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Are there other fish in the sea? Exploring the hedge, diversifier and safe-haven features of ESG investments

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Abstract

Purpose – This study aims to conduct an empirical investigation to assess the hedge, diversifier and safe-haven properties of different environmental, social and governance (ESG) assets (i.e. green bonds and ESG equity index) *vis-à-vis* conventional investments (namely, equity index, gold and commodities).

Design/methodology/approach – The authors examine the sample period 2007–2021 using the bivariate cross-quantilogram (CQG) analysis and a dynamic conditional correlation (DCC) multivariate generalized autoregressive conditional heteroskedasticity (GARCH) experiment with several extensions.

Findings – The evidence shows that the analyzed ESG investments exhibit mainly diversifying features depending on the asset class taken as a reference, with some potential hedging/safe-haven qualities (for the green bond) in peculiar timespans. Therefore, the results suggest that investors might consider sustainable investing as a new measure of risk reduction, which has interesting implications for both portfolio allocation and policy design.

Originality/value – To the best of the authors' knowledge, this study is the first that empirically investigates at once the dependence between different ESG investments (i.e. equity and green bond) with different conventional investments such as gold, equity and commodity market indices over a large sample period (2007–2021). Well-suited methodologies like the bivariate CQG and the DCC multivariate GARCH are used to capture the spillover effect and the hedging/diversifying nature, even in temporary contexts. Finally, a global perspective is used.

Keywords Cross-quantilogram, DCC GARCH, ESG, Investment strategies, Safe haven, Portfolio allocation

Paper type Research paper

1. Introduction

Recent years have seen a surge in the worldwide popularity of environmental, social and governance (ESG) [1] investments: a form of investing that incorporates ESG values. Once a

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niche practice, sustainable investments have gained momentum also due to an increased awareness of global sustainability challenges and a growing demand for purpose-driven investments accounting, in this way, for more than a third of global assets. Given their ability to reconcile economic development with environmental, ethical and social values, government regulations and policies have started to foster sustainable investing, recognizing a key role in accelerating the transition to sustainability-oriented economies, thus contributing to global sustainable development [2]. Moreover, during the past decade, investors have increasingly come to value sustainable assets, especially for their lower downside risk and higher resilience during volatile market conditions (Nofsinger and Varma, 2014; Lins *et al.*, 2017; Albuquerque *et al.*, 2020; Broadstock *et al.*, 2021). Scholars have proposed several potential explanations for such resiliency: some studies claim that ESG aspects attract socially responsible investors who are motivated by nonfinancial reasons and thus less likely to engage in selloffs, especially during market downturns (see, e.g. Heinkel *et al.*, 2001; Renneboog *et al.*, 2011; Ferriani and Natoli, 2020). Other research, in line with the stakeholder view of corporate social responsibility – *doing well by doing good* – suggests that social responsibility acts as a resilience factor against uncertainty (Freeman, 1984). In this vein, a good commitment to ESG values (i.e. a more sustainable business model, adequate governance, environment and workplace efficiency) provides an insurance effect during crisis periods, competitive advantages and risk reduction attitude over market shocks (see, e.g. Flammer, 2015; Albuquerque *et al.*, 2019, 2020).

Motivated by the growing trend of allocating portfolios to sustainable investments (Folger-Laronde *et al.*, 2020; Omura *et al.*, 2020; Díaz *et al.*, 2021), this paper empirically analyzes such features, shedding light on the potential safe-haven, hedge and diversifier properties of different ESG assets (i.e. green bonds and ESG equity index) relative to conventional investment practices (namely, equity indices, gold and commodities). Specifically, our paper examines the sample period 2007–2021 proposing two different methodologies: the bivariate cross-quantilogram (CQG) by Han *et al.* (2016), a nonparametric method which has proven to be extremely effective in analyzing asset comovements (Baumöhl and Lyócsa, 2017; Shahzad *et al.*, 2019; Uddin *et al.*, 2019; Ji *et al.*, 2020), and the more traditional dynamic conditional correlation (DCC) generalized autoregressive conditional heteroskedasticity (GARCH) (Engle, 2002) model with different extensions as in Baur and McDermott (2010) and Ratner and Chiu (2013).

As pointed out by Uddin *et al.* (2019), the CQG approach tends to be more informative and robust than common parametrical methods: by analyzing the correlation pattern between quantile hits of two given series, it allows for a detailed account of distributional features and interactions without particular underlying assumptions (differently from regression methods where distributional assumptions or moments conditions are needed). In this sense, it is a “model-free” measure. Moreover, the CQG directly shows the “reaction” of the series in extreme market conditions via tail-quantile correlations, also capturing the magnitude and duration of the spillover effects. Nevertheless, to further corroborate the results, we also couple the CQG with a more traditional analysis like the DCC experiment, which can contribute to extending the reach of the conclusions.

In this way, our paper reveals important findings: first, our analysis shows that, over the entire observed time span, all the considered ESG investments represent an outstanding diversification instrument for most of the asset classes taken as a reference. Second, even though there are no ESG investments that clearly emerge as a safe haven over the entire sample period, we uncover that the green bond demonstrates interesting, albeit weak, safe-haven or hedge properties under certain circumstances. Two main contributions with both practical and policy implications clearly emerge. First, despite the recently rekindled interest in safe-haven assets due to the COVID-19 pandemic (e.g. Cheema *et al.*, 2020; Corbet *et al.*, 2020;

Ji *et al.*, 2020; Mariana *et al.*, 2021; Capelle-Blancard *et al.*, 2021; Disli *et al.*, 2021; Salisu *et al.*, 2021; Umar *et al.*, 2021; Piserà and Chiappini, 2022; Lei *et al.*, 2023), little research has specifically analyzed the risk-hedging and/or safe-haven properties of ESG investments. Furthermore, it remains unclear *which* ESG assets can cover the ESG risk – a gap the present study seeks to address.

Second, this study is perhaps the first to overcome some limitations of the few existing studies of ESG investment resilience. Indeed, we empirically investigate at once the correlation between *different ESG investments* (i.e. equity and green bonds) with *different conventional investments* such as gold, equity and commodity markets over a *large* sample period (2007–2021). Well-suited methodologies *like the CQG and the DCC are used* to capture the spillover effect and the hedging/diversifying nature, even in temporary contexts. Finally, we maintain a *global* perspective. Our study, in this sense, helps to reconcile some apparently contradictory findings in the contemporaneous literature exploring the COVID-19 crisis period. While Piserà and Chiappini (2022) find some hedging properties and any safe-haven properties of ESG investments in the Chinese market, Capelle-Blancard *et al.* (2021) conclude that it is unclear on a global scale whether socially responsible investments have acted as an effective hedge, since a high positive correlation was detected with their conventional benchmarks. Our results hint that equity ESG indices have a high positive correlation with their equivalent non-ESG ones, ruling out hedging properties; however, when commodities are under analysis, milder correlations are spotted, indicating a diversifying nature. Moreover, in the case of financial outbreaks, some ESGs exhibit a declining trend in dependence with the stock and the commodity market, manifesting sometimes negative peaks: when this happens, safe-haven/hedging qualities emerge, as in the case of the green bond during the first COVID-19 period.

Finally, from a practical point of view, this paper provides interesting insights that can help investors and asset managers improve the portfolio diversification strategies and asset allocation process according to the market conditions. At the same time, a deep investigation of the characteristics of sustainable investments is provided: which is essential for implementing policy actions that reorient capital flows around more sustainable and inclusive growth.

The paper is structured as follows: Section 2 reviews and discusses the related literature. Section 3 explains the methodology and data. Section 4 summarizes the main results, and finally, Section 5 discusses the study's conclusions and limitations.

2. Literature review

This study follows the literature dealing with the risk analysis of ESG assets, as well as the literature on the performance of investors' preference for sustainable investments during episodes of market volatility.

Regarding the former stream, the literature dealing with the financial utility of ESG investments in terms of portfolio performance and diversification is far more limited. Some noteworthy exceptions are the contemporaneous papers by Piserà and Chiappini (2022) and Capelle-Blancard *et al.* (2021). While the former finds hedging properties of ESGs in the Chinese market during COVID-19, the second concludes that there is no clear evidence supporting the idea that socially responsible investment strategies acted as an effective hedge in the same period. Still, in the pandemic context, Rubbaniy *et al.* (2022) and Mousa *et al.* (2021), respectively, use a wavelet coherence approach and a GARCH model to discover that ESG stocks have limited safe-haven capabilities in emerging markets. On the contrary, Yousaf *et al.* (2022) use a portfolio analysis to suggest that clean energy investments and green bonds have the potential to serve as a safe haven. The study by Ferrer *et al.* (2021)

integrates wavelet methods with network analysis and finds that the interdependence between green bonds and traditional asset classes increases considerably during periods of heightened uncertainty, such as the European sovereign debt crisis. Other studies have shown significant comovements between the green bond and financial markets, suggesting that this asset class might have had diversification benefits for investors in the pre-pandemic period (Reboredo, 2018; Nguyen *et al.*, 2021; Pham and Nguyen, 2021). Although this stream of literature uses different methodologies to assess the safe-haven role of ESG investments, little research is based on the CQG analysis. An exception is a contemporaneous paper by Lei *et al.* (2023) that shows, on the basis of the CQG analysis and the quantile time–frequency connectedness framework, how precious metals tend to exhibit large extreme gains when ESG returns are at extreme losses. Existing studies, however, display some limitations that the current work, instead, addresses: they only focus on a *single time period* (for example, pandemic or European sovereign debt crises) and on a s*pecific asset class* (mostly green bonds or ESG stocks). Moreover, only a few contributions, such as the studies by Umar *et al.* (2020) and Gao *et al.* (2022), have analyzed the risk spillover pattern of *global* ESG markets.

