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On the connectedness between climate policy uncertainty, green bonds, and equity

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Abstract: This paper presents a first connectedness analysis using the novel Climate Policy Uncertainty Index (CUI) proposed by Gavriilidis (2021), Green equity and bonds (GE and GB – Green investments), and Dirty equity and bonds (DE and DB – dirty investments). Using data covering the years from 2007 to 2021, we show that the effect of climate policy uncertainty as measured by the CUI is far from constant through time. While static analysis indicates that green investments are isolated from fluctuations in the CUI, an inspection from a dynamic perspective shows that CUI is mostly a transmitter of shocks. This role as a transmitter is evident primarily in two crises since 2008: the subprime crisis and the European debt crisis. Interestingly, during recent years, the influence of climate change policy uncertainty as measured by the CUI has weakened, and it has even become a net recipient of shocks.

Keywords: climate risk, uncertainty, green investment, green bonds, green equity, returns, volatility

JEL classifications: G14, G15, G1, Q2, Q4.

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1. Introduction

Climate change has become a key issue in recent years, having become viewed as one of the century's leading human and environmental issues. As a result, addressing climate change has become a global concern and challenge. This increasing awareness has facilitated action, rules, and reforms to combat climate change nationally and globally. These may, in turn, induce changes and adjustments in the practices and business strategies of firms and consequently affect their performance. Besides the potential effects of such steps, the uncertainty associated with these reforms—and, more specifically, with the choice of policies to be implemented and how they will influence financial markets and the real economy—is also significant (Fernando et al., 2021; Gavriilidis, 2021). For example, the United States withdrew from the Paris Climate Agreement under the Trump administration and rejoined after President Biden assumed power, even taking on some new climate commitments. Two novel indices were recently created to track the dynamics of climate risk policies. Engle et al. (2020) have developed the WSJ Climate Change News Index, which tracks the climate news coverage in The Wall Street Journal (WSJ). Gavriilidis (2021) extends this idea by constructing a novel Climate Policy Uncertainty (CUI) Index by using a broader scope of news coverage, along with a focus on news discussing uncertainty related to climate policy.

In this study, we examine the connectedness between this novel CUI, green equity, green bonds (GE and GB – Green investments), and dirty equity and bonds (DE and DB

– dirty investments) for the period from 2007 to 2021. We use both static and dynamic approaches to identify the net transmitters and net receivers of risk spillovers. This will help us to understand the relationships between green and dirty investments and their possible mutual dependence, as well as their interaction with the CUI.

A careful examination of the literature suggests a relatively new but fast-growing body of work on the static and dynamic interactions between the returns and volatilities of traditional financial assets and green investments (Ferrer et al., 2021; Pham and Nguyen, 2021; Reboredo et al., 2020; Shahbaz et al. 2021). Our paper joins this line of research, particularly in light of the growing interest in the hedging role of green investments in the pandemic era (Arif et al. 2021; Dutta et al. 2021). More specifically, our paper contributes to the portion of this scholarship that examines the spillovers across different uncertainty measures, green investments, and traditional asset classes.

Ferrer et al. (2018) examine the time and frequency dynamics of connectedness among stocks of U.S. clean energy companies, high technology stocks, oil prices, the default spread, treasury bond yields, and volatility indices (The Chicago Board Options Exchange Volatility Index – VIX and the U.S. Treasury Note Volatility Index – TYVIX). The stock prices of high technology and renewable energy companies and the VIX emerge as net transmitters of return and volatility spillovers to other variables.

Lundgren et al. (2018) study the connectedness across renewable energy stock returns, traditional asset classes, and several sources of uncertainty: VIX, the Equity Pickup (EPU), and financial stress (FS). The uncertainty measures, and renewable energy stocks are found to be net transmitters of shocks to other variables. Broadstock and Cheng (2019) analyze the correlations between green and conventional bonds and their determinants, with the correlations shifting from negative to positive in mid-2013. Correlations are sensitive to macro-level factors, including the VIX and EPU.

Pham and Nguyen (2022) analyze the connectedness between three uncertainty indices (the VIX, the Crude Oil Volatility Index – OVX, and EPU) and green bond returns. They show that there is only a small level of connectedness between uncertainty and green bond returns during periods of low uncertainty, while the spillovers from uncertainty measures to green bond returns are significantly higher during periods of high uncertainty (such as the COVID-19 pandemic).

Saeed et al. (2021) analyze return spillovers across clean/green and dirty energy assets at different quantiles. Return connectedness is higher in extreme values, both low and high, and varies with time. VIX, OVX, TYVIX, and EPU have different effects on connectedness for low and high extreme values. For example, EPU positively affects connectedness at the middle quantile, while VIX has a positive (negative) impact at the upper (middle) quantiles. Finally, Liu et al. (2021) explore the spillover effects of economic uncertainty generated by COVID-19 (measured by the newspaper-based Infectious Disease Equity Market Volatility Tracker) on the U.S., European, and global renewable energy stock indices. Economic uncertainty transmits spillovers to renewable energy stock volatilities and returns. The impact on volatilities is higher than on returns. The spillover from uncertainty to returns (volatilities) is concentrated at high (low) frequencies. Our study contributes to this main strand in the literature by examining an uncertainty index that may be more related to returns than traditional uncertainty indices, such as the VIX or the EPU, in terms of climate risk and climate policy uncertainty.

