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Time-varying tail risk connectedness among sustainability-related products and fossil energy investments

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ABSTRACT

In this paper, we analyse the dynamic transmission of tail risk across a set of well-established sustainability-related financial indices & equities and energy assets using a novel CAViaR-TVP-VAR connectedness measure on daily data from 14 October 2014 to 31 August 2022. Findings suggest that the total risk connectedness is at medium level and the short-run effect of COVID-19 on the risk transmission was mild. Furthermore, ESG and green equities are persistent net risk *transmitters*, while green bond, carbon asset, and energy commodities are tail risk *takers*. The role of renewable energy stocks is inconclusive due to distinct time-varying characteristics. With reference to pairwise relationship, we show that sustainability equities strongly interact with crude oil futures and fossil energy equities. Furthermore, green bond, carbon, natural gas and coal futures weakly associate with the remaining assets in the system. Finally, we find that EPU, OVX, VIX, GPR, and the spread of US Treasury have asymmetric impact on the spillovers. Altogether, our results offer insightful implications for policymakers and especially for "green" and "brown" products investors in risk diversification from the VaR perspective.

1. Introduction

The importance of slowing down climate change is becoming more widely understood, which has led policymakers and investors to seek more sustainable developments and investment. The US has rejoined the Paris Agreement on climate change since 2021, along with nearly 200 countries around the globe, to reduce the emission of greenhouse gases. Achieving the goal of carbon neutrality has been adopted as a major target of several major countries for the next 30 years.[1]

Moving towards greener financialisation is not a new concept. As far back as 2007, the European Investment Bank (EIB) issued the first socially responsible fixed-income security product, known now as "Green Bonds" or "Climate Awareness Bonds". At that time there was no clear definition of this kind of products. In January 2014, the International Capital Market Association published the first edition of Green Bond Principles (GBP) as guidelines for green labelling of bonds, which is believed to further improve the quality and liquidity of green bonds. An 2017 report by the Climate Bonds Initiative Market Team pointed out that the green bond market had grown by 92% in the subsequent year after the release of the GBP.[2] By the end of 2021, the cumulative global green bond issuance stood at 1.7 trillion US Dollars and is still rapidly growing in 2022, where the euro area consistently contributes the most.[3] A better understanding of price relations between green bonds and other financial markets is therefore crucial for determining green bond performance and their usefulness in reducing portfolio risks, which in return will further promote the growth and development of the market underpinnings of a carbon-neutral society. Recently, there have been a number of studies examining the price co-movement between green bonds and other assets such as Reboredo (2018), Reboredo et al. (2022), Kanamura (2020), Reboredo and Ugolini (2020), Gormus et al. (2018), etc. Others have considered the volatility behaviour or the spillovers of green bonds (e.g., Zhang et al. (2022), Gormus et al. (2018), Pham (2016), Gao et al. (2021), Le et al. (2021), etc.).

At the same time, as an alternative to fossil energy, renewable energy has received more and more policy support in development due to its benefits on carbon emissions reduction. We have witnessed a exponential growth track in renewable energy industry in the last two decades. Even during the COVID-19 pandemic, the growth of

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[1] See https://www.iea.org/reports/world-energy-outlook-2020/achieving-net-zero-emissions-by-2050.
[2] https://www.climatebonds.net/files/files/2016%20GB%20Market%20Roundup.pdf
[3] https://climatedata.imf.org

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global adoption and production of renewable energy has been resilient and has continuously peaked higher (Hannah Ritchie and Rosado, 2020). The evolution of the renewable/alternative energy has gained considerable attention among investment communities and researchers. A wide range of clean energy related equity indices have been created to capture the performance of publicly listed alternative energy related companies. This enables scholars to study the price/volatility relationships between new energy stocks and other markets and the effectiveness of new energy in portfolio risk management (e.g., Ren and Lucey (2022), Shahbaz et al. (2021), Liu et al. (2021), He et al. (2019), Kuang (2021), Ahmad et al. (2018), etc.).

In fact, developing alternative energy is only one of the concrete approaches to achieve sustainable development and is within the energy sector. Nowadays, consumers, employees and even investors have increasing expectations for organisations to behave responsibly and sustainably. Regulators are also in favour of "greener" companies. Embedding standards of Environmental, Social, and Governance (ESG) in the business model or strategies is becoming more and more vital for a company to thrive in the new world. In this context, ratings agencies and financial institutions have created different sets of sustainability indexes providing benchmarks of high performing ESG companies for investors, such as MSCI ESG Leaders Indices, Dow Jones Sustainability Indices, FTSE4Good Indices, etc. These socially responsible products are extremely popular especially for the growing community of environmentally conscious investors.

To this far, we have seen that environmentally friendly or ESG products are advocated and may tend to be somehow more appealing in the current world context. However, are ESG products really a better choice than brown products taking into consideration of risk? As suggested by Baker et al. (2022), green stock investors may possibly be willing to hold a portion of brown stocks for hedge purpose. Do ESG products share similar risk exposure within group or even with brown products? How would green investors benefit from holding brown products and what are the implications? We attempt to answer these questions by diving into the spillovers between several green and brown investments in terms of the possibility of exposure to financial loss, the Value-at-Risk (VaR), on daily frequency.

Our study therefore contributes to the literature in several ways. First, we extend the variable set of Zhang et al. (2022) and Chatziantoniou et al. (2022a) who mainly focused on interconnectedness between green equities by including both carbon credit and fossil energy ("brown") assets. In particular, we not only used three primary energy commodity futures products (i.e., crude oil, natural gas, and coal), but also consider two energy equity indexes (i.e., oil & gas exploration and production companies and coal mining companies), while many previous studies have only considered oil & gas assets and ignored coal-related assets. This allowed us to comprehensively analyse not just the relationships within the sustainability ("green") group, but also the interactions between the sustainable and non-sustainable markets. Briefly, amongst the investments, we show that green equities share high level risk exposure with brown equities and oil futures. Second, we provide new and indicative evidence by employing a newly developed asymmetric slope Conditional Autoregressive Value-at-Risk (CAViaR) Time-Varying Parameter Vector Autoregressive (TVP-VAR) Connectedness measure by Chatziantoniou et al. (2022b) to analyse the dynamic transmission of tail risk, proxied by the VaR measure, among uniquely specified sustainable and non-sustainable markets variables, rather than price return or overall volatility. Our connectedness metrics measures how the degree of the exposure to extreme loss in one market affects the exposure in another or the rest of the markets. We found that risk connectedness significantly varies with major events such as the Brexit referendum, Paris agreement, and COVID-19 outbreak. However, unlike the majority of previous studies, we show that the effect of COVID-19 might be overestimated. We provide timely evidence that the recent Russia–Ukraine war may have altered the dependence of the respective markets. Moreover, since our approach measures the VaR spillovers which is a different objective from measuring the return and volatility; this has led to some different results from those of previous studies such as Zhang et al. (2022). For example, surprisingly in our case, we show that the sustainability-related equities are mostly risk transmitters, and highly interact with fossil energy equities; Green bond, carbon credit futures, and "brown" energy commodities (except the crude oil) are less involved in the risk transmission. Finally, our additional analysis based on a rolling window regression suggests that economic policy uncertainty, geopolitical risk, the spread of US yield curve, the implied volatility of US stock market, and the oil volatility, have had asymmetric and time-varying effects on the connectedness network. This helps explain why the pattern has been changing and what macroeconomic indicators we should pay attention to. Therefore, overall, our findings extend the understanding of risk relationship between or among green and non-green assets risk spillovers, and shed light to investing and risk management.

The remainder of this paper is organised as follows. We review some past research in Section 2. We then explain the methodology in Section 3, followed by Section 4 where we describe the data in great detail. We then present the empirical findings in Section 5 and lastly, we conclude and address the implications of our study in Section 6.

2. Literature review

Spillover effect can be understood as a network effect that events in one market or economy can have on another market or economy. It increases when the linkages between financial markets and trade activities among economies are stronger. In the context of globalisation, analysing the financial spillovers or connectedness between markets and assets becomes an essential issue and has important implications for market participants and policymakers.

One early strand of finance literature on spillover effects focuses on same type of conventional markets from a national or international perspective, such as equity market (Theodossiou and Lee, 1993; Susmel and Engle, 1994; Koutmos and Booth, 1995; Diebold and Yilmaz, 2008; Ng, 2000; Baele, 2005; Hammoudeh et al., 2009; Anderson et al., 2010), the commodity market (Kao and Wan, 2009; Kang et al., 2017; Nazlioglu et al., 2013), the bond market (e.g., Ciner (2007), Christiansen (2007), Skintzi and Refenes (2006), Aftab and Beg (2021)), and so on. Another strand of the financial spillovers literature tries to uncover the interconnectedness between different types of markets or assets. For example, Diebold and Yilmaz (2012) studied daily volatility spillovers across US stock, bond, foreign exchange and commodities markets. Ma et al. (2021) decomposed commodities' volatility into a fundamental component and a idiosyncratic component, and subsequently analysed the risk and sentiment spillovers among markets such as commodity, stock, foreign exchange, and so on. Arouri et al. (2011) investigated the volatility spillovers between oil prices and US stock sectors, while Ferrer et al. (2018) and Sadorsky (2012) focused particularly on the volatility spillovers between crude oil and emerging renewable energy technology stocks. Kanas (2000) found significant and symmetric volatility spillovers running from stock returns to exchange rate changes in the US, the UK, Japan, France and Canada, but not in the Germany. Yang and Zhou (2017) identified the roles of implied volatilities of US Treasury bonds, global stock indexes, and commodities in the volatility spillover network. They further investigated the impact of quantitative easing, interest rate and currency factors on the system. There are more examples such as Mensi et al. (2013), Yu et al. (2019), Kang et al. (2019), Bouri et al. (2018), Yoon et al. (2019), etc.

Growing concerns about climate change have piqued the interest of investors and policymakers in environmentally friendly investments such as renewable energies, green bonds, ESG stocks, etc. Since the financial markets for environmentally friendly investment has grown in both scope and size, scholars have found increasingly important to study the relationship between sub-class of green financial markets.

Many studies have considered the relationship among or between the green bond, clean energy, and conventional markets. For example, Hammoudeh et al. (2020) used a time-varying causality test to investigate the lead–lag relationships between green bond and other financial markets (i.e., clean energy, carbon emission allowances, and treasury bond). Ferrer et al. (2021) researched the return and volatility connectedness between green bond and several different financial markets including treasury and corporate bonds, aggregated world equity and renewable energy stocks, US exchange rate, and Brent crude oil prices by virtue of quantile and frequency. Naeem et al. (2021) used the same technique but concentrated on commodity markets and green bonds. They found that green bonds more strongly connected with gold and silver than with crude oil and natural gas and the connectedness is more significant in the short term. Park et al. (2020) examined the volatility spillovers between green bond and S&P 500 index proxied for equity market. They reported that both markets respond to positive but not negative shocks in the another market. Saeed et al. (2020) studied the time-varying relationship between green assets (i.e., green bond and clean energy) and fossil energy assets (i.e., WTI crude oil and oil & gas company ETF). They suggested that clean energy is even more effective in hedging "dirty" energy assets. Huynh (2022) found tail dependence and causal relationship between green bond and premium government bond using Student's t-copulas and transfer entropy, respectively. Pham and Do (2022) uncovered that there are stronger dynamic spillovers between green bonds and European and the US implied volatilities than with China and emerging markets. However, they are still significantly lower than spillovers between implied volatilities themselves.

