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Do geopolitical risks and global market factors influence the dynamic dependence among regional sustainable investments and major commodities?

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ABSTRACT

This paper uses the Quantile Vector-Autoregressive (Q-VAR) technique to examine the connectedness between three regional (North America, Europe and Asia-Pacific) sustainability indices and major natural resource commodities including energy commodities (crude oil and natural gas), precious metals (gold, silver, and platinum), and industrial metals (steel, aluminium, and copper). It also uses a linear regression model to investigate the macroeconomic and geopolitical factors that drive the connectedness among these investments. The QVAR results reveal asymmetric connectedness among these investment indices, with the levels of total connectedness during extreme downside and upside market conditions being significantly stronger than the level of connectedness during normal market condition. The results also show that, on average, the amount of shocks the regional sustainable investment indices each received from the studied energy and metal commodity markets are higher (lower) than what they transmit to the commodity market during the extreme upside (downside) market condition. During the normal market condition, however, only the Asian Pacific sustainable investment receives more shock than it transmits to the studied commodity market indices, making a net shock receiver. Finally, geopolitical risks, business environment conditions, gold and fixed income markets and economic policy uncertainty are important predictors of return connectedness, although the predictive strength and direction vary across market conditions. We discuss the implications of our findings.

1. Introduction

Sustainable investments have grown in prominence, scope and volume in the past couple of years, attracting the interest of investors, policymakers, and the general public (Global Sustainable Investment Alliance, 2020; Kotsantonis et al., 2016; Sciarelli et al., 2021). Although its history dates back to the 1758 Quaker Philadelphia that strictly forbid her members from taking part in slave and weapon trading (Lean & Nguyen, 2014; Renneboog et al., 2008), the nascent interest in and the surge of sustainable investments are inextricably linked to the global call for sustainable development. In particular, the underlying philosophy of sustainable investment is that the pursuit of financial returns should not preclude ethical considerations. Ethical considerations here are jointly denominated by intentional environmental, social, and governance concerns. Hence, sustainable investment provides one of the important pathways to achieving sustainable development as it provides firms and investors an avenue to contribute to sustainable development or ensure their activities does not exacerbate existing development challenges. It is, therefore, not surprising that in 2006 the United Nations which is at the forefront of the sustainable development goals (SDGs) unveiled the Principles for Responsible Investment (PRI), an initiative aimed at promoting sustainable investment consistently and systematically (Ng, 2019).

The importance of sustainable investments has led to the development of different sustainable investment indices as corporations and investors strive to include non-financial factors in their investment portfolios. Concurrently, academic research on sustainable investment has also grown in prominence. One of the often researched topics in this regard is the risk-return characteristics of sustainable investment, examining how such idiosyncratic behaviours and outcomes compare to other conventional investment options. To date, existing studies on the topic have failed to provide clear-cut empirical evidence on whether sustainable investment outperforms its counterpart (for an extensive literature review see (Conqueret, 2021). Such ambivalent results are reflective of the underlining theoretical construct as opposing arguments regarding their financial implications to corporations and investors

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abound in the literature. On the one hand, proponents argue that it is associated with a loyal customer, investor, and employee base which are expected to reduce the firm's susceptibility to systematic risk and translate into higher financial profit (see Ameur et al., 2020; Cerqueti et al. (2021)). Giese et al. (2019) also note that sustainable investment improves firm financial performance because it is associated with higher dividends and a lower tail risk and cost of capital. Opponents, on the other hand, argue that it may lower return, increase volatility and lead to less diversification due to the additional screening costs it imposes (see Ameur et al., 2020; Kempf & Osthoff, 2008). More recently, studies are now beginning to examine how the risk-return characteristics of sustainable investment commove or correlate with or are affected by developments in other financial or commodity markets (see Ameur et al., 2020; Ameur & Senanedsch, 2014; Iglesias-Casal et al., 2020; Sadorsky, 2014).

Analysis of the risk-return characteristics of sustainable investments as well as their connectedness and interdependences with other financial markets are important both from portfolio management and policy perspective. In particular, sustainable investment is a market-based instrument. From a portfolio risk management perspective, it is thus of utmost importance to understand their relative characteristics to other market-based instruments that may not be sustainable-focused to devise a strategy for risk reduction and return maximization. Akin to this, understanding the connectedness and interdependence between sustainable investments and other financial market is crucial to determining the performance of sustainable investments and their usefulness for hedging and managing portfolio risks. These cumulatively shape the incentives and preferences of corporations and investors towards the uptake of sustainable investments that are essential for achieving the global call for sustainable development. From a policy perspective, such analysis is important for policymakers to understand the characteristics of the sustainable investment as well as the factors driving the developments in the market which are crucial for developing appropriate policy incentives and strategies to promote sustainable investment.

In line with the foregoing, the first objective of this paper is to examine the connectedness and interdependence between sustainability indices (an indicator of sustainable investment) and major natural resource commodities including energy commodities (crude oil and natural gas), precious metals (gold, silver, and platinum), and industrial metals (steel, aluminium, and copper). In particular, our analysis examines how shocks are propagated among these commodities and sustainable investments, paying particular attention to how such shock propagation differs across market conditions and three regions including North America, Asia, and Europe. In this way, our paper provides empirical evidence on risk transmission across these markets under different market conditions. The motivation to examine the risk transmission across market conditions is not trivial. Indeed, institutional investors who are mostly interested in longer-term investment horizons are the ones at the forefront of sustainable investment. In this way, examining risk transmission across different market conditions is imperative to help them devise strategies on how to protect their investments against downside or upside risk and hold a long-term position on their investment. On the other hand, the motivation to consider different regional bloc draws from anecdotal evidence on heterogeneity of risk transmission among regional sustainable investments (e.g. (Ameur et al., 2020; Ameur & Senanedsch, 2014)). As our second research objective, we investigate the drivers of the risk transmission across the different market conditions. In this way, the paper also offers insights on possible factors investors could look at if, say, they want to decouple their investments to reduce market risks. At the same time, they could also serve as appropriate policy and surveillance tools for policymakers for managing small and extreme shocks.

To address our first research objective, we employ the quantile vector autoregressive (QVAR) method recently developed by Ando et al. (2022). Whereas the widely used spillover index approach proposed by Diebold and Yilmaz (2009, 2012; 2014) only estimates the average spillover effect that prevails when an average shock affects the system, the QVAR method combines the quantile regression and spillover index to measure spillovers effects across quantiles that correspond to different market conditions. Hence, we take advantage of the model's innate characteristics in addressing our research objective. As per the empirical data, we use daily frequency data on the returns of the commodities of interest as has become conventional in the extant literature (e.g. Farid et al., 2022; Gong & Xu, 2022; Urom et al., 2022a). We also follow past studies (e.g., Ameur et al., 2020; Ameur & Senanedsch, 2014; Balcilar et al., 2017; De Oliveira et al., 2020 in using the Dow Jones sustainability indices for North America, Asia-Specific, and Europe as empirical measures for sustainable investments. These sustainability indices track the stock performance of the leading companies in terms of economic, environmental, and social criteria in each region. Hence, they capture the aforementioned ethical consideration that underscores sustainable investment. It suffices to mention that such triple ethical consideration differentiates them from other indices such as green bond (see Mzoughi et al., 2022; Pham, 2021a, 2021b), environmental index (see Dutta et al., 2020), and climate bond and transition indices (see Dutta et al., 2021; Ndubuisi et al., 2022). In particular, whereas these other indicators could be argued to capture sustainable investments, they are only limited to environmental sustainability. Indeed, as Olofsson et al. (2021) rightly noted, social criteria in sustainable investments assure investors that company employees are treated adequately, implying that sustainable investments can be a response to humanitarian injustice and inequalities which are not captured by the above indices. As per the second research objective, we employ simple linear regression to model the drivers of the connectedness among sustainable investment and the chosen commodities across the different market conditions. We particularly examine how geopolitical risk, business environment conditions, economic policy uncertainty, and a host of other market uncertainty related to the equity, gold, oil, and fixed income market may drive the connectedness of the studied markets.

The rest of the paper is structured as follows. The next section presents a review of the related literature. Section 3 describes the research design by presenting the data sources, computation of variables, and estimation strategy. The third section presents the results, while we conclude with the fourth section.

2. Related literature

The sustainable development implications of sustainable investments alongside the growing interest of corporations and investors to include them in their investment portfolios has attracted the interest of scholars on the topic, leading to an expansive research strand. One such strand of literature that is related to the current study explores the correlations, comovements, or interdependence between sustainable investments and alternative investment options to determine market risk transmissions and optimal hedging strategies. As an empirical measure of sustainable investment, these studies rely on the return or volatility of sustainability indices such as the Dow Jones Sustainability Indexes (DJSI). Regarding alternative investment, they use commodity market indices, especially the oil and gold market indices. The focus on commodities is not trivial as commodities are conventionally believed to be inversely related to equity investments under which sustainable investments mostly fall (Mensi et al., 2017; Sadorsky, 2014). Hence, commodities are considered to be good portfolio diversifiers.

Sadorsky (2014) provides one of the earliest studies in this regard by estimating the volatilities and conditional correlations between DJSI, oil prices, and gold prices. They found that the risk of sustainable investment can be hedged by holding assets in oil and gold. Wei (2017) employed different multivariate GARCH models to analyse the mean and volatility spillover transmissions between the returns of the energy market (oil, electricity, natural gas, and coal) and different sustainability indices including DJSI, FTSE, KLD, and SSEGI. The results showed significant evidence of own mean and volatility effects of the studied investment indices as well as cross-mean or volatility spillover effects from the returns of energy price markets to the returns of sustainable investment indices, implying that the returns of the studied investment indices depend on their past returns while changes in energy price return results in mean and volatility transmission to the sustainable investment indices. In an empirical study on Brazil, De Oliveira et al. (2017) used both parametric and non-parametric methods and found that firms in Brazil that engaged more in sustainable investment are influenced by crude oil spot prices, especially the WTI crude.

Iglesias-Casal et al. (2020) analysed the volatility spillovers, conditional correlation, and optimal weights and hedge ratios of pairs of stocks containing sustainable investment in Brazil. They found that the greatest benefit from diversification is obtained through the acquisition of gold and crude oil as measured by its volatility index. Sariannidis et al. (2016) investigated the effect of oil prices on sustainable investment as measured by the DJSI and conclude that positive changes in international oil prices lead to depreciation of DJSI returns. Mensi et al. (2017) used the multivariate DECO—FIAPARCH model and the spillover index of Diebold and Yilmaz (2012) to examine the time-varying equicorrelations and risk spillovers between crude oil, gold, and the Dow Jones conventional, sustainability, and Islamic stock indices. Their results showed that these indices are intercorrelated with volatility significantly transmitting from the oil and gold markets to sustainability indices. Among others, Ali et al. (2021) examined the integration of SRI indices and conventional indices in the BRICS countries and found that the SRI equity indices are well integrated with conventional indices in all BRICS countries.

Maraqa and Bein (2020) used the Dynamic Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroscedasticity (DCC—MGARCH) to investigate the dynamic interrelationship and volatility spillover between crude oil prices, sustainable indices, and major stock indices of European oil-importing/exporting countries. Their spillover results showed evidence of significant volatility transmission between sustainable indices, international oil prices, and the major indices of oil-importing/exporting countries. Rehman et al. (2022) examined market risk spillover between sustainable investment and oil futures before and during the COVID-19 period. They found evidence of bidirectional spillover between oil and their measures of sustainable investment although the magnitude of the spillover is not very high. Additional analysis using hedging ratios and effectiveness measures showed that sustainable investment provides good hedge cover to WTI returns although to a lesser extent during bearish periods such as the COVID-19 pandemic period.

