What is the relationship between energy commodities and green assets?

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Dissertation written under the supervision of professor Eva Schliephake

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Abstract

This study focuses on the time-varying correlation between energy commodities and the green bond and clean energy equity markets. The correlations are computed using the DCC model (Engle, 2002), and the period under analysis starts at the beginning of the green bond market and ends in October 2022. The markets analyzed are highly influenced by the recent turmoil in the financial markets, which consequently influences their correlations. Overall, I find positive correlations between all assets, however the green bonds-energy commodities correlation tends to be low and is negative in some days. During the COVID-19 outbreak, the green bonds-energy commodities correlation decreased sharply, while the opposite happened with the clean energy-energy commodities correlation. In March 2021, both correlations (green bonds-energy commodities and clean energy-energy commodities) decreased significantly, as well as at the beginning of the war in Ukraine. Also, the correlation between clean energy and green bonds is the highest overall. This way, investors can benefit from diversification benefits by including green bonds in an energy commodities portfolio especially in periods of crisis like the COVID-19, inflation and energy crises. The opposite happens for a clean energy equity portfolio.

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Resumo

Este estudo foca-se na correlação condicional das commodities energéticas com o mercado das obrigações verdes, assim como com o mercado da energia limpa. Estas correlações são calculadas usando o modelo DCC (Engle, 2002) e o período em análise começa quando o mercado das obrigações verdes é criado e termina em outubro de 2022. Os mercados em análise são largamente influenciados pela recente instabilidade que, consequentemente, influencia as suas correlações condicionais. De modo geral, encontro correlações positivas entre todos os ativos em análise, no entanto a correlação obrigações verdes-commodities energéticas tende a ser pouco expressiva e atinge valores negativos em alguns dias. Durante o surto inicial de COVID-19, a correlação obrigações verdes-commodities energéticas diminuiu drasticamente, ao contrário da correlação energia limpa-commodities energéticas que aumentou. Em março de 2021, ambas diminuíram drasticamente, assim como no início da guerra na Ucrânia. Além disso, a correlação energia limpa-commodities energéticas é a maior, no geral. Assim, os investidores podem obter benefícios de diversificação ao incluir obrigações verdes num portfólio de commodities energéticas, especialmente em períodos de crise como os observados recentemente, no entanto o oposto acontece com um portfólio de ações de energia limpa.

Título: Qual é a relação entre *commodities* energéticas e ativos verdes?

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Palavras-chave: Obrigações Verdes, Energia Limpa, *Commodities* Energéticas, Correlação Condicional, COVID-19, Crise Energética, Benefícios de Diversificação.

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Introduction

Today we are living a climate crisis that puts our survival at risk and is already creating irreversible consequences (IPCC, 2021). If we don't act to limit the global warming to 1.5ºC and to become net zero (having 0 net greenhouse gas emissions) by 2050, the consequences will be even wider (IPCC, 2021). In COP26, several parties committed to sustainability goals, such as the net zero goal (UNFCCC, 2021). Sustainable finance plays a key role to reach them and to fight the climate crisis as it includes all investment decisions that consider ESG goals (European Commission, n.d.). Green bonds are included in sustainable finance since they are defined as bond instruments whose proceeds are applied to green projects align with the core components of the Green Bond Principles (Use of Proceeds, Process for Project Evaluation and Selection, Management of Proceeds, Reporting) (ICMA, 2021).

The first green bond was issued in 2008 by the World Bank (World Bank, n.d.). Since then, the green bond market has experienced an exponential growth. In 2021, the green debt market yielded a growth of 75% in the amount issued compared to 2020 (Harrison, MacGeoch and Michetti, 2022). Since 2014, the vast majority (81%) of Green Use of Proceeds went to Energy, Buildings and Transport sectors (Harrison, MacGeoch and Michetti, 2022). Also, green bonds are an important instrument for the energy transition as allow investors to invest in projects whose use of proceeds go to the clean energy or to other green projects without taking too much risk.

The clean energy equity market is also key to the energy transition as clean energies are one of the best ways to reach climate neutrality (IEA, n.d.). Clean energy can contribute to increase the domestic energy production. This is especially important for Europe to reduce the dependence of Russian imports and ensure the heating of households. Minister Habeck and Minister Jetten, among others, have recognized it (Federal Ministry for Economic Affairs and Climate Action, 2022).

This study aims to compute and analyze the time-varying correlations of the green bond and the clean energy markets with energy commodities. This is relevant to better understand how investors can benefit and diversify their portfolio while contributing to reach climate neutrality. Green bonds and clean energy production and investments will boost the energy transition while the energy commodities consumption and investment need to decrease sharply as they are responsible for most greenhouse gas emissions (United Nations, 2021). Some previous research has been done in the area however it is of special relevance to study the last few years, due to the high turmoil that followed the COVID-19 outbreak. Also, few authors have studied the post-pandemic period.

The COVID-19 pandemic generated a lot of turmoil in the financial markets (Albulescu, 2020). During the COVID-19 outbreak, energy prices (especially oil) decreased a lot due to the reduction of demand (IEA, 2022b) but have been rising since 2021. The increase in energy prices is due to the rapid economic recovery from the COVID-19 crisis, the reduction of investment in oil and gas by several energy exporters and supply cuts from Russia before the war in Ukraine started (IEA, 2022b). Also, the high energy prices generated high levels of inflation and consequently interest rate rises (Federal Reserve, 2022b), which impacts the whole economy, including the fixed income instruments.

Oil prices plunged at the beginning of the pandemic, reaching negative values. Natural gas prices spiked and reached record highs when the tension between Russia and Ukraine started as Russia is rich in fossil fuels production and was the main exporter of natural gas in 2021 (IEA, 2022a). A big portion of this natural gas exports are channeled to Europe (IEA, 2022a), contributing to a bigger impact of the energy crisis in this region. The historically high price of natural gas was a big opportunity to replace it with clean energy, however nations started to substitute natural gas by coal (IEA, 2022a), which contributed to the price increase of coal. The correlation of the green assets with the three commodities (oil, natural gas, and coal) is worth analyzing, due to the different price evolution of the different energy sources that might imply different conditional correlations.

Previous findings about the relationship between energy commodities and green bonds are not consensual. Some authors find diversification benefits between energy commodities and green bonds (Reboredo, 2018; Nguyen et al., 2020; Arif et al., 2022), while some find positive correlations (Kanamura, 2020; Dutta, Bouri and Noor, 2021; Abakah et al., 2023). I find a positive correlation in most days, however even in those days, the correlation tends to be low and close to 0, which can generate diversification benefits for investors by including green bonds in an energy commodities portfolio. Also, since the beginning of the pandemic the green bonds-energy commodities correlation has experienced significant decreases. The correlation hits one of its lowest values during the COVID-19 outbreak, in March 2021 and around the beginning of the war in Ukraine.

In line with previous research (e.g., Kumar, Managi and Matsuda, 2012; Nguyen et al., 2020; Reboredo and Ugolini, 2020), I find that the correlation of clean energy with energy commodities is mainly positive during the time frame analyzed. The commodities' correlation with clean energy increased a lot with the COVID-19 crisis, but it was followed by a big decrease, until March 2021. After that it started to increase until the war in Ukraine when it decreased again.

Literature Review

Green finance is a recent and growing field of research. There is some research done in the last few years in green finance and some authors have been studying the relationship of green and energy markets specifically. There is evidence that green bonds perform better than conventional bonds (Kanamura, 2020) and trade at a higher yield than the expected for their credit profile (Karpf and Mandel, 2017), which means that the greenness of the product is priced negatively by the market but offers better returns for investors that want to go green.

Several authors find that corporate and treasury bond markets spillover to the green bond market. Reboredo (2018) finds that the green bond market is closely correlated to the corporate and treasury bond market and Pham (2016) shows that both the labelled and unlabelled green bond markets have a positive correlation with the conventional bond market. The author defines labelled green bonds as bonds whose use of proceeds are clearly destined to green projects according to some external certification and unlabelled as bond "issued by firms whose businesses are naturally aligned with environmental causes" (Pham, 2016). Broadstock and Cheng (2019) study the conditional correlation of green bonds and conventional bonds and conclude that the correlation between the two is sensitive to macroeconomic factors, such as volatility, economic activity and uncertainty, and positive or negative green bonds' news sentiment (Broadstock and Cheng, 2019).

The research about the relationship between green bonds and energy commodities is divided. Some authors conclude that there is a negative correlation between the variables, while others conclude the opposite. Reboredo (2018) shows that green bonds and energy commodities weakly comove, using Barclays MSCI Green Bond Index and S&P GSCI Energy Spot Index. In line with this result, Nguyen et al. (2020) and Arif et al. (2022) argue that including green bonds in commodities' portfolios has diversification benefits. This diversification benefits are lower during times of turmoil (Nguyen et al., 2020).

Abakah et al. (2023) find that green bonds are positively correlated with natural gas most days, however this correlation decreased sharply to negative values with the COVID-19 outbreak. Dutta, Bouri and Noor (2021) find a positive correlation between climate bonds and oil, although this correlation is low, and the authors argue about the diversification benefits of including green bonds in an oil portfolio. Kanamura (2020) finds different correlation trends for different green bonds indices. This is opposite to Reboredo (2018), that argued that the main green bond indices are highly correlated and behave similarly. Kanamura (2020) argues that the Bloomberg Barclays MSCI and the S&P green bond indices have a positive correlation with crude oil prices (WTI and Brent), while Solactive green bond index has a negative correlation with the same commodities.

Although it is not the focus of this study, it is also relevant for sustainability to look at the interaction between the green bond and the carbon markets. There is causality running from carbon allowances and green bonds (Hammoudeh, Ajmi and Mokni, 2020) and green bonds are a good hedge for bearish carbon markets (Jin et al., 2020).