The second strand of literature addresses the resilience of ESG investments during crises, both in terms of demand and performance. Different studies have pointed out that ESG funds significantly outperform conventional ones during market turmoil, although not always to the same extent. For example, Becchetti *et al.* (2015) show that socially responsible funds outperformed conventional ones during the global financial crisis (GFC) but not during the Dot-com crisis. Moreover, emerging evidence suggests that the recent COVID-19 crisis has accelerated the trend toward more sustainable investing. Indeed, in the first quarter of 2020, when the virus first began to spread globally, financial markets became extremely volatile and investors shifted to "low-ESG-risk" funds (Ferriani and Natoli, 2020), finding refuge in ESG investment strategies (Singh, 2020). As COVID-19 has continued to propagate, the observable over-performance (Folger-Laronde *et al.*, 2020; Omura *et al.*, 2020; Díaz *et al.*, 2021) and lower volatility of ESG investments might have induced investors to consider sustainable investments as comparable alternatives to conventional safe havens. However, it is still an open question whether and by what means investors can leverage the ESG investment category to protect their wealth during different market conditions. As a matter of fact, a huge debate exists on the comparative performance of ESG funds with their conventional peers since mixed results have been found so far. For example, Renneboog *et al.* (2008) investigate the under- and overperformance of SRI funds across the world, finding no statistically significant difference with respect to conventional funds. Derwall and Koedijk (2009) show that the average SRI bond fund performed similarly to conventional funds in the period 1987–2003. On the other hand, Gil-Bazo *et al.* (2010) document that the US SRI funds outperformed the conventional funds for the period 1997–2005. Such inconsistent results are also related to two opposite views, namely, the stakeholder and the shareholder theory. The former predicts a positive relationship between ESG factors and the company's financial performance suggesting that firms that are better able to manage the interest of stakeholders should outperform those that do not (Freeman, 1984). On the contrary, shareholder theory asserts that the primary responsibility of a firm is to maximize the wealth of its shareholders (Friedman, 1962).

3. Data, methodology and definitions

3.1 Data

To investigate the role of ESG investments, we use daily data from 1st January 2007 to 1st November 2021 on the Dow Jones Sustainability World Index ("DJSI"), the Standard and Poor

Global Clean Energy Index ("SPCL") and the Standard and Poor Green Bond Index ("SPGB") [3]. DJSI comprises the top 10% of the largest 2,500 companies in the Standard and Poor Global Broad Market Index- S&P Global BMI according to the firms' sustainability performance defined via the SP Global ESG score, which weighs the environmental and sociopolitical dimensions of each constituent. SPCL, by contrast, includes 100 stocks from SP Global BMI that either derive at least 25% of their revenues from clean energy-related businesses or that exploit renewable energy for their production activity. Finally, SPGB refers to global bonds that have met the eligibility criteria by the Climate Bonds Initiative (CBI). Clearly, these indicators represent different aspects of the ESG ecosystem: the DJSI is the more comprehensive in terms of ESG standards, while the SPCL and SPGB are more environmentally oriented.

The hedge, diversifier and safe-haven capabilities of ESG assets are tested against global equities, commodities and other traditional hedging assets (such as gold), denominated in the US dollars over the same period. In line with Disli *et al.* (2021), we select the Dow Jones Global Index ("DJ") as our main proxy for equity performance. This is because of its extensive coverage of the global market. For the commodity market we select instead the SP Goldman Sachs commodity index (GSCI) Commodity Index ("SPCM) as in Graham *et al.* (2022).

Gold (SP GSCI Gold Index – "GLD") is chosen firstly because anecdotal evidence and financial media seem to suggest its hedging or safe-haven role for financial assets or portfolios. Indeed, in the era of globalization, where correlations among most types of assets have increased dramatically, gold is still known to be frequently uncorrelated (Baur and Lucey, 2010). A plausible explanation is that, in contrast to many other commodities, gold is durable, easily recognizable, storable, portable, divisible and easily standardized (Baur, 2013); besides, from a historical perspective, it was among the first forms of money and was traditionally used as an inflation hedge. We carry out the analysis from a world perspective to better capture a common and global tendency, necessary for the identification of the general ESG behavior.

Each series is expressed in terms of daily returns, computed as the logarithmic difference between the price at time t and $t-1$ [4]. All data are collected from Datastream.

Figures 1–2 graphically report both the price and the return series for the assets under consideration: as can be seen, both the DJSI and the SPCL prices exhibit a sharp fall during the two major financial turmoil events of the sample period, namely, the global financial crisis (GFC) in 2007–2008 and the first COVID-19 outbreak (2020–2021). This is reflected by volatility peaks in the return series. On the other hand, the SPGB prices and returns show major stability (save for some fluctuations) during the whole sample span.

As for the non-ESG investments, some similarities are in place: the equity index accurately reflects the DJSI behavior. The commodity index, instead, shows three major downturn events: during the GFC, during the second half of 2014 and the COVID-19 shock. The GLD series seems less affected by negative shocks, with the price showing overall increasing trends in 2009–2013 and 2019–2020. The volatility clusters of the returns are majorly shown across the well-known financial turmoil, but also in the subperiod 2011–2014.

Table 1 presents the main summary statistics for the return series under investigation: notably, all series are leptokurtic with negative skewness (apart from SPGB). Table 2 reports some diagnostic tests: the augmented Dickey–Fuller (here reported with the acronym ADF; Dickey and Fuller, 1979), the Philipps–Perron, i.e. PP (Phillips and Perron, 1988) and the KPSS (Kwiatkowski *et al.*, 1992) tests for stationarity; the ARCH–LM test (Engle, 1982) for conditional heteroskedasticity, and the Doornik–Hansen normality test (Doornik and Hansen, 2008). All series appear nonnormal, with ARCH/GARCH effects. Moreover, no unit roots seem to be detected [5].

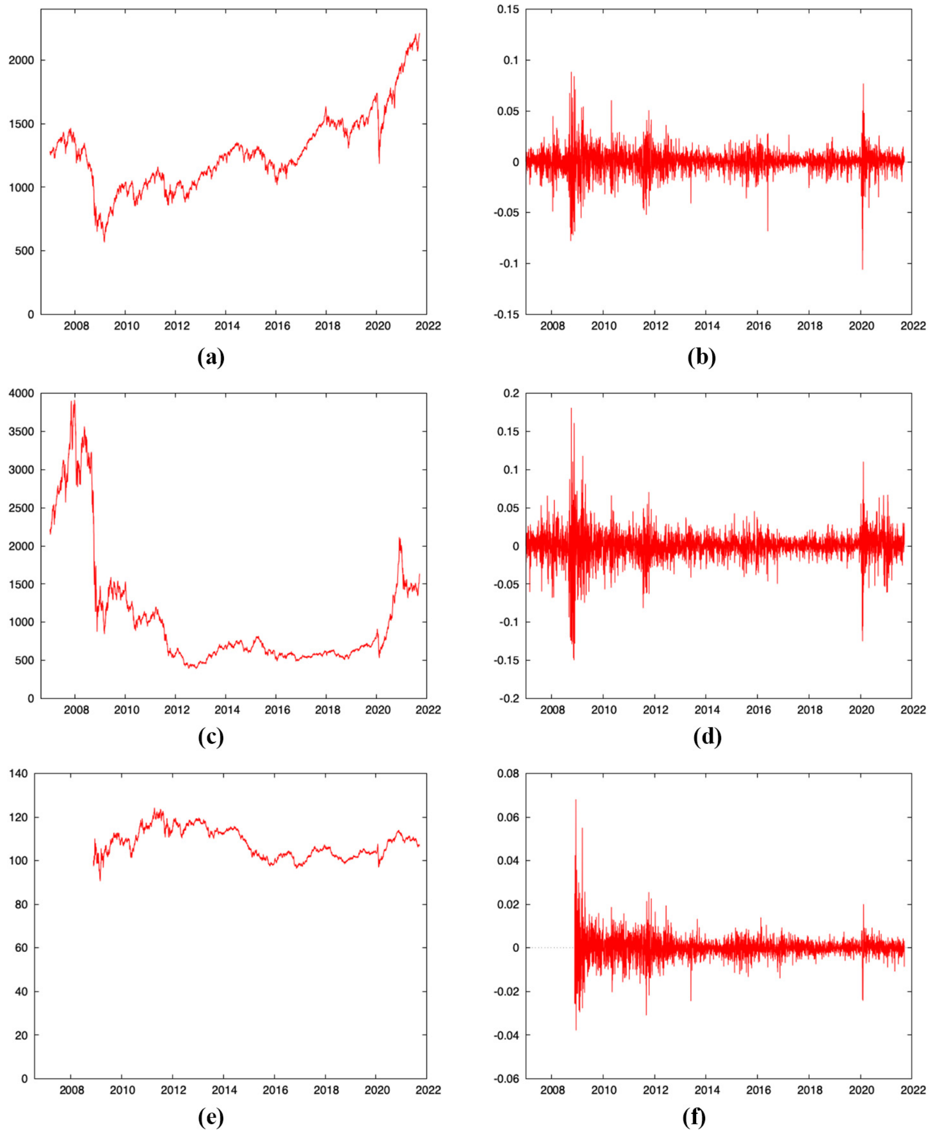


Figure 1.
ESG asset price (left) and return (right) series

Notes: The time period from January 1, 2007, to November 1, 2021 (daily); (a) DJSI – price; (b) DJSI – return; (c) SPCL – price; (d) SPCL – return; (e) SPGB – price; (f) SPGB – return
Source: Authors' own creation

3.2 The cross-quantilogram and the DCC-GARCH model

The CQG apparatus was introduced by Han *et al.* (2016) as a method to explore the quantile dependence for two series at a different lag order. Formally, given two strictly stationary time series (e.g. asset returns), $y_{1,t}$ and $y_{2,t}$, a quantile hit event is defined as $\mathbf{1}[y_{i,t} < q_{i,t}(\alpha_i)]$ for