Our paper contributes to the above studies in three important ways. First, the above-referenced studies reveal that extant studies on the interdependence between sustainable investments and commodities have predominantly focused on crude oil and gold. However, anecdotal evidence highlights high trading activities for both soft (e.g. livestock and cocoa), hard (e.g. gold, steel, copper, and cobalt), and energy (e.g. oil, natural gas, and coal) commodities in the cash and derivatives markets, a phenomenon that is often referred to as "financialization of commodities" (Creti et al., 2013; Tang & Xiong, 2012; Urom et al., 2021). Existing studies also suggest that these commodities have gained the interest of equity investors due to their inherent diversification and hedging attributes to both conventional and modern financial assets (e.g. Adekoya & Oliyide, 2021; Ji et al., 2020; Urom et al., 2022a). Consequently, the first contribution of our study is that we expand the set of considered commodities by including major natural resource commodities such as precious metals (gold, silver, and platinum) and industrial metals (steel, aluminium, and copper).

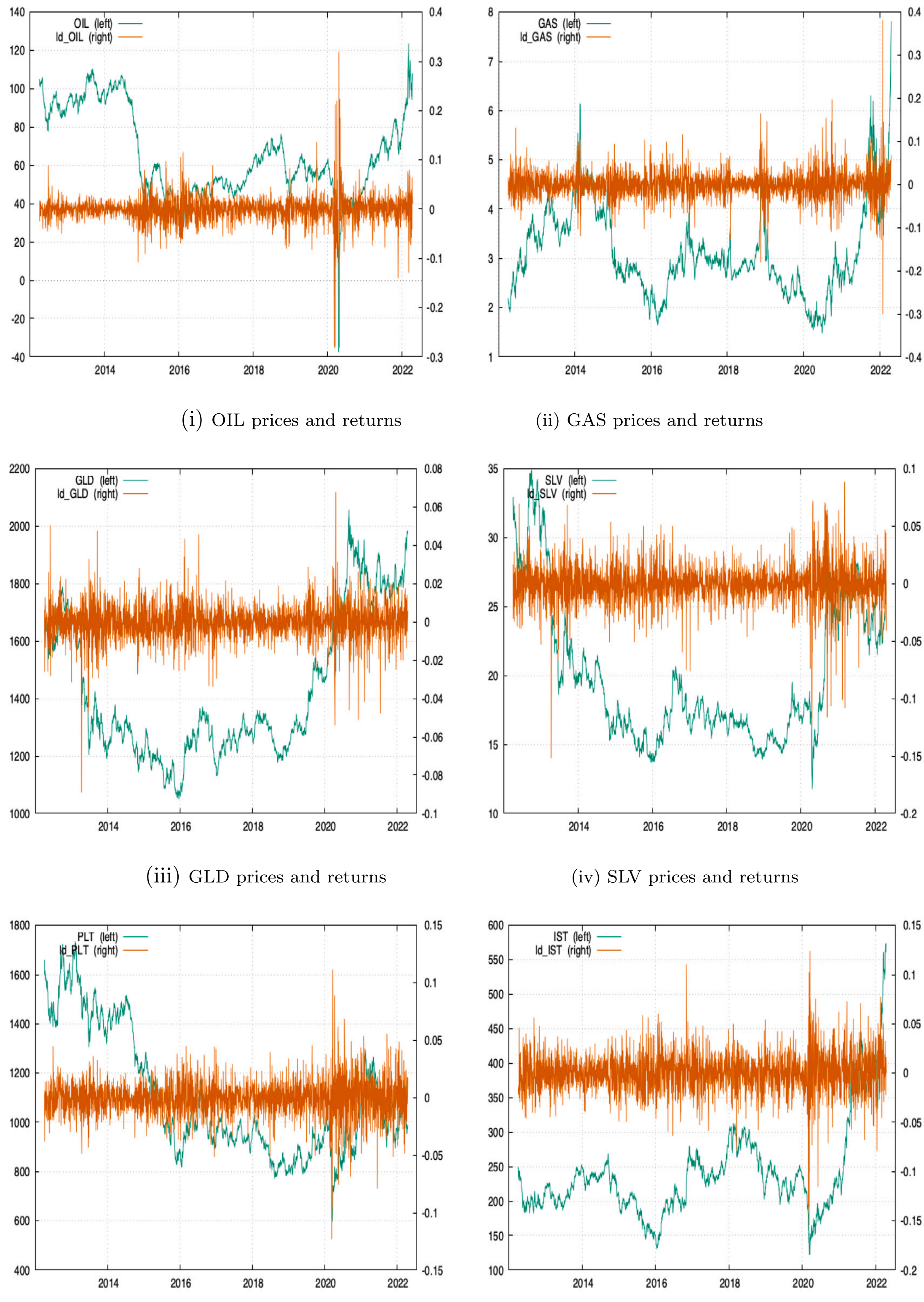
Second, we contribute to the literature by being the first to use the QVAR method recently developed by Ando et al. (2022) to analyse the interdependence between major natural resource commodities and sustainable investment. This methodology follows past leading studies on spillover in the quantiles (see e.g., Bouri & Harb, 2022; Bouri et al., 2020; Iqbal, Bouri et al., 2022; Iqbal, Naeem et al., 2022). As noted earlier, the method avails us the opportunity to characterize cross-market linkages and the propagation of shocks across different market conditions for the studied investment indices. The need to employ such an approach as opposed to conventional approaches such as the spillover index approach proposed by Diebold and Yilmaz (2009, 2012, 2014) is twofold. First, extant studies that employ a similar approach have shown that the propagation of shocks across different market conditions markedly differs from the mean shock that is observed whenever the constant-coefficient linear VAR model, such as those of Diebold and Yilmaz (2009, 2012; 2014), is used (e.g. Bouri et al., 2021; Jena et al., 2021; Khalfaoui et al., 2022). Second, institutional investors are the ones mostly at the forefront of sustainable investment. As these investors are mostly interested in longer-term investment horizons, examining risk transmission across different market conditions is imperative to help them devise strategies on how to protect their investments against downside or upside risk and hold a long-term position on their investment. Finally, we contribute to the literature by investigating the factors that drive the interdependences among the studied investment indices. Hence, our study goes beyond providing evidence in support or against cross-market linkages and interdependence to underscore factors that underline such linkages. Thus, it pinpoints surveillance variables investors could use to make an informed decision about their investments or policymakers could use to drive the market in the right direction.

3. Data and methods

3.1. Data

In line with our research objective, we use daily data on the S&P Dow Jones regional sustainability indices for North America (NAS), Europe (EUS) and Asian-Pacific (APS) as proxies for regional sustainability indices for North America, Europe and Asia and Pacific, respectively. The sample period for these indices are from April 02, 2012 to April 18, 2022. The start date for this sample is due to data availability on the relevant sustainability indices while the end date corresponds to the period of data curation and analysis for this study. Moreover, the data sample period enables us to examine the dynamic levels of connectedness and the effects of the explanatory variables across both calm market periods as well as during periods of heightened market volatility due to the COVID-19 pandemic and the Russia-Ukraine war. The Dow Jones regional sustainability indices track the performance of financial investments selected based through a best-in-class sustainability selection process across North America, Europe and Asian-Pacific regions. For the commodity markets, we use the West Texas Intermediate crude oil (OIL) and Henry Hub natural gas prices (GAS) to capture the energy commodity market. For the metal commodity market, we account for precious metals using gold (GLD), silver (SLV) and platinum (PLT) prices while for industrial metals, we use iron and steel (IST), aluminium (ALM) and copper (COP) prices. Data on commodities were retrieved from www.investing.com

Both the regional sustainability indices and commodities prices are converted to daily returns using the natural logarithm of daily price changes, given as; $ln(P_t/P_{t-1})$. Fig. 1 displays the evolution of all variables daily prices and returns for the sample period, while Table 1 presents the basic descriptive as well as contemporaneous correlation matrix among all variables. In Fig. 1, the effects of financial market crisis associated with the outbreak of the COVID-19 health crisis on prices and returns across both the chosen regional sustainability indices and commodity markets is evident, especially during the first wave of the crisis in 2020. As can be seen in Panel A of Table 1, the mean return for the sampled period is positive for all the variables, except platinum (PLT) and silver (SLV). Also, natural gas (GAS) possess the highest positive mean return, followed by both aluminium (ALM) and the North American sustainability index (NAS) while positive mean return is least

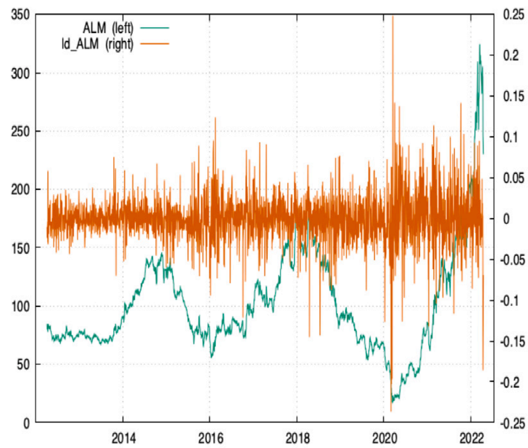


(i) OIL prices and returns
(ii) GAS prices and returns
(iii) GLD prices and returns
(iv) SLV prices and returns
(v) PLT prices and returns
(vi) IST prices and returns

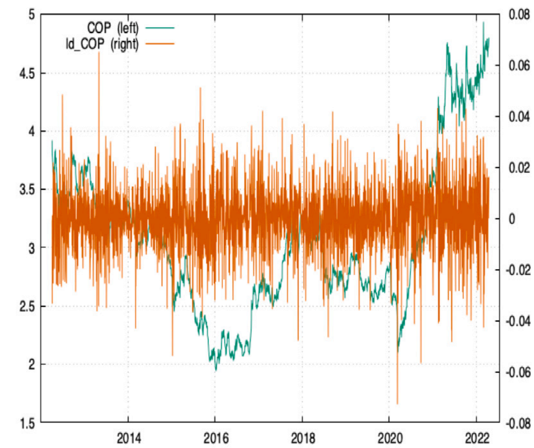
Fig. 1. Plots of prices and returns of sustainability indices, metals and energy commodities.
Note: North America sustainability index (NAS); Europe sustainability index (EUS); Asia and Pacific sustainability index (APS); WTI crude oil (OIL); Henry Hub natural gas price (GAS); gold (GOLD); silver (SLV); platinum (PLT); iron and steel (IST); aluminium (ALM) and copper (COP).

for gold (GLD) and copper (COP). As shown by the standard deviation, the natural gas market appears to be the most risky among all the variables during the sample period while the gold market is the least risky.