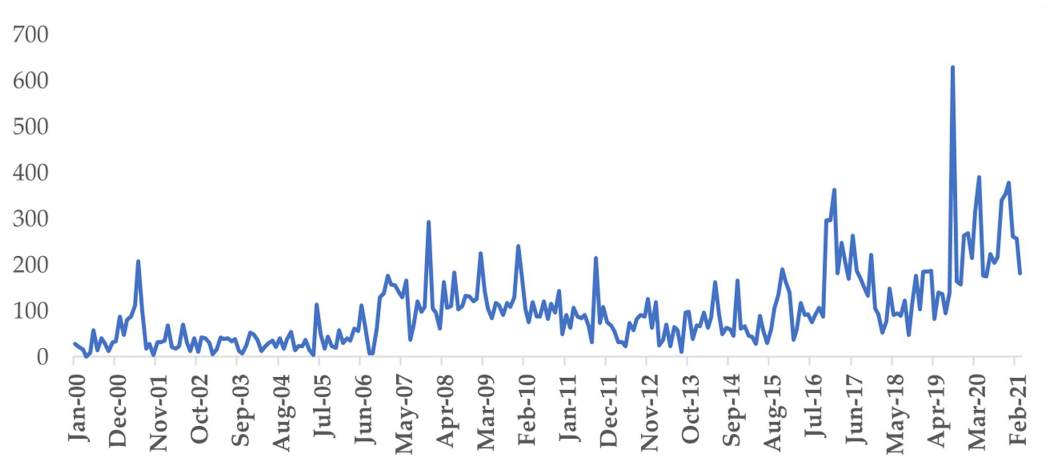
To our knowledge, we are the first to explore the connectedness between the CUI, green equity and bonds, and dirty equity and bonds by using the time-varying parameter vector autoregressive model (TVP-VAR) of Antonakakis, Chatziantoniou, & Gabauer (2020). The CUI has been used in only a limited number of studies. Gavriilidis (2021) explores the relationship between this index and CO2 emissions. Shocks to the CUI lead to lower emission levels on an aggregate basis. On a sectoral level analysis, the biggest impact is observed within the residential and commercial sectors, and the duration of the impact varies across industries. Apergis et al. (2021) find that the CUI can predict the air travel demand of U.S. citizens to eight overseas destinations. In this study, we find that while static analysis indicates that green investments are not influenced by climate policy uncertainty, dynamic analysis shows that the CUI represents a net transmitter of both return and volatility spillovers. This phenomenon is evident during the 2007–2008 subprime crisis and the European debt crisis. This transmission of risk spillovers by the CUI gets weaker over time, and it even functions as a net receiver during the COVID-19 period.

The rest of the paper is organized as follows. In Section 2, we present and explain the data. In Section 3, we explain the methodology. In Section 4, we present and discuss the findings. The last section concludes the paper.

2. Data

The data covers the period from January 2007 to April 2021. The choice of this period was mainly due to the availability of a consistent series of data points. This period contains key economic events and encompasses the 2007–2008 subprime crisis, large fluctuations in oil prices, the European sovereign debt crisis, and, more importantly, the COVID-19 pandemic. Therefore, our investigation offers an attempt to consider the interaction between green and dirty asset classes and fluctuations in the CUI proposed by Gavriilidis. Textual analysis has been recently used to form indices to quantify uncertainty and risk on a macro level (Baker et al., 2016; Caldara & Iacoviello, 2018). The CUI follows the construction by Baker et al. (2016) of the Economic Policy Uncertainty Index, which is based on the frequency of newspaper coverage of terms from three categories pertaining to uncertainty, the economy, and policy. Gavriilidis (2021) searches for terms related to uncertainty, climate, energy, and policy in articles from eight leading newspapers in the United States. The number of articles per month containing these terms is then scaled by the total number of articles per month. This frequency measure is then standardized to have a unit standard deviation and finally normalized and adjusted to have a mean value of 100 for the entire period**. Figure 1** shows the CUI over time. The peaks are associated with several significant events, such as the global strikes in September 2019 ahead of the UN Climate Action Summit. At this time, 24 states sued the Trump administration for revoking their right to set emission standards, as the Trump administration planned to scrap Obama's Clean Water Act reforms. In addition, the CUI is also higher during turbulent times such as the Dot-com bubble, the subprime crisis, and the COVID-19 pandemic.

Figure 1. Climate Policy Uncertainty index



Notes: The above Figure depicts the climate policy uncertainty Index by Gavriilidis (2021). For further information please refer to: https://www.policyuncertainty.com/climate_uncertainty.html.