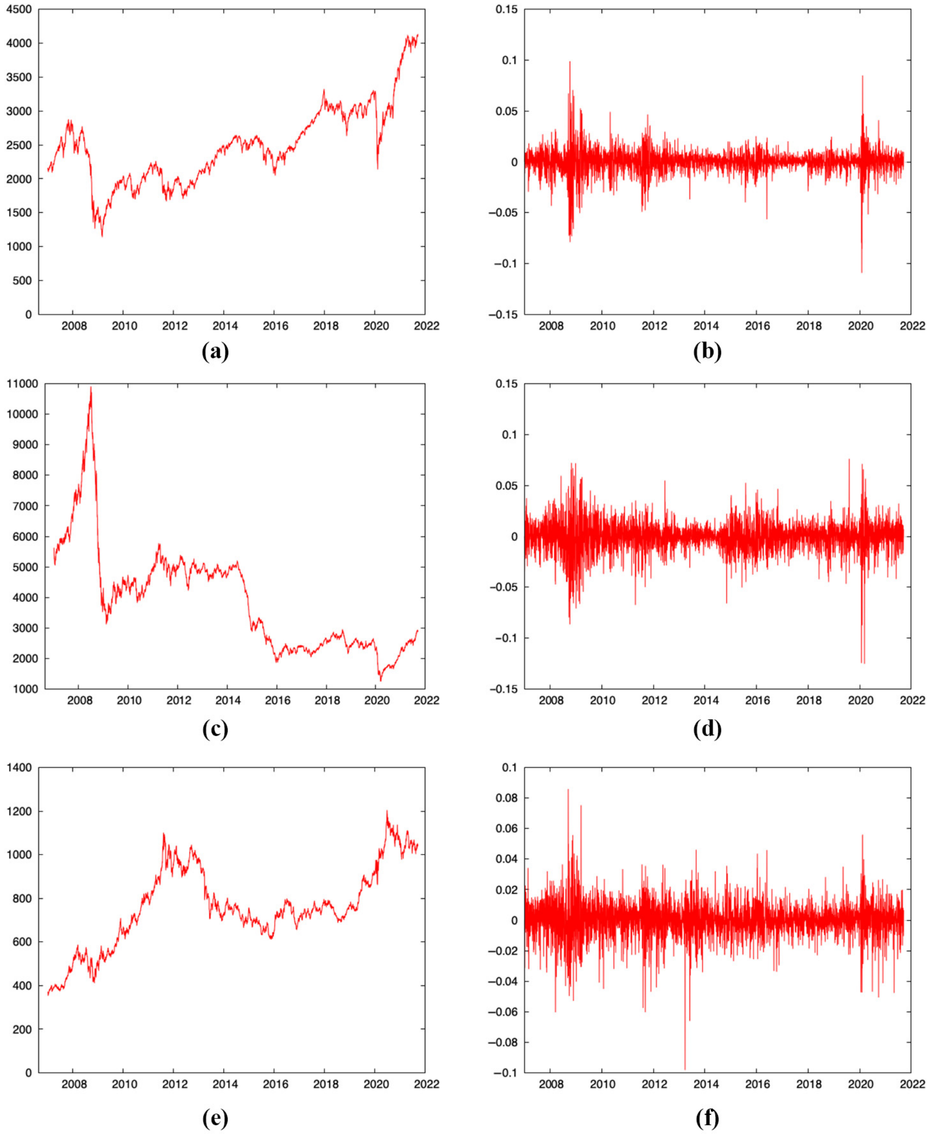


Figure 2. Non-ESG asset price (left) and return (right) series

Notes: (a) DJ – price; (b) DJ – return; (c) SPCM – price; (d) SPCM – return; (e) GLD – price; (f) GLD – return
Source: Authors' own creation

$i = 1, 2$, where $q_{i,t}(\alpha_i)$ is the $\alpha_i \in (0,1)$ quantile of $y_{i,t}$ and $1[\cdot]$ is the indicator function. In other words, a quantile hit process reports those observations falling below the range of a given quantile, potentially signaling outliers with suitable choices of α_i. The cross-correlation between two quantile hits, one for $y_{1,t}$ and another for $y_{2,t-k}$, for an arbitrary couple (α_1, α_2) with $k = 0, 1, \ldots$, is defined as CQG:

$$\rho_{(\alpha_1,\alpha_2)}(k) = \frac{E\left[\psi_{\alpha_1}(y_{1,t} - q_{1,t}(\alpha_1))\psi_{\alpha_2}(y_{2,t-k} - q_{2,t-k}(\alpha_2))\right]}{\sqrt{E\left[\psi^2_{\alpha_1}(y_{1,t} - q_{1,t}(\alpha_1))\right]}\sqrt{E\left[\psi^2_{\alpha_2}(y_{2,t-k} - q_{2,t-k}(\alpha_2))\right]}}, \tag{1}$$

where E[.] is the expected value operator and $\psi_\alpha(x) = 1[x < 0] - \alpha$ is the quantile hit function.

The sample counterpart of equation (1) is given by:

$$\hat{\rho}_{(\alpha_1,\alpha_2)}(k) = \frac{\sum_{t=k+1}^{T} \psi_{\alpha_1}(y_{1,t} - \hat{q}_{1,t}(\alpha_1))\psi_{\alpha_2}(y_{2,t-k} - \hat{q}_{2,t-k}(\alpha_2))}{\sqrt{\sum_{t=k+1}^{T} \psi^2_{\alpha_1}(y_{1,t} - \hat{q}_{1,t}(\alpha_1))}\sqrt{\sum_{t=k+1}^{T} \psi^2_{\alpha_2}(y_{2,t-k} - \hat{q}_{2,t-k}(\alpha_2))}}, \tag{2}$$

where $\hat{q}_{i,t}(\alpha_i)$ can be computed either via quantile regression on a set of covariates or via sample quantiles.

Table 1. Main summary statistics for the return series – full sample (from January 1, 2007, to November 1, 2021)

Series	Mean*	Median*	Min	Max	SD	Skewness	Ex.Kurtosis
ESG indices							
DJSI	1.434	5.104	−0.106	0.088	0.011	−0.590	10.924
SPCL	−0.746	6.223	−0.150	0.181	0.019	−0.582	12.526
SPGB	0.192	0.229	−0.038	0.068	0.005	0.951	19.957
Non-ESG indices							
DJ	1.700	5.772	−0.109	0.099	0.011	−0.720	12.493
SPCM	−1.702	0.807	−0.125	0.076	0.015	−0.590	6.203
GLD	2.673	1.256	−0.098	0.086	0.011	−0.276	6.113

Note: *The values have been multiplied by 10^4 for notational convenience
Source: Authors' own creation

Table 2. Main diagnostic tests for the return series

Series	ADF	KPSS	PP	ARCH LM (5)	DH
ESG indices					
DJSI	−10.89***	0.22	−57.90***	887.65***	3,762.81***
SPCL	−13.62***	0.49**	−54.22***	1,042.58***	4,538.59***
SPGB	−10.87***	0.08	−54.84***	301.24***	6,138.43***
Non-ESG indices					
DJ	−14.55***	0.12	−55.0***	966.52***	4,203.88***
SPCM	−29.11***	0.11	−64.32***	381.62***	1,653.28***
GLD	−19.73***	0.18	−61.93***	178.30***	1,972.57***

Notes: ADF = augmented Dickey–Fuller (Dickey and Fuller, 1979); PP = Philipps–Perron (Phillips and Perron, 1988) and the KPSS (Kwiatkowski *et al.*, 1992) tests for stationarity; ARCH–LM test (Engle, 1982) for conditional heteroskedasticity; DH = Doornik–Hansen (Doornik and Hansen, 2008) normality test. **p*-value < 0.10; ***p*-value < 0.05; ****p*-value < 0.01. Notice that for the ADF tests, an automated procedure based on Akaike's Information Criterion has been adopted to select the lag order
Source: Authors' own creation

Clearly, $\hat{\rho}_{(\alpha_1,\alpha_2)}(k) \in [-1,1]$ with the limiting values meaning perfect negative and perfect positive correlation, respectively. Needless to say, positive values of $\hat{\rho}_{(\alpha_1,\alpha_2)}(k)$ indicate a comovement in the same direction for the quantile hit processes; negative values, on the other hand, represent a comovement in opposite directions, that is, observations falling inside a given α_1-quantile for $y_{1,t}$ will correspond to observations of $y_{2,t-k}$ outside its α_2-quantile. For $k > 0$, the information pertaining to $y_{2,t-k}$ obviously predates $y_{1,t}$, implying the so-called directional predictability: a quantile hit $\mathbf{1}[y_{2,t-k} < q_{2,t-k}(\alpha_2)]$ is likely to be followed after k periods by a quantile hit $\mathbf{1}[y_{1,t} < q_{1,t}(\alpha_1)]$ if $\hat{\rho}_{(\alpha_1,\alpha_2)}(k) > 0$ or $\mathbf{1}[y_{1,t} > q_{1,t}(\alpha_1)]$ if $\hat{\rho}_{(\alpha_1,\alpha_2)}(k) < 0$. This information becomes particularly useful in evaluating the persistency and the dynamic of a shock. For example, a given correlation reported at $k = 0$ will appear smaller and smaller in magnitude the more k grows because of market efficiency.

Finally, the asymptotic distribution for $\hat{\rho}_{(\alpha_1,\alpha_2)}(k)$ is derived via the stationary bootstrap method (Politis and Romano, 1994); for instance, the $(1-\gamma)$ confidence interval for $\rho_{(\alpha_1,\alpha_2)}(k)$ is defined as $\left[\hat{\rho}_{(\alpha_1,\alpha_2)}(k) + T^{-\frac{1}{2}}c_{1,k,\gamma};\ \hat{\rho}_{(\alpha_1,\alpha_2)}(k) + T^{-1/2}c_{2,k,\gamma}\right]$, where $c_{1,k,\gamma}$ and $c_{2,k,\gamma}$ are the critical values obtained as percentiles of the bootstrapped distributions.