Our study particularly relates to the limited studies on spillovers specifically between green bonds and several specialised eco-friendly financial markets including renewable energy, green equity and most importantly the ESG/sustainability which is usually overlooked, in the same manner of Zhang et al. (2022) and Chatziantoniou et al. (2022a). Chatziantoniou et al. (2022a) investigated the dynamic return spillovers among four environmental financial indices (i.e., the S&P Green Bond Index, MSCI Global Environment Index, Dow Jones Sustainability Index World, and S&P Global Clean Energy Index) from both quantile and frequency perspectives. Zhang et al. (2022) also studied the spillovers among same group of environmental indices, but focused on the volatility transmission and further extended the choices of indexes. Specifically, they considered the carbon emission allowances (credit) futures. Carbon credit futures facilitates the efficiency and liquidity of the carbon emission trading system which is one of the sustainable innovations that effectively helps in reduction of greenhouse gas emissions by distributing the emission permits to carbon releasing companies. We have seen that the successful establishment of the first carbon trading scheme in the Europe has brought global imitators and borrowers. The futures products allow companies to hedge the price risk of holding, buying or selling the carbon emission allowances. It is very liquid and also popular among a broad range of investors even including those who do not have any emission reduction obligations. Recent studies such as Demiralay et al. (2022), Jiang and Ma (2022) and Zhang et al. (2017) have proven that carbon assets have some hedge and diversification benefits.

Our selection of sustainability-related indexes slightly differs but is more reasonable as we prefer indices provided by the same company to ensure the consistency of metrics and difference in choosing companies. Some previous studies showed that relevant indices, although offered by different companies such as MSCI World ESG Leaders Index and Dow Jones Sustainability Index World which were considered in Chatziantoniou et al. (2022a), have very similar price patterns because they include utmost same constituents (Reboredo (2018), Vicente-Ortega Martínez (2021), etc.). Such similarity can easily induce high spillovers in between. At the same time, we must not ignore the traditional energy market. Amongst the literature, the oil market is more often considered (e.g., Arouri et al. (2011, 2012), Chang et al. (2013), Tan et al. (2020), etc.). Crude oil is arguably the most important strategic reserve commodity in the world. Numerous studies such as Zhang (2017), Kang et al. (2015), Demirer et al. (2020),amongst others, have been looking at the impact of crude oil price shocks on other financial markets. Liu et al. (2022) detected significant oil risk spillovers to G20 during crisis periods. Ji et al. (2018) documented that crude oil, coal, and clean energy play an significant role in both returns and volatility of carbon-energy connectedness network. Similarly, Tan et al. (2020) studied the volatility spillovers in a comprehensive "Carbon-Energy-Finance" system given the context of the tight physical and financial connections. We have also seen less number of studies such as Saeed et al. (2020), Zhang and Sun (2016), Ji et al. (2018), etc, that have paid attention to alternative fossil energy assets such as coal and gas futures, and energy ETF products. Our research therefore adds to literature by considering a comprehensive selection of sustainable and non-sustainable investments

Our study covers the period of COVID-19 period in which the pandemic has been posing an unprecedented challenge to financial systems from early 2020. A large number of research has shown that the systemic risk and financial contagion sharply increased during early waves of the disease (e.g., Rizwan et al. (2020), Akhtaruzzaman et al. (2021), etc.). Of particular note is that the WTI price historically turned negative to –37.63 USD/barrel and losing about –300% on 20 April 20 2020 due to the demand squeeze in the context of travel and business restriction encountering the COVID-19 (Jawadi, 2023). It is always worth investigating the spillover patterns during the crisis period. The uncertainty and volatility have rapidly increased since the Russia–Ukraine war. There is still room for researchers to have a look at the changes in patterns resulted by the war. We add knowledge to the literature by showing the changes in scale of the tail risks during the period and the impact of important events and crises on the spillovers among the system variables. We also base on some previous studies (e.g., Zhang et al. (2023), Saeed et al. (2021), etc.) to investigate potential determinants (e.g., EPU, GPR, TERM, VIX, OVX) of the spillover network, which extends the knowledge of the deep reasons that cause the spillover changes.

3. Methodology

3.1. Tail risk spillovers

3.1.1. Conditional Autoregressive Value-at-Risk (CAViaR)

We follow Chatziantoniou et al. (2022b) to measure the tail risk of variables by the asymmetric slope Conditional Autoregressive Value-at-Risk (CAViaR) approach which was introduced by Engle and Manganelli (2004). Chatziantoniou et al. (2022b) suggested that the asymmetric slope CAViaR is more flexible than the other existing techniques as it estimates the Value-at-Risk (VaR) in a direct way and allows for asymmetric effects which is not the case for either the symmetric absolute value or the indirect GARCH(1,1) approach.

The asymmetric slope CAViaR model assumes that the VaR of a certain quantile follows an Autoregressive (AR) process which can be written as:

$$f_{\alpha,t}(\beta) = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x^+_{t-1} + \beta_3 x^-_{t-1} \tag{1}$$

where $f_{\alpha,t}$ is the VaR at the α level in period t, β_0 is the constant, β_1 and $f_{\alpha,t-1}(\beta)$ are the weights of the lagged VaRs and the lagged VaRs, respectively. β_2 and β_3 are the effects of positive and negative returns on the VaR, respectively.

3.1.2. Time-varying parameter vector autoregressive (TVP-VAR) connectedness

We considered applying a time-varying parameter VAR model (TVP-VAR) proposed by Antonakakis et al. (2020) on changes in CAViaR to examine the tail risk spillovers across sustainable and non-sustainable investments. The TVP-VAR approach should have advantages over the DY connectedness framework (Diebold and Yilmaz, 2012; Diebold and

Yılmaz, 2014) that is based on a rolling window VAR approach as this does not require a window size to be biasedly assigned. It also avoids losing observations as it introduces a time-varying variance–covariance matrix by adopting the Kalman filter in estimation with forgetting factors assigned (Antonakakis et al., 2020).

The TVP-VAR model with p lags is defined as the following:

$$\begin{aligned} y_t &= \Phi_t z_{t-1} + \epsilon_t & \epsilon_t \mid I_{t-1} \sim N\left(0, \Sigma_t\right), \\ vec\left(\Phi_t\right) &= vec\left(\Phi_{t-1}\right) + e_t & e_t \mid I_{t-1} \sim N\left(0, E_t\right), \end{aligned} \tag{2}$$

where y_t represents $m \times 1$ vector of endogenous variables, while z_{t-1} represents $pm \times 1$ vector of lagged y_t from $t-p$ to $t-1$. ϵ_t and e_t are vectors of error terms. I_{t-1} denotes all known information until $t-1$. Σ_t and E_t are time-varying variance–covariance matrices.

We introduced the time-varying coefficients and the time-varying variance–covariance matrices in the step of generalised forecast error variance decomposition. For generalised VAR model, $\phi_{ij}(H)$, the H-step ahead generalised forecast error variance will be first decomposed and then normalised by its row sum. Before doing that, based on the Wold representation theorem, we transform the estimated TVP-VAR model into TVP- vector moving average (VMA) as: $y_t = \sum_{i=1}^{p} \Phi_{it} y_{t-i} + \epsilon_t = \sum_{j=0}^{\infty} A_{jt}\epsilon_{t-j}$

$$\begin{aligned} \phi_{ij}(H) &= \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)}, \\ \tilde{\phi}_{ij}(H) &= \frac{\phi_{ij}(H)}{\sum_{j=1}^{N} \phi_{ij}(H)} \end{aligned} \tag{3}$$

where the σ_{jj} denotes the estimated SD of the error term for variable j, Σ is the variance matrix for the error-term vector ϵ, and e_i is the selection vector with one as the ith element and zero otherwise.

Following Antonakakis et al. (2020), we initiate the Kalman filter using the Minnesota prior, followed by using the benchmark decay factors of (0.99, 0.99) in the estimation step.[4]

The total connectedness/spillovers (TC), directional connectedness received by asset i from j ($DC_{i \leftarrow j}$), directional connectedness transmitted to j by i ($DC_{i \rightarrow j}$), and net directional connectedness (NET) indices are calculated as the following:

$$TC(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{4}$$

$$DC_{i \leftarrow j}(H) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\phi}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ij}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\phi}_{ij}(H)}{N} \times 100 \tag{5}$$

$$DC_{i \rightarrow j}(H) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\phi}_{ji}(N)}{\sum_{i,j=1}^{N} \tilde{\phi}_{ji}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\phi}_{ji}(H)}{N} \times 100 \tag{6}$$

$$NET_i(H) = DS_{i \rightarrow j}(H) - DS_{i \leftarrow j}(H) \tag{7}$$

As the total connectedness by this measure is not in the range of [0, 1], adjusted total connectedness computed by $\frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\phi}_{ij}(H)}{N-1} \times 100$ was used.

3.2. Drivers of spillovers

Finally, to investigate the potential drivers of the connectedness network over time, we resorted to a dynamic estimation based on a rolling window size of 120 days, which essentially covers the rough number of observations during each wave of the COVID-19 pandemic. Specifically, the model is written as:

$$TC(H) = \beta_0 + \beta_1 EPU_t + \beta_2 GPR_t + \beta_3 TERM_t + \beta_4 VIX_t + \beta_5 OVX_t + \varepsilon_i \tag{8}$$

where EPU, GPR, TERM, VIX, OVX denote the Economic Policy Uncertainty Index, Geopolitical Risk Index, the spread between the 10-year and 3-month US Treasury Constant Maturity rates, the Chicago Board Options Exchange (CBOE) Volatility Index and the CBOE Crude Oil ETF Volatility Index, respectively.

4. Data

We aimed to investigate the tail risk connectedness among sustainability-related indexes, carbon credit futures, and fossil energy assets. The sustainability-related indexes we selected include the MSCI World ESG Leaders Index, the MSCI Global Environment Index, the MSCI Global Alternative Energy Index, and the Bloomberg Barclays MSCI Global Green Bond Index, à la Zhang et al. (2022) and Chatziantoniou et al. (2022a). Our selection of sustainability-related indexes slightly differs as we prefer indices provided by the same company to ensure the consistency of metrics. Some previous studies showed that relevant indices provided by different companies have similar patterns (Reboredo (2018), Vicente-Ortega Martínez (2021), etc.). The MSCI World ESG Leaders Index is a broad, diversified sustainability benchmark, computed for investors seeking investments in companies with leading Environmental, Social and Governance (ESG) performance relative to their sector peers. The Bloomberg Barclays MSCI Global Green Bond Index was designed in 2014 after the establishment of the Green Bond Principles and in respond to the growing interest among investors in fixed-income securities in which the proceeds will be exclusively and formally applied to projects/activities that will promote environmental sustainability. The MSCI Global Environment Index tracks the performance of companies that derive at least 50% of their revenues from environmentally beneficial products and services in alternative energy, sustainable water, green building, pollution prevention or clean technology sectors globally. The MSCI Global Alternative Energy Index tracks the performance of companies that derive 50% or more of their revenues from products and services in global alternative energy industry.