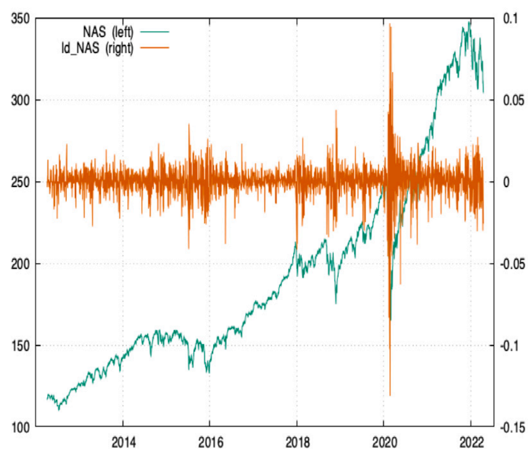
Furthermore, Panel A of Table 1 also shows the results of statistical tests relating to Skewness (Skew.), Kurtosis (Ex. Kurt.), Jarque–Bera (J-B), Ljung–Box Q (LB-Q) and Augmented Dickey–Fuller (ADF) for skewness, normality, autocorrelation and unit roots. In particular, the



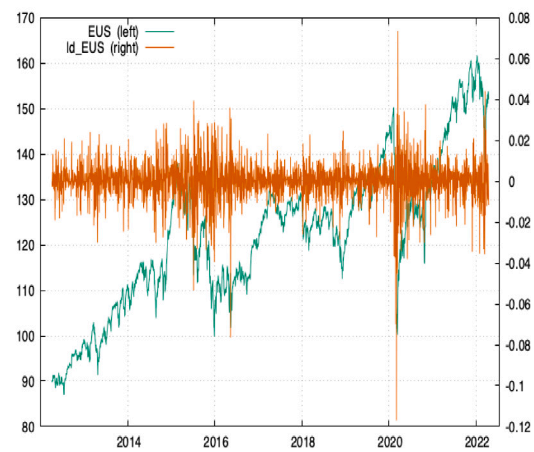
(vii) ALM prices and returns



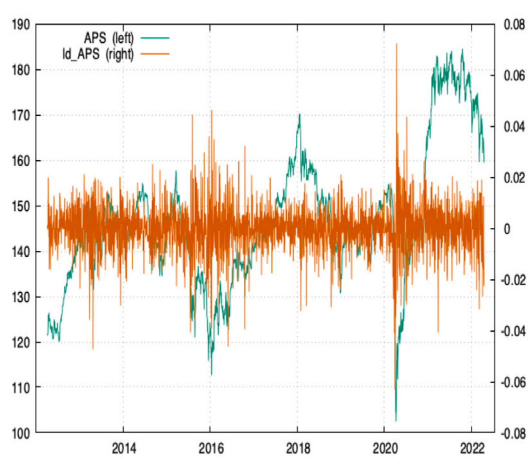
(viii) COP prices and returns



(ix) NAS prices and returns



(x) EUS prices and returns



(xi) APS prices and returns

Fig. 1. (*continued*).

significant coefficients of the skewness tests suggest that all the price return series possess negative skewness while the Ljung–Box Q results indicate the presence of autocorrelation in all the series. The Kurtosis and Jarque–Bera tests suggest that the hypothesis of normality can be rejected while Augmented Dickey–Fuller unit roots test show that all daily prices become stationary after the first difference. Besides, as a preliminary analysis, Panel B of Table 1 displays the unconditional correlation coefficients among the chosen regional sustainability indices and commodities prices. As can be seen, correlations are negative between the Asian-Pacific sustainability index and most of the remaining commodities prices as well as with its European counterpart. However,

Table 1
Descriptive statistics and correlation matrix.

Panel A: Descriptive statistics

	OIL	GAS	GLD	SLV	PLT	COP	IST	ALM	NAS	EUS	APS
Mean	0.0002	0.0005	0.0001	−0.0001	−0.0002	0.0001	0.0003	0.0004	0.0004	0.0002	0.0001
Min.	−0.2822	−0.3005	−0.0891	−0.1518	−0.1232	−0.0728	−0.1544	−0.2366	−0.1312	−0.1170	−0.0631
Max.	0.3196	0.3817	0.0679	0.0890	0.1118	0.0655	0.1243	0.2490	0.0971	0.0738	0.0728
Std. Dev.	0.0278	0.0329	0.0093	0.0175	0.0155	0.0130	0.0201	0.0297	0.0104	0.0099	0.0093
Skew.	0.153***	0.424***	−0.578***	−0.727***	−0.266***	−0.082*	−0.223***	−0.266***	−0.995***	−1.089***	−0.202***
Ex.Kurt.	26.913***	12.548***	6.642***	7.721***	5.510***	1.647***	4.821***	7.947***	24.225***	13.266***	5.083***
JB	76336.8***	16666.7***	4788.9***	6505.1***	3229.4***	288.75***	2469.9***	6685.3***	62257.8***	19043.4***	2739.4***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LB-Q(10)	23.400***	25.572***	8.580	15.031***	20.396***	9.524*	30.410***	12.549**	197.442***	9.907*	13.244**
	(0.000)	(0.000)	(0.133)	(0.005)	(0.000)	(0.087)	(0.000)	(0.020)	(0.000)	(0.073)	(0.014)
LB-Q^2(10)	872.6***	442.1***	34.81***	155.4***	524.1***	53.8***	840.4***	375.8***	2382.8***	481.2***	579.8***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF	−50.39***	−54.27***	−49.05***	−34.93***	−33.41***	−52.82***	−34.61***	−33.37***	−35.40***	−50.71***	−33.31***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B: Correlation matrix

OIL	GAS	GLD	SLV	PLT	COP	IST	ALM	NAS	EUS	APS	
1	0.1027	0.0084	0.0225	0.0174	0.0144	−0.0277	0.0107	−0.029	−0.0427	0.0094	OIL
	1	−0.0096	0.0143	−0.0126	−0.0076	−0.0029	−0.0212	0.0139	−0.0078	−0.0129	GAS
		1	0.2176	0.0715	0.0147	0.0105	0.0022	0.0038	0.0389	−0.0389	GLD
			1	0.072	0.0244	0.0015	0.0012	0.0232	−0.0201	0.0009	SLV
				1	0.0176	0.1055	0.0753	0.0169	−0.0405	−0.011	PLT
					1	0.0863	0.0754	−0.0296	−0.0224	−0.0432	COP
						1	0.6288	−0.0113	0.0316	−0.0201	IST
							1	−0.0154	0.0327	0.0058	ALM
								1	0.2171	0.0043	NAS
									1	−0.0078	EUS
										1	APS

Note: Skew., Ex. Kurt., J-B, LB-Q and ADF denote the Skewness, Excess Kurtosis, Jarque–Bera, Ljung–Box Q and Augmented Dickey–Fuller tests for skewness, normality, autocorrelation and stationarity. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively. North America sustainability index (NAS); Europe sustainability index (EUS); Asia and Pacific sustainability index (APS); WTI crude oil (OIL); Henry Hub natural gas price (GAS); gold (GOLD); silver (SLV); platinum (PLT); iron and steel (IST); aluminium (ALM) and copper (COP).

correlations are mainly positive between the North American sustainability index and the chosen commodities prices, except with industrial metals (ALM, IST and COP). Between same asset classes, correlations are positive and stronger as shown by the correlations between SLV and GLD as well as between NAS and EUS, but least across markets, especially between APS and SLV. This first pieces of evidence suggest potential heterogeneous connection among the regional sustainable investment indices and the energy and metal commodities.

Following our second major contribution, which relates to documenting how important global market factors as well as geopolitical risks predict the degree of total connectedness among regional sustainability indices and the chosen commodities markets, we employ the Chicago Board Options Exchange (CBOE) Volatility Index (VIX), Oil volatility index (OVX), Gold volatility index (GVZ), Merrill Lynch Option Volatility Estimate (MOVE), and U.S economic policy uncertainty index (EPU) as proxies for the effects of uncertainties associated with equity, oil, gold, fixed income markets and economic policy on total connectedness. Moreover, to account for global macroeconomic condition and geopolitical risks, we rely on the Business Conditions Index proposed by Aruoba et al. (2009) (ADS); the term spread between the 10-year and 3-month U.S. Treasury bonds (Term) and the Geopolitical Risk index (GPRI) of Caldara and Iacoviello (2022). We retrieved the daily data for these variables from Federal Reserve Economic Database of St. Louis (FRED), except for ADS business condition index that was taken from Federal Reserve Bank of Philadelphia database and GPRI that were retrieved from www.policyuncertainty.com Lastly, we account for the effects of the COVID-19 pandemic using a dummy variable with the value 1 for the period from January 1, 2020 to August 1, 2020, and 0 otherwise. This set of explanatory variables have recently been used to analyse the effects of global financial and economic factors on the degree of connectedness among different financial markets (see e.g., Mensi et al., 2022; Pham et al., 2022; Urom et al., 2022b).

3.2. Methods

3.2.1. Quantile return connectedness

In line with our first research objective, we use the newly introduced Quantile Autoregressive (Q-VAR) connectedness technique proposed by Ando et al. (2022). This methodology adds to the group of VAR-based spillover models dominated by the models of Diebold and Yilmaz (2012), Diebold and Yılmaz (2014); Antonakakis and Gabauer (2017), by providing for the analysis of tail behaviour of the topology of financial assets. For allowing the estimation of relative spillover intensity in both the right and left tails of the conditional distribution, this method provides a very crucial and timely composite measure of systemic financial fragility that has important application in risk management and monitoring (Ando et al., 2022). Thus, relying on the empirical design of this approach, we examine the propagation of shocks among regional sustainability indices and the chosen energy and metals commodities market across different market conditions, such as the normal, bearish as well as bullish markets.

As stated in Chatziantoniou et al. (2021), the Q-VAR connectedness index technique generates the set of important connectedness indicators from a basic Q-VAR(p) model expressed as follows:

$$y_t = \mu(\tau) + \sum_{j=1}^{p} \vartheta_j(\tau) y_{t-j} + \upsilon_t(\tau). \tag{1}$$

where y_t, and y_{t-j} denotes an $m \times 1$ dimensional vectors consistent with the relevant returns series; τ ranges from 0 to 1, relating to the chosen quantiles of the return distributions. As hinted earlier, we are primarily concerned with three return quantiles, which enables us to explore connectedness across the normal, bearish and bullish market conditions including the 0.5, 0.05 and 0.95 quantiles, respectively. Furthermore, p represents the lag length of the Q-VAR model; $\mu(\tau)$ denotes an $m \times 1$ dimensional vector of conditional mean while $\vartheta_j(\tau)$ is to an $m \times m$ dimensional matrix of Q-VAR coefficients. $\upsilon_t(\tau)$ is the

$m \times 1$ dimensional vector of error terms corresponding to an $m \times m$ dimensional variance–covariance matrix while $\sum(\tau)$.

Moreover, relying on the Wold's theorem, the Q-VAR(p) model above maybe transformed into a Q-VAR Moving Average (QVMA) (∞) expressed as follows:

$$y_t = v(\tau) + \sum_{j=1}^{p} \vartheta_j(\tau) y_{t-j} + \upsilon_t(\tau) = v(\tau) + \sum_{i=0}^{\infty} \varphi_i(\tau) \upsilon_{t-i}$$

Following this, the H-step ahead Generalized Forecast Error Variance Decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998), which may be explained as the effect that a shock in variable j has on variable i, may be computed as follows:

$$\psi_{ij}^{g}(H) = \frac{\Sigma(\tau)_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' \varphi_h(\tau) \Sigma(\tau) e_j)^2}{\sum_{h=0}^{H-1} (e_i' \varphi_h(\tau) \Sigma(\tau) \varphi_h(\tau)' e_i)} \tag{2}$$

$$\tilde{\psi}_{ij}^{g}(H) = \frac{\psi_{ij}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij}^{g}(H)}$$

The normalization of e_i into a zero vector with unity on the ith position offers the following two equalities: $\sum_{j=1}^{k} \tilde{\psi}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{k} \tilde{\psi}_{ij}^{g}(H) = K$. The Total Directional Connectedness *TO* others represents the total impact the ith variable has on all other variables *j*. Similarly, the Total Directional Connectedness *FROM* others denotes the total impact on the ith variable, resulting from shocking all other variables *j* in the system. These may respectively, be expressed as follows:

$$C_{i \to j}^{g}(H) = \sum_{j=1, i \neq j}^{k} \tilde{\psi}_{ji}^{g}(H) \times 100 \tag{3}$$

$$C_{i \leftarrow j}^{g}(H) = \sum_{j=1, i \neq j}^{k} \tilde{\psi}_{ij}^{g}(H) \times 100 \tag{4}$$

In the next step, the *Net Total Directional Connectedness*, denoted by the difference between the total directional connectedness *TO* others and the total directional connectedness *FROM* others, captures the net impact that the ith variable exerts on the system of interest. This may be written as:

$$C_i^g = C_{i \to j}^{g}(H) - C_{i \leftarrow j}^{g}(H) \tag{5}$$

where $C_i^g > 0$ denotes that the ith variable is a net transmitter of shocks, implying that it influences all others more than it is been influenced by them. In contrast, ($C_i^g < 0$) suggests that the ith variable is a net receiver of shocks, implying that it receives more influence from all others than it influences them.