The DCC model, on the other hand, belongs to the well-known family of multivariate GARCH and allows to assess the time-varying conditional correlations of a set of m asset returns $\boldsymbol{y_t} = y_{1,t}, y_{2,t}, \ldots, y_{m,t})$. The underlying assumption postulates that the process $\boldsymbol{u_t} = \boldsymbol{y_t} - \mathrm{E}(\boldsymbol{y_t}|\boldsymbol{I_{t-1}})$, where $\boldsymbol{I_{t-1}}$ denotes the information set at time $t-1$, as follows:

$$\mathrm{E}\left(\boldsymbol{u_t}\boldsymbol{u_t}^\top\right) = V_t^{1/2} R_t V_t^{1/2}$$

where $V_t = diag(v_t)$ is the diagonal matrix of conditional variances and R_t is the dynamic correlation matrix, which is further rewritten as:

$$R_t = \tilde{Q}_t^{-1/2} Q_t \tilde{Q}_t^{-1/2},$$

with:

$$Q_t = \Gamma + A \odot \left(\eta_{t-1}\eta_{t-1}^\top - \Gamma\right) + B \odot (Q_{t-1} - \Gamma) \tag{3}$$

$$\tilde{Q}_t = diag(Q_t)$$

where $\eta_t = V^{-1/2}u_t$; A, B, Γ are symmetric parameter matrices to estimate and $\odot$ denote the Hadamard product. Notice that Γ represents the unconditional correlation matrix $\mathrm{E}\left(\eta_{t-1}\eta_{t-1}^\top\right)$. Estimation is commonly performed via a two-step procedure where firstly, the estimated residuals u_t and their variance v_t are retrieved (commonly via univariate GARCH models), then equation (3) is computed, and the parameters are estimated via maximum likelihood.

3.3 Safe-haven, hedge and diversifier asset with the cross-quantilogram

Scholars lack consensus on how exactly defining safe-haven assets. Currently, the most comprehensive definition is that strong (vs weak) safe havens show negative dependence (vs absence of any dependence) with other assets in extreme market conditions (Baur and Lucey, 2010). While the search for safe-haven assets mainly occurs during market downturns, there is always a need to hedge or diversify an investment portfolio (Baur and McDermott, 2010). Accordingly, we differentiate between a diversifier, hedge and safe haven

(Baur and Lucey, 2010; Ratner and Chiu, 2013). A diversifier is an asset that has, on average, a weak positive dependence with another asset; while a weak (strong) hedge is an asset that on average has no association (negatively dependence) with another one.

Recalling that a safe-haven asset is uncorrelated or negatively associated with the benchmark series during financial downturns, the corresponding CQG requirement is zero or negative correlation for the ESG at the lower quantile hits for the stock or commodity asset. More formally, we inspect the quantile hits in all combinations of deciles for the two assets, and we deem a series $y_{ESG,t}$ to have safe-haven properties with respect to the concurring series $y_{non-ESG,t-k}$ at time lag k, if $\hat{\rho}_{(\alpha_{ESG},\alpha_{non-ESG})}(k) \leq 0$ for $\alpha_{non-ESG} = 0.10$ versus any α_{ESG}. This categorization extends the one proposed by Shahzad *et al.* (2019), Cho and Han (2021) and Ji *et al.* (2020), which relies only upon extreme quantile combinations such as ($\alpha_{ESG} = 0.10$, $\alpha_{non-ESG} = 0.10$). The reasoning can be easily understood via an example: the quantile hit combination ($\alpha_{ESG} = 0.10$, $\alpha_{non-ESG} = 0.10$) signals, in case of negative correlation, that a downturn in non-ESG returns is followed by ESG returns falling above the 0.10 quantile. This case contains potential above-median returns but also some below-median ones which clearly cannot properly convey safe-haven qualities. On the other hand, considering all the combinations in α_{ESG} rules out this possibility. Moreover, we expect that an *ideal* safe-haven asset would exhibit increasing negative correlations (in absolute terms) moving from ($\alpha_{ESG} = 0.10$, $\alpha_{non-ESG} = 0.10$) to ($\alpha_{ESG} = 0.90$, $\alpha_{non-ESG} = 0.10$).

By contrast, a diversifier or hedge asset requires, respectively, small positive or null-negative dependence in "normal times": a diversifier behavior can be acknowledged for $y_{ESG,t}$ with respect to $y_{non-ESG,t-k}$ when small positive correlations ($0 < \hat{\rho}_{(\alpha_{ESG},\alpha_{non-ESG})}(k) < 0.50$) are detected along most of the quantile combinations; a hedge, conversely, should mainly report $\hat{\rho}_{(\alpha_{ESG},\alpha_{non-ESG})}(k) \leq 0$. Finally, an asset is a diversifier/hedge/safe haven in the *strict sense* only when the above classifications are consistent and compatible for different k of the non-ESG series [6].

3.4 Safe-haven, hedge and diversifier asset with the DCC model

Aligning the previous definitions with the DCC model is more immediate; in particular, the estimate of Γ from equation (3) conveys (static) information on the correlation pattern of the series $\boldsymbol{y_t} = (y_{ESG1,t}; y_{ESG2,t}; \ldots; y_{non-ESG1,t}; y_{non-ESG2,t}; \ldots)$ over the whole sample period. This provides hints for judging the diversifying or hedging nature of a couple ($y_{ESG,t}$; $y_{non-ESG,t}$) when mild positive or null-negative effects are spotted, similarly to CQG analysis. In the same way, the estimated dynamic correlation $\hat{R}_t$ should display an analogous overall tendency. Safe-haven qualities may be indirectly recognized by identifying temporary null or negative correlation peaks in $\hat{R}_t$ during financial downturn events.

However, to further improve upon the previous classification, we introduce two regression models derived from the DCC results: the first one borrowed from Baur and McDermott (2010) and Ratner and Chiu (2013) postulates:

$$\hat{R}_{(ESG,non-ESG),t} = \gamma_0 + \gamma_1 d_t + \epsilon_t \tag{4}$$

where $\hat{R}_{(ESG,non-ESG),t}$ represents the estimated dynamic conditional correlation from the DCC model between an ESG asset and a non-ESG one; $d_t = \psi_{0.1}\ [y_{non-ESG,t} - q_{non-ESG,t}(0.10)]$ is the quantile hit series for the non-ESG at $\alpha = 0.10$. Thus, the coefficients γ_0 and γ_1 represent, respectively, the diversifier/hedge component and the safe-haven one: when γ_0 is slightly positive and significant, a diversifying nature can be spotted; when null or significantly negative, a hedging component is recognized. A null or negative γ_1 may identify safe-haven qualities, especially with $|\gamma_1| \geq |\gamma_0|$.

In the second regression framework, we propose the following modification:

$$\hat{R}_{(ESG,non-ESG),t} = \gamma_0 + \gamma_1 d_t + \gamma_2 C_t + \gamma_3 (d_t \cdot C_t) + \epsilon_t \tag{5}$$

where C_t identifies a temporal dummy variable that assumes the value 1 during a financial turmoil event/period: the temporal dummy and the interaction term are here introduced to clearly disentangle a temporal effect from the coefficient γ_1 in equation (4).

To summarize, while the interpretation of γ_0 and γ_1 remains mostly the same, if γ_2 and γ_3 are negative or null may indicate a *temporary* hedging (γ_2) or safe haven (γ_3) property when $|\gamma_2|$ and/or $|\gamma_3|$ are large enough to induce a huge negative variation in the correlation pattern.

4. Empirical results

4.1 Cross-quantilogram results

We report the results of the CQG approach in the form of heatmaps, where we consider the $y_{ESG,t}$ on the x-axis and the concurring $y_{non-ESG,t-k}$ on the y-axis; as previously mentioned, all deciles combinations are explored. Red tones identify positive correlations, blue ones negative, while white is associated with uncorrelation. We consider lags $k = (0,1)$ to capture the immediate ESG return adjustment with respect to the stock-commodity benchmark; we do not account for major order lags since the main portfolio reallocations are expected to occur near the event.

Figure 3 displays the quantile cross-correlations considering $k = 0$ for the non-ESG asset: the DJSI shows a high positive correlation along the main diagonal with respect to DJ, suggesting a strong comovement not only in adverse market conditions (bottom-left corner) but also in normal and favorable times. In this sense, the DJSI does not seem to belong to any previously defined category. The comparison with the SPCM reveals again an overall positive correlation, but smaller in magnitude. On this basis, one could possibly classify the DJSI as a diversifier for the commodity index. Milder correlations are spotted with respect to GLD. The SPCL pattern replicates the DJSI one: high positive quantile correlations are reported versus the equity index along most quantile combinations, while softer tones are detected when considering the commodity or the gold series. The SPGB, by contrast, exhibits much weaker positive correlations with respect to DJ: this may be a weak hint for a diversifier nature. This line of reasoning becomes even more appealing when considering quantile dependency with the SPCM. The comparison with GLD is close in spirit; however, it is worth mentioning that the SPGB manifests a more marked positive correlation with this commodity with respect to the other two ESG assets. Safe-haven qualities, represented by white-blue tones in the bottom line, are absent for all ESGs under investigation.

Moving to the CQG with $k = 1$ for the non-ESG series, Figure 4 reports how most ESG assets hugely reduce the correlation magnitude, hinting at diversifying properties with reference to both stock and commodity markets. The DJSI shows small positive (and sometimes null) correlations over most quantile combinations when coupled with DJ. The same applies to both SPCL and SPGB. The comparisons with the commodity index reveal a similar tendency, strengthening the evidence of ESG indices having a diversifying nature. Interestingly, we detect some negative correlations as well, especially in the bottom right corner (note that this result does not contradict the possible positive correlation in the opposite corner). This is, however, rather limited evidence for hedging or safe-haven qualities. Finally, null quantile cross-correlation (with both positive and negative peaks) appears when considering DJSI and SPCL with respect to GLD; the sole exception is SPGB, which exhibits an overall positive correlation.