As a surrogate for green and dirty assets classes, we collect the following data series: the Bloomberg U.S. aggregate green bond index (GB) as the proxy for green bonds, the Wilderhill clean energy index (GE) representing the green equity (stocks), the iBoxx USD Oil & Gas index bonds (DB) as a proxy for "dirty" bonds, the iShares U.S. Oil & Gas Exploration & Production ETF (Ferrer et al. [2018] and Saeed et al. [2021] among others use one or more of these series). (DE) as a proxy for "dirty" equity. Finally, as mentioned above, CUI is the Climate Policy Uncertainty Index proposed by Gavriilidis (2021).

Table 1 provides descriptive statistics for returns from the main key indices under consideration through the entire period under investigation (for brevity, we have not reported the summary statistics of the volatility series; the findings are available upon request). For each series of returns, we compute the first difference in the log price, while for CUI, we compute the first difference in the closing prices. In Figure 2, we present the index returns.

Table 1. Descriptive Statistics

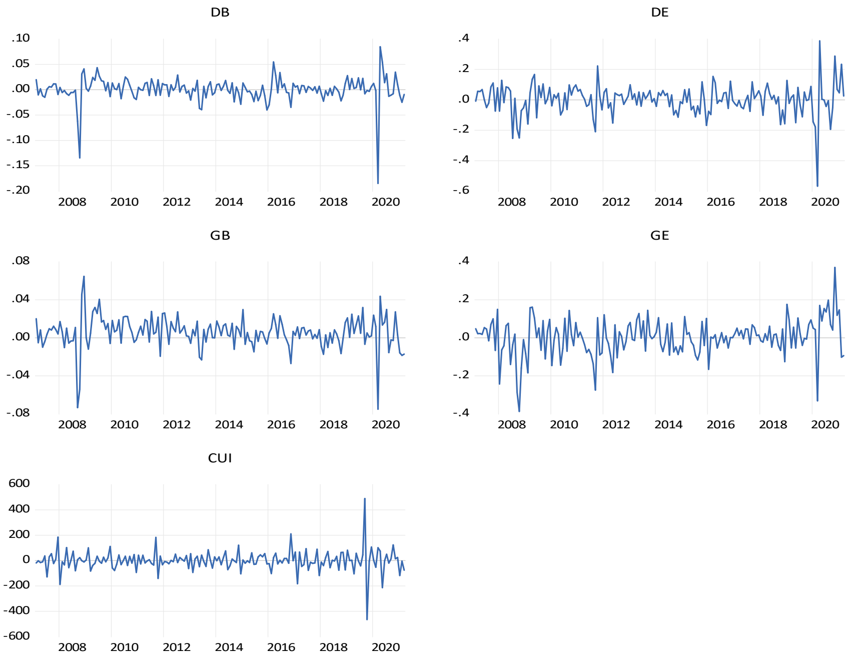
	GB	GE	DB	DE	CUI
Mean	0.00031	-0.00008	0.00563	0.00059	0.02541
Median	0.00136	0.00531	0.00577	0.00498	-2.16500
Maximum	0.08438	0.38631	0.06450	0.36931	488.05000
Minimum	-0.18441	-0.56685	-0.07488	-0.38657	-464.26000
Std. Dev.	0.02505	0.10046	0.01671	0.09833	80.84704
Skewness	-3.00667	-0.84294	-1.10825	-0.52555	0.15198
Kurtosis	24.23905	9.44177	9.23639	5.45814	16.06622
Jarque-Bera	3451.408	314.0647	3.10E+02	50.62637	1209.964
Probability	0.000	0.000	0.000	0.000	0.000
N	170	170	170	170	170

Notes: The table shows the summary statistics for our key variables. GB is the Bloomberg U.S. aggregate green bond index as the proxy for green bonds, GE is the Wilderhill clean energy index representing the green equity (stocks), DB stands for "dirty" bonds and is represented by the iBoxx USD Oil & Gas index bonds, DE is the iShares U.S. Oil & Gas Exploration & Production ETF as a proxy for "dirty" equity and finally CUI is the Climate Policy Uncertainty Index of Gavriilidis (2021). The descriptive statistics reported here are calculated on a basis. Log differences for returns series are computed for the GB, GE, DB and DE, and first differences for the CUI. The reported descriptive statistics are Mean, Median, Maximum, Minimum, Skewness, Kurtosis (Kurt), the Jarque-Bera test statistic and its corresponding probability, and finally, the total number of observations for the common sample is 170 (N).

The statistics in Table 1 imply that all series are leptokurtic, characterized by excess positive kurtosis, which hints at heavy tails and peakiness of the distribution. The findings also show negative skewness for all series, excluding the CUI index, which has positive skewness. In addition, variability in equity is higher than in bonds, as implied by both the minimum-maximum range and the standard deviation. Surprisingly, the average return of green equity is the lowest, while "dirty" bonds have the highest average return. Notably, green equity has the highest standard deviation, while "dirty" bonds have the lowest standard deviation. Overall, our proxies for equity investment are more volatile than their debt counterparts.

Finally, the Jarque-Bera (JB) test rejects the assumption of normality in all series, while the Augmented Dickey-Fuller and Phillips-Perron unit root tests confirm a stationary process in both the returns and volatility series. For brevity, we have not included the unit root test results, but these are available upon request.