Authors like Henriques and Sadorsky (2008), Kumar, Managi and Matsuda (2012), Managi and Okimoto (2013), Reboredo (2015), Reboredo, Rivera-Castro and Ugolini (2017) Asl, Canarella and Miller (2021) or Geng et al. (2021) study the relationship between energy commodities and the clean energy market. Henriques and Sadorsky (2008) find that oil prices granger cause clean energy stocks prices. Kumar, Managi and Matsuda (2012) and Managi and Okimoto (2013) find a positive relationship between clean energy stocks and oil prices. Similarly, Geng et al. (2021) find that the correlation between brent and clean energy companies is positive most of the times, by using the DCC model to compute the conditional correlation. Reboredo (2015) finds tail dependency between clean energy and oil. Also, Reboredo, Rivera-Castro and Ugolini (2017) find bidirectional causality between oil and clean energy markets. Asl, Canarella and Miller (2021) findings are not in line with these as the authors find diversification benefits in portfolios with energy commodities and clean energy markets.

The green bond and the clean energy markets have a positive tail dependence, which indicates that green bonds are a bad hedging tool for clean energy markets (Liu et al., 2021). Additionally, Nguyen et al. (2020) find a positive and high correlation between green bonds and the clean energy market. These conclusions are not surprising considering that both investments have the same final goal, which is climate action and reducing our impact on the world. Moreover, Energy and Transport are the predominant sectors of the funds collected with green debt (Harrison, MacGeoch and Michetti, 2022), which are related to the clean energy industry.

To analyze the relationship between energy commodities, green bonds, and clean energy indices there are two main approaches. One of them is to simply compute the correlation between the variable. For that most authors use multivariate GARCH models, mainly the Dynamic Conditional Correlation (Engle, 2002). These include Pham (2016), Sadorsky (2014), Broadstock and Cheng (2019), Kanamura (2020), Geng et al. (2021), and Abakah et al. (2023). Pham (2016) claims to be the first to apply this multivariate GARCH to green bond market. Another possible approach is a quantile-based approach, which is used by authors such as Reboredo (2018), Guo and Zhou (2021), and Arif et al. (2022). My research follows the DCC methodology, with an approach like Pham (2016), for example. However, my research adds to the current literature the changes in the correlations between energy commodities and green assets during the recent turbulent periods (the COVID-19, inflation, and energy crises).

Methodology

The methodology explained in this section is used to study several hypotheses. The first hypothesis is that the energy commodities correlation with the green bond and the clean energy markets is time-variant. I am also studying if the correlation of energy commodities with the green bond and the clean energy markets spiked during the COVID-19 outbreak until late 2022 due to the subsequent macroeconomic consequences and energy crisis.

The expected result for this study is that the energy commodities correlation with the green bond and the clean energy markets is time-variant as the data set used seems to have volatility clusters and is in agreement with what several authors find (e.g., Kanamura, 2020; Dutta, Bouri and Noor, 2021; Abakah et al., 2023). A positive correlation between green bonds and energy commodities is expected, given that Energy and Transport are some of the biggest use of proceeds sectors in the green bond market (Harrison, MacGeoch and Michetti, 2022). Hence, an increase in energy commodities prices encourages investment in clean energy and low carbon investments (Dutta, Bouri and Noor, 2021), which implies that the correlation between energy commodities and green bonds would be positive. This expectation is in line with Kanamura (2020), Dutta, Bouri and Noor (2021), and Abakah et al. (2023) findings. Although, it is important to mention that the existing literature is not consensual, and some authors show a negative correlation and diversification benefits by including green bonds in an energy commodities portfolio (Reboredo, 2018; Nguyen et al., 2020; Arif et al., 2022).

For the correlation of energy commodities with the clean energy market, the same is expected based on the same reasons stated. The correlation is expected to be positive in most days, in line with the results of most authors mentioned in the literature review. For example, findings from Kumar, Managi and Matsuda (2012), Managi and Okimoto (2013), Reboredo (2015), Nguyen et al. (2020), Geng et al. (2021), and Liu et al. (2021) lead us to expect a positive correlation between energy commodities and the clean energy market. The correlation between the green bond and the clean energy markets is expected to be positive, as both markets have the goal of dealing with the climate crisis. The Energy sector is the one that receives the biggest percentage of the green bonds' use of proceeds (Harrison, MacGeoch and Michetti, 2022) which helps to explain this positive correlation as well.

During times of turmoil, it is expected that the correlations between financial assets increases (Benhmad, 2013). This way it is expected that the correlation between the energy commodities and the clean energy index increases substantially after the beginning of the pandemic. Another incentive to this increase in the correlation is the fact that both assets are in the energy market. The energy market suffered a lot during the COVID-19 outbreak as the demand for energy decreased in general (IEA, 2022b). Also, in the last few years the awareness to the energy transition has increased after the Paris Agreement and the implementation of several other regulations and incentives. The COVID-19 pandemic was an opportunity to increase even more that awareness and investment, as renewables should be at the center of post-covid recovery (IEA, 2022c).

Based on the same arguments and considering that a big proportion of green bonds funds are destined to the Energy and Transport sectors (Harrison, MacGeoch and Michetti, 2022), it is expected an increase in the correlation between green bonds and energy commodities, similarly to Nguyen et al. (2020) and Dutta, Bouri and Noor (2021) findings.

The Dynamic Conditional Correlation (DCC) model is used to compute the time-varying correlation between the green bond and clean energy markets with energy commodities. The correlations obtained and its dynamics will allow to conclude about the above-mentioned hypotheses.

The DCC model is a multivariate GARCH model developed by Engle (2002) and is based on GARCH model from Bollerslev (1986). GARCH is an autoregressive model, commonly used to study the volatility of financial assets. The innovation of this model is that it allows to compute nonconstant variances, in which volatility depends on past returns (lagged errors) and on itself (lagged volatility).

In a GARCH(p,q) model, volatility is defined as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2$$

Where the error term depends on the returns (y_t):

$$y_t = \mu + x'_t \theta + \epsilon_t$$

The returns can be modelled as a constant μ (and θ is 0) or as a linear regression using different explanatory variables (x'_t) (Bollersev, 1986) as in the equation above. An AR or ARMA processes are frequently used in the return equation to deal with serial correlation found on the data set (e.g., Abakah et al., 2023).

Although Hansen and Lunde (2005) compare several GARCH models and conclude that different mean equations don't produce significantly different results, the mean equations for the variables in this study were chosen based on the serial correlation levels of each variable and the Akaike Information Criterion (AIC). This is one of the most used tools in statistical modelling (Cavanaugh and Neath, 2019) that scores different models according to the information lost by applying that model to represent the data.

The Ljung-Box[1] test statistic and the autocorrelation function show that the returns of all the variables under analysis have significant serial correlation influencing them. Autoregressive return equations with the adequate number of lags eliminate the serial correlation present in the returns of each variable. Given this, the number of past returns lags included in each variable's mean equation was defined such that it eliminates the serial correlation to reduce its influence in the results. Once the best mean equations were chosen, I compared several multivariate GARCH models: with a constant mean equation, with an autoregressive equation with a one-period lagged return and an equation with the best AR model for the two variables in question. The comparison of these approaches was made based on the AIC and on the significance of the coefficients.

According to the author, the DCC model is a less complex model (Engle, 2002) and results in a conditional covariance matrix as follows:

$$\mathrm{H_t} = \mathrm{D_t R_t D_t}$$

Where $\mathrm{D_t}$ represents the diagonal matrix with the time-varying volatility of each variable and $\mathrm{R_t}$ represents the conditional correlation matrix. The volatility of each variable is calculated using a univariate GARCH as described before. After that, the correlations are computed as follows:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}}$$

Where $q_{i,j,t}$ represents the conditional covariances $q_{i,j,t} = cov\left(z_{i,t}, z_{j,t} \middle| I_{t-1}\right)$ and $z_{i,t}$ represent the standardized residuals ($z_{i,t} = \epsilon_{i,t}/\sigma_{i,t}$).

In this study, I use the GARCH(1,1) model. Several authors like Hoti, McAleer and Pauwels (2005), Sadorsky (2014), Pham (2016), Kanamura (2020), Dutta, Bouri and Noor, (2021), or Abakah et al. (2023) use the DCC model (or other multivariate GARCH models, such as the ADCC) with a GARCH(1,1) specification to study the correlation between energy

[1] $H0: \rho_1 = \rho_2 = \cdots = \rho_t = 0$

commodities, green bonds, clean energy equities, carbon markets or socially responsible investments. Moreover, most of this authors use and conclude that a constant mean equation or an AR(1) mean equation are the best fit for their variables. Also, Hansen and Lunde (2005) compare several ARCH and GARCH models in stock and exchange rate markets and conclude that GARCH(1,1) is not outperformed in most cases.

One of the assumptions of the model is that the returns follow a normal distribution, which creates a likelihood function for the optimization of the parameters used to compute the volatilities and correlations (Engle, 2002). However, it is possible to accommodate another distribution to the returns, like the t-student distribution. By using this distribution, the model will be more accurate for situations in which the variables have heavy tails, although, in this situation the estimation process is no longer a maximum likelihood function but rather a quasi-maximum likelihood whose interpretation is the same (Engle, 2002).

Furthermore, to test if the results obtained would hold, I performed the same tests after removing the outliers of the data set. The 1% highest and lowest returns of each variable were removed to avoid biases created by extreme daily returns and to see if the results hold for a slightly different data set.

Data

As this study analyses the conditional correlation of the returns of energy commodities, with the green bond and the clean energy markets it is necessary to use historical prices data. I obtain this data from Refinitiv Datastream as a time series with daily prices.

There are several bond indices tracking the green bond market, but as the major green bond indices are highly correlated (Reboredo, 2018), only the S&P Green Bond Index (SPGBIndex) is used. This index includes bonds labelled as green by the Climate Bonds Initiative and it tracks the global green bond market (S&P Dow Jones Indices, 2022b). S&P Global Clean Energy Index (SPClean) is the proxy used for the clean energy market. This is an index created in January 2007 to track the global clean energy market and it’s composed of 100 companies with clean energy related businesses both in developed and emerging markets (S&P Dow Jones Indices, 2022a). These variables are also used by Nguyen et al. (2020) and Liu et al. (2021) in their research.