Combining these facts with the heatmap findings of lag $k = 0$ leads us to the conclusion that SPGB acts as a diversifier in the strict sense for the equity and the commodity market,

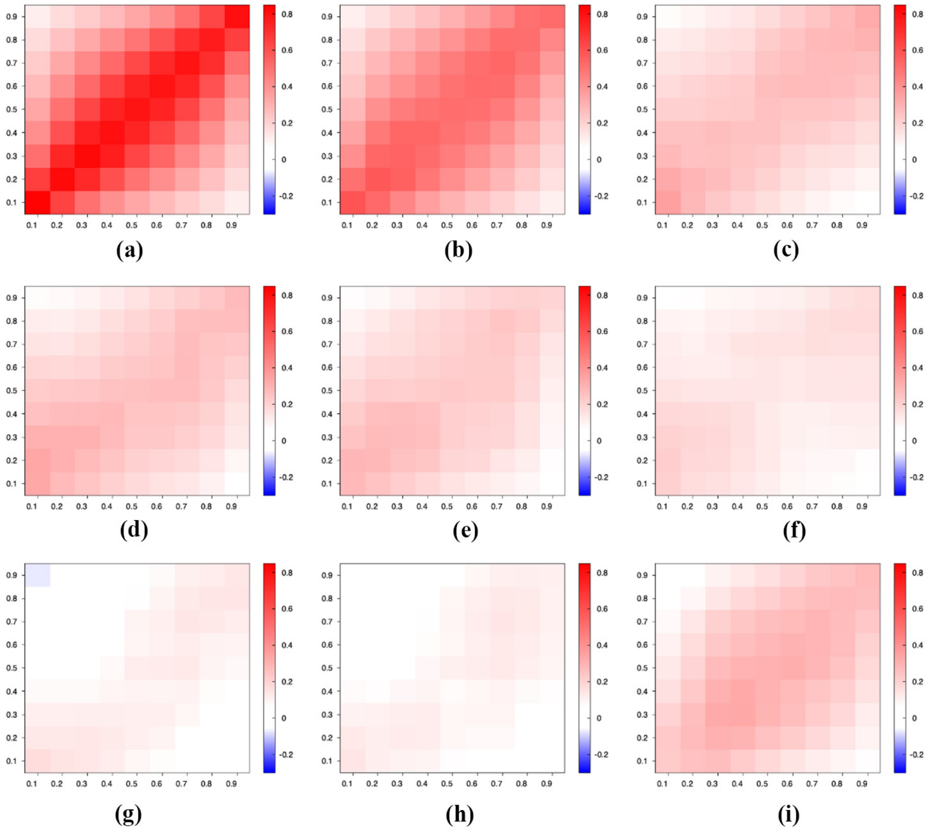


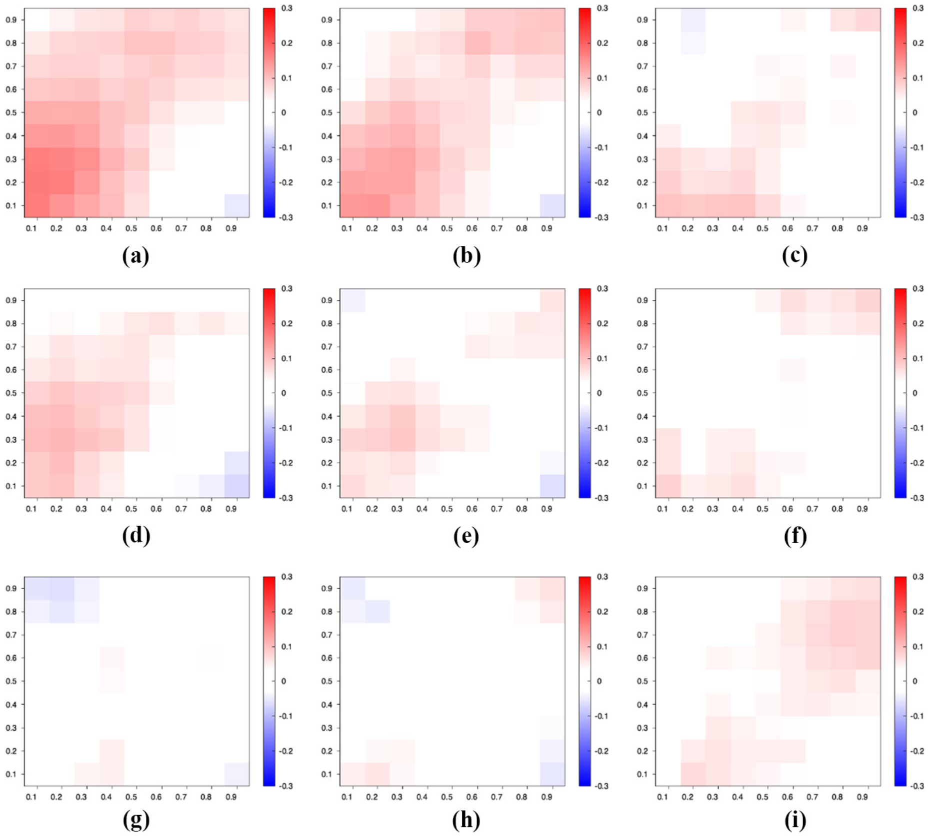
Figure 3.
Cross-quantilograms of ESG assets (DJSI on the first column, SPCL on the second column and SPGB on the third one) versus DJ, SPCM and GLD at lag 0

Notes: Correlations are tested for significance at size 0.05 with bootstrapped distributions (10,000 iterations). If insignificance is detected, the corresponding value is set to zero. The color scale is homogenous and adapted to the minimum and maximum of this experiment; (a) DJSI vs DJ (k = 0); (b) SPCL vs DJ (k = 0); (c) SPGB vs DJ (k = 0); (d) DJSI vs SPCM (k = 0); (e) SPCL vs SPCM (k = 0); (f) SPGB vs SPCM (k = 0); (g) DJSI vs GLD (k = 0); (h) SPCL vs GLD (k = 0); (i) SPGB vs GLD (k = 0)
Source: Authors' own creation

while DJSI and SPCL have this property for the sole commodity. The comparison with GLD shows, again, diversification effects for all ESG indices. We refer, however, to Appendix 1 for a more detailed and comprehensive analysis of the GLD role. In Appendix 2, we present an extension of our framework based on the partial CQG so as to control for the effects of external variables on cross-quantile dependence.

4.2 Quantile cross-dependence using rolling windows

To strengthen the validity of our results and to further explore the ESG investment properties, in this subsection, we report the result of the quantile cross-dependence using rolling windows. As pointed out by Shahzad *et al.* (2019) and Uddin *et al.* (2019), the CQG analysis over a specific time span is a static picture of reality and does not account for time-



Notes: Correlations are tested for significance at size 0.05 with bootstrapped distributions (10,000 iterations). If insignificance is detected, the corresponding value is set to zero. The color scale is homogenous and adapted to the minimum and maximum of this experiment; (a) DJSI vs DJ (k = 1); (b) SPCL vs DJ (k = 1); (c) SPGB vs DJ (k = 1); (d) DJSI vs SPCM (k = 1); (e) SPCL vs SPCM (k = 1); (f) SPGB vs SPCM (k = 1); (g) DJSI vs GLD (k = 1); (h) SPCL vs GLD (k = 1); (i) SPGB vs GLD (k = 1)
Source: Authors' own creation

Figure 4.
Cross-quantilograms between ESG assets and non-ESGs at lag 1

varying dynamics. To overcome this issue, we undertake the following exercise: the CQG is computed over recursive samples of 261 days (a single year), obtained by simply shifting the window by a single day ahead until the end of the sample (November 1, 2021).

Rather than evaluate all quantiles, we opt for simplicity and consider the quantile combinations ($\alpha_{ESG} = 0.1$; $\alpha_{Not\ ESG} = 0.1$), ($\alpha_{ESG} = 0.5$; $\alpha_{Not\ ESG} = 0.1$) and ($\alpha_{ESG} = 0.9$; $\alpha_{Not\ ESG} = 0.1$) using again lag $k = 0, 1$. This choice reflects our interest in discovering temporary safe-haven properties that may not be visible in "static" representations. Moreover, we solely focus on the equity (Figures 5–6) and commodity index (Figures 7 – 8).

All the figures display the dynamic CQG for the related quantile combinations under the blue line; the red ones, instead, represent the 95% confidence interval limits. We derive these values using the stationary bootstrap with 5,000 replications. The columns report the quantile combinations following the order of appearance presented above. The result for the couple (ESG_t; DJ_{t-k}) at $k = 0$ is presented in Figure 5: for the quantile combination ($\alpha_{ESG} = 0.1$; $\alpha_{DJ} = 0.1$), both DJSI and SPCL reveal a strong positive correlation with some marked fluctuation during the major financial shock events. The SPGB displays again milder correlations with negative peaks appearing during market turmoil, such as the case of the COVID-19 pandemic (the window January–March 2020, corresponding to the first outbreak, is an example). The combinations ($\alpha_{ESG} = 0.5$; $\alpha_{Not\ ESG} = 0.1$) and ($\alpha_{ESG} = 0.9$; $\alpha_{Not\ ESG} = 0.1$) produce similar conclusions: all ESG series, except for the SPGB, are mostly positively correlated. SPGB, instead, shows null or negative trends after 2014, with outliers occurring during both the sovereign debt crisis and the COVID-19 pandemic.

When considering a day lag ($k = 1$) as in Figure 6, all ESGs exhibit overall smaller correlations: DJSI and SPCL display negative fluctuations with peaks occurring more frequently the further we move from ($\alpha_{ESG} = 0.1$; $\alpha_{Not\ ESG} = 0.1$) to the other two quantiles