Figure 2. Return series



Notes: Log differences for returns series are computed for the GB, GE, DB and DE, and first differences for the CUI. GB is the Bloomberg U.S. aggregate green bond index as the proxy for green bonds, GE is the Wilderhill clean energy index representing the green equity (stocks), DB stands for "dirty" bonds and is represented by the iBoxx USD Oil & Gas index bonds, DE is the iShares U.S. Oil & Gas Exploration & Production ETF as a proxy for "dirty" equity and finally CUI is the Climate Policy Uncertainty Index of Gavriilidis (2021).

3. Methodology

Diebold and Yılmaz (2009, 2012, 2014) (hereafter, DY) pioneered the use of Forecast Error Variance Decomposition (FEVD) as an interpretation for the connectivity between the variables of a certain system. Using a rolling-window VAR-based approach, they construct the familiar connectedness measures from the FEVD. Due to its novelty, the VAR approach proposed by Diebold and Yılmaz (2009, 2012, 2014)—the DY approach—has been the workhorse in connectedness studies. Antonakakis, Chatziantoniou, and Gabauer (2020) took a step forward to improve the DY approach by proposing a dynamic connectedness procedure based on the TVP-VAR method. Antonakakis, Chatziantoniou, and Gabauer (2020) applied a time-varying parameter vector autoregressive model (TVP-VAR) based on a time-varying covariance structure as proposed by Primiceri (2005) and managed to overcome several flaws of the common DY approach. One of these weaknesses is the requirement for a random length of rolling time window. By contrast, the approach proposed by Antonakakis, Chatziantoniou, and Gabauer (2020) utilizes a time-varying parameter that avoids the potential loss of observations, is more robust in its treatment of outliers, and is critical in the case of small time-series data (for a more detailed discussion of the merits of the TVP-VAR approach, please refer to Antonakakis, Chatziantoniou, and Gabauer [2020]). Therefore, this approach is particularly suitable for our study of dynamic connectedness and has been employed in several recent connectedness studies (e.g., Mensi et al., 2022; Tiwari et al., 2022; Pham & Nguyen, 2022; Guo & Zhou, 2021; Yousaf et al. 2022).

The TVP-VAR(p) model can be represented as:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t,\ \varepsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + \vartheta_t,\ \vartheta_t \mid \Omega_{t-1} \sim N(0, R_t). \tag{2}$$

where Y_t and Y_{t-1} are $N\times 1$ and $Np\times 1$ vectors, respectively, and Ω_{t-1} represents all available information in the period t-1. If Y_t is covariance stationary Eq. (1) can be transformed to its vector moving average (VMA) representation as follows in Eq. (3) below:

$$Y_t = \sum_{j=0}^{\infty} \Theta_{jt}\varepsilon_{t-j}, \tag{3}$$

where Θ_{it} is an $N\times N$ dimensional matrix.

To achieve the dynamic connectedness measures, we use the time-varying parameters and variance-covariance matrices of the TVP-VAR model in the measure of connectedness proposed by Diebold and Yilmaz (2009, 2012, 2014). Accordingly, the elements of the dynamic H-step generalized variance decomposition matrix $D_t^{gH} = [d_{ij,t}^{gH}]$ can be defined as:

$$d_{ij,t}^{gH} = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1}\left(e_i^{'}\Theta_{h,t}\Sigma_t e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i^{'}\Theta_{h,t}\Sigma_t\Theta_{h,t}^{'}e_j\right)}, \tag{4}$$

where $\sigma_{jj,t}^{-1}$ is the j^{th} diagonal element of Σ_t. The normalized terms

$$\tilde{d}_{ij,t}^{gH} = \frac{d_{ij,t}^{gH}}{\sum_{j=1}^{N} d_{ij,t}^{gH}} \tag{5}$$

are used to determine the *dynamic total directional connectedness*, *net total directional connectedness*, and *total connectedness*. The *total connectedness index* (TCI) is:

$$C_t^{gH} = \frac{\sum_{i,j=1,\, i\neq j}^{N} \tilde{d}_{ij,t}^{gH}}{\sum_{j=1}^{N} \tilde{d}_{ij,t}^{gH}} \times 100. \tag{6}$$

The *directional spillover* received by variable *i* from all other variables *j*, is measured as:

$$C_{i\leftarrow j}^{gH} = \frac{\sum_{j=1,\, i\neq j}^{N} \tilde{d}_{ij,t}^{gH}}{\sum_{i=1}^{N} \tilde{d}_{ij,t}^{gH}} \times 100. \tag{7}$$

Similarly, the *spillovers received* by variable *j* from all other variables *i*, is calculated as:

$$C_{i\rightarrow j}^{gH} = \frac{\sum_{j=1,\, i\neq j}^{N} \tilde{d}_{ij,t}^{gH}}{\sum_{j=1}^{N} \tilde{d}_{ij,t}^{gH}} \times 100. \tag{8}$$

To measure the *net pairwise directional connectedness*, we subtract the total directional connectedness FROM others from total directional connectedness TO others. This can be considered as the role of variable *i* has in the framework of the analyzed system. That is,

$$C_{ij,t}^{gH} = C_{j\leftarrow i,t}^{gH} - C_{i\leftarrow j,t}^{gH}. \tag{9}$$

At last, the *net pairwise directional connectedness* is defined as:

$$NPDC_{ij}^{gH} = (\tilde{d}_{ji,t}^{gH} - \tilde{d}_{ij,t}^{gH}) \times 100. \tag{10}$$

If the value is greater than zero, this implies that variable *i* dominates variable *j*; otherwise, the latter dominates the former.