Lastly, the Total Connectedness Index (TCI) represents the average of the ith variable's forecast error variance share explained by all other variables. Indeed, this metric indicates the degree with which a shock in one variable influences all other variables in the system, on average. Intuitively, this is a crucial barometer of the level of market risk and systemic fragility across market conditions. Thus, the higher the TCI, the higher the intensity of risk spillovers, which has important information for portfolio design and risk management. This may be written as:

$$TCI(H) = \frac{\sum_{i,j=1, i \neq j}^{m} \tilde{\psi}_{ij}^{g}(H)}{m} \times 100 \tag{6}$$

3.2.2. The effects of global factors on time-varying total connectedness

In line with the second major objective of our study, we rely on a linear regression model to examine how some important macroeconomic and geopolitical factors predict the degree of total connectedness among regional sustainability indices and the energy and metal commodity markets across different market conditions. To achieve this, we specify the following regression model:

$$TCI_t = v + \gamma_1 X_t + \gamma_2 D_t + \mu_t \tag{7}$$

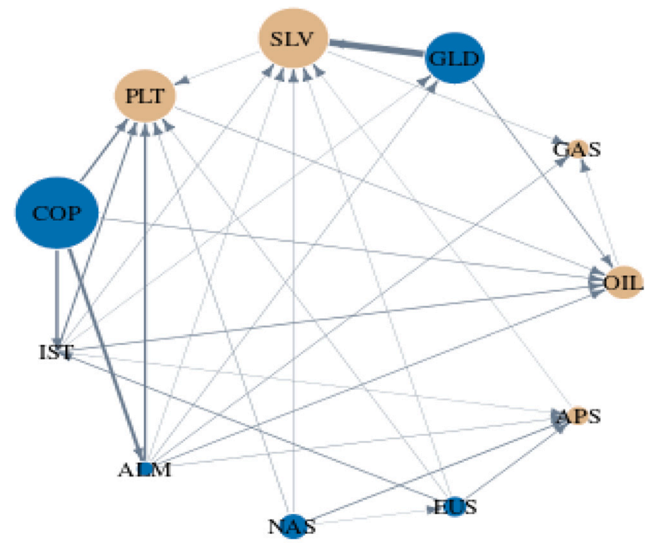


Fig. 2. Network plots of net pairwise directional return connectedness among sustainability indices, metals and energy commodities for the mean VAR–based on the standard approach of Diebold and Yilmaz (2012).
Note: Blue and yellow nodes denote net transmitter and receiver of shocks, respectively. Also, vertices are weighted using averaged net pairwise directional connectedness measures while the size of nodes represent weighted average of net total directional connectedness. North America sustainability index (NAS); Europe sustainability index (EUS); Asia and Pacific sustainability index (APS); WTI crude oil (OIL); Henry Hub natural gas price (GAS); gold (GOLD); silver (SLV); platinum (PLT); iron and steel (IST); aluminium (ALM) and copper (COP).. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

where TCI_t denotes the total connectedness index retrieve from both the static VAR and from a Q-VAR for the normal, bearish and bullish market conditions estimated. X_t corresponds to a set of chosen global market factors and geopolitical risk indicator. This includes the implied volatility indexes for the global equity (VIX), oil (OVX) and gold (GVZ) markets; global economic policy uncertainty (EPU) proxied by the economic policy uncertainty index for the United States; the fixed income market uncertainty captured by the Bank of America Merril Lynch Option Volatility Estimate (MOVE) index; the term spread between the ten-year and three-month Treasury Bonds (Term); the Aruobi–Diebold–Scotti business condition index (ADS) of Aruoba et al. (2009); and the geopolitical risk index (GPRI) of Caldara and Iacoviello (2022), which tracks adverse geopolitical events and associated risks while D_t is associated with a dummy that captures the effects of the COVID-19 pandemic on the level of connectedness. v is the intercept while γ are the relevant estimated regression coefficients. Lastly, μ_t represents the error term.

4. Results and discussion

This section proceeds in two steps. First, we present and discuss the results for the connectedness and interdependence between sustainable investment indices and the chosen energy and commodity markets investment indices across different market conditions. The second section then focuses on the drivers of such connectedness.

4.1. Connectedness among sustainable investment and commodities

In this section, we present the results for the return–risk spillovers among regional sustainability indices and the commodity indices. As in previous studies such as Bouri et al. (2021), we first explore the

Table 2
Return connectedness estimated at the mean and median of the conditional distribution.

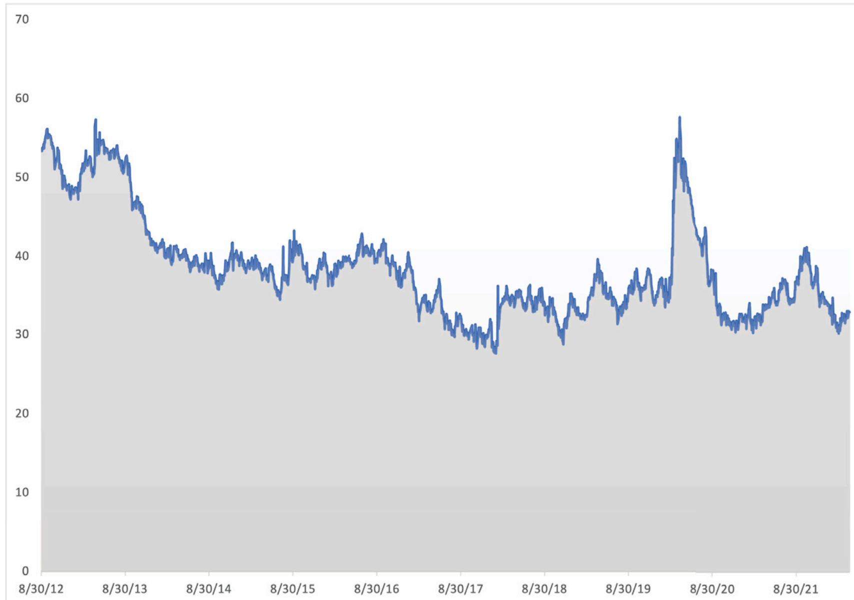
Panel A: Connectedness measures based on the standard mean-based approach of Diebold and Yilmaz (2012)												
	OIL	GAS	GLD	SLV	PLT	COP	IST	ALM	NAS	EUS	APS	FROM others
OIL	64.37	2.67	3.83	3.06	3.88	4.31	4.81	4.08	3.18	2.98	2.83	35.63
GAS	3.26	69.85	2.56	2.57	3.41	3.34	2.50	3.15	3.24	2.88	3.24	30.15
GLD	2.42	2.46	64.48	9.16	4.48	2.86	2.60	2.82	2.96	2.66	3.10	35.52
SLV	2.92	1.88	18.94	53.99	4.04	3.47	3.10	2.66	2.93	2.77	3.30	46.01
PLT	2.93	3.37	4.81	4.61	58.46	6.20	4.77	5.42	3.06	3.23	3.13	41.54
COP	3.12	2.91	2.72	3.27	3.12	67.61	3.99	4.02	2.99	3.33	2.92	32.39
IST	3.14	2.49	2.04	2.37	2.36	7.75	51.77	18.35	2.84	4.38	2.50	48.23
ALM	2.67	2.19	2.05	2.06	2.34	8.70	18.12	53.09	2.44	3.68	2.67	46.91
NAS	2.94	2.88	2.79	2.17	2.20	2.99	2.51	2.42	65.16	11.07	2.87	34.84
EUS	2.82	2.64	2.78	2.19	2.57	3.47	2.74	3.49	11.58	62.51	3.21	37.49
APS	2.80	2.86	3.15	2.80	2.75	3.36	3.08	3.48	4.69	4.64	66.38	33.62
TO others	29.03	26.36	45.67	34.24	31.16	46.46	48.22	49.89	39.90	41.63	29.77	422.33
Inc. own	93.40	96.20	110.15	88.23	89.62	114.07	99.99	102.98	105.07	104.14	96.15	
NET	−6.60	−3.80	10.15	−11.77	−10.38	14.07	−0.01	2.98	5.07	4.14	−3.85	**TCI = 38.39%**
Panel B: Connectedness measures based on the quantile VAR of Ando et al. (2022) (mean quantile $\tau_{0.5}$)												
	OIL	GAS	GLD	SLV	PLT	COP	IST	ALM	NAS	EUS	APS	FROM others
OIL	62.32	3.13	3.66	3.26	4.31	4.76	4.54	4.33	3.48	3.03	3.18	37.68
GAS	3.58	65.75	3.07	3.06	3.48	3.70	2.83	3.58	3.83	3.41	3.72	34.25
GLD	2.82	2.76	61.49	8.50	4.89	3.15	3.13	2.91	3.53	3.17	3.63	38.51
SLV	3.37	2.31	16.34	54.54	4.30	3.32	3.20	2.81	3.27	2.97	3.57	45.46
PLT	3.55	3.57	4.89	4.67	56.20	6.14	5.01	5.20	3.61	3.65	3.49	43.80
COP	3.40	3.29	2.93	3.42	3.21	64.66	4.43	4.35	3.36	3.44	3.49	35.34
IST	3.63	3.16	2.82	2.81	2.84	7.89	50.33	15.48	3.18	4.64	3.20	49.67
ALM	3.05	2.62	2.63	2.59	2.56	7.73	15.34	53.22	3.03	4.12	3.12	46.78
NAS	2.95	3.13	3.35	2.52	2.38	2.85	2.64	2.96	64.16	10.23	2.84	35.84
EUS	2.91	2.90	3.16	2.77	2.89	3.68	3.10	3.44	10.78	61.16	3.21	38.84
APS	2.99	3.07	3.45	3.31	3.28	3.56	3.15	3.94	4.83	5.08	63.33	36.67
TO others	32.25	29.95	46.31	36.92	34.15	46.78	47.37	48.99	42.91	43.75	33.46	442.83
Inc. own	94.57	95.70	107.80	91.46	90.35	111.44	97.71	102.20	107.07	104.91	96.79	
NET	−5.43	−4.30	7.80	−8.54	−9.65	11.44	−2.29	2.20	7.07	4.91	−3.21	**TCI = 40.26%**

Total connectedness index based on the standard mean-based approach of Diebold and Yilmaz (2012) and the quantile VAR of Ando et al. (2022) at the 50th quantile ($\tau_{0.5}$). Note: TCI denotes total connectedness index, with all indices estimated based on a 100 days window length and a forecast horizon of 10. NET represents the net total directional connectedness; TO others denotes the total directional connectedness from asset *i* to other assets while FROM others is the total directional connectedness from other assets to asset *i*. North America sustainability index (NAS); Europe sustainability index (EUS); Asia and Pacific sustainability index (APS); WTI crude oil (OIL); Henry Hub natural gas price (GAS); gold (GOLD); silver (SLV); platinum (PLT); iron and steel (IST); aluminium (ALM) and copper (COP).

degree of spillovers among these variables using the conditional mean standard approach of Diebold and Yilmaz (2012) and the conditional median ($\tau_{0.5}$), which offers us the opportunity to compare the results of dynamic total spillover at the extreme tails (upper and lower quantiles). Estimations are based on 100 days rolling window length, 10 days forecast horizon and optimal lag order of 2 chosen based on Bayesian information criterion (BIC). In Table 2 Panel A and Panel B, we compare the estimated measures of connectedness from the conditional mean and median, respectively. First, the results show high similarities in the various estimated connectedness measures. For instance, the level of total spillovers as shown by the total connectedness indices are 38.39% and 40.83% at the conditional mean and conditional median, respectively. This shows that the contribution to 10-day-ahead forecast error variance in each variable explained by innovations within the estimated system is slightly higher when measured using the quantile VAR at the mean quantile ($\tau_{0.5}$).