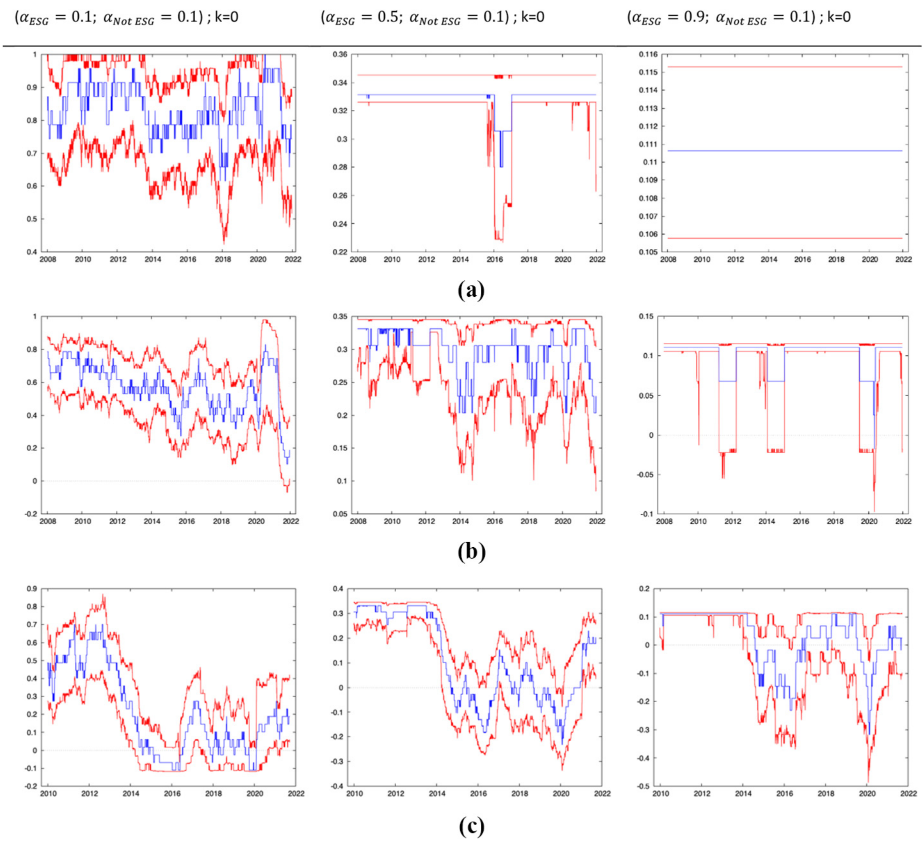


Figure 5.
Cross-quantilograms (blue line) of ESG assets (DJSI on the first row, SPCL on the second and SPGB on the third) versus DJ at lag 0. A rolling window of 261 days is used (a year), which advances on a daily base

Notes: The red lines represent respectively the upper and the lower limits of a 95% confidence interval built with 5,000 replications of the stationary bootstrap: (a) DJSI vs DJ; (b) SPCL vs DJ; (c) SPGB vs DJ
Source: Authors' own creation

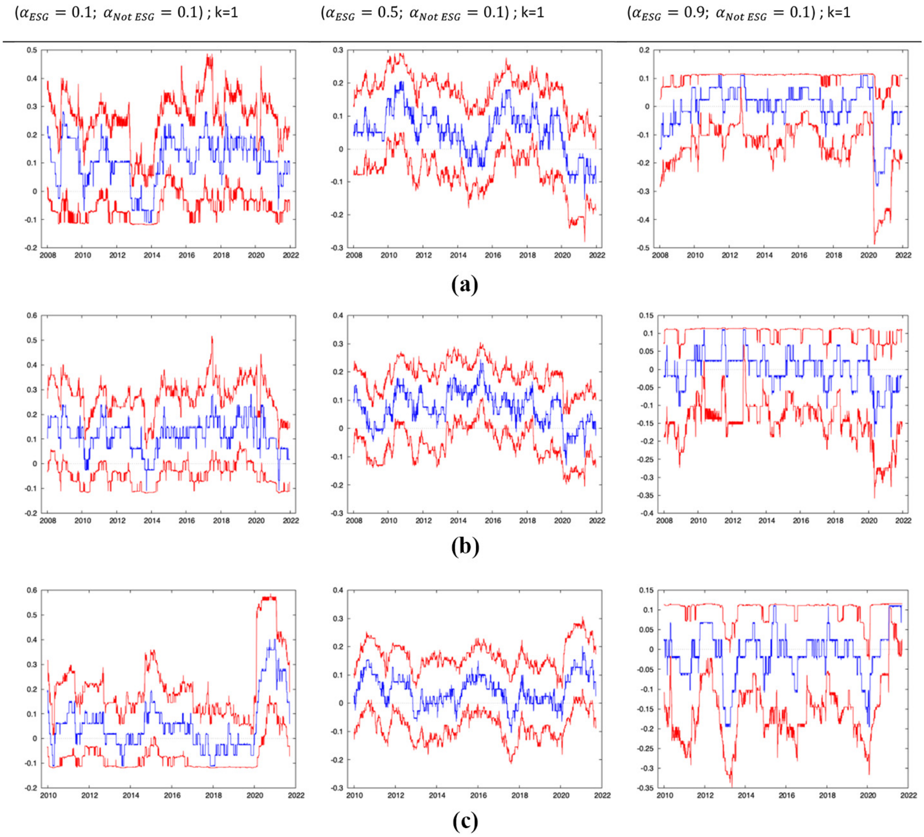


Figure 6.
Cross-quantilograms (blue line) of ESG assets (DJSI on the first row, SPCL on the second and SPGB on the third) versus DJ at lag 1

Notes: (a) DJSI vs DJ; (b) SPCL vs DJ; (c) SPGB vs DJ
Source: Authors' own creation

(especially during COVID-19). The same is partly true for SPGB: as reported in the first column, negative correlations appear, but a marked positive break is present at the end of the sample. Columns 2 and 3 are in line with the other ESGs. An interpretation of this dual behavior of ESGs versus DJ moving from $k = 0$ to $k = 1$ could be the following: when the equity market is shocked, the impact is immediately transmitted to the ESG market with an analogous effect (positive correlation). However, with a one-day lag, investors move to the ESG market expecting more profitability and resiliency (decreasing positive and negative correlation).

Figure 7 reports the analysis with respect to the SPCM at lag $k = 0$: this time, the instantaneous response at ($\alpha_{ESG} = 0.1$; $\alpha_{Not\ ESG} = 0.1$) shows less pronounced correlations, with some null or even negative events for the DJSI and more markedly for SPCL. This result is even clearer moving to ($\alpha_{ESG} = 0.9$; $\alpha_{Not\ ESG} = 0.1$). SPGB once again reflects better performance in terms of smaller positive correlations and null-negative ones over the different quantile combinations. With $k = 1$ (Figure 8), the ESGs manifest a clearer tendency for negative correlations aligning with the previous analysis versus DJ.

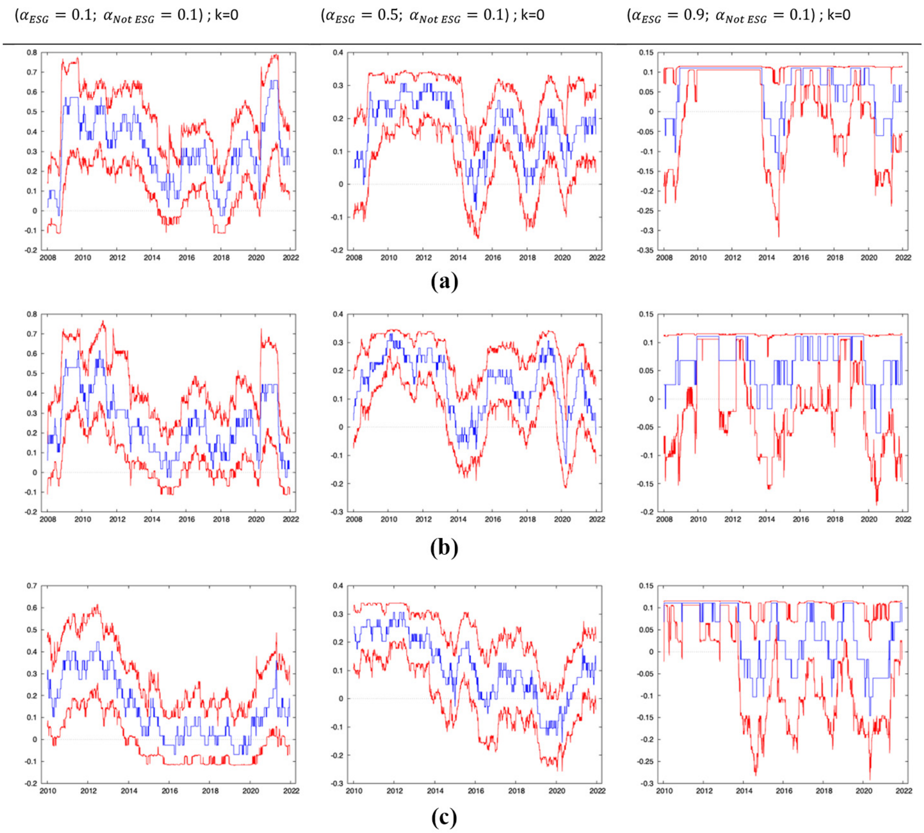


Figure 7. Cross-quantilograms (blue line) between ESG assets and SPCM at lag 0. A rolling window of 261 days is used (a year), which advances on a daily basis

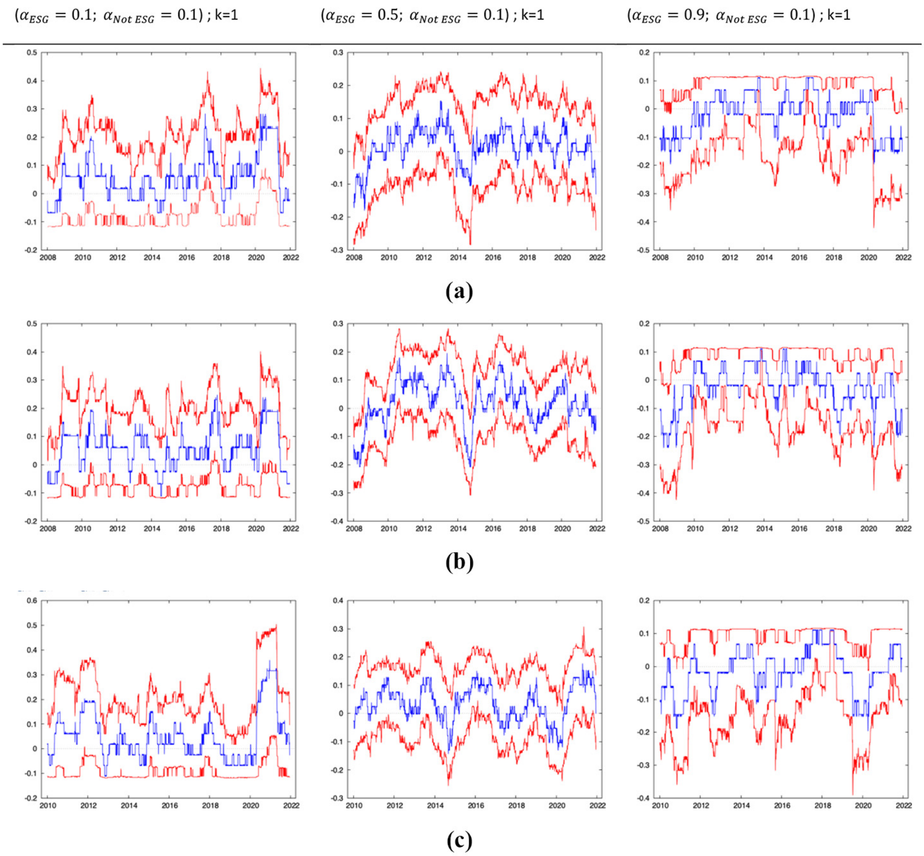
Notes: The red lines represent respectively the upper and the lower limits of a 95% confidence interval built with 5,000 replications of the stationary bootstrap; (a) DJSI vs SPCM; (b) SPCL vs SPCM; (c) SPGB vs SPCM
Source: Authors' own creation

To sum up, the time dynamics of CQG suggest that quantile dependence is actually affected by the time span. In this regard, we observe *plausible* safe-haven conditions for SPGB versus DJ and SPCM: all the considered quantile combinations simultaneously experienced null or negative correlations at both $k = 0$ and $k = 1$, with an increasing magnitude from ($\alpha_{ESG} = 0.1$; $\alpha_{Not\ ESG} = 0.1$) to ($\alpha_{ESG} = 0.9$; $\alpha_{Not\ ESG} = 0.1$). The SPCL and DJSI share some similarities only at $k = 1$ and in the commodity market.