4. Empirical Findings

We begin our discussion of results with a static connectedness framework and then turn to a dynamic analysis of connectedness across time. Table 2 presents the static analysis. We will discuss the dynamic connectedness analysis using Figures 4-6.

4.1.Static spillover analysis

Our static analysis deals with the estimation of the interaction between five system variables. In Table 2, we present a static spillover analysis over the full period. The diagonal values refer to the "own" variation for each variable itself and are a measure of self-dependence. "TCI" is a measure of the degree of total connectedness in the system. The row "TO" represents the total spread of shocks that a variable delivers to each of the other variables in the system, while the last column, "FROM," represents the total shocks that a certain variable receives from its counterpart system variables. Subtracting the difference between the contribution TO and the contribution FROM yields the "NET" row, which refers to the net-pairwise summation of the directional spillovers. A negative (positive) value indicates a net receiver (transmitter) of shocks.

Table 2: Static Connectedness Tables

Panel A: Static Connectedness – Returns						
	GB	GE	DB	DE	CUI	FROM
GB	48.7	7.9	35.9	6.8	0.6	51.3
GE	8.3	55	16	20.3	0.4	45
DB	30.8	12	41.9	14.8	0.5	58.1
DE	7	20.5	19.2	53.1	0.2	46.9
CUI	0.9	0	0.4	0.1	98.5	1.5
TO	47.1	40.4	71.4	42.1	1.7	202.8
NET	-4.2	-4.6	13.3	-4.8	0.2	TCI=40.56
Panel B: Static Connectedness – Volatility of Returns						
	GB	GE	DB	DE	CUI	FROM
GB	45.1	11.9	26.6	15.9	0.4	54.9
GE	12.8	57.3	15.3	14.5	0	42.7
DB	24.2	11.6	41.5	22.1	0.6	58.5
DE	14.6	13.5	21.6	47.8	2.4	52.2
CUI	0.6	0.1	1.3	5	93	7
TO	52.2	37	64.9	57.7	3.5	215.2
NET	-2.7	-5.6	6.4	5.4	-3.5	TCI=43.04

Note. This table shows the connectedness measures between the system variables under a TVP-VAR approach. VAR order is 1 as determined by the Schwarz information criterion. Panels A and B report the findings for the Returns, and the volatility of returns. The sample period is January 2007–March 2021. The table shows the estimated contribution to a 10-day-ahead forecast error variance decomposition. The bold diagonal elements are the (individual) variance percentages for each variable. TCI is the total connectedness index. The off-diagonal values illustrate the bi-directional interaction between the different system variables. The row "From" shows the total spillovers absorbed by a certain variable from all system variables, and "To" is the spillover of shocks by a certain variable to all other variables.

To determine the degree of system connectivity, we look at the total spillover index. In **Table 2**, the TCI (right bottom corner) is 40.56% for the yield curve components and 43.04% for the volatility series. According to these relatively high values, and as expected, the system of green and dirty investments (both bonds and equity) and the CUI are strongly connected. More specifically, around 40% of the variation in the returns of green and dirty investments and climate policy uncertainty is explained by their co-movements. In terms of return spillovers TO the system, dirty bonds (71.4%) have the strongest influence on other system variables, but also, when we look at the spillover that each variable receives FROM the system, dirty bonds have the highest risk absorption (58.1%). Similarly, when we look at the volatility spillovers presented in Panel B, dirty bonds remain the dominant variable in terms of delivering shocks TO (64.9%) the system as well as absorbing shocks from FROM (58.5%) the system. Lastly, looking at the last NET row, we observe that dirty bonds (DB) are the most influential variable. For both the returns and volatility examinations, DB remains a significant transmitter. On the other hand, dirty equity (DE) is a net receiver of spillovers in the returns series but a transmitter of risk spillovers in the volatility series. Green equity (GE) and green bonds (GB) are net receivers in both the returns and volatility of returns analyses. **Figure 3** offers a visual illustration of these relationships. The LHS (RHS) figure illustrates the network connectedness in terms of returns (volatility of returns). The arrows signal the net directional connectedness between two variables in the system with a one-way direction arrow. The source of each arrow defines the transmitter, and the point of the arrow indicates the receiver of shocks. The more arrows, the more dominant the variable in the system. Red arrows indicate that a variable is the dominant transmitter of pairwise spillover, while a blue arrow indicates the dominant receiver of spillover. As can be seen from the figure, the conclusions are similar to the static connectedness analysis shown in **Table 3**. In the case of returns, DB is the dominant net transmitter, while DE is the dominant net receiver. In terms of volatility, DB is the dominant net transmitter, while GE is the dominant net receiver.