The choice of the energy commodities variables was made with the end goal of using the most well-known and most used benchmarks for each commodity. These are:

- Crude Oil-WTI Spot Cushing U$/BBL (WTI)
- Europe Brent Spot FOB U$/BBL Daily (Brent)
- ICE Natural Gas 1 Mth.Fwd. P/Therm - ICE Natural Gas (NatGas)
- Coal ICE API2 CIF ARA Nr Mth $/MT (Coal)
- S&P GSCI Energy Total Return (GSCIEnergy)

The sample starts when S&P Green Bond Index is created (28/11/2008) and ends on the 17th of October 2022. The dataset includes the most recent data to capture the information from recent events of the energy crisis with high uncertainty and volatility in the market.

The extreme outlier event with a negative price is excluded (WTI price was -37.63, on 20/04/2020). Furthermore, in days where there are no quotes for some variable, an average of the previous day’s value and the next quoted day’s value is considered. This was performed to avoid excluding several observations from the dataset and to avoid including days with 0 return that would add up volatility to the model and could introduce biases in the results. Lastly, I have computed the returns using the natural log of the current day observation divided by the previous day value.

	Mean	Std Dev	Skew	Kurt	Min	Max	Dickey-Fuller p-value	Shapiro-Wilk p-value
WTI	0.02%	3.01%	-3.30	106.55	-71.81%	30.02%	0	3.6E-59
Brent	0.02%	2.90%	-4.57	163.83	-77.27%	41.20%	0	2.5E-62
NatGas	0.04%	4.16%	0.58	20.76	-36.01%	41.16%	0	3.3E-54
Coal	0.03%	2.18%	-3.22	146.14	-53.69%	32.62%	0	5.8E-71
GSCIEnergy	-0.02%	2.19%	-2.10	43.72	-40.57%	15.98%	0	5.4E-49
SPClean	0.01%	1.69%	-0.31	9.57	-12.80%	11.79%	0	6.9E-48
SPGBIndex	0.00%	0.52%	0.87	21.25	-3.77%	6.82%	0	1.2E-30

Table 1 - Descriptive Statistics of the daily returns of the variables used. Dickey-Fuller tests for stationarity, and the null hypothesis is of non-stationarity.

One can see that all variables have a mean close to 0, Natural Gas (0.04%) being the highest and GSCI Energy (-0.02%) the lowest. Looking at nonconditional volatility, S&P Green Bond Index is the variable with less volatility, and Natural Gas the one with more. Among the energy commodities variables, Coal and GSCIEnergy are the less volatile.

It is also possible to see that all variables have high values of kurtosis (specially WTI, Brent, and Coal) and that the skewness levels are also far from the normal distribution, especially for the commodities. In line with these values, the Shapiro-Wilk test[2] shows that neither variable is normality distributed, reinforcing the need to use other distribution. In this case, I use the t-student distribution because it's supported by the multivariate GARCH model and accommodates the heavy tails.

The existence of heavy tails (leptokurtic distribution) and mainly negatively skewed distributions is bad for the investors as they should expect more extreme negative returns. For most of the variables, the minimum and maximum daily return are high (in absolute value), which is in line with the high kurtosis. Brent registered the lowest (-77.27%) and the highest (41.20%) daily return of the whole sample. The variables with the extremes closer to 0 are the clean energy equity and the green bond indices, which is in line with the expectations considering the levels of risk of each market. Also, the current turmoil in energy commodities is contributing to more extreme descriptive statistics on this sample. Finally, all variables are stationary allowing the application of the multivariate GARCH model.

[2] $H0$: Returns follow a normal distribution.

	WTI	Brent	NatGas	Coal	GSCIEnergy	SPClean	SPGBIndex
WTI	1						
Brent	0.69	1					
NatGas	0.08	0.12	1				
Coal	0.13	0.12	0.24	1			
GSCIEnergy	0.90	0.75	0.13	0.16	1		
SPClean	0.27	0.27	0.04	0.08	0.34	1	
SPGBIndex	0.15	0.15	0.01	0.07	0.17	0.42	1

Table 2 – Nonconditional correlation matrix.

Most of the nonconditional correlations are relatively low (except for the correlations between WTI, Brent, and GSCI Energy) and positive. GSCI Energy is highly correlated to WTI and Brent Oil (0.90 and 0.75, respectively) and WTI has a high correlation with Brent (0.69). The S&P Global Clean Energy Index is more correlated with oil variables (WTI and Brent) and the energy commodity index (GSCI), with correlations of 0.27 and 0.34, respectively. Also, it is worth mentioning that the S&P Green Bond Index has low unconditional correlation with the commodities.

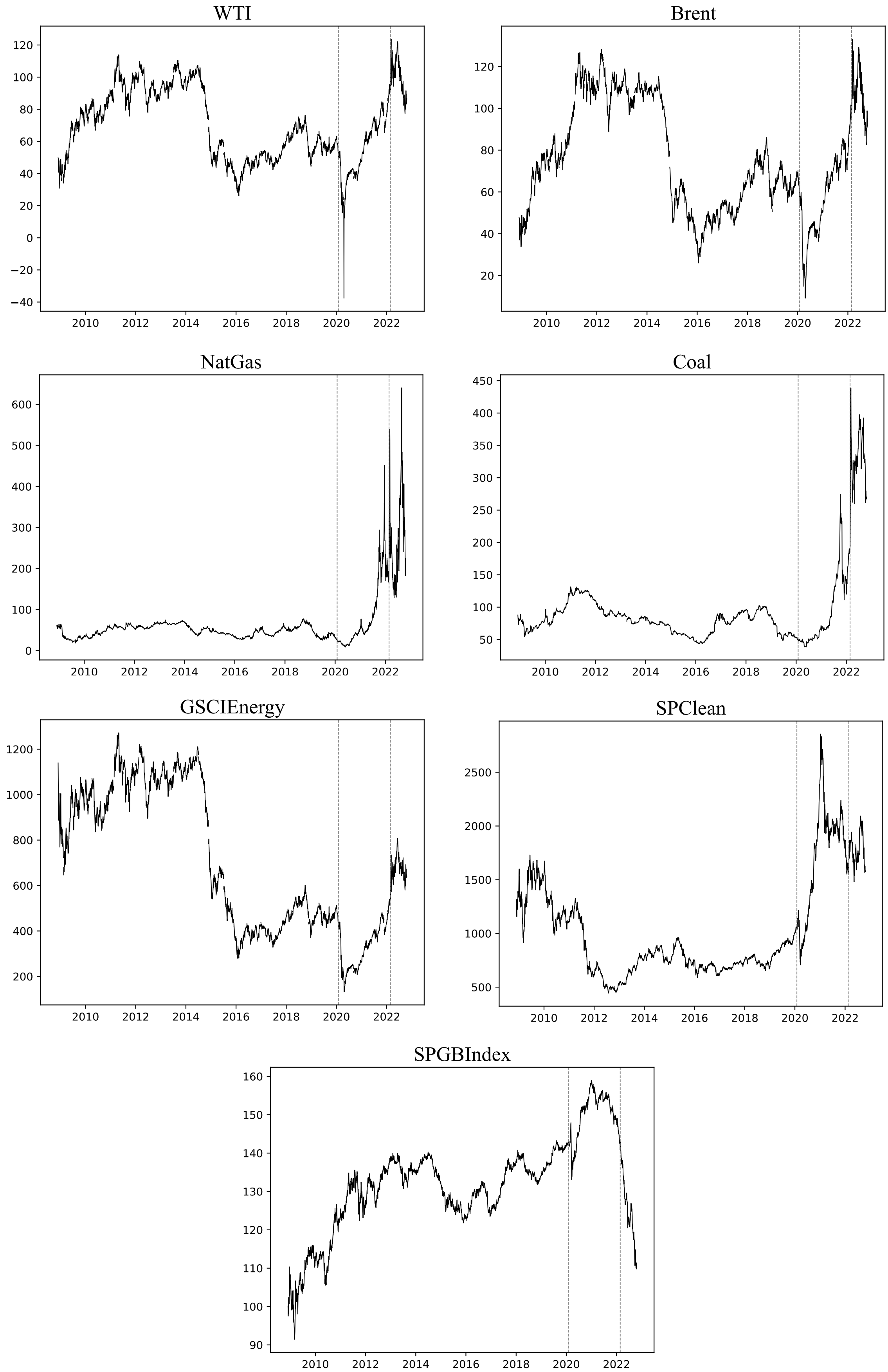

Figure 1 - Daily prices of all variables. The vertical dashed lines represent the day WHO declared COVID-19 as a Public Health Emergency of International Concern (30.01.2020) and the day of the Russian invasion in Ukraine (24.02.2022)