4.3 DCC GARCH analysis

For our design, we assume a DCC model with normal innovations where $\boldsymbol{y_t} = y_{DJSI,t}, y_{SPClean,t}, y_{GreenBond,t}, y_{DJ,t}, y_{Comm,t}, y_{Gold,t}$), v_t modeled as GARCH(1,1) and A and B as scalars. The sample ranges from January 1, 2009 to November 1, 2021 [7].

The estimates for Γ, A, B are reported in Table 3: the coefficients for Γ are all positive and significative, signaling the absence of hedging properties. However, the magnitude of



Notes: (a) DJSI vs SPCM; (b) SPCL vs SPCM; (c) SPGB vs SPCM
Source: Authors' own creation

Figure 8.
Cross-quantilograms (blue line) between ESG assets and SPCM at lag 1

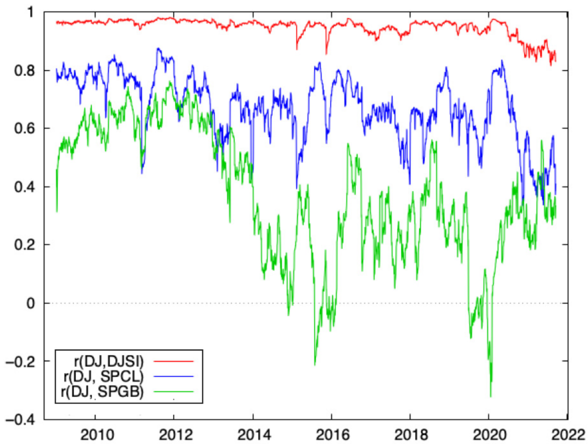
the correlation between the SPGB and DJ may suggest a diversifying nature; the same finding arises when comparing the correlation of all ESGs with the commodity ones. The inspection of $\hat{R}$ in Figures 9–10 reveals similar conclusions. Figure 9 displays the dynamic correlation between the three ESGs with respect to DJ: only the SPGB case shows a moderate-small correlation compatible with diversifying qualities. Moreover, note that a few negative peaks are also reported during the main financial turmoil events, hinting at potential safe-haven properties. Figure 10, instead, compares the correlations of ESGs versus SPCM: in this case, all three series seem to act as diversifiers, with some potential safe-haven properties for the SPGB.

To further deepen the analysis, Table 4 collects the estimation results from equation (4), where we regress $\hat{R}_{(ESG,DJ),t}$ for the various ESG indices on a constant and on a 0.1-quantile hit for the DJ index: all coefficients appear positive and significant, excluding both hedging and safe-haven possibilities. The SPGB confirms to be a diversifier for the equity market as suggested by the intercept coefficient. Table 5 reports instead the linear model for

Parameter	Coefficient	Std. error	Z	
Γ [DJSI, SPCL]	0.625	0.018	35.70	***
Γ [DJSI, SPGB]	0.538	0.024	22.05	***
Γ [DJSI, DJ]	*0.954*	*0.002*	*418.50*	***
Γ [DJSI, SPCM]	*0.394*	*0.032*	*12.42*	***
Γ [DJSI, GLD]	*0.180*	*0.032*	*5.57*	***
Γ [SPCL, SPGB]	0.336	0.034	9.78	***
Γ [SPCL, DJ]	*0.668*	*0.015*	*44.68*	***
Γ [SPCL, SPCM]	*0.310*	*0.038*	*8.22*	***
Γ [SPCL, GLD]	*0.149*	*0.039*	*3.80*	***
Γ [SPGB, DJ]	*0.447*	*0.028*	*16.09*	***
Γ [SPGB, SPCM]	*0.251*	*0.040*	*6.23*	***
Γ [SPGB, GLD]	*0.426*	*0.026*	*16.50*	***
Γ [DJ, SPCM]	0.405	0.031	13.01	***
Γ [DJ, GLD]	0.134	0.032	4.23	***
Γ [SPCM, GLD]	0.263	0.036	7.23	***
A	0.023	0.001	27.77	***
B	0.967	0.001	722.50	***

Notes: The sample size goes from January 1, 2009, to November 1, 2021; *significant at size 0.1; **significant at size 0.05; ***significant at size 0.01. Italics is associated with correlations of interest
Source: Authors' own creation

Table 3.
DCC–GARCH model estimates

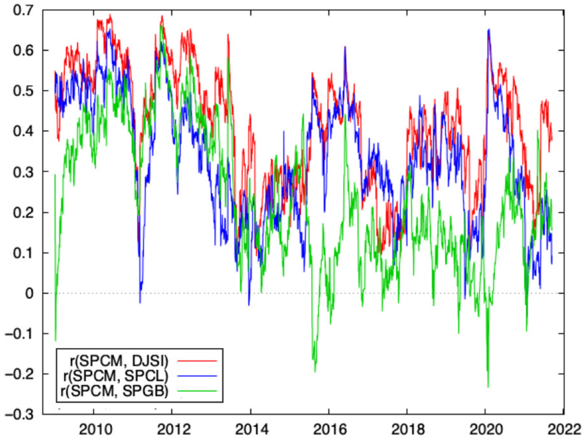


Source: Authors' own creation

Figure 9.
Conditional correlation between ESGs and DJ

$\hat{R}_{(ESG,SPCM),t}$ with a constant and a commodity market quantile hit: all ESG series confirm the diversifying nature.

Finally, the extension as in equation (5) is reported in Table 6 for $\hat{R}_{(ESG,DJ),t}$ and in Table 7 for $\hat{R}_{(ESG,SPCM),t}$ where the temporal dummy C_t is set to 1 during the first COVID-19 outbreak (from January 1, 2020, to March 31, 2020) [8]. In Table 6, we find that the estimated coefficients for γ_2 and γ_3 are statistically null for both DJSI and SPCL, as opposed to γ_0 and γ_1, which are positive. It is reasonable to conclude that despite the null coefficients for the temporal dummy and the interaction term, the overwhelming effect of γ_0 rules out the possibilities for any hedge



Source: Authors' own creation

Figure 10. Conditional correlation between ESGs and SPCM

Table 4. OLS coefficients from regressing the dynamic correlations between ESGs and DJ on equity market quantile hit, equation (3)

Regressor	(i) R(DJSI, DJ)	(ii) R(SPCL, DJ)	(iii) R(SPGB, DJ)
const	0.948 (0.001)***	0.670 (0.002)***	0.369 (0.004)***
d_{DJ}	0.009 (0.002)***	0.051 (0.006)***	0.039 (0.013)***

Notes: R(ESG, non-ESG) = dynamic correlation between ESG and non-ESG from DCC estimates; d_{DJ} = 0.1-quantile-hit series for DJ. Standard errors are reported in parenthesis; *significant at size 0.1; **significant at size 0.05; ***significant at size 0.01
Source: Authors' own creation

Table 5. OLS coefficients from regressing the dynamic correlations between ESGs and SPCM on commodity market quantile hit, equation (3)

Regressor	(i) R(DJSI, SPCM)	(ii) R(SPCL, SPCM)	(iii) R(SPGB, SPCM)
const	0.409 (0.003)***	0.326 (0.003)***	0.233 (0.003)***
d_{CM}	0.051 (0.008)***	0.068 (0.009)***	−0.010 (0.010)

Notes: d_{CM} = 0.1-quantile-hit series for SPCM. Standard errors are reported in parenthesis; *significant at size 0.1; **significant at size 0.05; ***significant at size 0.01
Source: Authors' own creation

or safe-haven property. The SPGB case, instead, manifests not only negative and significant γ_2 and γ_3, but their magnitude is large enough to counter the positive effect of γ_0. Overall, the SPGB seems to be a diversifier for the stock market, but during the COVID-19 period, it temporally evolves into a hedge and safe haven, a finding which is confirmed by the rolling window experiment in Section 4.2. In Table 7, all ESGs seem to act as diversifiers for the commodity index, with the SPGB manifesting once again hedging and safe-haven qualities.

Concluding, the regression experiments confirm the results of Sections 4.1–4.2 to the extent that SPGB works as a diversifier for both stock and commodity markets, showing safe-haven (and hedging) quality in peculiar timeframes. DJSI and SPCL, instead, belong only to the first category when compared to the commodity index.