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Panel A: Static Connectedness – Returns						
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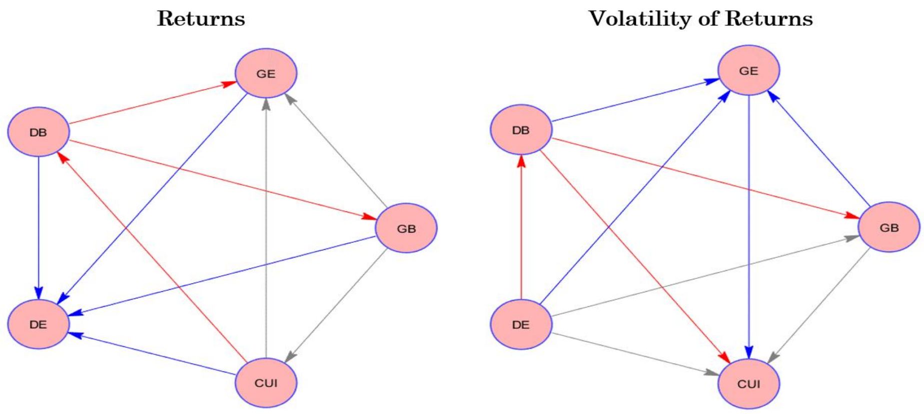
Surprisingly, the CUI seems to have only a minor influence on the system variables. In fact, its total aggregate influence is only 1.7%, and its absorption of risk spillovers is only 1.5%. Consequently, the net spillover of CUI is only +0.2%. A similar picture arises from the analysis of the volatility of returns shown in Panel B. Even though it seems that the impact in terms of volatility is more evident, the impact is still low when we observe the total impact in terms of TO and FROM the system. Further support for this independence of the CUI may be seen from its diagonal values (98.5% and 93% in Panel A and Panel B, respectively). Over 90% of the fluctuations in the CUI are not connected to changes in other variables.

A major limitation of the static analysis may be that the relationship is assumed to be constant across time. To delve deeper into the relationship between the system variables, we turn to a dynamic connectedness analysis.

4.2. Dynamic spillover analysis

Figure 3 refers to the return series connectedness (left panel) and its right panel depicts the volatility connectedness. The values in the vertical axis are the total connectedness index (%): on average, the proportion of the variation that can be referred to the dynamics between the system variables.

Figure 3. Pairwise Static Net Connectedness



Notes: The above graphical descriptions illustrate the symbiosis network connectedness of the system variables. The system includes the following variables: GB (Green Bonds), GE (Green Equity), DB ("Dirty" Bonds), DE ("Dirty Equity") and CUI (the Climate Uncertainty Index). The left (right) figure illustrates the network connectedness in terms of returns (volatility of returns). Arrows signal the net directional connectedness between two variables in the system with a one-way direction arrow. The source of the arrow shows the transmitter, and the point of the arrow shows the receiver of spillover. More arrows mean a more influential variable in the connectedness. Red arrows mean that a certain variable is the largest transmitter of pairwise spillover, and blue arrows indicate the largest receiver of spillover.

Figures 4-6 present a dynamic picture of the connectedness analysis across the sample period. More specifically, **Figure 4** shows the total connectedness index (in percentage terms) between the system variables, while **Figure 5** and **Figure 6** describe the NET spillover (TO minus FROM) of each variable versus the rest of the system variables, in terms of the returns and volatility series, respectively.

Figure 4 describes the (average) proportion of the variation that can be attributed to mutual fluctuations in the system variables. **Figure 4.1** shows the return series connectedness, while **Figure 4.2** depicts the volatility connectedness. As can be seen from the two figures**,** connectedness is far from being constant across time, and peaks during periods of market turbulence. The first period, around the years 2007 to 2008, can be attributed to the outbreak of the subprime crisis and the subsequent global financial crisis. The second period is around the years 2009–2011, at the time of the European debt crisis. Finally, the third period begins in early 2020, when the COVID-19 pandemic erupted. These results also conform to the results obtained by Pham (2021) showing that the connectedness between green bonds and green equity is stronger during extreme market conditions. Relatively low levels of connectedness are observed during the years preceding the COVID-19 crisis.