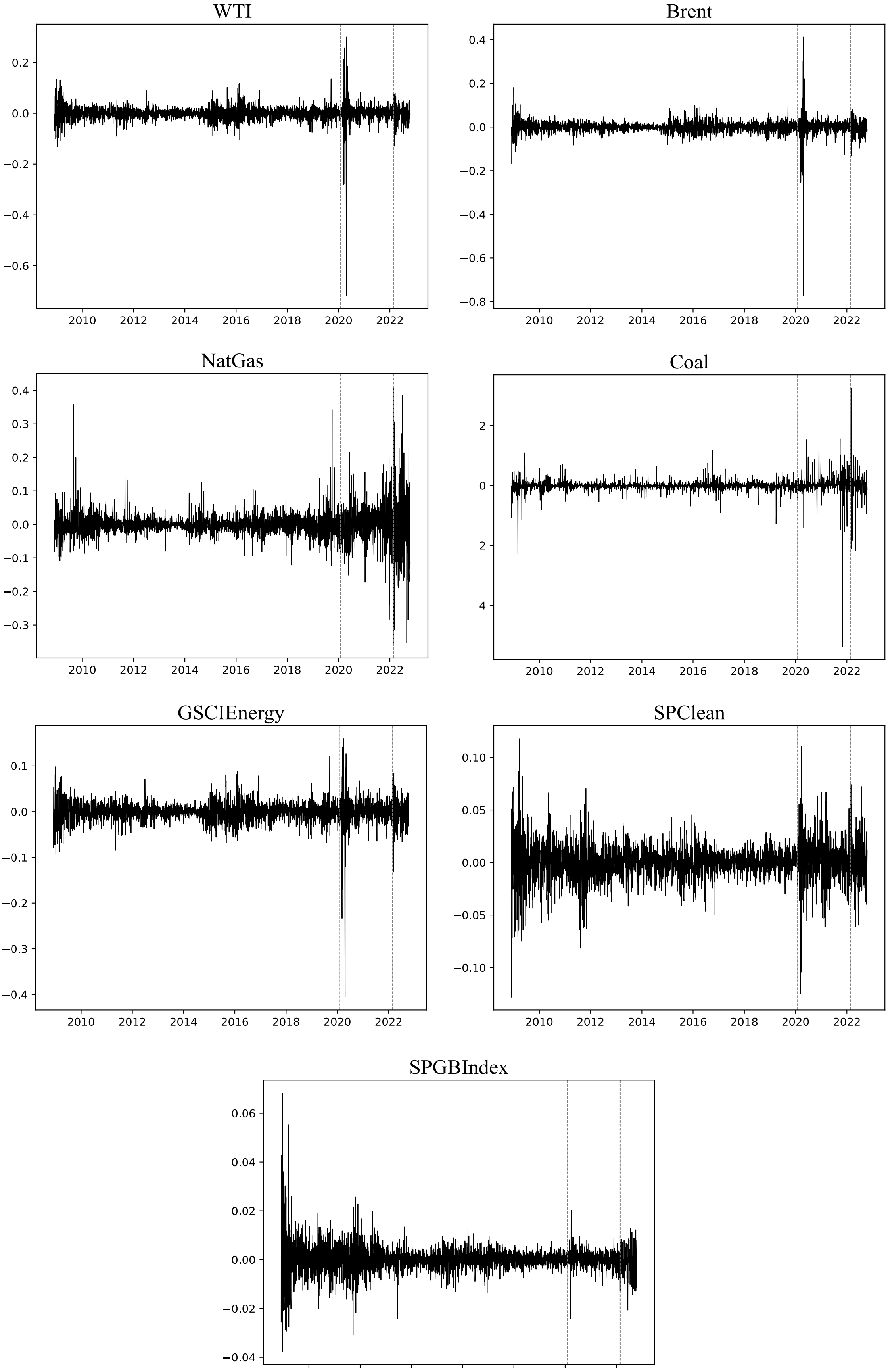

Figure 2 - Daily returns of all variables. The vertical dashed lines represent the day WHO declared COVID-19 as a Public Health Emergency of International Concern (30.01.2020) and the day of the Russian invasion in Ukraine (24.02.2022)

At the beginning of the pandemic, WTI, Brent and GSCIEnergy prices plunged, while NatGas and Coal prices decreased less extremely. Although, it is possible to notice a clear upward trend between the beginning of the pandemic and the invasion of Ukraine in all energy commodities. The SPClean also has a big price increase since the beginning of the pandemic, but at the beginning of 2021 entered a downward trend.

When looking at the daily returns, one can see that there are volatility clusters, which indicates that the unconditional volatility and correlation models are likely to poorly estimate the real parameters of these variables. WTI and Brent have higher absolute returns at the beginning of the sample (the global financial crisis period) and around 2016, an oil crisis period (Stocker et al., 2018). But the period with more extreme returns is at the beginning of the pandemic. The returns seem to then reduce to values closer to 0, in general. Even with the invasion of Ukraine, the oil variables don’t have a volatility cluster as obvious as the natural gas and coal variables do. Since the beginning of the pandemic, the daily returns of natural gas and coal variables are more extreme, even more after the war in Ukraine started.

The S&P Green Bond Index (SPGBIndex) has higher absolute returns at the beginning of the sample. With time, the returns got closer to 0, but at the beginning of the COVID-19 crisis and afterwards the returns moved away from 0 again. In terms of price, the fixed income variable has a big decrease at the beginning of the pandemic, followed by a rapid recovery. Until the beginning of 2021 there was a moderate upward trend, but now there is a clear downward trend in its price.

Empirical Results

As explained in the Methodology, the mean equations are analyzed by comparing DCC models with different mean equations (constant, an autoregressive equation with one-period lagged returns and one that eliminates the serial correlation of each variable) based on the AIC. For the DCC models with the green bond index and energy commodities, the best mean equation is always a constant one, except for the model with the green bond index and coal. In this case, the best mean equation is an autoregressive equation with one-period lagged returns. For the DCC models with the clean energy index and energy commodities, the best mean equation is always an autoregressive equation with one-period lagged returns, except for the model with the clean energy index and coal. In this case, the best mean equation is not equal for the 2 variables, being constant for the clean energy index and an autoregressive equation with one-period lagged returns for coal.

The coefficients of the DCC model including the mean equations and the GARCH parameters are shown on Table 3. One can see that all α and β coefficients are significant and positive, which means the correlations are nonconstant and time-variant. An important feature of GARCH models is:

$$\sum_{k=1}^{\max(p,q)} \alpha_k + \beta_k < 1$$

This condition ensures the wide-sense stationarity (Bollersev, 1986), which means that there is a constant mean and variance over time. This condition is met for almost all the DCC models analyzed, except the ones that include natural gas and coal variables. In these cases, the sum of the coefficients exceeds 1 by a small amount. Similar situations happen, when excluding the outliers from the original data set. When this condition is not met, the stationarity is not ensured, which means that the correlations are not mean reverting (Sadorsky, 2014) and this model is not adequate to describe the volatility and correlation dynamics of these variables (Dutta, Bouri and Noor, 2021). For this reason, the four dynamic correlations affected by this (NatGas-SPGBIndex, NatGas-SPClean, Coal-SPGBIndex and Coal-SPClean) won't be analyzed.

On Table 3, two λ parameters are reported. Both are positive and significant for all models. These are adjustment parameters and if they are different from 0, the correlation between the variables is time-variant. If they are equal to 0, the DCC model becomes a CCC model, where the volatilities are time-variant but the correlation between the variables is assumed to be constant (Aielli, 2013). Also, μ represents the constant part of the mean equation and

θ_1 represents the coefficient of the one-period lagged returns included in the mean equation of some GARCH computations. As an example, the coefficient for the one-period lagged return included in the mean equation of SPClean in the computation of the correlation between SPClean and WTI is 0.137 and it is significant at the 1% level.

	SPGBIndex					SPClean					
	WTI	Brent	GSCIEnergy	NatGas	Coal	WTI	Brent	GSCIEnergy	SPGBIndex	NatGas	Coal
SPGBIndex/SPClean											
α_0	8.34e-08***	7.91e-08***	8.21e-08***	7.13e-08***	1.59e-07**	2.00e-06***	2.01e-06***	1.89e-06***	2.25e-06***	2.06e-06***	4.26e-06***
	(2.48e-08)	(2.48e-08)	(2.49e-08)	(2.56e-08)	(6.34e-08)	(5.52e-07)	(5.66e-07)	(5.31e-07)	(5.69e-07)	(6.14e-07)	(1.57e-06)
α_1	0.0519***	0.0526***	0.0530***	0.0574***	0.114***	0.0782***	0.0786***	0.0753***	0.0742***	0.0916***	0.196***
	(0.00652)	(0.00658)	(0.00657)	(0.00758)	(0.0217)	(0.0103)	(0.0104)	(0.00982)	(0.00978)	(0.0121)	(0.0363)
β_1	0.944***	0.945***	0.944***	0.943***	0.951***	0.916***	0.916***	0.919***	0.917***	0.908***	0.914***
	(0.00650)	(0.00640)	(0.00649)	(0.00704)	(0.00686)	(0.0104)	(0.0105)	(0.00998)	(0.0104)	(0.0115)	(0.0122)
μ	0.000105**	9.37e-05*	0.000105**	8.17e-05	9.24e-05*	0.000512***	0.000486***	0.000526***	0.000306*	0.000396**	0.000565***
	(5.06e-05)	(5.01e-05)	(5.04e-05)	(5.06e-05)	(4.90e-05)	(0.000181)	(0.000181)	(0.000180)	(0.000178)	(0.000183)	(0.000180)
θ_1					0.0159	0.137***	0.120***	0.132***	0.115***	0.141***	
					(0.0162)	(0.0159)	(0.0160)	(0.0158)	(0.0156)	(0.0168)	
Other variables											
α_0	9.12e-06***	5.70e-06***	3.65e-06***	3.63e-06***	1.76e-05***	9.67e-06***	6.26e-06***	4.16e-06***	1.01e-07***	3.49e-06***	1.80e-05***
	(2.00e-06)	(1.36e-06)	(1.01e-06)	(1.25e-06)	(2.80e-06)	(2.09e-06)	(1.45e-06)	(1.09e-06)	(2.74e-08)	(1.21e-06)	(2.74e-06)
α_1	0.0992***	0.0890***	0.0830***	0.110***	0.448***	0.108***	0.0942***	0.0882***	0.0552***	0.103***	0.421***
	(0.0105)	(0.00926)	(0.00964)	(0.0138)	(0.0724)	(0.0111)	(0.00960)	(0.00979)	(0.00678)	(0.0129)	(0.0661)
β_1	0.885***	0.901***	0.909***	0.896***	0.640***	0.877***	0.895***	0.903***	0.940***	0.901***	0.638***
	(0.0111)	(0.00910)	(0.00994)	(0.0116)	(0.0241)	(0.0115)	(0.00945)	(0.0101)	(0.00690)	(0.0111)	(0.0242)
μ	0.000591**	0.000522**	0.000433*	-0.000288	-4.30e-05	0.000949***	0.000805***	0.000710***	0.000106**	-0.000260	-2.30e-05
	(0.000280)	(0.000256)	(0.000228)	(0.000299)	(9.71e-05)	(0.000280)	(0.000261)	(0.000230)	(4.97e-05)	(0.000300)	(9.88e-05)
θ_1					0.106***	-0.0188	0.0207	0.00147	0.00221	0.0402**	0.102***
					(0.0158)	(0.0163)	(0.0161)	(0.0161)	(0.0156)	(0.0168)	(0.0158)
λ_1	0.0223***	0.0354***	0.0257***	0.00660**	0.0242***	0.0213***	0.0221***	0.0222***	0.0380***	0.00781***	0.0128*
	(0.00449)	(0.00468)	(0.00518)	(0.00264)	(0.00724)	(0.00430)	(0.00530)	(0.00384)	(0.00730)	(0.00285)	(0.00767)
λ_2	0.969***	0.953***	0.965***	0.986***	0.958***	0.967***	0.964***	0.967***	0.953***	0.985***	0.958***
	(0.00661)	(0.00613)	(0.00760)	(0.00381)	(0.0119)	(0.00711)	(0.00951)	(0.00566)	(0.0101)	(0.00409)	(0.0126)
Obs	3,600	3,600	3,600	3,600	3,599	3,599	3,599	3,599	3,599	3,599	3,599