We used the IHS Markit Global Carbon Index as a proxy for the performance of global carbon credit futures markets. The IHS Markit Global Carbon Index is the first and investable benchmark for the global market, which consists of most liquid futures contracts on European Union Allowances (EUA), California Carbon Allowances (CCA) and the Regional Greenhouse Gas Initiative (RGGI), with pricing data from OPIS by IHS Markit Pricing (North American Pricing) and ICE Futures Pricing (European Pricing).

We considered both fossil energy commodities and equities as proxies for the performance of the fossil energy markets. Specifically, we used prices of several global benchmarks of the energy commodities including the ICE West Texas Intermediate (WTI) Crude Oil futures, the ICE Natural Gas futures, and the ICE Newcastle Coal futures. Finally, similar to Saeed et al. (2020), we used a Global Oil & Gas Exploration and Production Price Return Index by Refinitiv as a proxy for the performance of companies involved in global oil & gas exploration/production. We additionally used the Refinitiv Global Coal Price Return Index as a proxy for the performance of companies involved in global coal mining/production industry.

We employed daily data from 14 October 2014 to 31 August 2022, where the start date is when the MSCI Green Bond Index started to be daily computed. To remove the influence of the exchange rate on results, all price data are denominated in US Dollars. Our data came from multiple sources. The price data for MSCI World ESG Leaders Index, the MSCI Global Environment Index, and the MSCI Global Alternative Energy Index, the ICE WTI Crude Oil futures, the ICE Natural Gas futures, and the ICE Newcastle Coal futures were from Refinitiv Datastream. The price data for MSCI Global Green Bond Index was from Bloomberg. The price data for IHS Markit Global Carbon Index is available on the official website of the IHS Markit which is now

[4] We also used another benchmark suggested, 0.96, to check the robustness, results remain similar. For the sake of brevity, results are available upon request.

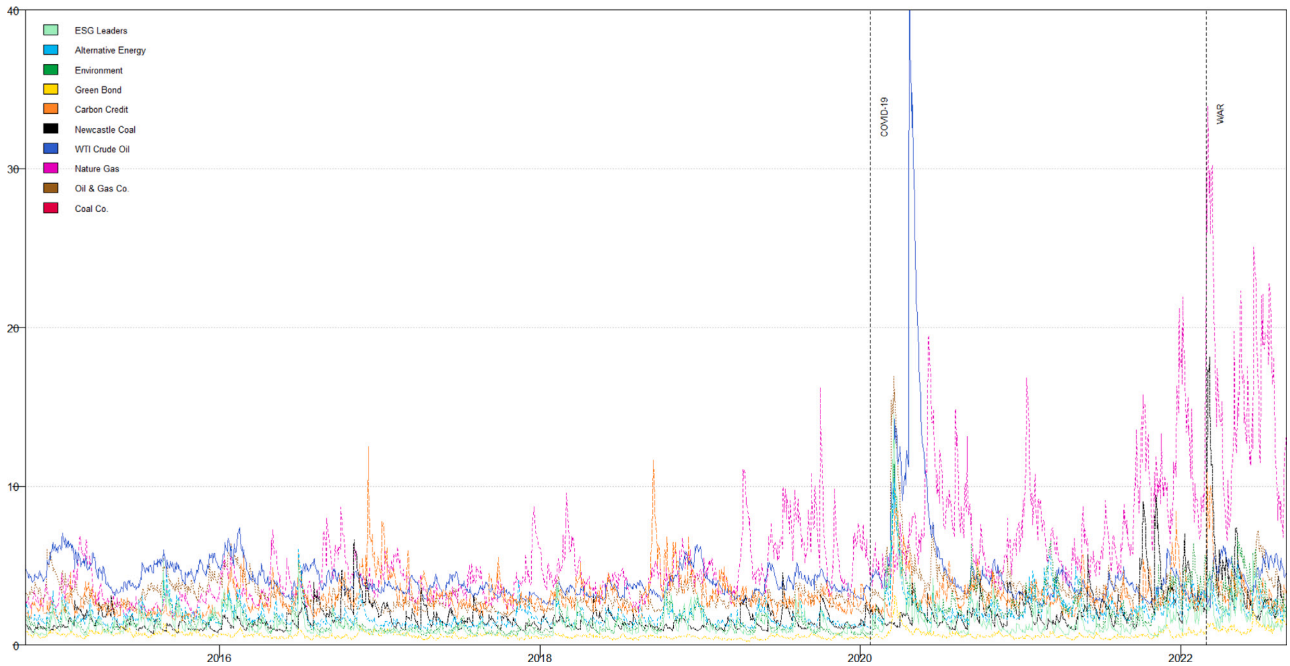


Fig. 1. Tail risk measured as 5% VaR using the asymmetric slope CAViaR model.

a part of the S&P Global.[5] The price data for Refinitiv Global Oil & Gas Exploration and Production Price Return Index and the Refinitiv Global Coal Price Return Index were from Refinitiv Eikon. [Regarding the determinants, the TERM, VIX, and OVX are available on Federal Reserve Bank of St. Louis website (https://fred.stlouisfed.org). The EPU Index constructed by Baker et al. (2016a) is available on their website (https://www.policyuncertainty.com/index.html). The GPR Index by Caldara and Iacoviello (2022) is available on Iacoviello's website (https://www.matteoiacoviello.com/gpr.htm).

5. Results

5.1. CAViaR estimates

We visualised the tail risk series measured as 5% VaR using the asymmetric slope CAViaR model to show the co-movements across series in Fig. 1. Most series clustered in early 2020 when the COVID-19 pandemic started. The green bond tends to have smallest tail risk on average. The WTI crude oil futures exhibits the largest tail risk around the day of historic negative price in 2020. The natural gas futures shows significant increased tail risk in the post-COVID-19 era. Using other levels such as 10% and 2.5% provides robust results with qualitatively similar pattern and slightly different magnitude (see Figs. A.1 and B.1).

We then calculated the logarithm differences of the tail risk representing the changes in probability of expected loss. Table 1 summarises the descriptive statistics of the tail risk changes. All series are stationary according to the ERS unit root test (Elliott et al., 1996) results, and are not normally distributed based on the JB test (Jarque and Bera, 1980) results. Table 2 presents the Kendall rank correlation coefficients between pairs. We notice that correlations between sustainability-related indexes are all positive, which indicates that a positive (negative) change in one "green" index is likely to cause a positive (negative) change in another "green" index. Similar statement can be applied to carbon credit futures as it is positively correlated to all other products. When it comes to the correlations between energy products, or between energy and "green" products, the results are rather mixed. Surprisingly, despite some insignificant estimates, the correlation between WTI crude oil futures and all other indexes including sustainability-related products (except the nature gas futures) are all positive, and the correlation between the coal companies and all other indexes are also positive. These encourage us to further analyse the spillovers among the variables.

5.2. TVP-VAR connectedness measures

5.2.1. Static (average) results

We first compute the static (average) results of the tail risk transmission among four sustainability-related indexes (ESG Leaders, Alternative Energy, Environment, Green Bond), Carbon futures, three primary fossil energy commodity futures (crude oil, natural gas, and coal), and two aggregated energy equities (Oil & Gas Co. and Coal Co.) in Table 3. The values in the ith row and jth column are the pairwise directional connectedness between variable i and variable j. The column of "FROM" measures the spillover effects that variable i receives from all other markets. Similarly, "TO" measures the spillover effects transmitted from variable j to other markets. "NET" is the net directional connectedness of variable j, which represents the general role of the variable j in the system. "NPT" counts the times of variable j's pairwise TO values exceeding its pairwise FROM values. "TCI" is the adjusted total connectedness index of the whole network. Values outside and in parentheses are results before and after the COVID-19 outbreak, respectively. We used January 24, 2020 when human transmission of the COVID-19 was discovered by Huang et al. (2020) and reported in *Lancet*, which lifted the global concern, as the break date.

First of all, we consider that the average total connectedness level (33.20% in pre-COVID-19 period or 28.56% during COVID-19 crisis) is at best moderate. This number indicates the proportion of the volatility forecast error variance in the system we construct comes from spillover effects. In our case, the relatively low to medium level of total connectedness implies some extent of interdependence among variables. Surprisingly, we find that the highest (top 3) spillover transmitters are all sustainability-related indexes in the order of ESG Leaders, Environment, and Alternative Energy Index before the COVID-19, although

[5] https://indicesweb.ihsmarkit.com/Carbon/Home

Table 1
Summary statistics of tail risk changes.

	ESG Leaders	Alt. Energy	Environment	Green Bond	Carbon Credit	Newcastle Coal	WTI Crude Oil	Nature Gas	Oil & Gas Co.	Coal Co.
Mean	0.047	0.018	0.029	0.025	0.036	0.022	−0.009	0.07	−0.012	−0.039
Variance	399.644	186.166	203.073	165.525	204.973	247.461	47.6	168.192	76.143	125.137
Skewness	1.894***	1.772***	1.828***	1.179***	1.481***	4.233***	6.526***	1.611***	1.966***	1.656***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	4.833***	4.360***	4.447***	1.644***	3.718***	25.243***	117.576***	5.947***	7.942***	3.628***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	3033.364***	2539.921***	2666.726***	664.861***	1817.725***	57033.185***	1125970.506***	3680.610***	6319.356***	1941.395***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−8.328***	−4.621***	−11.272***	−5.272***	−16.173***	−12.669***	−13.072***	−9.091***	−9.579***	−22.468***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes:
1. The null hypothesis of Jarque–Bera (JB) test: the series is normally distributed.
2. The null hypothesis of Elliott–Rothenberg–Stock (ERS) test: the series is non-stationary.
3.***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

Table 2
Kendall rank correlation coefficients.