Figure 4. Total Connectedness Index

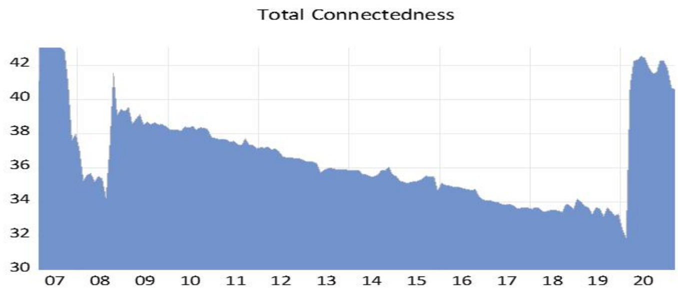


Figure 4.1: Returns

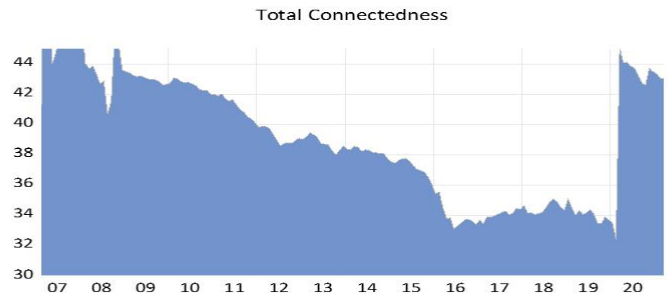


Figure 4.2: Volatility of Returns

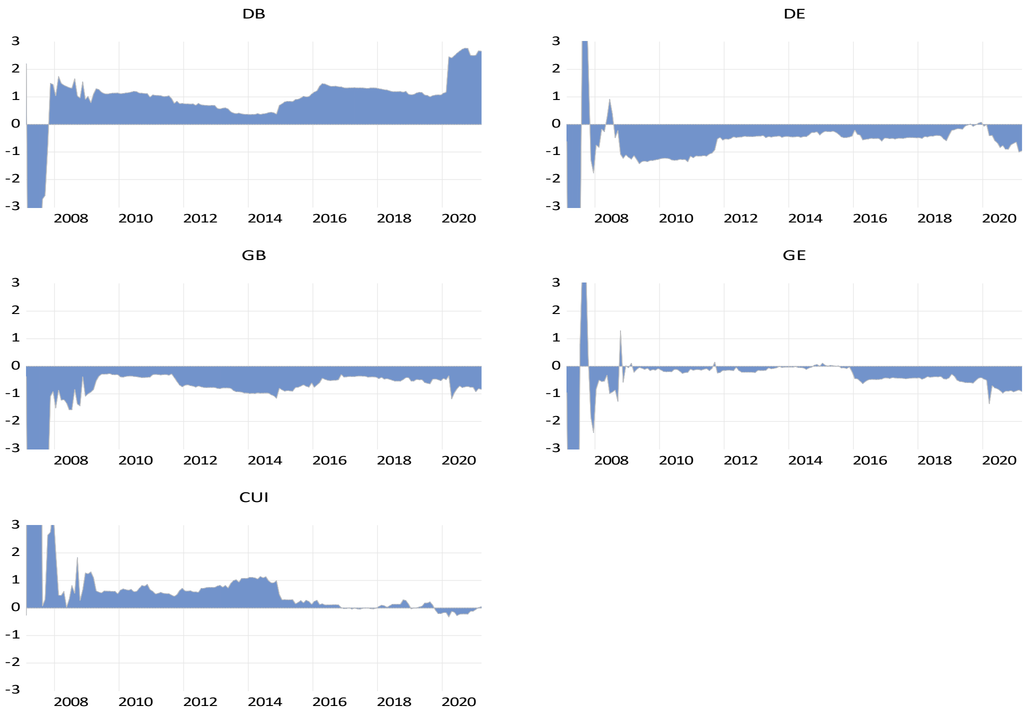
Notes: Total Connectedness Index. The figures above track the total connectedness index across time.

Next, we turn to the discussion of the return and volatility connectedness between a certain variable and the whole system over the full sample period. To achieve that, **Figures 5** and **6** display the NET spillover (TO minus FROM) of each variable versus the other system variables. The nature of the relationship is determined by the value (positive/negative) of the connectedness.

In terms of returns, and according to **Figure 5,** it seems that dirty bonds (DB) and the CUI are mostly transmitters over the full sample period, whereas dirty equity (DE), green bonds (GB), and green equity (GE) are mostly net receivers. Two important points arise from the current analysis. First, as opposed to the static analysis implying that the bond and equity measures are immune to fluctuations in the CUI, the dynamic analysis provides evidence that CUI can be a transmitter of return shocks. Second, this role as a transmitter is clear during the time of several important episodes, especially around the subprime crisis and the European debt crisis. This evidence for CUI as a net transmitter is consistent with former studies, such as Lundgren et al. (2018), showing other uncertainty indices, such as the VIX and the Economic Policy Uncertainty Index (EPU by Baker et al, 2016) were net transmitters of volatility connectedness for green investments during the subprime crisis and the European sovereign debt crisis. However, we find that the transmission of shocks by the CUI has weakened over the last five years. Interestingly, its contribution is very small even during the COVID-19 crisis, and it even turns out to be a recipient of spillovers from the system. These findings may explain the apparently mild impact of CUI found in the framework of the static analysis. This illustrates the way that static analysis may hide different episodes and patterns across time and underscores the importance of performing dynamic analysis.