*Table 3 - Coefficients from the DCC model. Standards errors reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

	Mean	Std Dev	Min	Max	# days <0	# days >0
SPGBIndex-WTI	0.16	17%	-0.25	0.61	536	3,064
SPGBIndex-Brent	0.15	20%	-0.36	0.65	864	2,736
SPGBIndex-GSCIEnergy	0.17	19%	-0.27	0.66	661	2,939
SPGBIndex-SPClean	0.30	22%	-0.40	0.76	323	3,276
SPClean-WTI	0.27	15%	-0.11	0.63	76	3,523
SPClean-Brent	0.27	12%	-0.12	0.61	35	3,564
SPClean-GSCIEnergy	0.31	15%	-0.13	0.64	16	3,583

Table 4 - Summary statistics of dynamic conditional correlations with the S&P Green Bond Index and the S&P Global Clean Energy Index from 01.12.2008 until 17.10.2022.

	Mean	Std Dev	Min	Max	# days <0	# days >0
SPGBIndex-WTI	0.04	9%	-0.25	0.24	206	499
SPGBIndex-Brent	0.03	13%	-0.36	0.33	246	459
SPGBIndex-GSCIEnergy	0.04	10%	-0.27	0.26	254	451
SPGBIndex-SPClean	0.24	17%	-0.39	0.62	45	660
SPClean-WTI	0.19	15%	-0.07	0.62	62	643
SPClean-Brent	0.21	12%	-0.04	0.61	15	690
SPClean-GSCIEnergy	0.23	15%	-0.06	0.64	9	696

Table 5 - Summary statistics of dynamic conditional correlations with the S&P Green Bond Index and the S&P Global Clean Energy Index from 30.01.2020 until 17.10.2022.

Table 4 has the summary statistics of the dynamic correlation between the green bonds and clean energy market and energy commodities. It is possible to see that all variables have positive average correlations. Also, in all cases the number of days with positive correlations surpasses largely the number of days with negative correlations. This is even more pronounced for the correlation of the clean energy market and the energy commodities, where the number of days with negative correlations is always lower than 80 days, in a sample of 3,599 days.

Table 5 discloses the summary statistics for the period in the day WHO declared COVID-19 as a Public Health Emergency of International Concern (30.01.2020) until the end of the sample (17.10.2022). Compared with the data on Table 4, one can see that the mean of all correlations decreases. The standard deviation of the green bonds' correlation with the commodities decreases when looking at the subsample and the standard deviation of the correlations with the clean energy index are similar in the subsample and in the entire sample. Moreover, the number of days with positive and negative correlation between green bonds and the commodities is more balanced for the subsample, comparing to Table 4. For the correlation between the clean energy index and the commodities, the number of days with negative correlation remains low.

Based on Table 4 and 5, Figure 3 and 4, it is possible to say that all correlations analyzed are time-variant, as expected. Also, on Figures 3 and 4 one can observe that the correlations are positive in some days and negative in others, but on Table 4 and 5 it is possible to observe that the average energy commodities-green bonds and energy commodities-clean energy correlations are positive. These is in line with the expectation of positive energy commodities correlation with the green bond and the clean energy markets. A positive energy commodities-clean energy correlation is line with the findings from authors like Kumar, Managi and Matsuda (2012), Nguyen et al. (2020) and Reboredo and Ugolini (2020).

A positive green bonds-energy commodities correlation is in line with Kanamura (2020) and Dutta, Bouri and Noor (2021) findings. Also, according to Kanamura (2020) argument, a positive correlation means that the greenness of the green bond index is ensured, meaning that the S&P Green Bond Index is indeed green and composed by sustainable products. Nowadays, there are external trustworthy entities and standards that ensure the greenness of the products, independently of their correlation with non-sustainable assets, such as the energy commodities. The Climate Bonds Standard (Climate Bonds Initiative, 2014) and the European green bond standard (European Commission, n.d.) are some of the examples of these standards that label the bonds and define which bonds are indeed green or not.

Besides being positive most days, the correlation between green bonds and energy commodities tends to be low, especially since the last quarter of 2013, approximately. On Table 5 it is possible to see that the average correlation decreases a lot since the beginning of the pandemic. This indicates that it is possible to have diversification benefits from including green bonds in energy commodities portfolios, especially for oil. This is in line with the findings from Reboredo (2018), Nguyen et al. (2020) and Arif et al. (2022). Even Dutta, Bouri and Noor (2021) findings are in line with this as the authors find a positive but low correlation between energy commodities and green bonds. Also, the variation in the correlation of green bonds and energy commodities is lower in the subsample that includes the recent turmoil experienced by these markets, which is good for investors, as the diversification power of the green bonds seems to hold in periods of crisis. By including green bonds in an energy commodities portfolio, investors can create a greener portfolio in a less risky market (the fixed income market) while diversifying it. On top of that, as a good percentage of the use of proceeds from green bonds is channeled to energy (Harrison, MacGeoch and Michetti, 2022), investors can diversify while investing in the same industry. To note that, this approach should only be considered as a transition approach, considering that to become net zero by 2050, the fossil fuels use should decrease severely (IEA, 2021).

On Figure 3, one can see that in the first years of the S&P Green Bond, the index had a higher correlation with all energy commodities than it has today. The first years of this analysis (approximately between 2008 and the last quarter of 2013) influence a lot the summary statistics described above, as the correlation between green bonds and energy securities (commodities and clean energy index) was positive and high during most days of that period. At the beginning of the analyzed period, the green bonds were recent in the market and had been issued for the first time during the Global Financial Crisis, which was followed by the European Sovereign Crisis and an oil crisis between 2014 and 2016 (Stocker et al., 2018). During these periods, it is not surprising a higher correlation, considering that it is expected more co-movement in times of turmoil (Benhmad, 2013).

Regarding the time varying correlation between the S&P Global Clean Energy and the S&P Green Bond indices, it is the highest overall comparing with the correlation of the S&P Green Bond Index with the commodities. This is in accordance with Nguyen et al. (2020) and Liu et al. (2021) findings. When it reaches its highest value in December 2011, this correlation goes almost until 0.8. This result is not surprising considering that green bonds and clean energy markets are both focused on sustainability matters, including in the net zero goal and as the

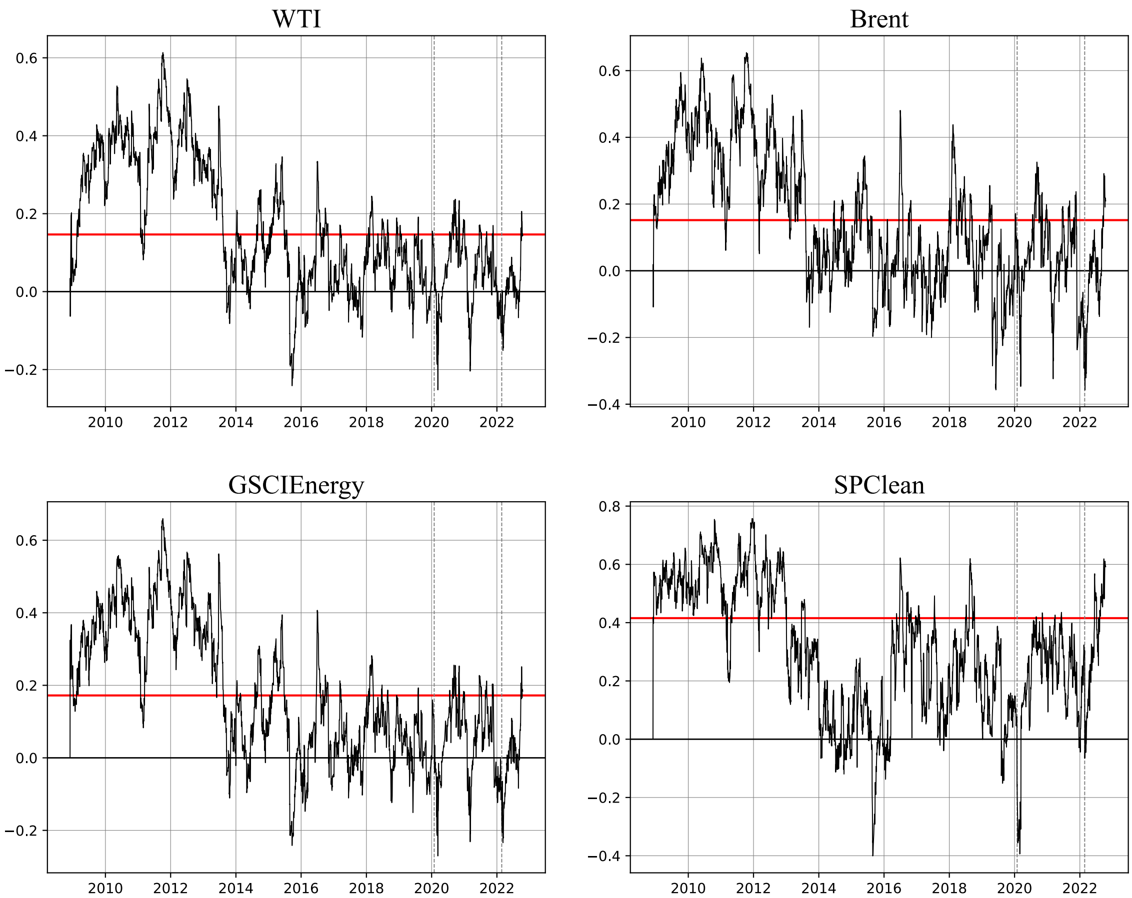

Figure 3 - Time-varying correlation with the S&P Green Bond Index. The horizontal line represents the unconditional correlation. The vertical dashed lines represent the day WHO declared COVID-19 as a Public Health Emergency of International Concern (30.01.2020) and the day of the Russian invasion in Ukraine (24.02.2022).

green bonds use of proceeds goes in a big portion to Energy and Transport sectors (Harrison, MacGeoch and Michetti, 2022).

