the associations among these variables, it matters whether the magnitude of their movements is historically high or low. For example, we are likely to observe a special association between intermarket spillovers and US CPU during the global financial crisis, when the former was rising sharply and the latter's increase was relatively small, as compared to another period. Admittedly, there are other factors at work that affect the connectedness among fossil fuel markets and clean energy stocks (in terms of volatility spillovers) beyond what is under the purview of this study. Notwithstanding, from an analysis of Figure 13, we conclude that disruptions in demand and supply of energy commodities have an especially potent effect on the connectedness among fossil fuels and clean energy stocks.

CHAPTER SIX

CONCLUSION

6.1 Summary of findings and implications for policy

Driven by the observation that the energy sources underlying clean energy stocks are in competition with incumbent fossil fuels, the study sought to assess the volatility connectedness among these markets. Building on this foundation, the study made two contributions. First, the study developed a framework that more fully accounts for the links among non-green energy commodities and clean energy stocks. Second, and more pertinently, we examined the impact of climate policy uncertainty and geopolitical risk on the volatility spillovers between clean energy stocks and fossil fuels.

Employing a TVP-VAR methodology, the study arrives at some important findings. First, on average, clean energy stocks receive greater contributions in terms of forecast error variance from fossil fuels (WTI crude oil, Brent crude oil, etc.) than they transmit. Second, petroleum fuels exhibit the strongest intermarket spillovers. Third, natural gas differs greatly in its role as receiver/transmitter compared to the other fossil fuels. Its contribution of spillovers to the network is near negligible. Conversely, natural gas is vulnerable to spillovers from the other fossil fuels. However, these spillovers have diminished consistently since the early 2000s. Fourth, the study applied the causality-in-quantiles technique of Balcilar et al. (2016) and found that US CPU and GPR had a significant impact on the spillovers between clean energy stocks and fossil fuels. Fifth, the study extended this causality analysis by appealing to the Quantile-on-Quantile regression technique of Sim and Zhou (2015). We found that the effects of US CPU and GPR were heterogeneous across the different states of the fossil fuel and clean energy stock intermarket spillovers.

The shift toward sustainable economies, and clean energy generation in particular, is a great undertaking that requires the combined effort of the public and private sectors. For policymakers, the findings uncovered in this study provide more information about the links among green financial assets and fossil fuels. For investors and financial practitioners, the study gives an accounting of the extent of risks emanating from incumbent dirty energy sources under a dynamic framework. Consequently, these parties will have a better understanding of how clean energy stocks behave in relation to fossil fuels during ordinary periods as well as extreme events.

6.2 Limitations and suggestions for future research

Although the study arrives at some important findings, it has some limitations. Foremost of these is our focus on the United States economy. Apart from using local U.S. fossil fuel prices, the study employs a U.S. based climate policy uncertainty index. Given that political and economic realities vary across developed and developing countries, the results obtained in this study may not be directly applicable to countries/regions like China, the European Union, Russia, and India. For example, in the case of China, its political system differs markedly from that of the United States. Moreover, the study is constrained by the monthly frequency of the US CPU and GPR indices. Although daily data would yield the same general connectedness among our variables, we are not able to see the daily fluctuations in clean energy stocks and fossil fuel prices.

For future research, it may of interest to investors and financial practitioners to disaggregate clean energy stocks among solar, wind, energy efficiency, and electric vehicles, among others. This would improve our understanding of the link between clean energy investments and dirty energy. Furthermore, the analysis taken up in this study may also be applied to Europe. In this endeavor, it may be helpful to appeal to the European Renewable Energy Price Index (ERIXP) as the proxy for green energy stocks.

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APPENDIX

Table A1: Unit root test for volatility data

Variable	Augmented Dickey Fuller (ADF) test	Phillips Perron (PP) test	Order of integration
ECO WilderHill Volatility	-4.355***	-4.333***	I(0)
WTI crude oil Volatility	-8.503***	-5.563***	I(0)
Brent crude oil Volatility	-8.580***	-6.037***	I(0)
NY gasoline Volatility	-8.755***	-8.339***	I(0)
GC gasoline Volatility	-9.044***	-8.702***	I(0)
Diesel Volatility	-6.443***	-5.545***	I(0)
Heating oil Volatility	-5.968***	-5.469***	I(0)
Propane Volatility	-5.383***	-4.517***	I(0)
Jet fuel Volatility	-6.697***	-6.764***	I(0)
Natural gas Volatility	-11.809***	-11.708***	I(1)

Source: Author's computation.

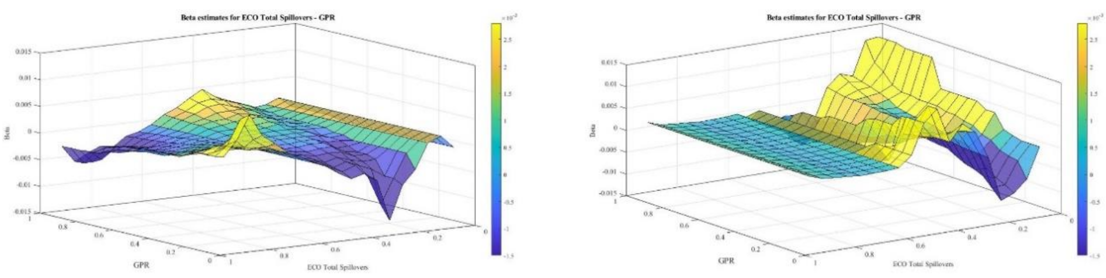
Table A2: Unit root tests for intermarket spillovers

Variable	Augmented Dickey Fuller (ADF) test	Phillips Perron (PP) test	Order of integration
CFIS	-16.220***	-16.253***	I(1)

Note: Table shows stationarity test results for intermarket spillovers. The variable is stationary after differencing. Source: Author's computation.

Figure A1: Quantile-on-quantile regression REVERSE SIDE

a. US CPU b. GPR



Note: Figure shows the relationship between two variables across each of their distributions. ECO total spillovers are the dependent variable. US CPU or GPR is the independent variable. Source: Author's computation.