These levels of total connectedness index are lower than the total spillover level of 79.79% reported in Mensi et al. (2017), which considered the dynamic risk spillovers among Dow Jones sustainability world index, conventional equities, gold and oil prices. The higher level of risk spillover index may not be unconnected with the inclusion of several conventional equity indices and the longer sample period. Moreover, as shown in Table 2 Panel A and Panel B, the energy market, represented by OIL and GAS, is a net-receiver of risk spillover while among precious metals, silver (SLV) and platinum (PLT) are net-receivers of risk whereas gold (GLD) is a net-transmitter of risks. This finding is consistent with those of past studies that document that the energy market, especially crude oil is a net-receiver of risks spillover from green economy markets (see e.g., Ferrer et al., 2018; Gunay et al., 2022; Zhao et al., 2023). In contrast, both industrial metals and sustainability indices are mainly net-transmitters of risks, except for iron & steel as well as Asia-Pacific sustainability index that are net-receivers of risks. Given that risk spillovers estimated at the mean of the return distribution quantile ($\tau_{0.5}$) can be interpreted as risk spillovers under normal financial market condition, these results underscore the relative net-positive influence of the industrial metals and sustainability indices as well as the relative vulnerability of investments in conventional energy assets such as crude oil and natural gas under normal financial market condition.

In Figs. 2 and 4, we present the network plot of pairwise net directional risk spillovers among all variable pairs estimated at the conditional mean and conditional median, respectively. Similarly, Figs. 3 and 5 display the time-varying total spillover index estimated at the conditional mean and conditional median, respectively. As shown by both network plots, it is evident that connectedness estimates measured at the conditional mean and median suggest that the strongest pairwise connectedness is between gold and silver. Also, in decreasing order, copper (COP), gold (GLD) and the North American sustainability (NAS) indices are the main net-transmitters of risk while platinum (PLT), silver (SLV) and the crude oil (OIL) markets are the main net-receivers of risk spillover. These findings suggest that copper, gold and the North American sustainability indices are the main contributors of error variance in the forecast of the remaining variables in the system while platinum, silver and crude oil are the main receivers of shocks in forecast error variance in the system. Besides, the plots of time-varying total spillover at both the conditional mean and median suggest that over the sample period, the level of total spillover appear to have intensified during the first wave of the COVID-19 pandemic in the first two quarters of 2020, especially when total spillover is measured at the conditional mean using the standard Diebold and Yilmaz (2012)



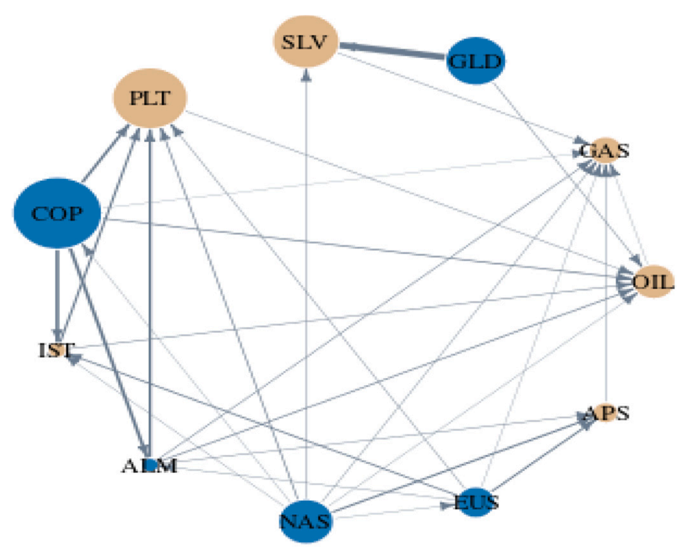
Time-varying connectedness index

Fig. 3. Time-varying connectedness for the mean VAR — based on the standard approach of Diebold and Yilmaz (2012).

approach. Significant increase in the levels of risk spillovers among sustainable and conventional assets during the peak of the COVID-19 pandemic has been documented in previous studies (see e.g., Iqbal, Bouri et al., 2022; Iqbal, Naeem et al., 2022; Zhao et al., 2023).

Table 3 Panel A and Panel B present the results of estimated connectedness measures for the upper ($\tau_{0.95}$) and lower ($\tau_{0.05}$) return quantiles, respectively, using the quantile VAR approach. In contrast to the results in the previous table, which was estimated at the mean quantile, this table reports the level of connectedness across both tails of the return distribution. This enables us to explore the connectedness dynamics across two market conditions, namely, the bullish and bearish markets. Results in Table 3 suggest that risk spillovers intensify at both tails of the distribution, especially in the left tail (lower quantile). Specifically, the total connectedness index (TCI) indicate that total spillovers among sustainability indices, metals and energy commodities is about 85.68% when estimated at the upper quantile of the distribution while it slightly increases to about 87.58% when computed at the lower quantile. These results suggest that during extreme market periods, the level of information spillovers between regional sustainability indices and the chosen commodity markets become very substantial, with the level of forecast error variance increasing from about 40.83% estimated at the mean quantile ($\tau_{0.40}$) to 85.68% and 87.58% for the upper and lower quantiles, respectively.

The significantly higher levels of total spillover observed at both extreme tails indicate that when the financial market condition become either bullish (higher returns and low volatility) or bearish (lower returns and higher volatility), information about each of the markets is processed more rapidly and propagated across other markets in the system. While this may suggest that positive news about market performance may be easily sent across these markets during bullish market periods, it also indicates that bad news (risk) may easily spillover from each market to others during market downturns (bearish market). The former suggests an active portfolio redesign and risk management to reduce losses during financial market downturns. These results agree with those of prior studies, which indicate that spillovers among traded financial and commodity indices become higher during extreme market conditions (see e.g., Pham (2021); Urom et al. (2020); Liu et al. (2021); Chen et al. (2022)). The relatively higher level of spillovers estimated at the lower quantile (bearish market) than at the upper quantile (bullish market) is also in line with results of previous studies, which document stronger risk spillover among traded financial and commodity indices during periods of financial stress (see e.g., (Adekoya & Oliyide,



Network plots of net pairwise directional connectedness

Fig. 4. Network plots of net pairwise directional return connectedness among sustainability indices, metals and energy commodities for quantile VAR (mean quantile - $\tau_{0.5}$) based on the approach of Ando et al. (2022).
Note: Blue and yellow nodes denote net transmitter and receiver of shocks, respectively. Also, vertices are weighted using averaged net pairwise directional connectedness measures while the size of nodes represent weighted average of net total directional connectedness. North America sustainability index (NAS); Europe sustainability index (EUS); Asia and Pacific sustainability index (APS); WTI crude oil (OIL); Henry Hub natural gas price (GAS); gold (GOLD); silver (SLV); platinum (PLT); iron and steel (IST); aluminium (ALM) and copper (COP).. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

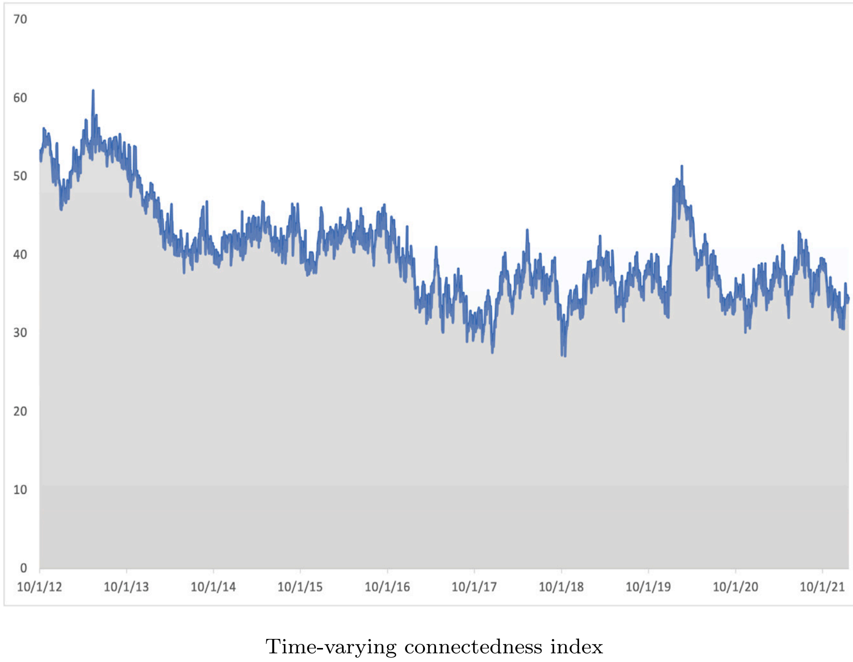


Fig. 5. Time-varying connectedness for the quantile VAR (mean quantile - $\tau_{0.5}$) based on approach of Ando et al. (2022).

2021; Bouri et al., 2021)). Moreover, Bouri et al. (2021) argue that the differentiation of risk spillovers under bullish and bearish market periods enables us to distinguish between extreme negative shocks and extreme positive shocks. In our case, the relatively higher TCI obtained during bearish and bullish periods indicate higher impacts of extreme negative/positive shocks on the system, which as noted in Londono (2019), may be interpreted as the results of the arrival of unexpected good or bad news, which are seen as either beneficial or adverse shocks in the market.

In comparison to the reference results of connectedness measures estimated at the mean quantile, Table 3 Panel A and Panel B present some interesting pattern with regards to the net directional total connectedness. In particular, as shown in Table 3 Panel A, while natural gas (GAS) becomes a net-transmitter of shocks, crude oil remains a net-receiver under bullish market period. Similar to the normal market period (mean quantile), gold (GLD) is a net-transmitter of risks while silver (SLV) and platinum (PLT) remain net-receivers of shocks. This suggests that as the market condition moves from normal to become bullish, the interactions between indicators of the precious metals market and the remaining indices in the system remain mainly similar in terms of the direction of risks spillover. That is, gold (GLD) remains a net-transmitter of risks irrespective of whether the market is in normal or bullish condition, while silver (SLV) and platinum (PLT) remain net-receivers of shocks in both normal and bullish market condition. In contrast, results show that all the industrial metals indices including copper (COP), iron & steel (IST) and aluminium (ALM) become net-transmitters of shocks while the three regional sustainability indices including the North American Sustainability (NAS), Europe Sustainability and Asia-Pacific sustainability (APS) indices are net-receivers of shocks. This finding corroborates with results from previous studies which document that regional sustainability indices are net-receivers of risk from other financial assets, including energy, equities and cryptocurrencies (see e.g., Pham, 2021; Chakrabarti & Sen, 2021; Urom et al., 2021; Sharif et al. (2023)). This highlights the fragility of regional sustainability indices to industrial metals commodities as well as natural gas and gold commodities during bullish market periods, given that these commodities transmit higher shocks to regional sustainability markets at the higher quantile.

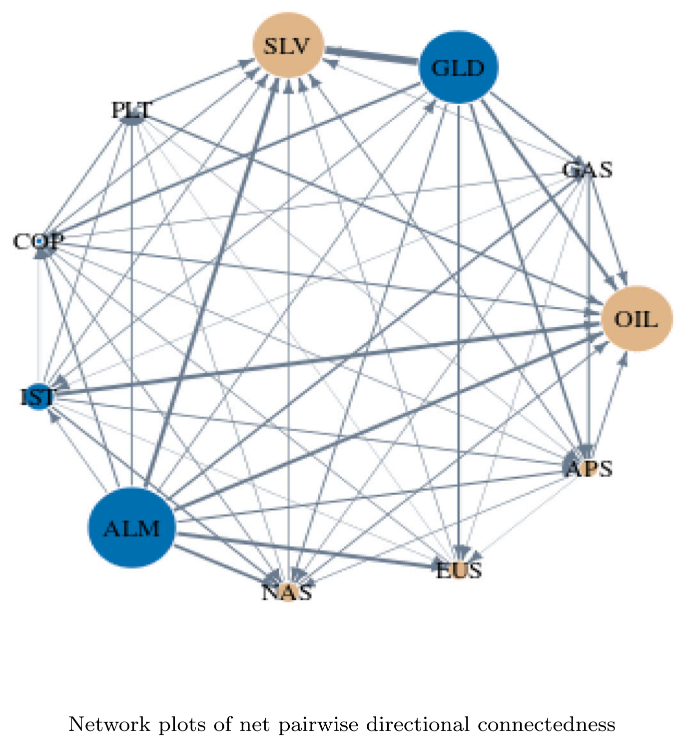


Fig. 6. Network plots of net pairwise directional return connectedness among sustainability indices, metals and energy commodities for the upper quantile ($\tau_{0.95}$). Note: Blue and yellow nodes denote net transmitter and receiver of shocks, respectively. Also, vertices are weighted using averaged net pairwise directional connectedness measures while the size of nodes represent weighted average of net total directional connectedness. North America sustainability index (NAS); Europe sustainability index (EUS); Asia and Pacific sustainability index (APS); WTI crude oil (OIL); Henry Hub natural gas price (GAS); gold (GOLD); silver (SLV); platinum (PLT); iron and steel (IST); aluminium (ALM) and copper (COP).. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Dynamic connectedness across the upper and lower return quantiles.