If investors want to have a green portfolio without investing in fossil fuels by investing in green bonds and clean energy stocks, the portfolio won't be well diversified. Green bonds and clean energy have positive and high correlation during most days, which make them bad diversifiers. So, one can conclude that a portfolio composed only by these assets won't have diversification benefits most of the time. This finding is similar to what Nguyen et al. (2020) and Liu et al. (2021) find.

Green bonds correlation with energy commodities dropped with the COVID-19 crisis. This result is not in line with the initial expectations identified in the Methodology. Oil experienced a big shock with COVID-19 as the demand for energy decreased sharply (IEA, 2022b). The green bond market also suffered during the COVID-19 outbreak, but the magnitude of the losses was lower. Moreover, later the fixed income instruments had a big price pressure of macroeconomic factors, such as interest rates, inflation, and unemployment. The shock on the financial market created by COVID-19 and later the historically high energy prices created impact in these macroeconomic factors. Inflation started to increase widely around 2021, as a late consequence of COVID-19 and the central banks were pressured to increase the interest rates (Federal Reserve, 2022b).

After the initial shock in the first semester of 2020, the correlation between energy commodities and the green bonds started to recover quickly, until the first quarter of 2021. In March 2021, the oil-green bonds correlation reached a local minimum (-0.204 for WTI and -0.324 for Brent on the 8th of March 2021). The quarterly meeting of the Fed in March 2021 (Federal Reserve, 2021b) had a more hawkish tone than the previous meeting in January 2021 (Federal Reserve, 2021a), which helps to understand the decrease in the prices of the green bonds and the clean energy equity indices. Consequently, this can be influencing the correlation between energy commodities and the green bond market. After that point, the correlations increased, until the beginning of the war in Ukraine, where it decreased sharply again. The dynamics of the correlation between green bonds and energy commodities observed after the COVID-19 outbreak can be largely influenced by the energy crisis and its consequences.

At the same time there is a lot of economic instability initiated by the COVID-19 pandemic which influences the conventional and green bond markets alike. This is not independent from the energy crisis described before (European Central Bank, 2022b). Fixed income markets dynamic is related with inflation and other macroeconomic factors. Since the second half of 2021 (Federal Reserve, 2022b), the inflation all around the world is at historical highs and central banks are acting upon that. This means the central banks are pressured to raise rates. The Fed raised rates since March 2022 (Federal Reserve, 2022a) and the ECB since July 2022 (European Central Bank, 2022a). A rate hike influences the fixed income markets, creating incentives for a decrease in bond prices. A rate hike implies that fixed income instruments become less attractive for investors and consequently less expensive, given the fact that the risk-free rate increases and the newly issued bonds will generate higher coupons for the same level of risk. This creates incentives for investors to sell their bonds and buy bonds with higher coupons.

Looking at the time varying correlations of energy commodities with the clean energy market (represented by the S&P Global Clean Energy Index) in Figure 4, one can see that the correlations are positive in the vast majority of the days, as it is also possible to see on Table 4 and 5. This is similar to the findings of authors like Kumar, Managi and Matsuda (2012), Reboredo (2015), Nguyen et al. (2020), and Reboredo and Ugolini (2020). Overall, the correlation of energy commodities with the clean energy market is higher than the correlation with the green bond market, especially since the beginning of the pandemic as the maximum correlation between green bonds and energy commodities decreased substantially in that period.

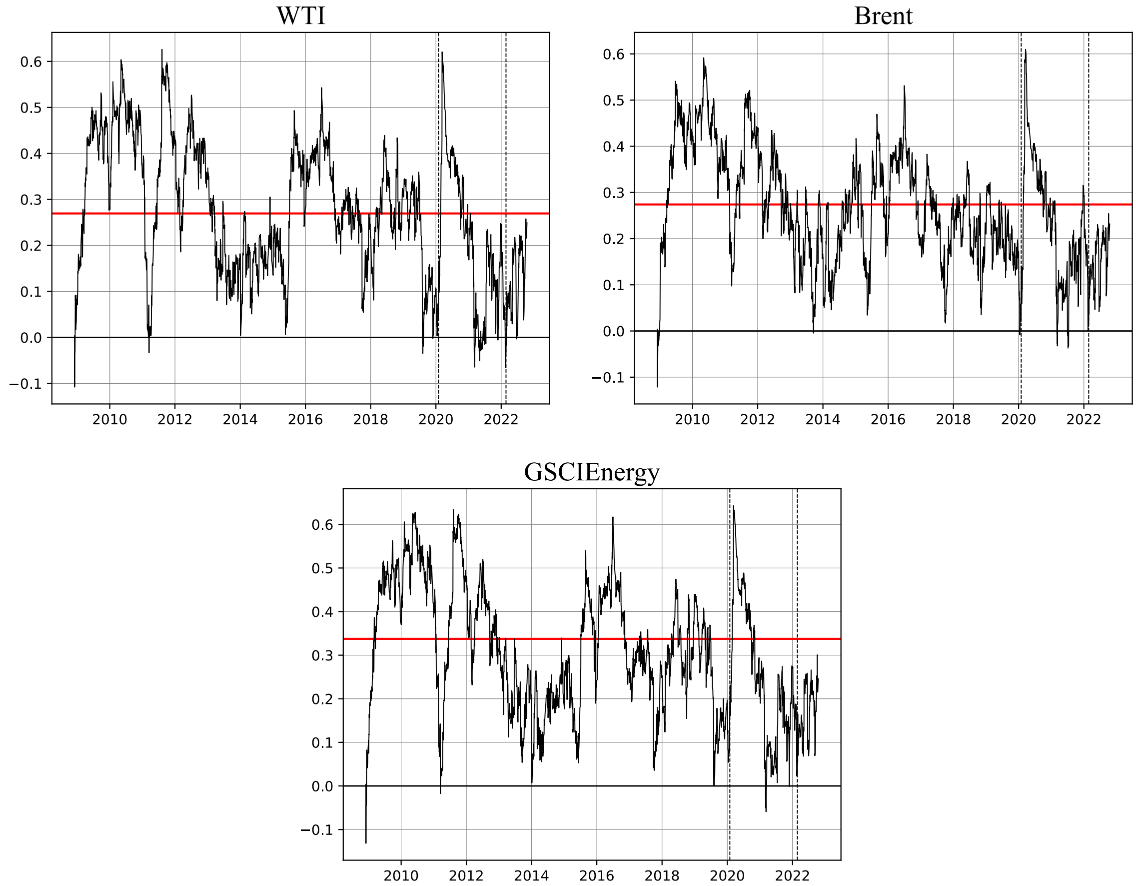

Figure 4 - Time-varying correlation with the S&P Global Clean Energy Index. The horizontal line represents the unconditional correlation. The vertical dashed lines represent the day WHO declared COVID-19 as a Public Health Emergency of International Concern (30. 01.2020) and the day of the Russian invasion in Ukraine (24.02.2022).

Unlike the green bond market, the correlation of energy commodities and the clean energy market spiked with the COVID-19 outbreak, as expected. WTI and Brent correlation with the clean energy market reached its peak at the beginning of the pandemic (11^{th} and 19^{th} March 2020, respectively) and entered a downward trend right after. This means the increase was not long lasting and after that the correlation reached negative values by March 2021 for both oil variables. As the prices of oil and clean energy plunged when COVID-19 appeared, the correlation increased. The clean energy index price recovered quickly from the initial COVID-19 downturn and reached historical high prices, hitting the maximum price on the 8^{th} of January 2021. After this the prices started to decrease and the lowest daily return was registered in March 2021, when the clean energy index price dropped substantially. When the clean energy prices entered a downward trend, the oil prices continued to increase, which contributed to the negative correlation in March 2021.

At the beginning of the Russian war in Ukraine, the oil correlation with clean energy decreased, but not as extremely as the correlation with the green bonds. In fact, only the WTI-clean energy correlation experienced negative correlations in that period, during 9 days in February 2022. However, the expectation was to see an increase in the correlation due to the increasing awareness of the climate crisis and the importance of the energy transition associated with the historically high energy prices.

After this main analysis, I have performed the same tests after excluding the outliers (1% highest and lowest returns of each variable) from the original data set. In this test, I have repeated the process to choose the best mean equations based on the serial correlation levels and on AIC. This implied slight changes in the mean equations used. In general, they became simpler as most of the best mean equations are constant in this new optimization. In this analysis, the main conclusions are the same for all variables. The only difference worth mentioning is the spike in the correlation between clean energy and energy commodities during the COVID-19 outbreak. After removing the outliers, this spike is less aggressive and the local maximum is lower, however it is still evident that there is a spike in the correlation between clean energy and energy commodities.

For further research it is worth studying potential explanatory variables for the variations in the correlations, to evaluate if there is some variable affecting the conditional correlations I find. Some of the variables that might be interesting to look at are periods of crisis, such as the global financial crisis, the European sovereign crisis, the oil crisis between 2014 and 2016, the COVID-19 crisis and the current energy and inflation crisis. Incentives to sustainable finance and to energy transition from the government or other entities (e.g., the Paris Agreement in 2015, the EU Taxonomy in 2020 or standards such as the Climate Bonds Standards in 2010) might also be worth studying. For example, Monasterolo and de Angelis (2020) find that low carbon investments started to be more attractive to investors as their systemic risk decreases after the Paris Agreement. Despite this, investors do not suppress carbon intensive investments as it would be desirable to contribute to the net zero goal (Monasterolo and de Angelis, 2020).