	ESG Leaders	Alt. Energy	Environment	Green Bond	Carbon Credit	Newcastle Coal	WTI Crude Oil	Nature Gas	Oil & Gas Co.	Coal Co.
ESG Leaders	1.000***	0.324***	0.384***	0.036**	0.038**	−0.017	0.160***	−0.009	0.200***	0.203***
Alt. Energy	0.324***	1.000***	0.325***	0.084***	0.042***	−0.011	0.078***	−0.017	0.117***	0.195***
Environment	0.384***	0.325***	1.000***	0.021	0.038**	−0.005	0.098***	−0.006	0.145***	0.168***
Green Bond	0.036**	0.084***	0.021	1.000***	0.049***	0.032**	0.013	0.013	−0.011	0.063***
Carbon Credit	0.038**	0.042***	0.038**	0.049***	1.000***	0.017	0.038**	0.027	0.025	0.056***
Newcastle Coal	−0.017	−0.011	−0.005	0.032**	0.017	1.000***	0.012	0.031**	−0.009	0.006
WTI Crude Oil	0.160***	0.078***	0.098***	0.013	0.038**	0.012	1.000***	−0.002	0.187***	0.123***
Nature Gas	−0.009	−0.017	−0.006	0.013	0.027	0.031**	−0.002	1.000***	−0.003	0.032**
Oil & Gas Co.	0.200***	0.117***	0.145***	−0.011	0.025	−0.009	0.187***	−0.003	1.000***	0.164***
Coal Co.	0.203***	0.195***	0.168***	0.063***	0.056***	0.006	0.123***	0.032**	0.164***	1.000***

Notes:
1. ***, ** and * denote the rejections of the null hypothesis at the significance level of 1%, 5% and 10%, respectively.

the Oil & Gas companies Index has taken the place of Alternative Energy Index in the post-COVID-19 period to be a new transmitter. Both Green Bond Index and carbon credit futures have relatively low FROM and TO effects. However, they are not as low as those of coal futures, which is interesting as coal as one of the most important energy sources for heating does not affect the other markets much. In fact, all energy commodities have significantly lower spillovers with others compared to either "green" or "brown" equities. Lastly, we note that the average total connectedness has decreased in the post-COVID-19 era, which implies that the average tail risk transmission has weakened in recent years, unexpectedly. We see that the spillovers transmitted by the sustainability-related indexes and energy commodities have all decreased, while only the energy equities have transmitted more spillovers to other assets, which may be resulted by the increased interest in more sustainable products and the declined production and trade activities in oil as these impulses higher risks in energy companies' performance.

We visualise the pairwise connections over the full sample as shown in Fig. 2, which helps the readers quickly distinguish the role of each variable. There are two node colours, blue and yellow; blue colour denotes the role of a general tail risk transmitter within the system while yellow is for risk receivers. Node size indicates the magnitude of TO spillover effects; the larger the node size, the greater the effects. Arrow shows the direction of the spillovers transmission between two variables; also, the larger the interaction, the thicker the arrow. The coal futures looks isolated as there is no arrow pointing to or out from it and the node size is quite small. This is because, as we described earlier, although the coal futures transmits slightly higher spillovers to high ESG and alternative energy companies, carbon futures, and natural gas futures at a comparable level as green bond, it receives even lower risk than the green bond while green bond is a complete risk receiver as expected as a lower-risk product. If we go back to look at the Table 3, we see that the average net spillovers of coal futures is almost zero especially in the post-COVID era. The Alternative Energy Index receives risks from both leading ESG firms and Environment Index, which is not so surprising if considering that the ESG Leaders Index and Environment Index both cover broader sectors including the alternative energy industry. There is not much transmission among energy commodities and carbon credit futures, which implies the diversification benefits of constructing such portfolio. In any way, these interesting results encourage us to look at the evolution of the connectedness within the system over time.

5.2.2. *Time-varying results*

Fig. 3 shows the time-varying evolution of the total connectedness which extends the understanding of transmissions within the system. Apart from the CAViaR-based spillovers at 5% level (brown area), we also plotted the 10% and 2.5% level results to ensure robustness, represented by red and green lines, respectively. With the help of the dynamic total connectedness plot, we are able to explain what we have found earlier that the average total connectedness has decreased in the post-COVID-19 era. Although we do observe that there was an exceptionally sharp increase in the tail risk transmission at the beginning of the COVID-19 which is greater in extent than that in the late 2016, the peak is not as high as that in the latter after the Brexit referendum. The tail risk spillovers had significantly decreased around the time when the Paris agreement was going effective from late 2016, which is reasonable as our dataset comprises of sustainability-related indexes and carbon credit futures that directly deal with the climate issues. However, the slowing down of the industrial activities, the falling investors' confidence, the US–China Trade War, and the COVID-19 had led the market crash over a long period, which is reflected in our graph where we see the rapid growth of tail risk spillovers in early 2018 and relatively substantially high level in 2018–2019, followed by the second all-time peak in early 2020. Fortunately, the tail risk spillovers have retained at relatively low level since late 2021, which leads to the lower average risk spillover during & in the post-COVID-19 era than that before COVID-19.

Now we move on to the dynamic net connectedness plots which enable us to distinguish the overall roles of each variable has played

Table 3
Average total connectedness.

Pre- (During) COVID-19	ESG Leaders	Alt. Energy	Environment	Green Bond	Carbon Credit	Newcastle Coal	WTI Crude Oil	Nature Gas	Oil & Gas Co.	Coal Co.	FROM
ESG Leaders	41.62 (50.56)	14.61 (10.77)	23.76 (16.65)	0.90 (1.08)	0.55 (0.74)	0.30 (0.89)	3.55 (3.04)	0.41 (0.24)	7.86 (8.01)	6.44 (8.01)	58.38 (49.44)
Alt. Energy	16.94 (12.43)	48.31 (57.98)	18.57 (12.93)	1.99 (0.71)	0.73 (0.70)	0.39 (1.08)	2.18 (1.36)	0.64 (0.59)	3.99 (6.28)	6.26 (5.96)	51.69 (42.02)
Environment	24.55 (18.19)	16.81 (12.30)	42.63 (55.85)	1.09 (0.51)	0.66 (1.23)	0.23 (0.51)	2.25 (1.82)	0.34 (0.53)	5.22 (4.97)	6.22 (4.08)	57.37 (44.15)
Green Bond	1.93 (2.81)	3.50 (1.84)	2.00 (1.70)	85.44 (85.53)	2.26 (1.41)	0.92 (0.35)	0.60 (0.79)	0.91 (1.07)	0.78 (1.51)	1.66 (2.98)	14.56 (14.47)
Carbon Credit	1.50 (1.39)	1.47 (0.96)	1.56 (2.46)	2.56 (0.85)	88.31 (88.17)	0.73 (0.95)	0.76 (0.93)	1.00 (1.29)	1.03 (1.11)	1.08 (1.88)	11.69 (11.83)
Newcastle Coal	0.58 (1.04)	0.58 (0.56)	0.62 (0.55)	1.04 (0.71)	0.62 (0.54)	92.14 (93.48)	1.28 (0.67)	1.49 (1.48)	0.83 (0.52)	0.81 (0.45)	7.86 (6.52)
WTI Crude Oil	5.91 (4.05)	3.01 (1.74)	3.53 (2.39)	0.31 (0.49)	0.65 (0.72)	0.92 (0.35)	64.63 (75.20)	0.78 (0.42)	15.50 (11.22)	4.76 (3.42)	35.37 (24.80)
Nature Gas	1.33 (0.58)	1.29 (1.41)	0.98 (1.01)	0.95 (1.29)	1.25 (1.75)	1.71 (1.46)	1.01 (0.60)	89.63 (88.77)	0.85 (1.28)	0.99 (1.87)	10.37 (11.23)
Oil & Gas Co.	10.43 (9.29)	4.82 (6.37)	6.90 (5.26)	0.70 (0.74)	0.44 (0.62)	0.59 (0.35)	13.37 (8.95)	0.61 (0.53)	55.51 (58.45)	6.64 (9.46)	44.49 (41.55)
Coal Co.	9.27 (10.48)	7.84 (6.71)	8.74 (4.76)	1.02 (1.95)	1.22 (1.34)	0.54 (0.36)	3.91 (2.98)	0.85 (0.51)	6.80 (10.47)	59.82 (60.44)	40.18 (39.56)
TO	72.43 (60.27)	53.94 (42.66)	66.66 (47.71)	10.57 (8.31)	8.38 (9.04)	6.32 (6.30)	28.92 (21.15)	7.02 (6.66)	42.86 (45.38)	34.88 (38.10)	TCI
NET	14.05 (10.83)	2.25 (0.64)	9.29 (3.56)	−3.99 (−6.16)	−3.31 (−2.79)	−1.55 (−0.22)	−6.45 (−3.65)	−3.35 (−4.57)	−1.63 (3.83)	−5.30 (−1.46)	33.20 (28.56)
NPT	9.00 (9.00)	7.00 (6.00)	8.00 (8.00)	3.00 (2.00)	2.00 (2.00)	2.00 (2.00)	4.00 (4.00)	0.00 (1.00)	6.00 (6.00)	4.00 (5.00)	

Note:
Values outside and in parentheses are results prior to and during the COVID-19 outbreak, respectively.

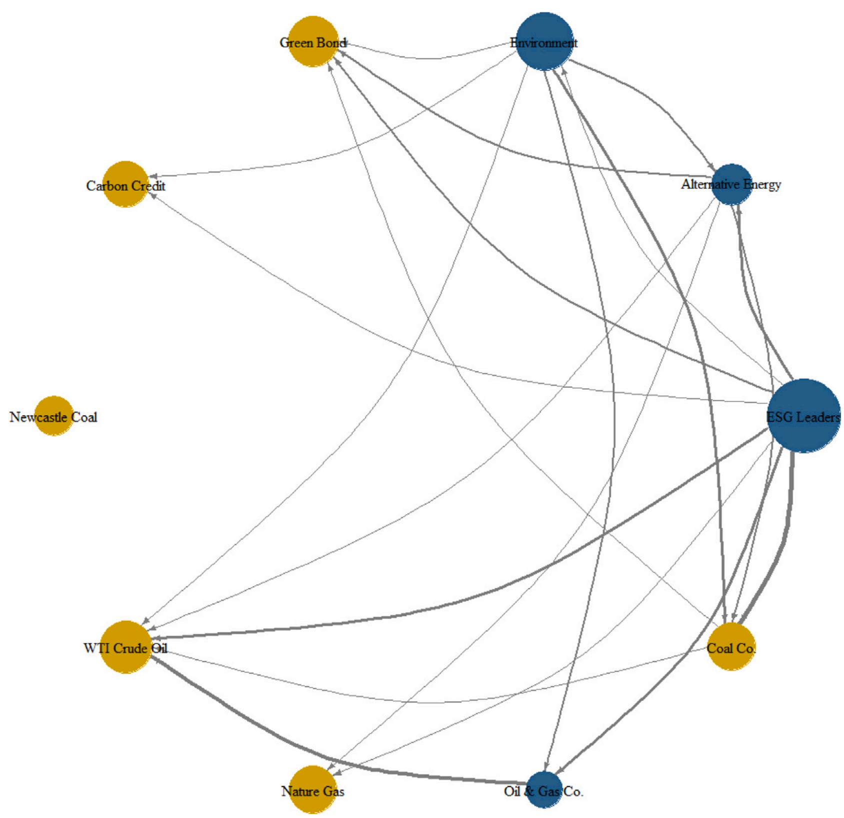


Fig. 2. Visualisation of average pairwise directional tail risk transmission network. Note: Blue — risk transmitter; Yellow — risk receiver; Node size — magnitude of TO spillover effects; Arrow — direction of the spillovers; Thickness — intensity of the interaction. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

over the whole sample period (Fig. 4). Apparently, there are only two persistent net transmitters of tail risk in the system — the ESG Leaders Index and the Global Environment Index, although the latter might have emitted some risks in quite negligibly short periods (e.g., early 2022). The patterns between the two are quite different, particularly, the risks transmitted from Environment Index had significantly reduced to 0 prior the 2018 and the risk level in recent period has been much lower than in previous risky times and that of the ESG Leaders Index. Alternative Energy Index was evidenced as the third largest transmitter in pre-COVID-19 period. However, from the dynamic plot, we see that it had switched roles several times since 2018. Prior to the COVID-19, the alternative energy industry seemed to be a net risk receiver rather than the transmitter. It was again the transmitter at the beginning of the pandemic but quickly lost it. Notably, in the most recent period while the Europe is suffering from the energy crisis caused by the Russia invasion to Ukraine, the alternative energy industry has become risk transmitter again. The dynamic result of green bond's role is expected and consistent with the static result. Green bond has long been a risk receiver, despite a short-lived positive period in the mid 2015. All futures products except for coal can be generally viewed as risk takers. Coal has been a risk transmitter when entering the year of 2022. The two energy equities also behave differently. While the coal