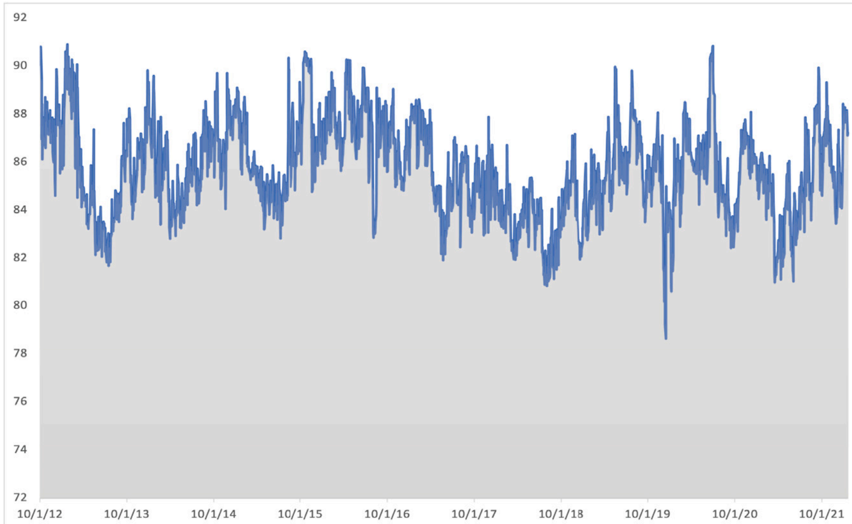
	OIL	GAS	GLD	SLV	PLT	COP	IST	ALM	NAS	EUS	APS	FROM others
Panel A: Connectedness measures based on the quantile VAR (upper quantile $\tau_{0.95}$)												
OIL	14.70	8.75	8.56	8.29	8.71	8.46	8.62	8.80	8.23	8.26	8.62	85.30
GAS	8.49	14.51	8.81	8.43	8.51	8.63	8.45	8.69	8.37	8.44	8.66	85.49
GLD	8.12	8.49	14.70	9.13	8.85	8.55	8.31	8.69	8.44	8.24	8.48	85.30
SLV	8.28	8.54	10.14	13.86	8.82	8.57	8.24	8.46	8.31	8.40	8.40	86.14
PLT	8.39	8.47	8.83	8.55	14.14	8.69	8.70	8.80	8.67	8.29	8.46	85.86
COP	8.20	8.48	8.94	8.37	8.47	14.18	8.98	8.96	8.31	8.62	8.47	85.82
IST	8.06	8.53	8.47	8.07	8.53	8.92	13.66	10.68	8.24	8.42	8.41	86.34
ALM	8.31	8.37	8.53	7.93	8.60	8.71	10.54	14.11	8.16	8.26	8.47	85.89
NAS	8.03	8.49	8.66	8.17	8.56	8.47	8.51	8.59	14.72	9.34	8.46	85.28
EUS	8.29	8.52	8.54	8.28	8.23	8.48	8.49	8.79	9.39	14.56	8.42	85.44
APS	8.42	8.91	8.84	8.21	8.54	8.60	8.63	8.75	8.33	8.36	14.42	85.58
TO others	82.59	85.56	88.31	83.44	85.83	86.09	87.49	89.20	84.43	84.63	84.85	942.43
Inc. own	97.29	100.07	103.01	97.30	99.97	100.27	101.15	103.31	99.16	99.20	99.28	
NET	−2.71	0.07	3.01	−2.70	−0.03	0.27	1.15	3.31	−0.84	−0.80	−0.72	**TCI = 85.68%**
Panel B: Connectedness measures based on the quantile VAR (lower quantile $\tau_{0.05}$)												
OIL	12.80	8.81	8.59	8.64	8.57	8.68	8.60	8.75	8.56	9.09	8.89	87.20
GAS	8.84	12.84	8.63	8.45	8.25	8.97	8.44	8.78	8.73	9.16	8.91	87.16
GLD	8.62	8.58	12.72	9.22	8.61	8.72	8.51	8.62	8.61	8.96	8.84	87.28
SLV	8.59	8.66	9.92	11.67	8.63	8.80	8.63	8.57	8.81	8.81	8.91	88.33
PLT	8.68	8.56	8.97	8.89	11.95	8.84	8.69	8.85	8.86	9.04	8.66	88.05
COP	8.65	8.78	8.72	8.59	8.40	12.60	8.66	8.70	8.94	9.23	8.73	87.40
IST	8.90	8.63	8.54	8.30	8.48	9.21	11.83	9.77	8.51	9.04	8.79	88.17
ALM	8.63	8.44	8.51	8.53	8.54	9.13	9.53	12.10	8.65	8.87	9.07	87.90
NAS	8.79	8.53	8.91	8.39	8.45	8.83	8.42	8.61	12.33	9.89	8.86	87.67
EUS	8.67	8.47	8.67	8.48	8.31	8.73	8.61	8.54	9.55	13.01	8.94	86.99
APS	8.68	8.70	8.87	8.55	8.38	8.76	8.61	8.74	8.92	9.05	12.74	87.26
TO others	87.05	86.16	88.33	86.04	84.61	88.67	86.70	87.94	88.14	91.15	88.61	963.39
Inc. own	99.85	99.00	101.05	97.71	96.56	101.27	98.53	100.04	100.46	104.16	101.35	
NET	−0.15	−1.00	1.05	−2.29	−3.44	1.27	−1.47	0.04	0.46	4.16	1.35	**TCI = 87.58%**

Total connectedness index for the 95th ($\tau_{0.95}$) and 5th ($\tau_{0.05}$) quantiles. Note: TCI denotes total connectedness index, with all indices estimated based on a 100 days window length and a forecast horizon of 10. Note: TCI denotes total connectedness index, with all indices estimated based on a 100 days window length and a forecast horizon of 10. NET represents the net total directional connectedness; TO others denotes the total directional connectedness from asset *i* to other assets while FROM others is the total directional connectedness from other assets to asset *i*. North America sustainability index (NAS); Europe sustainability index (EUS); Asia and Pacific sustainability index (APS); WTI crude oil (OIL); Henry Hub natural gas price (GAS); gold (GOLD); silver (SLV); platinum (PLT); iron and steel (IST); aluminium (ALM) and copper (COP).

However, as shown in Panel B of Table 3, when connectedness measures are estimated at the lower quantile ($\tau_{0.05}$), all the three regional sustainability indices (NAS, EUS, APS) become net-transmitters of shocks while the two energy commodities (OIL, GAS) become net-receivers of shocks. Further, compared to spillover measures at the upper quantile ($\tau_{0.05}$), no notable changes in net directional total connectedness occur within the precious metals market, as gold (GLD) remains the only net-transmitter of shocks while platinum (PLT) and silver (SLV) remain net-receivers of risk. In contrast, among industrial metals, both copper (COP) and aluminium (ALM) remain net-transmitters of shocks while iron & steel becomes a net-receiver of shocks. Taken together, these results indicate that when connectedness is estimated at the lower quantile, the stronger shocks emanating from regional sustainability indices is revealed, indicating that regional sustainability market become the dominant source of risks within the system under bearish market condition. In this case, regional sustainability indices may not be a good addition to a portfolio containing the remaining assets during financial market downturns, due to substantial out-flow of shocks from these indices to commodities, especially energy commodities. Similar results are documented in Gunay et al. (2022), which shows that regional green economy indices dominate volatility risks transmission in the context of commodities (gold and oil).

Moreover, Figs. 6 and 8 display the network plots for the net total directional connectedness estimated at the upper quantile and lower quantile, respectively. In particular, Fig. 6 shows that when market condition is bullish, shocks spillover mainly emanated from aluminium (ALM) and gold (GLD) while the crude oil (OIL) and silver (SLV) markets were the main receiver of shocks from the system. This underscores the high sensitivity of silver and oil assets to risks from the remaining assets in the system, especially aluminium and gold. In contrast, Fig. 8 suggests that when measures of connectedness are estimated at the lower quantile, shocks spillover is mainly driven by risks from Europe sustainability index (EUS) while platinum (PLT) and silver (SLV) are the main receivers of shocks spillover. This further highlight the vulnerability of investments in precious metals market to risks from the remaining markets in the system both under bullish and bearish market periods as they are main receivers of shocks. This implies that they are more likely to affected by developments in other markets than the drive developments in other market. The exception to this is gold assets. Besides, Figs. 7 and 9 show the time-variation in the level of total spillover across the sample period, estimated at both the upper and lower quantiles, respectively. These plots enable us to examine how total connectedness has evolved across time and at both the upper quantile and lower quantiles. The effects of key global events such as the United States shale oil boom and bust, during which the prices for WTI crude oil fell from $ 106 per barrel in June 2014 to $32 per barrel in January 2016 as well as the COVID-19 pandemic, especially at the upper quantile. It is also crucial to note that total connectedness appear to have fluctuated more rapidly when measured at the lower quantile.

To offer more insight on changing total spillover across more quantiles, we estimated the total connectedness across the upper, shoulders as well as lower quantiles. Fig. 10 presents the total connectedness index for 21 quantiles plotted against the total connectedness index estimated at the conditional mean quantile ($\tau_{0.5}$). As shown in Fig. 10, there is a high level of similarity, suggesting a symmetry between total connectedness at both upper and lower quantiles as we move away from the mean quantile. A similar result of total connectedness across upper and lower quantiles is documented in Bouri et al. (2021). Intuitively, the observed high level of similarity in the increases in total connectedness index at both the upper and lower quantiles indicates that investors in regional sustainability indices, metals and energy



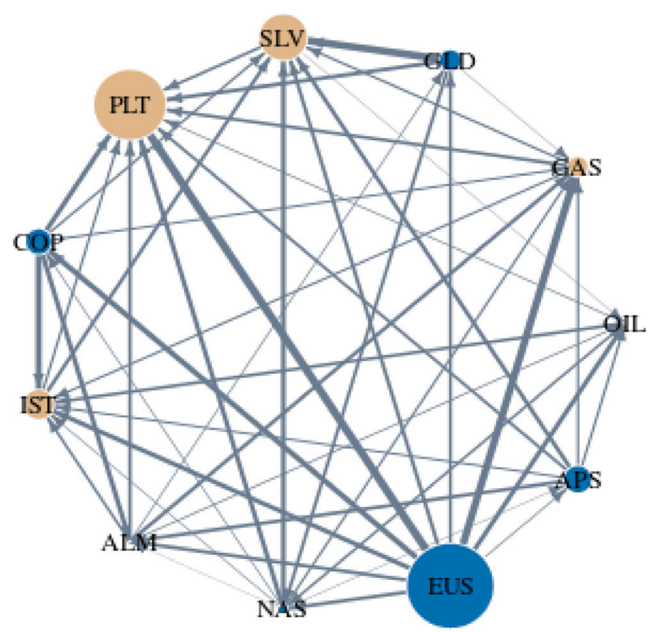
Time-varying connectedness index

Fig. 7. Time-varying connectedness for the quantile VAR (upper quantile - $\tau_{0.95}$).

commodities become more sensitive to both extreme positive as well as extreme negative news. This can be explained in terms of information content of extreme financial market events prompting investors in these markets to act based on a particular event happening in the tail, while also acting based on a similar information about an event occurring in the other tail. Thus, positive (negative) events in the upper tail connectedness is associated with positive(negative) events in lower tail connectedness, indicating that periods of increasing vulnerability due to rising tendency for negative shocks to propagate, appear to be also associated with periods of rising propagation of positive shocks, and vice-versa.