Oil and climate related events such as the COP conferences or OPEC meetings and announcements might influence these correlations. Lin and Tamvakis (2010) find that the market reacts to OPEC announcements from conferences and meetings. The reaction depends on the OPEC quota decisions and on the current price of oil on the market.

Boulle, Kidney and Oliver (2014) report that in 2013 the labelled green bond market shifted from a niche market to a spotlight with three times the amount issued in the previous year and new issuers entering the market. Firms and municipalities started issuing labelled green bonds besides the pioneering development banks (Boulle, Kidney and Oliver, 2014). Nguyen et al. (2020) highlights this growth in 2013 and my findings show a decrease in the green bonds-energy variables (commodities and clean energy index) in the last quarter of 2013. Given this, it might be interesting to look at the effect of the green bond market size in the green bonds-energy variables correlation.

Individual characteristics of the green bonds, such as the sector, the use of proceeds or the ESG score (and its changes) of the issuer might be interesting to analyze. If the green bond is in the energy sector, it is expected to be more correlated with energy commodities than bonds with biodiversity use of proceeds, for example. Also, Immel et al. (2021) find evidence that changes in the ESG score impact the green bonds' price. Despite this, using a green bond index such as the one used in this study does not allow to do this analysis.

Furthermore, looking at the country of origin of the bond or the company (for the clean energy variable) might be relevant as the market size, government support and regulations regarding climate issues differ across regions. For example, the EU and China have well defined taxonomies and have the biggest amount of bonds issued, while the US doesn't have a taxonomy defined or in draft (Harrison, MacGeoch and Michetti, 2022). The EU also has the EU green bond standard which helps to define the greenness of the product and therefore might influence the correlation green bonds-energy commodities.

The conventional bond and the carbon markets as explanatory variables may also produce interesting results. Hammoudeh, Ajmi and Mokni (2020) find causality running from the US 10-year Treasury bond index to green bonds, from the end of 2016 onwards. Also, other authors find that the conventional bond and the green bond markets are correlated (e.g., Pham, 2016; Reboredo, 2018; Broadstock and Cheng, 2019).

Limitations

This study analyses the conditional correlation of energy commodities and green securities by using the DCC model (Engle, 2002) with a t-student distribution to accommodate heavy tails. However, these results can be biased, given that the distribution doesn't account for the asymmetrical distribution as it seems to be the case of the variables under study. For example, the asymmetric DCC (ADCC) is a multivariate GARCH that includes these effects in its computation, although it was not possible to compute it due to constraints with the statistics program used for the analysis.

With regard of the variables used, using the natural gas and coal variables doesn't ensure the stationarity of the errors which makes the results analysis less rich. Only oil and a commodity index are analyzed within the energy commodities category and the commodity index is highly correlated with WTI (Table 2). Natural gas and coal would be especially interesting to analyze due to its unprecedent price increase that began in 2021.

The S&P Green Bond Index facilitates the computation as it is considered a proxy for the green bond market, however it poses some challenges and barriers to study the correlation between green bonds and energy commodities. More concretely, it doesn't allow to separate individual characteristics of the bonds, such as sectors and use of proceeds or the country where the bond is issued. Moreover, the S&P Dow Jones Indices claims that their green bond indices are composed only by labeled green bonds by the Climate Bonds Initiative (S&P Dow Jones Indices, 2022b), however the Climate Bonds Standards was created in 2010 (Climate Bonds Initiative, 2014), while the S&P Green Bond Index was created in 2008. This might raise questions about the greenness of the index in the first years since the creation of the index. Also, Dutta, Bouri and Noor (2021) claim that green bonds can be a target of greenwashing due to being a widely known asset. If the greenness of the green bond index used in this study is not ensured, the correlations presented can be biased by that information.

Conclusions

This study analyses the relationship between green assets (green bonds and clean energy stocks) and energy prices. This analysis is important to understand the dynamics of green finance, a relatively new and very important market to deal with the climate crisis. The recent turmoil in the markets allows to add more information about the correlation between energy commodities and green securities (green bonds and clean energy equities) to the existing literature.

Since the first green bond issuance in 2008, the green bond market has been experiencing an exponential growth and most of its funds are used in the Energy, Buildings and Transport industries (Harrison, MacGeoch and Michetti, 2022).

To analyze the correlation between the variables I use the DCC model created by Engle (2002) similarly to what authors like Sadorsky (2014), Pham (2016) and Dutta, Bouri and Noor (2021) did. This model allows to compute time-varying correlation where the volatility of each variable is computed with a GARCH model. The parameters for the GARCH model mean equations are defined based on the serial correlation levels and on the AIC. To accommodate the heavy tails present in the data, I used the t-student distribution instead of the normal distribution.

After computing the correlations, I find that the correlation of the S&P Green Bond Index with all other variables is generally decreasing since the inception of the index and in the vast majority of the days the correlation is positive. This is in line with Kanamura (2020), Dutta, Bouri and Noor (2021), and Abakah et al. (2023) findings. During the COVID-19 outbreak there is a significant decrease in the correlation green bonds-energy commodities, but it recovered quickly and increased until approximately the first quarter of 2021 when it decreased sharply again. In March 2021, the correlation decreased again and reached a local minimum. After that the correlation increased until the beginning of the war in Ukraine, when it decreased again. Since the beginning of the pandemic, the average correlations are lower than the average for the entire sample (2008-2022).

Moreover, in line with previous studies the correlation between green bonds and clean energy is mainly positive and the highest when compared to the energy commodities. For investors, this means that a green portfolio with bonds and renewable energy stocks won't be well diversified. Also, green bonds can be used as a diversifier in oil portfolios, especially after the last quarter of 2013 when the correlations decrease and start being negative in some days. Although, if investors implement this, it is important to keep in mind that the correlation is not strictly negative or low and there are periods where it can be reasonably high.

The correlation of clean energy with energy commodities is mainly positive during the time frame analyzed. This conclusion is in line with previous research by Kumar, Managi and Matsuda (2012), Nguyen et al. (2020), Reboredo and Ugolini (2020), among others. The commodities' correlation with clean energy increased a lot with the COVID-19 crisis, but it was followed by a big decrease, until March 2021. After that it started to increase until the war in Ukraine when it decreased again.

The conclusions found in this study introduce new information about the recent turmoil in the markets, with the analysis of the entire period since green bonds were created until October 2022. This includes an analysis of recent important events, such as the COVID-19 pandemic and the inflation and energy crises that followed. My analysis is focused on investors, who can better understand what happens to the correlation of energy commodities with green assets in such events and do better risk management of their green and energy portfolios. Investors need to be aware that the diversification benefits of green bonds vary with time. I find evidence of decreases in the correlation green bonds-energy commodities, which indicates to investors that the diversification benefits are bigger during periods of crisis such as COVID-19. My results can also help to understand what the possible implications of a future crisis are and how policymakers and investors can act. Lastly, my results can be useful in future research namely to study the effect of variables in the correlations I find.

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Appendix

	Mean	Std dev	Min	Max	# days <0	# days >0
WTI-SPGBIndex	0.16	16%	-0.26	0.57	547	2,911
Brent-SPGBIndex	0.14	19%	-0.40	0.64	805	2,653
GSCIEnergy-SPGBIndex	0.16	17%	-0.27	0.58	648	2,810
SPClean-SPGBIndex	0.26	20%	-0.46	0.69	297	3,161
SPClean-WTI	0.25	13%	-0.13	0.58	124	3,334
SPClean-Brent	0.25	11%	-0.14	0.56	44	3,414
SPClean-GSCIEnergy	0.27	12%	-0.14	0.60	40	3,418

Table 6 - Summary statistics of dynamic conditional correlations with the S&P Green Bond Index and the S&P Global Clean Energy Index from 01.12.2008 until 17.10.2022 after excluding the outliers from the sample.