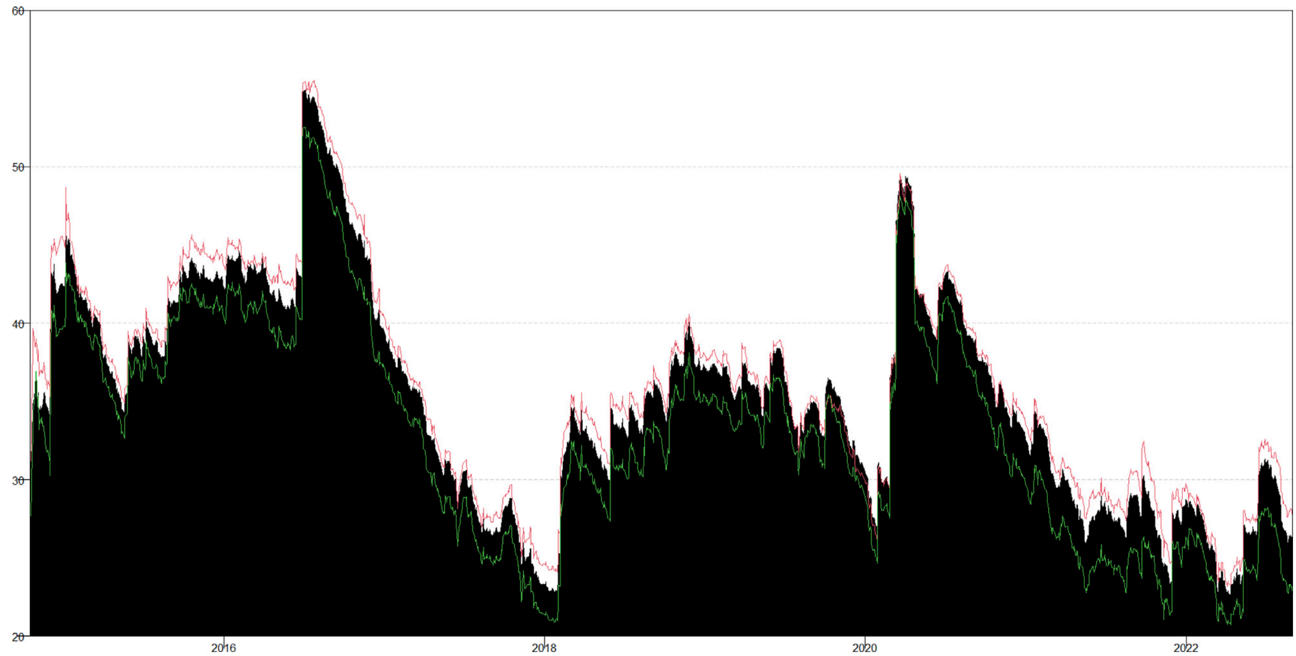


Fig. 3. Dynamic total connectedness index (%). Notes: Black area — CAViaR-based spillovers at 5% level; Red line — CAViaR-based spillovers at 10% level; Green line — CAViaR-based spillovers at 2.5% level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

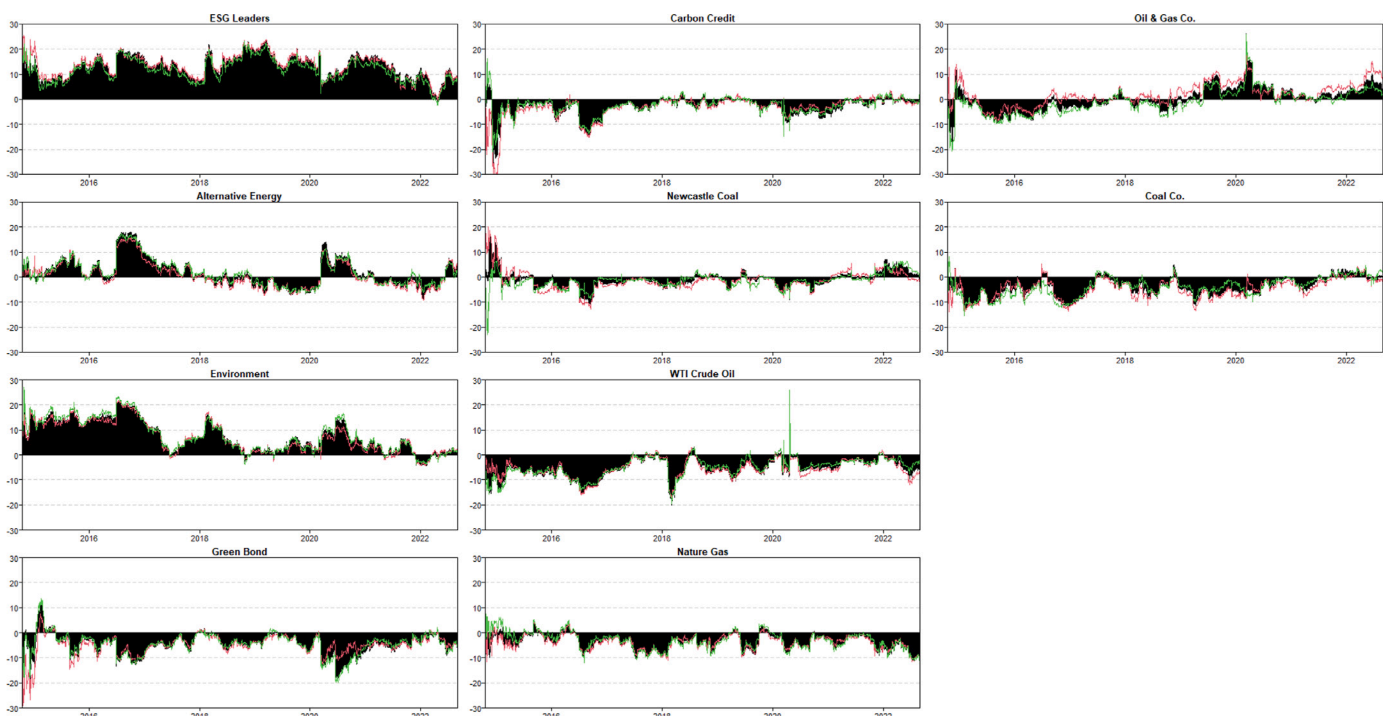


Fig. 4. Net total connectedness. Notes: Black area — CAViaR-based spillovers at 5% level; Red line — CAViaR-based spillovers at 10% level; Green line — CAViaR-based spillovers at 2.5% level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

companies are risk takers except for a short period around 2022, the oil and gas companies have already transformed to transmitter roles since late 2019. These results suggest a diversified portfolio is essential for investors as different assets even within the same group behave differently in the system. However, we still need to figure out the pairwise relations to uncover the tail risk transmission between pairs and provides more useful insights for the policy markers and investors.

Fig. 5 plot the dynamic net connectedness results between pairs. Notably, ESG Leaders Index is generally a risk transmitter for almost all others over the sample period. However, we do observe that the risk transmissions from ESG to futures products have significantly reduced, or even reversed (e.g., coal futures) in recent times. Green bond, although it is a persistent risk receiver in the system, is not a persistent risk taker for every other market. Instead, it frequently switches roles especially for energy commodities and equities. More recently it is more likely to be a transmitter for carbon and energy futures evidenced by the up trending pattern towards the end of the study period. On average, we notice that the transmissions among sustainability-related equity indexes and energy equities are much more intensive than those between sustainability-related indexes (including green bond) between the futures products or between the energy equities and the futures products (except the WTI crude oil futures), which are consistent with our static results. These may be resulted by some extent of the systematic co-movement in the equity markets and dominating position of crude oil as the strategic commodity. The WTI crude oil futures has been a risk taker for almost all equities indexes. Future products other than the WTI crude oil are more isolated in the system. Besides, we should not ignore that the coal futures transmitted quite a lot and significant tail risks to the alternative energy industry and carbon credit futures since the energy crisis around 2022. In return, the performance of the alternative energy equities transmitted back the risks to the coal companies. Coal as a strong substitute to natural gas being a heating source has been sought-after since the energy crisis, where we see that the coal companies expelled significant risks to the natural gas futures than the oil & gas companies did.