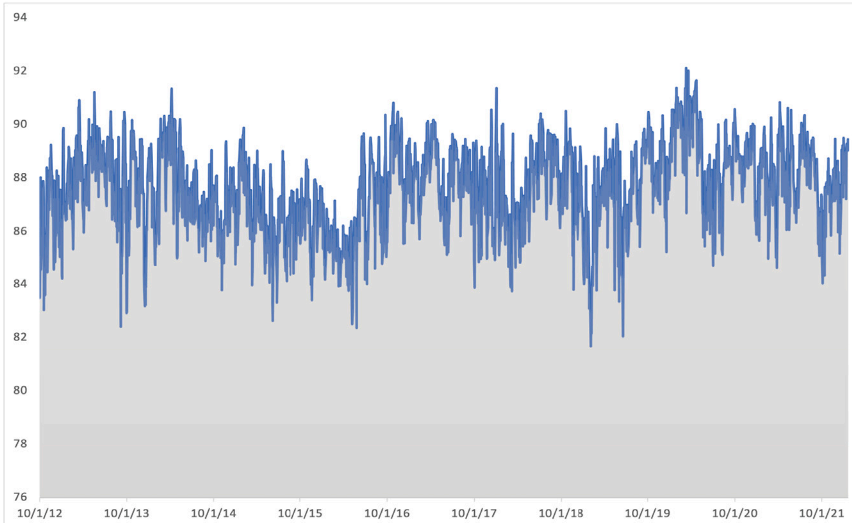
Lastly, in Figs. 11 and 12, we plot the Relative Tail Dependence (RTD) for the extreme tails based on the 95th and 5th quantiles ($TCI_{\tau_{0.95}} - TCI_{\tau_{0.05}}$) as well as the 90th and 10th quantiles ($TCI_{\tau_{0.90}} - TCI_{\tau_{0.10}}$). As can be seen in Figs. 11 and 12, relative tail dependence across the sample period is mainly negative for the 95th and 5th quantiles while it is mainly negative for the 90th and 10th quantiles. In particular, as shown in Fig. 11, relative positive tail dependence peaked around early 2016 for the 95th and 5th quantiles while it peaked around 2015 for the 90th and 10th quantiles. However, for both extreme quantile combinations, relative negative tail dependence peaked during the first wave of the COVID-19 pandemic in early 2020. As noted in Bouri et al. (2021), positive relative tail dependence suggest an increase in the fragility of connectedness due to higher dependence at the higher quantile than at lower quantile while negative relative tail dependence indicate higher dependence at the lower quantile than the upper quantile and thus, a decrease in the fragility of the connectedness network at the tails. In contrast to Bouri et al. (2021), Figs. 11 and 12 show that relative tail dependence dynamics at the 95th and 5th quantiles posses more variability than the 90th and 10th quantiles, suggesting that the asymmetric pattern is sensitive to the chosen levels of upper and lower tail dependence measures. Thus, our choice of 95th and 5th quantiles as measures of extreme quantiles enables us to explore richer dynamics in the measures of connectedness at the extreme tails.

Overall, some important economic intuitions can be drawn from the above results for the sake of investors and policymakers regarding investments in regional sustainability indices. First, variations in the degree and direction of risk spillovers both among regional sustainability indices and in the context of the selected commodities buttresses the need for dynamic portfolio management strategy. Thus, investors that are increasingly integrating regional sustainability indexes in their portfolio should design and implement hedging strategies across different market conditions with better understanding of the structure of network connectedness, transmission channels and the effects of contagion among regional green economies and commodities in the context of financial market crash or boom. Indeed, the dynamics of



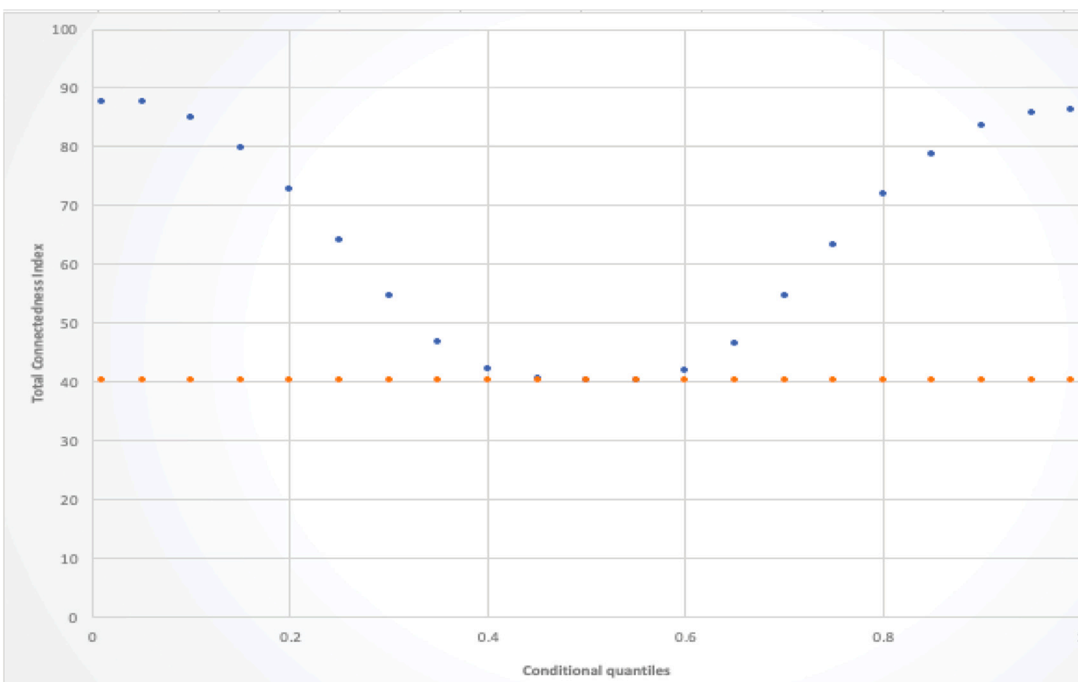
Network plots of net pairwise directional connectedness

Fig. 8. Network plots of net pairwise directional return connectedness among sustainability indices, metals and energy commodities for the lower quantile ($\tau_{0.05}$). Note: Blue and yellow nodes denote net transmitter and receiver of shocks, respectively. Also, vertices are weighted using averaged net pairwise directional connectedness measures while the size of nodes represent weighted average of net total directional connectedness. North America sustainability index (NAS); Europe sustainability index (EUS); Asia and Pacific sustainability index (APS); WTI crude oil (OIL); Henry Hub natural gas price (GAS); gold (GOLD); silver (SLV); platinum (PLT); iron and steel (IST); aluminium (ALM) and copper (COP).. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



Time-varying connectedness index

Fig. 9. Time-varying connectedness for the quantile VAR (upper quantile - $\tau_{0.05}$).



Total connectedness index for various quantiles

Fig. 10. Variations in the TCI across various quantiles. The orange horizontal line is the TCI estimated at the conditional mean.. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

directional spillovers among the markets considered in this study is useful as a guide for portfolio optimization for both retail and institutional investors who wish to combine sustainability indices and commodities, especially under extreme market conditions. For policymakers and institutions such as central banks that are responsible for ensuring financial stability, these results are indications of the need for effective interventions using appropriate policies to enhance the safe harbour potentials for diversification purposes of regional green economy indexes.

4.2. Drivers of static and dynamic conntectedness

Table 4 presents the results on the drivers of both static and dynamic total connectedness using the choosing macroeconomic, geopolitical, and market-related variables as discussed earlier. Results for the static total connectedness are reported in column 1, while those for the three quantiles (i.e. dynamic connectedness) corresponding to the normal, bullish and bearish market conditions are reported in columns 2–4. Beginning with column 1, the reported estimated coefficients are only

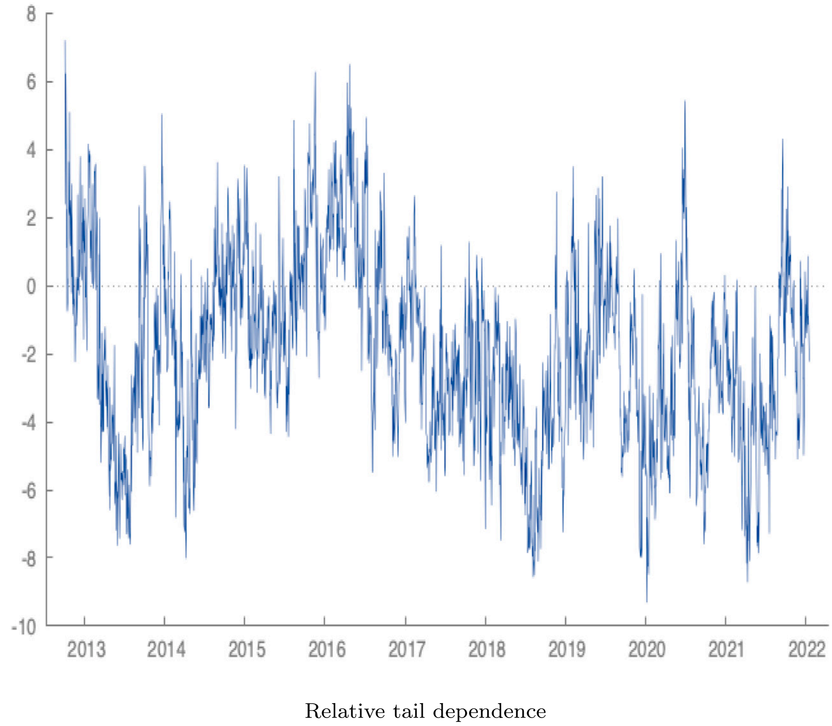


Fig. 11. Relative tail dependence ($TCI_{\tau_{0.95}} - TCI_{\tau_{0.05}}$).
Note: This figure displays the time-varying difference between the TCI at the 95th quantile and the TCI at the 5th quantile, with both indices estimated based on a 100 days window length and a forecast horizon of 10.

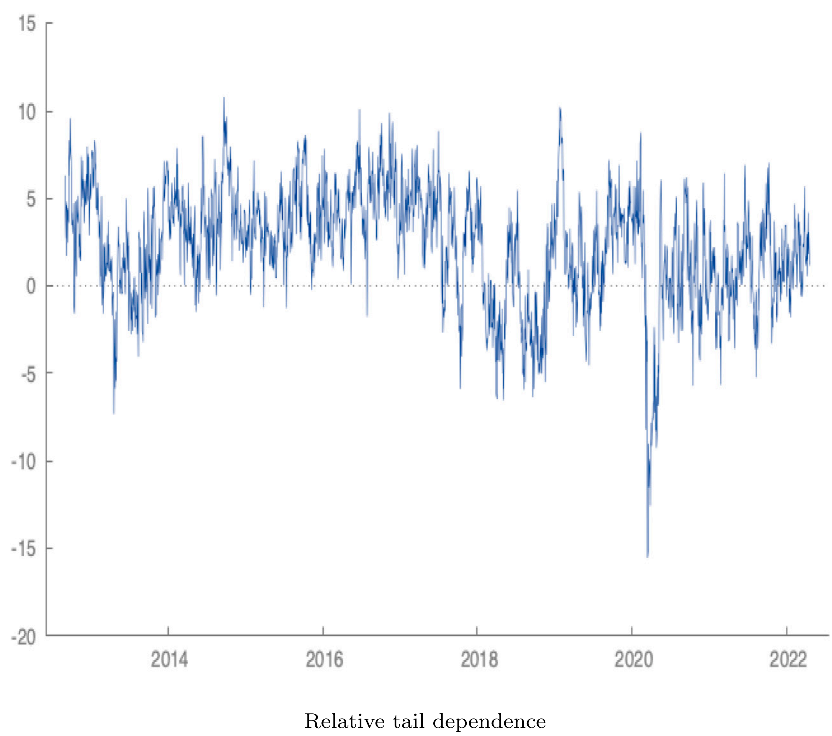


Fig. 12. Relative tail dependence ($TCI_{\tau_{0.90}} - TCI_{\tau_{0.10}}$).
Note: This figure displays the time-varying difference between the TCI at the 90th quantile and the TCI at the 10th quantile, with both indices estimated based on 100 days window length and a forecast horizon of 10.

significant for economic policy uncertainty (EPU), business environment condition (ADS) and the oil (OVX), gold (GVZ), and fixed-income (MOVE) market uncertainty. This implies that the studied commodities and sustainable investment increase dependence in response to the changes in these variables. Except for OVX which has a statistically significant negative estimated coefficient, other statistically significant

Table 4
Drivers of total connctedness indexes.