	SPGBIndex					SPClean					
	WTI	Brent	GSCIEnergy	NatGas	Coal	WTI	Brent	GSCIEnergy	SPGBIndex	NatGas	Coal
SPGBIndex/SPClean											
α_0	3.65e-08*	3.51e-08**	3.52e-08**	2.86e-08	3.09e-08	1.38e-06***	1.27e-06***	1.22e-06***	1.71e-06***	1.41e-06***	1.53e-06*
	(1.71e-08)	(1.73e-08)	(1.70e-08)	(1.79e-08)	(3.01e-08)	(5.08e-07)	(4.76e-07)	(4.71e-07)	(5.57e-07)	(5.39e-07)	(7.81e-07)
α_1	0.0393***	0.0402***	0.0399***	0.0437***	0.0680***	0.0641***	0.0604***	0.0605***	0.0684***	0.0755***	0.105***
	(0.00532)	(0.00546)	(0.00529)	(0.00611)	(0.0114)	(0.0101)	(0.00959)	(0.00959)	(0.0102)	(0.0115)	(0.0188)
β_1	0.959***	0.958***	0.959***	0.957***	0.957***	0.930***	0.934***	0.934***	0.923***	0.922***	0.930***
	(0.00556)	(0.00564)	(0.00547)	(0.00599)	(0.00663)	(0.0113)	(0.0107)	(0.0106)	(0.0115)	(0.0120)	(0.0119)
μ	8.84e-05*	7.60e-05	8.99e-05*	7.51e-05	9.44e-05*	0.000519***	0.000487***	0.000536***	0.000370**	0.000451**	0.000554***
	(5.11e-05)	(5.07e-05)	(5.10e-05)	(5.10e-05)	(4.93e-05)	(0.000186)	(0.000187)	(0.000185)	(0.000183)	(0.000187)	(0.000182)
Other variables											
α_0	2.97e-06***	1.61e-06**	1.03e-06**	2.70e-06***	1.09e-05***	3.15e-06***	1.92e-06**	1.14e-06**	4.88e-08**	2.36e-06**	1.24e-05***
	(1.11e-06)	(6.89e-07)	(5.01e-07)	(1.04e-06)	(1.59e-06)	(1.17e-06)	(7.80e-07)	(5.40e-07)	(2.09e-08)	(9.69e-07)	(1.75e-06)
α_1	0.0589***	0.0548***	0.0494***	0.0972***	0.349***	0.0625***	0.0602***	0.0519***	0.0440***	0.0910***	0.364***
	(0.00835)	(0.00791)	(0.00735)	(0.0117)	(0.0419)	(0.00860)	(0.00822)	(0.00740)	(0.00636)	(0.0110)	(0.0431)
β_1	0.935***	0.942***	0.948***	0.906***	0.631***	0.932***	0.937***	0.946***	0.954***	0.911***	0.606***
	(0.00951)	(0.00834)	(0.00783)	(0.0106)	(0.0294)	(0.00961)	(0.00864)	(0.00781)	(0.00674)	(0.0101)	(0.0303)
μ	0.000496*	0.000434*	0.000373	-0.000265	-4.15e-05	0.000837***	0.000724***	0.000632***	0.000102**	-0.000296	-5.43e-05
	(0.000280)	(0.000256)	(0.000229)	(0.000305)	(0.000103)	(0.000280)	(0.000262)	(0.000230)	(4.99e-05)	(0.000302)	(0.000105)
θ_1										0.0387**	
										(0.0174)	
λ_1	0.0267***	0.0416***	0.0282***	0.00862***	0.0168**	0.0208***	0.0248***	0.0212***	0.0428***	0.00816***	0.0332**
	(0.00478)	(0.00574)	(0.00468)	(0.00324)	(0.00716)	(0.00420)	(0.00879)	(0.00418)	(0.00747)	(0.00293)	(0.0167)
λ_2	0.961***	0.940***	0.961***	0.983***	0.950***	0.965***	0.951***	0.965***	0.940***	0.984***	0.796***
	(0.00732)	(0.00848)	(0.00673)	(0.00588)	(0.0193)	(0.00732)	(0.0238)	(0.00681)	(0.0119)	(0.00462)	(0.0737)
Obs	3,458	3,458	3,458	3,458	3,458	3,458	3,458	3,458	3,458	3,457	3,458

*Table 7 - Coefficients from the DCC model after excluding the outliers from the sample. Standard errors are presented inside parenthesis. *** p<0.01, ** p<0.05, * p<0.1*

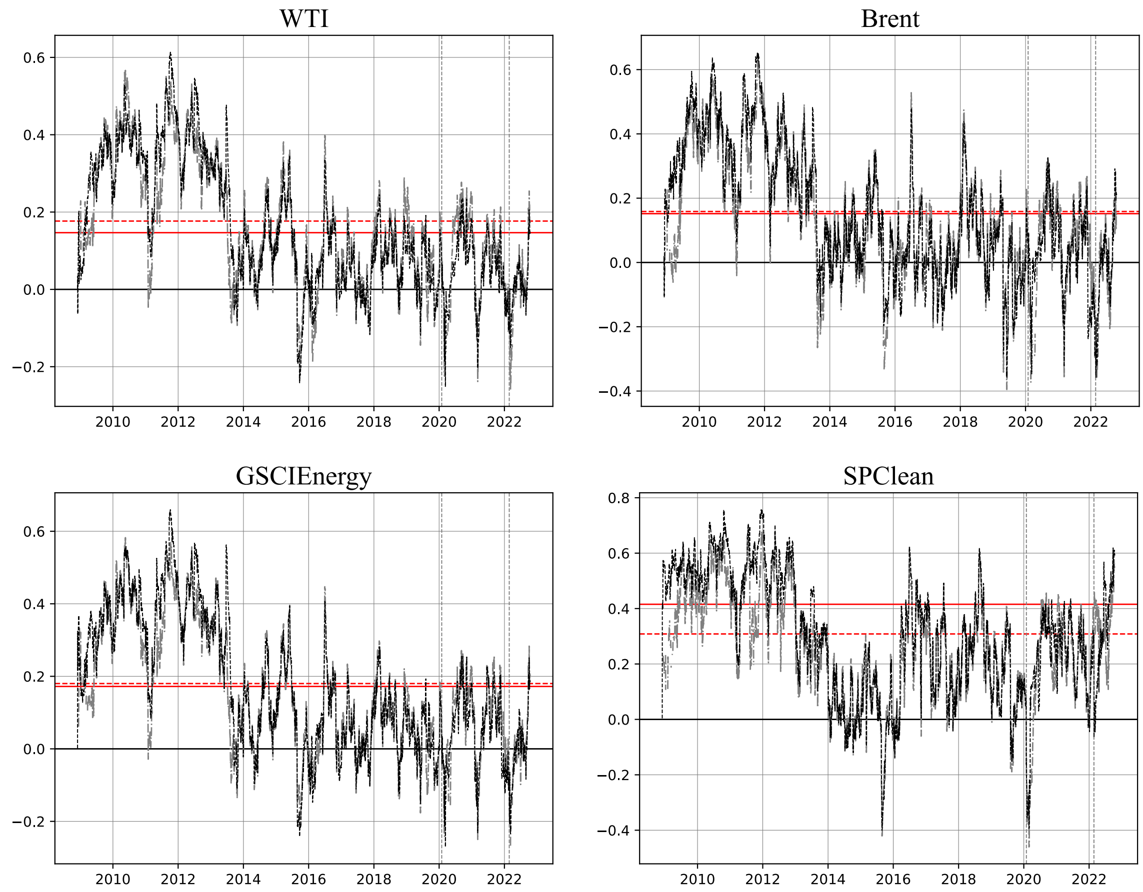

Figure 5 - Time-varying correlations with the S&P Green Bond Index with and without outliers (1% highest and lowest daily returns) included in the data set. The black dashed line represents the time-varying correlation before excluding the outliers. The grey dashed line represents the time-varying correlations after excluding the outliers. The horizontal line represents the unconditional correlation before excluding the outliers. The horizontal dashed line represents the unconditional correlation after excluding the outliers. The vertical dashed line represents the day WHO declared COVID-19 as a Public Health Emergency of International Concern (30.01.2020) and the day of the Russian invasion in Ukraine (24.02.2022).

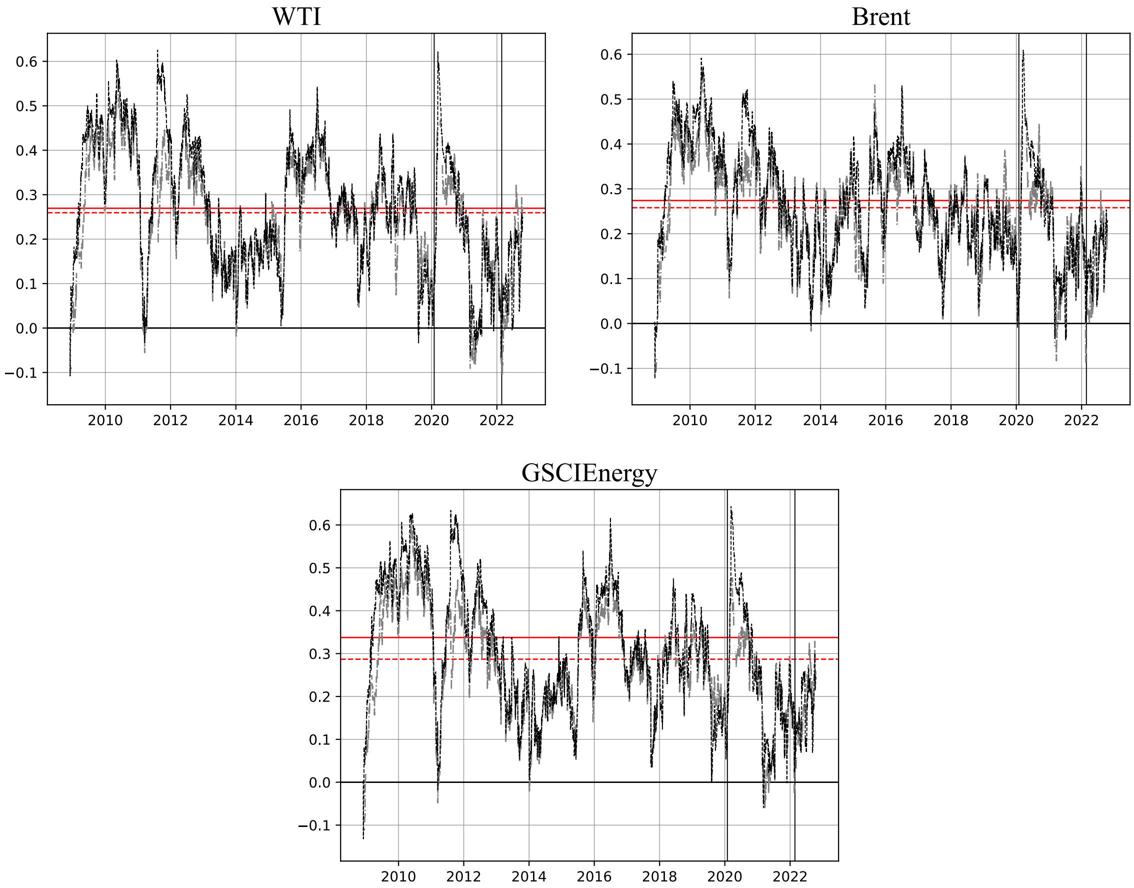

Figure 6 - Time-varying correlations with the S&P Global Clean Energy Index with and without outliers (1% highest and lowest daily returns) included in the data set. The black dashed line represents the time-varying correlation before excluding the outliers. The grey dashed line represents the time-varying correlations after excluding the outliers. The horizontal line represents the unconditional correlation before excluding the outliers. The horizontal dashed line represents the unconditional correlation after excluding the outliers. The vertical dashed line represents the day WHO declared COVID-19 as a Public Health Emergency of International Concern (30.01.2020) and the day of the Russian invasion in Ukraine (24.02.2022).