5.3. Drivers of spillover intensity

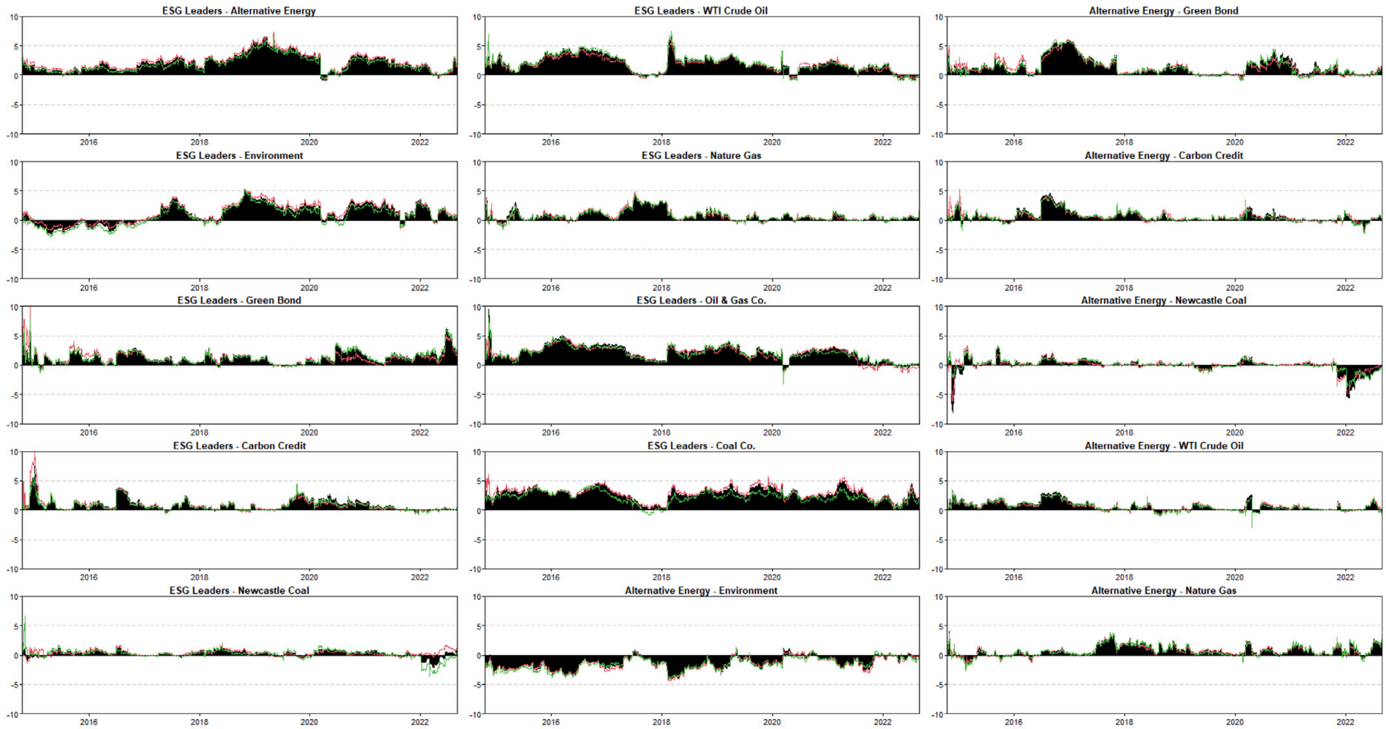
Fig. 6 depicts the t-statistics of estimated coefficients using rolling window regression (Eq. (8)). Two horizontal red lines above and below the x-axis represent the critical value at 5% level — +1.96 and −1.96, respectively. Therefore, lines of studied potential determinants above and below the respective horizontal lines are statistically significant estimates. It is not surprising that all potential driving variables have had asymmetric effects on the connectedness network and such relationships are time-varying. TERM, the yield spread which can be viewed as the US expectation of economics recession, has had the greatest effect on the connectedness network. We show that the negative impact of TERM on the connectedness during the peak of COVID-19 and Russia–Ukraine War was much higher than non-crisis period in 2018/02–2020/02, which makes sense as the expectations of long-term recession during these periods was indeed very low, as indicated by the high TERM rate. The economic policy uncertainty (EPU) had no significant impact on the connectedness prior to the COVID-19. During the beginning phase of COVID-19 with the travel restrictions being imposed, we find that higher EPU leads to higher risk exposure spillovers. The effect decreased with the decreasing threat of COVID-19, and has been increasing with the tension of the war in 2022. Similarly, we see that the geopolitical risk (GPR) has almost opposite effect on the risk spillovers than the EPU does on the network, although during most of time the impact has been insignificant. OVX, stands for the expectation of crude oil price volatility, has had relatively high impact on the risk exposure. The effect of OVX was relatively consistently positive and significant during non-crisis period, and more unstable during crisis period. Especially when the oil price was pushed higher in late 2021 and spiked high at the beginning of Russia invasion, the expectation of oil volatility has had much negative effect on the risk exposure among the market, which possibly because both ESG and fossil energy stocks were performing well during positive expectations to the oil price in early 2022. Therefore, we can also see that the effect of OVX has been decreasing following the oil price collapse afterwards. VIX has relatively high asymmetric impact on the connectedness. This is reasonable as the biggest risk exposure transmitters and receivers in our system are equity indexes. The larger the expectation of higher volatilities in the equity market, the higher the fear in unexpected financial loss in the equities. During the crisis periods, higher fear in the US equity market leads to higher risk exposures.

6. Conclusions

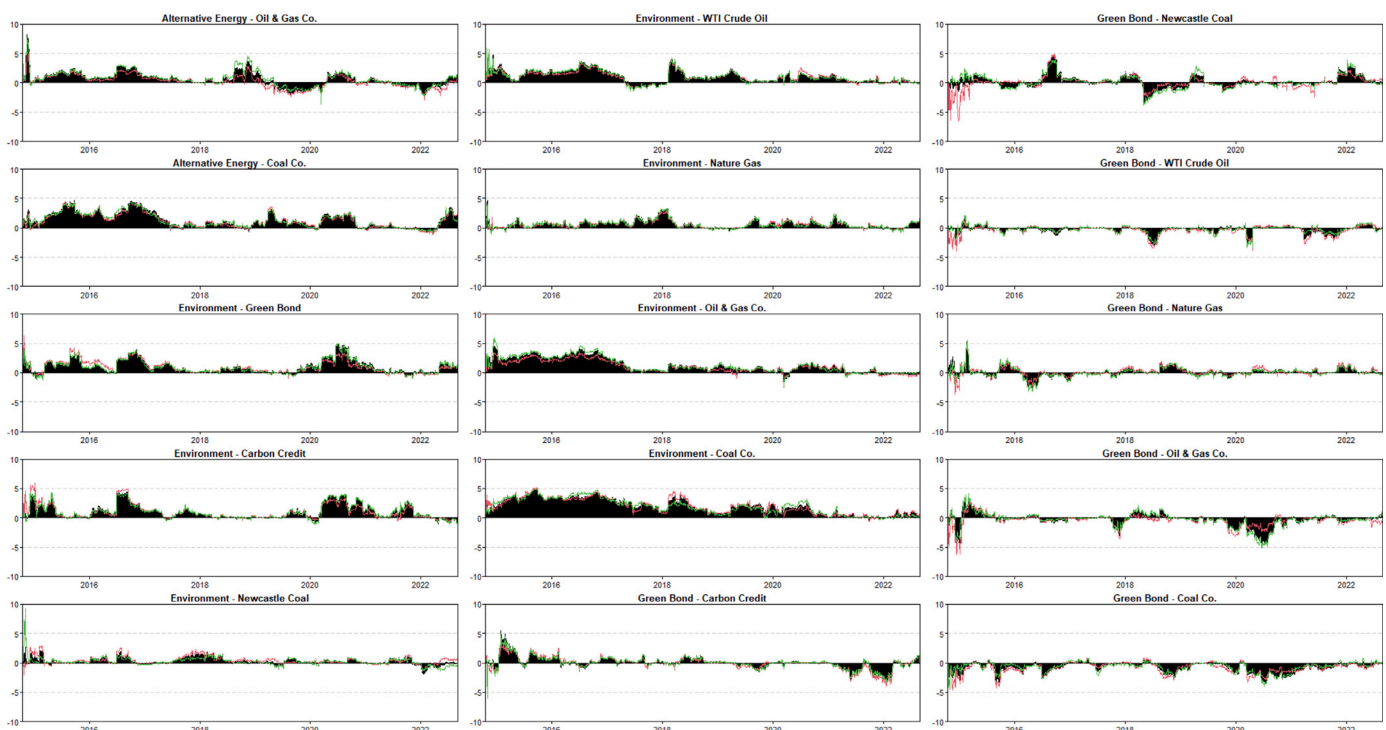
We investigated the tail risk spillovers among sustainability-related products, energy futures, and energy equities. Specifically, we considered five types of representative sustainable ("green") products, including three equity indices (i.e., the MSCI World ESG Leaders Index, the MSCI Global Environment Index, and the MSCI Global Alternative Energy Index), one treasury index (i.e., the Bloomberg Barclays MSCI Global Green Bond Index) and one futures index (i.e., the IHS Markit Global Carbon Index). On the other hand, we included two types of primary fossil energy ("brown") investments, including three global commodity futures products (i.e., the ICE WTI Crude Oil futures, the ICE Natural Gas futures, and the ICE Newcastle Coal futures) and two equity indices (i.g., the Global Oil & Gas Exploration and Production Price Return Index and Global Coal Price Return Index). With the help of a novel CAViaR-based TVP-VAR models developed by Chatziantoniou et al. (2022b), we were able to directly measure the conditional VaR of each asset or index at a defined level, and further incorporate them into a dynamic connectedness model to comprehensively analyse the time-varying transmission of the extreme uncertainty/risk of potential substantial loss among the "green" and "brown" markets. Our sample spans from 14 October 2014 to 31 August 2022 covering several global events. Particularly, we divided our sample by late January of 2020 to explicitly take the COVID-19 pandemic into consideration.

Some interesting findings aroused. First, the static result of the average total connectedness reveals an at best medium-level spillovers among the system variables. The decrease in the overall average connectedness after COVID-19 outbreak suggests that the impact of COVID-19 on the sustainability-fossil energy nexus is not as severe as we may have expected. Moreover, keep in mind that our approach measures the spillovers of tail risks proxied by the conditional VaR, which is a completely different objective from measuring the volatility; this has led to some different results from those of previous studies, e.g., Zhang et al. (2022). Specifically, we found that the ESG Leaders Index is both the largest risk transmitter and receiver, followed by the Global Environment Index and Global Alternative Energy Index. Within the sustainability products, both of the carbon emission allowance futures and the green bond are net risk receivers. The carbon futures even outperforms the green bond index being more neutral, although it transforms slightly more risks in the post-COVID-19 period. Additionally, in the fossil energy group, equity indexes transfer quite a lot but lower risks than "green" products in the system, while energy futures products are significantly more isolated and even less involved in the system than the green bond and carbon credit futures. An exception is the WTI crude oil futures which tends to be more vulnerable and involved in this system, given its global dominance among commodities.

With respect to the dynamic results which not just verify the previous static results but also depict more insightful pictures, we showed that the rate of the increase in the spillover at the beginning of COVID-19 is phenomenal. However, the magnitude of the peak of the daily tail risk spillovers during the first wave of COVID-19 is lower than that in the year around mid 2016 when the Brexit referendum and Paris Agreement took place. This suggests that the initial effect of COVID-19 is overestimated on a daily basis, which is somehow in line with the inferences in Chatziantoniou et al. (2022a). The relatively low-level of spillovers since late 2021 and the overall less extent of variations compared to previous years explains the lower average connectedness revealed by the static results. Besides, previous static results suggest all sustainability-related equity indices (ESG Leaders, Environment, Alternative Energy) are net transmitters, but the dynamic plots indicate that alternative energy stocks had become a net receiver two year before the COVID-19 outbreak. Its role of transmitter after the outbreak was short-lived in early times; however, after the Russian invasion in Ukraine, the alternative energy stocks has regained the transmitter position. All futures products seem to have long been risk receivers but each behave differently. Notably, we found that the crude oil and natural gas futures started to receive more since 2022 than at the beginning of the plague; On the contrary, coal futures has become a transmitter since 2022 but has weakened more recently, while the role of carbon futures has become more inconclusive. Regarding energy equities, we see that coal companies had been a receiver until late 2021 and has