	Total connectedness index for the mean	Quantile total connectedness index		
	1	2	3	4
Variables		Normal market	Bullish market	Bearish market
ln(VIX)	−1.554	−1.523	−0.857**	−0.808**
	(1.133)	(1.158)	(0.421)	(0.344)
ln(OVX)	−8.091***	−7.932***	0.316	0.044
	(0.963)	(0.911)	(0.348)	(0.273)
ln(GVZ)	9.917***	10.44***	0.796	0.772**
	(1.362)	(1.239)	(0.512)	(0.377)
ln(EPU)	1.166***	0.411	0.152	0.301***
	(0.412)	(0.362)	(0.136)	(0.096)
ln(MOVE)	12.91***	12.70***	3.707***	−1.940***
	(1.621)	(1.387)	(0.464)	(0.350)
ln(GPRI)	−0.492	−0.499	0.628***	−0.108
	(0.343)	(0.350)	(0.158)	(0.106)
ln(TEU)	0.188	−0.177	0.059	0.125
	(0.285)	(0.282)	(0.104)	(0.088)
COVID	2.579	−0.203	−1.088**	1.797***
	(1.730)	(1.583)	(0.513)	(0.429)
δ(Term)	−0.218	−0.755	−1.559**	0.284
	(1.653)	(1.158)	(0.753)	(0.530)
δ(ADS)	4.051***	2.661***	−0.666	0.816***
	(0.945)	(0.790)	(0.590)	(0.250)
Constant	20.84***	26.12***	75.76***	88.88***
	(3.626)	(3.572)	(1.554)	(1.105)
Ω_{Mean}	38.39	40.25	85.67	87.58
Ω_{Max}	57.68	61.01	90.9	92.12
Ω_{Min}	27.67	27.08	78.62	81.67
$\Omega_{Std.Dev.}$	6.366	6.112	1.959	1.627
R-squared	0.529	0.539	0.215	0.152

Note: Robust standard errors are presented in brackets while ***, ** and * represent significance at 1%, 5% and 10% levels, respectively. Ω Mean, Ω Max and Ω Min are the mean, maximum and minimum values of total connectedness index at the mean using the standard Diebold and Yilmaz (2012) method and dynamic total connectedness indexes for the three market conditions while Std. Dev. is the standard deviation of total return and volatility connectedness indexes for the three market conditions. The three market conditions including normal, bullish and bearish markets are represented by the 50th ($\tau_{0.5}$), 95th ($\tau_{0.95}$) and ($\tau_{0.05}$) quantiles. Volatility indexes for equity (VIX), oil (OVX) and gold market (GVZ) markets; Economic policy uncertainty (EPU); Merril Lynch Option Volatility Estimate (MOVE) index; the term spread (Term); Aruobi–Diebold–Scotti business condition index (ADS); geopolitical risk index (GPRI) and COVID-19 pandemic dummy (COVID).

estimated coefficient reported in that column is positive implying that positive changes in the associated variable increase the static total connectedness. As per the OVX, it means that it decreases it.

Moving on to column 2, the results are largely similar to those of static total connectedness except that the estimated coefficient of economic policy uncertainty is no more statistically significant although it is still positive. Put together, the result in column 2 leads to the further conclusion that business environment condition (ADS) and the oil (OVX), gold (GVZ), and fixed-income (MOVE) are the driver of small cross-shock among the studied commodities and sustainable investments, with OVX being a puling force while the others act as a pushing force. Regarding the bullish and bearish market conditions which characterize the extreme upside and downside market conditions, interesting results emerge. At a first glance, the results indicate that except for the equity market uncertainty (VIX) other variables are either non-predictors of return connectedness of the studied the investment indices or they have opposing effects on their return connectedness during both extreme market conditions. Beginning with the VIX, the estimated coefficient is significantly negative for both the bullish and bearish market conditions, although the size of the estimated coefficient is larger for the bullish market condition. This implies that an increase in equity market uncertainty decreases the connectedness among the studied commodities and sustainable investment during extreme market conditions, with the effect being higher during extreme upside than extreme downside market conditions.

The result also shows that fixed income market uncertainty (MOVE) significantly predicts the total connectedness both during the extreme market condition, albeit with an opposing effect. In particular, it has a significant positive (negative) effect during the bullish (bearish) market condition. Further, the estimated coefficients of the gold market and economic policy uncertainty, and business environment conditions are only significant under the bearish market condition, with the estimated coefficients being positive. Economically, this result implies that these variables increase the connectedness among the studied investments during extreme bad times, leading to exposure to large negative shocks on their returns. Market participants in the green economy and commodity markets should therefore, monitor the evolution of these variables to be able to mitigate their effects on shocks transmission among regional sustainability indices and the commodity market. However, geopolitical risk (GPRI) and bond spread (Terms), on the other hand, have a significant effect only during the bullish market condition, with the estimated coefficient being positive for GPRI and negative for Term. Regarding the effect of geopolitical risk, a related analysis of the nexus among global as well as regional green finance and geopolitical risk in the context of environmental management decisions, Zhang et al. (2023) document a heterogeneous causal relations between geopolitical risks and green finance. Lastly, the COVID dummy shows a significantly positive (negative) effect during the bullish (bearish) market condition.

5. Conclusion

The analysis of the risk-return features of sustainable investments as well as their interdependences with other traditional financial assets possess crucial implications from both portfolio managers and policy-markers' front. In line with this, this study investigates the connectedness and interdependences among three regional sustainable investment indices (North America, Europe and Asia-Pacific) and investments in major natural resource commodities including energy commodities (crude oil and natural gas), precious metals (gold, silver, and platinum), and industrial metals (steel, aluminium, and copper). The paper particular examines how the level of connectedness among these investments vary across different market conditions. Hence, we employed the Quantile Vector-Autoregressive (QVAR) connectedness approach, which enables us to examine how the connectedness and risk propagation among these variables evolve across different quantiles that correspond to different market conditions. As a second research objective, we use the linear regression model to investigate how geographical risks and global macroeconomic factors drive the levels of connectedness among the studied investments across different market conditions.

Results from the QVAR technique demonstrate that the connectedness among regional sustainability indexes, energy and commodity markets indexes vary across market conditions, with the levels of total connectedness during extreme downside and upside market conditions being higher. This implies that higher levels of risk transmission among sustainable investments and investment in the energy and metal market during extreme market conditions. However, our results show that, on average, the amount of shocks the regional sustainability indices each received from the studied energy and metal commodity markets are higher (lower) than what they transmit to the commodity market during the extreme upside (downside) market condition. On the one hand, this implies that innovations in the studied commodity markets largely drive developments across the regional sustainable investments indices during extreme upside market condition, while the reverse is the case during extreme downside market condition. In which case, investors and market participants interested in the studied assets need to account for both in their trading strategy. On the other hand, that the regional sustainable investment indices are net receivers of shock during extreme upside market condition makes them attractive hedging and safe-haven options for investors that are interested in portfolio consisting the studied assets during periods of economic downturns. On the other side of the spectrum, we find evidence suggesting that oil, gas, silver, platinum and steel offer similar opportunity to the regional sustainable investment indices during the same period. During the normal market condition, however, we find sustainability investments in the Asian Specific to be the only one driven by developments in the commodity market (i.e. it is a net receiver).

Our results also show heterogeneous risk transmissions from the energy and metal markets to the different regional sustainable investment indices, suggesting substantial differences on how each regional market are susceptible to developments in the different commodity markets and across market condition. In this case, investing across the regional markets becomes a better alternative to hedge against the varying susceptibility of each market to extreme negative shocks in the commodity market as well as reap the gains therefore in the case extreme upside market conditions. On the drivers of connectedness among sustainable investments and investments in the energy and metal commodity markets, we find that better business environment and uncertainty about the gold and fixed income markets are responsible in increasing their connectedness level during the normal market condition, while uncertainty about the oil and equity markets drive down this connectedness level. In which case, better business environment and uncertainty about the gold and fixed income markets are the push factors of risk transmission among the studied investment indices during the normal market condition, while uncertainty about the oil and equity markets play the role of pull factors that reduce the levels of transmissible risks. During the extreme downside market conditions, the push (pull) factors are dominated by business environment conditions and uncertainty about gold market and economic policy (fixed-income and equity market uncertainty). On the other hand, bond terms spread and equity market uncertainty (fixed income market uncertainty and geopolitical risks) are the pull (push) factors during extreme upside market conditions.

A number of further practical policy implications for both market participants and policy-makers can be drawn from the main findings of this study. First, results from our analyses are directly useful to institutional investors that manage portfolios of assets with less allocation to individual stocks. These group of market participants are better equipped with information about risk transfers among the assets in our study. Importantly, given new evidence on the hedging roles of new financial assets such as sustainable investments, our finding of a heterogeneous shock spillover among these assets emphasizes the need for a more dynamic portfolio management strategy. Moreover, the higher levels of risk transfers at both extreme market situations emphasize the likelihood of high portfolio losses during market downturns due to joint losses. This implies that regional sustainable indexes may not be suitable hedging instruments for risk reduction in a portfolio containing the natural resources assets in our sample, except under calm market condition. Indeed, the higher connectedness among these markets suggest that it may be difficult for investors and portfolio managers to derive diversification opportunities across regional sustainability and commodity indexes, especially during periods of heightened financial turmoil, in their attempt to suppress contagion risk. Moreover, dependence and spillovers between sustainability indexes and other assets are also of interest to policy-makers, as sustainable investments are expected to be able provide significant incentives to investors in order to mobilize the needed funds towards climate-friendly projects to support climate transition, while offering financial rewards and portfolio optimization benefits.

With regards to the driving factors of risk transmission among these indexes across different market conditions, investors and portfolio managers could profit from monitoring the evolution of geopolitical risks, business environment conditions, the fixed income market and economic policy uncertainty in the process of designing dynamic portfolio strategies. In particular, the positive effects of fixed income market uncertainty (MOVE) on the degree of risk transmission suggest that unless during bearish market periods, heightened volatility in fixed income market is an indication that portfolio managers should decrease the allocation of sustainability indexes in their portfolio on commodity indexes. On the part of policymakers, this result implies that reducing uncertainty in the fixed income market with relevant economic policies will promote the attractiveness of sustainable investments, which will promote its potential to mobilize adequate funds towards green projects. Similar results and implications can be found across both the gold market and the conditions of the global business environment, which are other crucial drivers of risk transmission among the studied indexes. However, the negative effects of equity market uncertainty under both bullish and bearish market conditions is an indication that portfolio managers will benefit from the addition of sustainability indexes in their portfolio with commodity assets during periods of increased volatility in equity prices.

Lastly, this paper has some limitations, mainly as regards the scope of our study. Whereas we focused on regional sustainability markets for the three main regions including North America, Asia and Pacific and Europe, its will be interesting to further this study by examining these dynamics in the context of other regions such as Africa, Middle East and South America. Another limitation of our paper is also the fact that we have used regional sustainability index, which does not permit us to offer insights on potential variations in the degree of connectedness across countries within the regions in our sample. In this regard, it will be interesting for future studies to explore the possible heterogeneity in the level of connectedness and the relevant push/pull factors across different countries within the regions in our sample and those not covered in this study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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