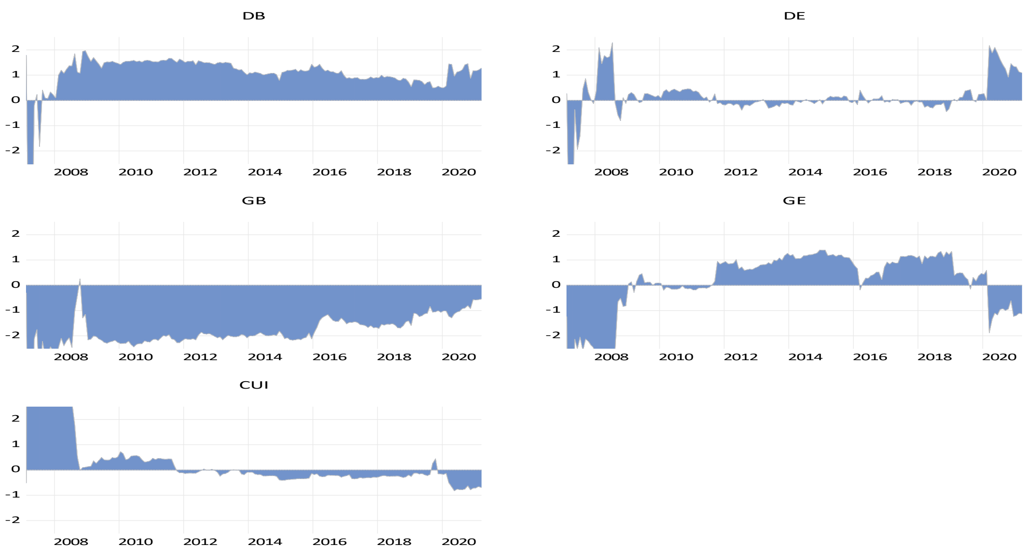
Figure 6 presents similar results in terms of the volatility of returns. According to the trends shown in this figure, DB, DE, and CUI are the main transmitters through most of the sample period, while GB is the dominant receiver of risk spillovers. Interestingly, GE seems to be a net receiver of volatility spillovers during two major turbulent periods, namely the subprime crisis and the COVID-19 pandemic. However, during the remaining years, GE is a net transmitter of volatility shocks. As in the results for returns (Figure 5), the CUI performs as a net transmitter of volatility shocks around the subprime crisis and the European debt crisis, but this effect then weakens, and it turns into a net recipient of spillovers during the five most recent years, including the COVID-19 period.

Figure 5. Dynamic Net Connectedness Index – Returns



Notes: The above graphs depict the dynamic NET spillover (TO minus FROM) of each variable versus the rest of the system variables in terms of returns. The symbiotic nature of the relationship is determined by the value of the connectedness. Positive (negative) values imply transmission (absorption) by a system variable.

Figure 6. Dynamic Net Connectedness Index – Volatility of Returns



Notes: The above graphs depict the dynamic NET spillover (TO minus FROM) of each variable versus the rest of the system variables in terms of *volatility of returns*. The symbiotic nature of the relationship is determined by the value of the connectedness. Positive (negative) values imply transmission (absorption) by a system variable.

5. Conclusions

In this paper, we examine the connectedness between green equity and bonds (GE and GB: green investments), dirty equity and bonds (DE and DB: dirty investments), and the novel Climate Policy Uncertainty Index (CUI) proposed by Gavriilidis, (2021). We use both static and dynamic approaches to identify the net transmitters and net receivers of risk spillovers. Given the increasing public interest in climate change, economic sustainability and the corresponding investment flows that fuel green investments, we present here an important attempt to characterize the relationships between green and dirty investments and their possible dependence on the CUI. While our static analysis shows that green investments (both bonds and equity) are immune to fluctuations in the CUI, a deeper examination through the lens of dynamic analysis shows that CUI performs as a net transmitter of both return and volatility spillovers. This phenomenon is evident around the 2007–2008 subprime crisis and the European debt crisis. However, during the five most recent years the transmission of risk spillovers by the CUI has weakened, and it has even turned into a net receiver during the COVID-19 period.

Our paper has several implications for both policy decision-makers and market participants. For policy-makers, our results show that the connectedness between green and dirty investments is high, especially during turbulent times. Therefore, the addition of any further uncertainty in the form of climate policy uncertainty may even exacerbate risk spillovers between the two asset classes. Given the growing interest and awareness of climate issues, policy-makers in the climate field should consider the timing of proposed reforms, which, as exogenous events, may significantly impact green and dirty investments. Hence, policy-makers should endeavor to disclose sufficient information about their future policy plans. This may alleviate the detrimental effect of policy shocks. For investors aiming to exploit the diversification benefits of green and dirty investments, our findings show that these benefits are dependent on market conditions. In cases such as the COVID-19 pandemic, as opposed to the subprime crisis, for example, risk spillovers can be fueled by overall uncertainty in the market, rather than climate policy uncertainty itself. However, it is evident that in stressful times, the spillovers between green and dirty bonds and green and dirty equity are considerably higher.

Future studies may extend our examination to consider the impact and connectedness of the CUI with alternative investments such as Bitcoin, Ethereum, and other major cryptocurrencies, which several of them are known to be extremely polluting in their mining process. Our attempt to quantify the relationship between the CUI and green and dirty investments is restricted by the fact that the CUI index is available only monthly. Therefore, an examination of the relationship over narrower time periods, using daily or weekly observations, would assist in a better understanding of the dynamics between the CUI and green and dirty investments.

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