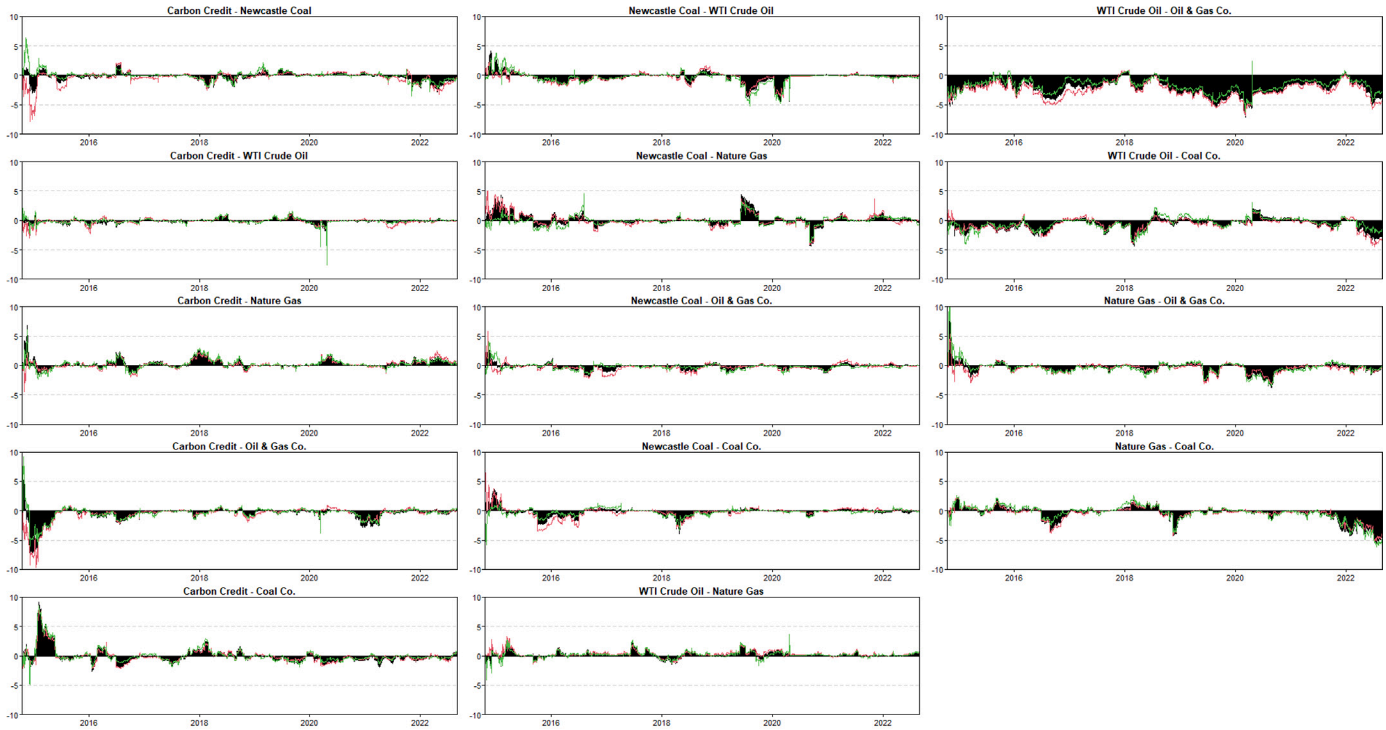
(a)



(b)

Fig. 5. Pairwise net total connectedness (a), (b) and (c). Notes: Black area — CAViaR-based spillovers at 5% level; Red line — CAViaR-based spillovers at 10% level; Green line — CAViaR-based spillovers at 2.5% level. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

been switching role in more recent period, while oil and gas companies has started transmitting tail risks since late 2019. An possible reason is that coal has criticised for being harmful to the environment, which leads to the passive position in the investments. Finally, the pairwise results further provide support and extend the understanding of the relations between pairs. Here we address a notable finding that the spillovers among sustainability-related equities and energy equities are much more intensive than those between sustainability-related indexes (including green bond) between the futures products or between the energy equities and the futures products (except the WTI crude oil futures). Finally, regression results reveal that economic policy uncertainty, geopolitical risk, the spread of US yield curve, the



(c)

Fig. 5. (*continued*).

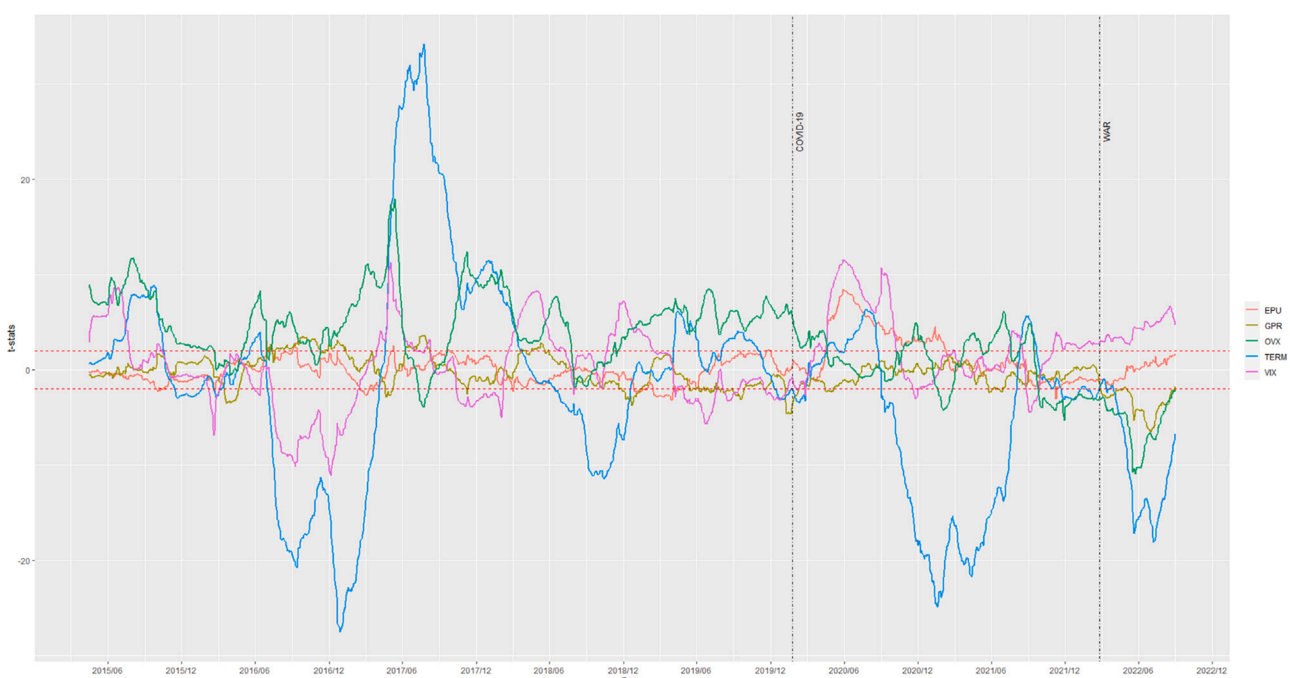


Fig. 6. Rolling t-statistic based on a rolling-window (120 observations) regression. Notes: The horizontal red lines indicate 5% critical value of (±1.96). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

implied volatility of US stock market, and the oil volatility, impact the connectedness network asymmetrically.

These results provide valuable insights. From the investors' perspectives, how to effectively diversify their portfolio to minimise the risk (VaR) remains an essential task. Our study suggests that equities, regardless of whether they are sustainable more or less, share similar tail risk pattern to some extent. Investors in sustainability equities are encouraged to choose non-equity products such as carbon credit futures or green bond as constituents to diversify the extreme risks. A better risk minimising but worse decision in faith would be to include a small portion of fossil energy futures such as coal and natural gas as long as it does not harm the carbon-neutral portfolio too much. There is more flexibility for investors in fossil energy investments that they can either diversify the risks by investing more in combination of energy futures and energy equities, or further considering the emerging assets such as green bond and carbon credit futures. The latter may lead to

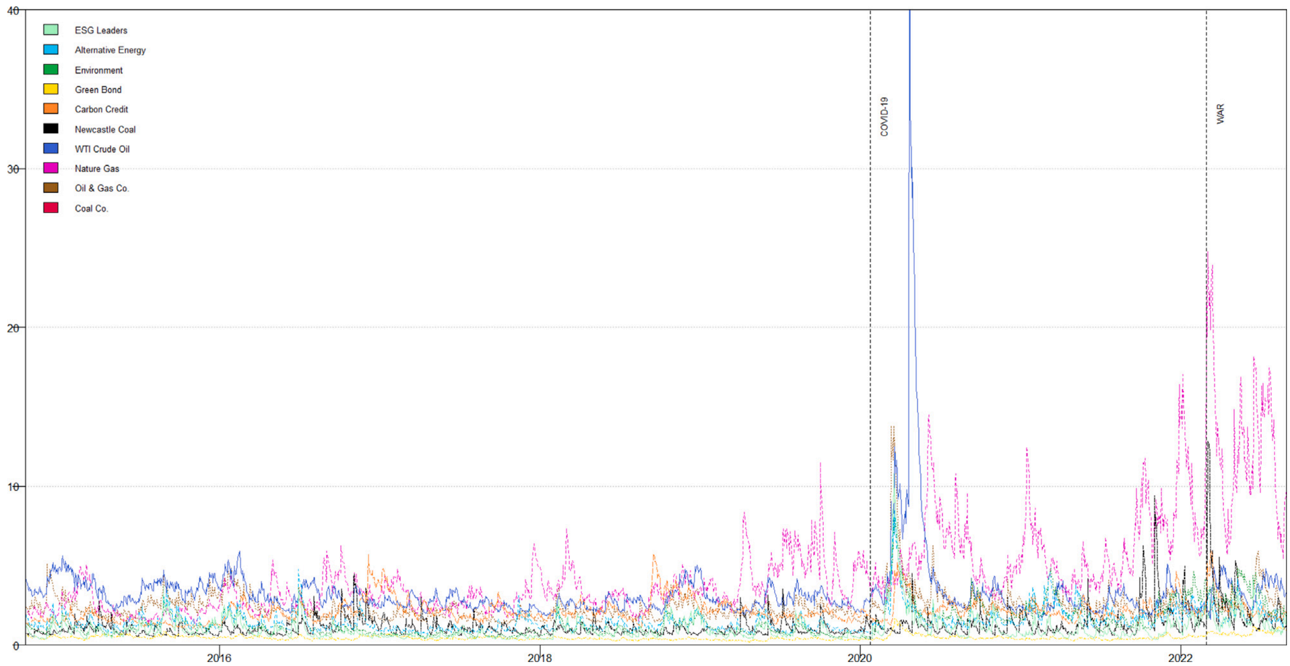


Fig. A.1. Tail risk measured as 10% VaR using the asymmetric slope CAViaR model.

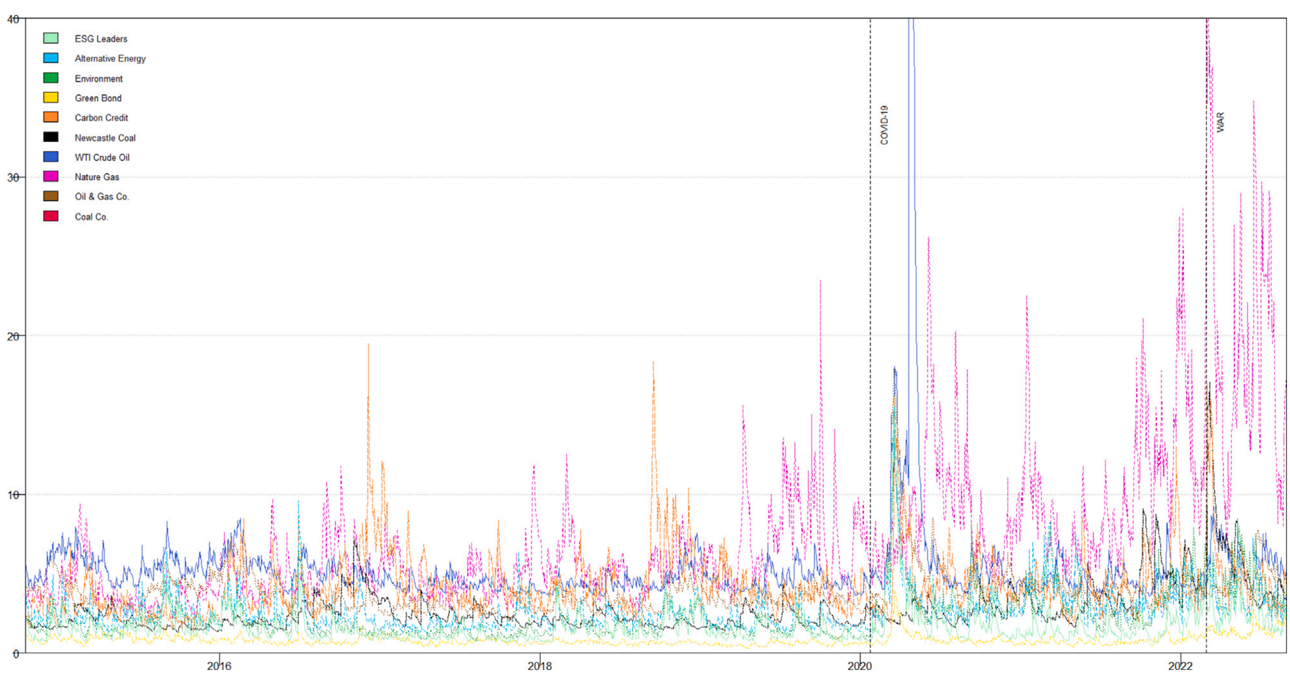


Fig. B.1. Tail risk measured as 2.5% VaR using the asymmetric slope CAViaR model.

better performance in portfolio VaR and mitigation in damage to the sustainability. Future research might be interested in capturing these by creating and examining the performance of dynamic VaR-optimised portfolios. For policymakers, our findings indicate that sustainability-related equities especially the leading companies in ESG performance transmit significant tail risk to other sustainable industry and fossil energy industries; in retrospect, green bond and futures products could be useful to stabilise the market given their general role as risk receivers. How to balance the relationships and maintain the healthy development of markets is one of the priorities. Meanwhile, careful consideration of external driving forces such as EPU, yield curve, VIX, GPR, OVX, etc, is critical. Other promising directions of future research might be considering the time-domain tail risk relationship between these or with additional markets by taking frequency effect into account (Baker et al., 2016b).

CRediT authorship contribution statement

Brian Lucey: Project management, Final editing, Conceptualization. **Boru Ren:** Econometrics, Data management.

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Table C.1
Average total connectedness at 10%.

Pre- (During) COVID-19	ESG Leaders	Alt. Energy	Environment	Green Bond	Carbon Credit	Newcastle Coal	WTI Crude Oil	Nature Gas	Oil & Gas Co.	Coal Co.	FROM
ESG Leaders	40.98 (49.84)	14.51 (10.72)	23.72 (16.59)	0.80 (0.95)	0.48 (0.46)	0.30 (0.58)	3.55 (3.21)	0.38 (0.25)	8.69 (9.06)	6.60 (8.35)	59.02 (50.16)
Alt. Energy	17.07 (12.50)	48.29 (57.85)	18.49 (12.95)	1.63 (0.62)	0.59 (0.67)	0.40 (0.92)	2.22 (1.43)	0.64 (0.63)	4.30 (6.10)	6.35 (6.31)	51.71 (42.15)
Environment	24.76 (18.30)	16.67 (12.28)	42.26 (55.54)	1.00 (0.47)	0.60 (1.01)	0.24 (0.42)	2.31 (2.04)	0.32 (0.51)	5.45 (5.07)	6.39 (4.36)	57.74 (44.46)
Green Bond	1.95 (2.18)	3.18 (1.40)	2.08 (1.20)	85.76 (86.80)	2.04 (1.74)	0.97 (0.50)	0.70 (0.91)	0.82 (1.15)	0.81 (1.38)	1.69 (2.75)	14.24 (13.20)
Carbon Credit	1.50 (0.88)	1.38 (0.88)	1.59 (1.89)	2.34 (1.05)	88.31 (88.82)	0.90 (1.18)	0.59 (0.85)	1.40 (1.90)	1.03 (0.81)	0.95 (1.73)	11.69 (11.18)
Newcastle Coal	0.64 (0.92)	0.62 (0.59)	0.74 (0.56)	1.00 (0.74)	0.59 (0.74)	91.83 (93.57)	1.33 (0.59)	1.34 (1.46)	0.90 (0.50)	1.00 (0.33)	8.17 (6.43)
WTI Crude Oil	5.69 (4.29)	2.93 (1.84)	3.42 (2.64)	0.26 (0.58)	0.49 (0.60)	0.96 (0.31)	61.86 (71.59)	0.74 (0.46)	18.55 (13.55)	5.10 (4.15)	38.14 (28.41)
Nature Gas	1.30 (0.56)	1.27 (1.38)	0.91 (1.00)	0.95 (1.42)	1.48 (2.39)	1.52 (1.41)	1.08 (0.67)	89.73 (88.38)	0.83 (1.17)	0.95 (1.61)	10.27 (11.62)
Oil & Gas Co.	11.05 (10.08)	4.77 (5.90)	6.80 (5.32)	0.50 (0.81)	0.31 (0.54)	0.56 (0.39)	16.07 (10.95)	0.48 (0.49)	52.82 (55.82)	6.65 (9.71)	47.18 (44.18)
Coal Co.	9.67 (10.93)	7.84 (6.93)	8.96 (4.98)	0.92 (1.81)	1.08 (1.23)	0.61 (0.35)	4.38 (3.51)	0.76 (0.50)	7.31 (11.24)	58.48 (58.51)	41.52 (41.49)
TO	73.62 (60.64)	53.17 (41.91)	66.71 (47.14)	9.40 (8.44)	7.67 (9.39)	6.46 (6.06)	32.22 (24.16)	6.89 (7.35)	47.87 (48.88)	35.67 (39.31)	TCI
NET	14.60 (10.48)	1.46 (−0.24)	8.97 (2.68)	−4.84 (−4.77)	−4.02 (−1.79)	−1.71 (−0.37)	−5.92 (−4.25)	−3.39 (−4.27)	0.69 (4.69)	−5.84 (−2.18)	33.97 (29.33)
NPT	9.00 (9.00)	7.00 (5.00)	8.00 (8.00)	3.00 (2.00)	2.00 (2.00)	2.00 (3.00)	4.00 (4.00)	0.00 (1.00)	6.00 (7.00)	4.00 (4.00)	

Note:
Values outside and in parentheses are results prior to and during the COVID-19 outbreak, respectively.

Table D.1
Average total connectedness at 2.5%.

Pre- (During) COVID-19	ESG Leaders	Alt. Energy	Environment	Green Bond	Carbon Credit	Newcastle Coal	WTI Crude Oil	Nature Gas	Oil & Gas Co.	Coal Co.	FROM
ESG Leaders	43.98 (53.66)	14.24 (9.83)	23.91 (16.31)	0.98 (1.22)	0.53 (0.64)	0.30 (1.08)	3.35 (3.60)	0.42 (0.25)	7.08 (6.97)	5.19 (6.45)	56.02 (46.34)
Alt. Energy	16.12 (11.23)	50.83 (62.07)	18.35 (11.93)	2.29 (0.80)	0.74 (0.73)	0.30 (0.97)	2.10 (1.30)	0.64 (0.74)	3.44 (5.58)	5.19 (4.65)	49.17 (37.93)
Environment	24.30 (17.49)	16.48 (11.17)	44.45 (58.57)	1.16 (0.53)	0.71 (1.31)	0.25 (0.57)	2.13 (1.92)	0.38 (0.59)	4.69 (4.43)	5.45 (3.43)	55.55 (41.43)
Green Bond	1.98 (2.99)	3.77 (1.59)	2.05 (1.62)	85.16 (85.77)	2.24 (1.44)	0.87 (0.35)	0.53 (0.51)	0.94 (0.92)	0.78 (1.67)	1.68 (3.13)	14.84 (14.23)
Carbon Credit	1.36 (1.15)	1.51 (0.93)	1.55 (2.59)	2.58 (0.90)	88.59 (89.08)	0.56 (0.92)	0.84 (0.75)	0.98 (1.21)	0.95 (0.94)	1.07 (1.53)	11.41 (10.92)
Newcastle Coal	0.63 (0.99)	0.57 (0.62)	0.63 (0.53)	0.96 (0.64)	0.68 (0.57)	92.12 (93.34)	1.18 (0.55)	1.58 (1.62)	0.86 (0.73)	0.79 (0.40)	7.88 (6.66)
WTI Crude Oil	5.00 (4.45)	2.87 (1.54)	3.07 (2.52)	0.38 (0.36)	0.74 (0.58)	0.85 (0.27)	63.83 (74.72)	0.69 (0.38)	18.78 (12.11)	3.80 (3.06)	36.17 (25.28)
Nature Gas	1.30 (0.61)	1.29 (1.47)	0.97 (1.02)	0.94 (1.11)	1.21 (1.61)	1.59 (1.62)	1.06 (0.50)	89.82 (88.77)	0.89 (1.26)	0.93 (2.01)	10.18 (11.23)
Oil & Gas Co.	8.99 (7.98)	4.23 (5.57)	6.14 (4.67)	0.78 (0.77)	0.48 (0.56)	0.63 (0.46)	16.59 (10.41)	0.70 (0.55)	55.92 (61.09)	5.53 (7.94)	44.08 (38.91)
Coal Co.	7.45 (8.31)	6.70 (5.29)	7.89 (4.16)	1.13 (2.21)	1.27 (1.20)	0.55 (0.29)	3.35 (2.76)	1.04 (0.65)	5.80 (8.79)	64.82 (66.35)	35.18 (33.65)
TO	67.12 (55.20)	51.67 (38.01)	64.56 (45.35)	11.19 (8.54)	8.60 (8.65)	5.91 (6.52)	31.14 (22.32)	7.39 (6.91)	43.27 (42.49)	29.64 (32.60)	TCI
NET	11.10 (8.85)	2.50 (0.07)	9.01 (3.92)	−3.65 (−5.69)	−2.81 (−2.27)	−1.98 (−0.14)	−5.04 (−2.95)	−2.79 (−4.32)	−0.80 (3.58)	−5.54 (−1.05)	32.05 (26.66)
NPT	9.00 (8.00)	7.00 (5.00)	8.00 (7.00)	2.00 (2.00)	3.00 (2.00)	1.00 (5.00)	4.00 (4.00)	2.00 (0.00)	6.00 (7.00)	3.00 (5.00)	

Note:
Values outside and in parentheses are results prior to and during the COVID-19 outbreak, respectively.

Appendix A. Tail risk measured at 10%

See Fig. A.1.

Appendix B. Tail risk measured at 2.5%

See Fig. B.1.

Appendix C. Average total connectedness at 10%

See Table C.1.

Appendix D. Average total connectedness at 2.5%

See Table D.1.

Appendix E. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106812.

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