5. Discussion and conclusion

Recent crises have destabilized financial markets and amplified the uncertainty around international/traditional investments. Consequently, many investors have struggled to achieve the benefits of a diverse portfolio and thus increased their search for investments that would provide a potential hedging opportunity – hence, the rising interest in safe-haven assets. In this context, sustainable investing has experienced significant growth as a result of satisfying stakeholders' desire for higher economic value alongside lower ESG risks. In fact, the ongoing debate on sustainable investing has shown that firms with the best ESG practices are better able to mitigate environmental, reputational and stakeholder-related risks (Falck and Heblich, 2007; Pollard *et al.*, 2018), resulting in higher performance (Verheyden *et al.*, 2016). Previous studies have highlighted that ESG investments possess properties that can lower downside risk and be more resilient *vis-à-vis* conventional investments, especially during market turmoil. These qualities have become especially relevant during the COVID-19 pandemic, as investors have engaged in a documented shift toward sustainable investments. However, more recent evidence supports the idea that ESG stocks provide limited insurance and act as a temporary risk-mitigating device in severe crises (Eisenkopf *et al.*, 2022). Consequently, there is still a question as to *whether* investors can use selective ESG investing to protect their wealth during economic downturns and/or diversify/hedge their portfolios and through *what types* of ESG investments.

In this paper, we addressed this issue by studying the quantile correlation from conventional investment practices (equity index, gold and commodities) to ESG ones using the CQG and DCC approaches. We found that none of the ESG assets we considered (i.e. green bonds and ESG equity index) could be deemed as a safe haven over the entire

Table 6. OLS coefficients from regressing the dynamic correlations between ESGs and DJ on equity market quantile hit, temporal dummies for COVID-19 and their interaction, equation (4)

Regressor	(i) R(DJSI, DJ)	(ii) R(SPCL, DJ)	(iii) R(SPGB, DJ)
const	0.948 (0.001)***	0.670 (0.002)***	0.375 (0.004)***
d_{DJ}	0.008 (0.002)***	0.052 (0.006)***	0.061 (0.012)***
C	−0.0003 (0.004)	0.014 (0.016)	−0.406 (0.032)***
$d_{DJ}C$	0.011 (0.008)	−0.022 (0.032)	−0.157 (0.063)**

Notes: d_{DJ} = 0.1-quantile-hit series for DJ; C = temporal dummy series for COVID-19 (from January 1, 2020, to March 31, 2020). Standard errors are reported in parenthesis; *significant at size 0.1; **significant at size 0.05; ***significant at size 0.01
Source: Authors' own creation

Table 7. OLS coefficients from regressing the dynamic correlations between ESGs and SPCM on commodity market quantile hit, temporal dummies for COVID-19 and their interaction, equation (4)

Regressor	(i) R(DJSI, SPCM)	(ii) R(SPCL, SPCM)	(iii) R(SPGB, SPCM)
Const	0.409 (0.003)***	0.326 (0.003)***	0.236 (0.003)***
d_{CM}	0.046 (0.009)***	0.063 (0.009)***	0.006 (0.010)
C	−0.039 (0.022)*	−0.029 (0.023)	−0.204 (0.003)***
$d_{CM}C$	0.096 (0.039)**	0.095 (0.040)**	−0.086 (0.045)*

Notes: d_{CM} = 0.1-quantile-hit series for SPCM; C = temporal dummy series for COVID-19 (from January 1, 2020, to March 31, 2020). Standard errors are reported in parenthesis; *significant at size 0.1; **significant at size 0.05; ***significant at size 0.01
Source: Authors' own creation

observation period (from January 1, 2007 to November 1, 2021). That said, our analysis affirmed that all ESG assets represent an outstanding diversification asset for the commodity markets and the SPGB for the equity too.

We also find that quantile dependence is affected by the time span. Indeed, when we extended our investigation using rolling windows analysis to capture the time dynamics of CQG, we observed that the SPGB seemed to exhibit a correlation pattern compatible with a plausible safe haven during most of the well-acknowledged financial turmoil events. This fact is further acknowledged via the DCC extensions proposed, where we found compatible hedging-safe haven features for the SPGB during the first outbreak of COVID-19.

Some limitations deserve to be noted and will be addressed in future research. First, although we discuss the role of ESG investment from a global perspective, comparison among single countries, such as Europe (that accounts for the largest concentration of ESG assets worldwide) versus the USA, could probably highlight market-specific peculiarities. Second, given that this study represents one of the first empirical contributions examining safe-haven and hedging properties of ESG assets compared to traditional assets, a possible line of future research could be aimed at replicating this analysis, exploring the diversification benefits of ESG compared to innovative safe haven (such as cryptocurrencies). Finally, our research is based on ESG indices, which lack a more refined classification of ESG themes. Although the results remain confirmed when changing the ESG index, using different sectoral themes could be further investigated to provide a heterogeneous analysis of safe-haven assets under various ESG themes. Moreover, the paucity of specific information underlying the construction of ESG ratings, that are the bases for the construction of ESG indices, makes them a “black box,” with a form of information overload and inevitable distortion effects.

In sum, our evidence enlarges the debate on sustainable investing by providing valuable implications on how investors and portfolio managers can hedge their portfolio risks. The COVID-19 pandemic has underlined the importance of reorienting the business agenda around a set of ESG initiations and actions. As a result, the field needs to see sustainable investment as no longer just a strategy for environmentally conscious investors but rather as a new hedging and diversification opportunity.

Notes

1. The European Sustainable Investment Forum (EUROSIF) defines sustainable and responsible investment (“SRI”) as a “a long-term oriented investment approach which integrates ESG factors in the research, analysis and selection process of securities within an investment portfolio. It combines fundamental analysis and engagement with an evaluation of ESG factors in order to better capture long-term returns for investors and to benefit society by influencing the behaviour of companies.” Growing global interest in responsible investment demands greater standardization of terminology to develop common sustainable finance-related terms and definitions, including those relating to responsible investment approaches, to ensure consistency throughout the global asset management industry. In response, CFA Institute, the Global Sustainable Investment Alliance and the Principles for Responsible Investment recently came together to harmonize definitions for some responsible investment terms. Coherently, they identify ESG integration as “the incorporation of ESG factors into an investment process, based on the beliefs that ESG factors can affect the risk and return of investments and that ESG factors are not fully reflected in asset prices. ESG integration involves seeking out ESG information, assessing the materiality of that information, and integrating information deemed to be material into investment analysis and decisions. The details of implementation can vary.”
2. See, for example, the Action Plan: Financing Sustainable Growth of the European Commission (2018).
3. SPGB is available starting from 28th November 2018.

4. We have run additional experiments using other world ESG series, such as the MSCI World ESG Leaders Index and MSCI Global Environment Index, but the results of the analysis did not change. For the sake of brevity and to keep the exposition as concise and consistent as possible, we decided to focus solely on the series presented in the main text since it is more representative; however, these additional results are available upon request.
5. As we will see in the next section, the major requirement for the applicability of the CQG is the strictly stationarity of the series: return series are strictly stationary even in the presence of highly persistent (and potentially integrated) GARCH effects (see Ling and McAleer, 2002; Liu, 2006; Han *et al.*, 2016).
6. For example, when a positive/negative correlation at $k = 0$ progressively diminishes and/or disappears (null correlation) at $k > 0$.
7. Since SPGB has missing observations till the end of 2008, we decided to make the sample size homogenous by starting from January 1, 2009.
8. The subperiod is suggested by the previous rolling window analysis, where the first months of the COVID-19 pandemic signaled a potential safe haven nature for the SPGB.
9. For simplicity, we are assuming to measure the quantile hit processes at lag $k = 0$, but nothing prevents to impose $k > 0$.

References

Albuquerque, R., Koskinen, Y. and Zhang, C. (2019), "Corporate social responsibility and firm risk: theory and empirical evidence", *Management Science*, Vol. 65 No. 10, pp. 4451-4469.

Albuquerque, R., Koskinen, Y., Yang, S. and Zhang, C. (2020), "Resiliency of environmental and social stocks: an analysis of the exogenous COVID-19 market crash", *The Review of Corporate Finance Studies*, Vol. 9 No. 3, pp. 593-621, doi: 10.1093/rcfs/cfaa011.

Baumöhl, E. and Lyócsa, Š. (2017), "Directional predictability from stock market sector indices to gold: a cross-quantilogram analysis", *Finance Research Letters*, Vol. 23, pp. 152-164, doi: 10.1016/j.frl.2017.02.013.

Baur, D. (2013), "Gold—fundamental drivers and asset allocation", available at: SSRN:http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2240831

Baur, D.G. and Lucey, B.M. (2010), "Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold", *Financial Review*, Vol. 45 No. 2, pp. 217-229, doi: 10.1111/j.1540-6288.2010.00244.x.

Baur, D.G. and McDermott, T.K. (2010), "Is gold a safe haven? International evidence", *Journal of Banking and Finance*, Vol. 34 No. 8, pp. 1886-1898.

Becchetti, L., Ciciretti, R., Dalò, A. and Herzel, S. (2015), "Socially responsible and conventional investment funds: performance comparison and the global financial crisis", *Applied Economics*, Vol. 47 No. 25, pp. 2541-2562.

Broadstock, D.C., Chan, K., Cheng, L.T.W. and Wang, X. (2021), "The role of ESG performance during times of financial crisis: evidence from COVID-19 in China", *Finance Research Letters*, Vol. 38, p. 101716, doi: 10.1016/j.frl.2020.101716.

Capelle-Blancard, G., Desroziers, A. and Zerbib, O.D. (2021), "Socially responsible investing strategies under pressure: evidence from the COVID-19 crisis", *The Journal of Portfolio Management*, Vol. 47 No. 9, pp. 178-197.

Cheema, M.A., Faff, R.W. and Szulczuk, K. (2020), "The 2008 global financial crisis and COVID-19 pandemic: how safe are the safe haven assets?", *Available at SSRN 3590015*.

Cho, D. and Han, H. (2021), "The tail behavior of safe haven currencies: a cross-quantilogram analysis", *Journal of International Financial Markets, Institutions and Money*, Vol. 70, p. 101257.

Corbet, S., Hou, Y., GregHu, Y., Larkin, C. and Oxley, L. (2020), "Any port in a storm: cryptocurrency safe havens during the COVID-19 pandemic", *Economics Letters*, Vol. 194, p. 109377, doi: 10.1016/j.econlet.2020.109377.

Derwall, J. and Koedijk, K. (2009), "Socially responsible fixed-income funds", *Journal of Business Finance and Accounting*, Vol. 36 Nos 1/2, pp. 210-229.

Díaz, V., Ibrushi, D. and Zhao, J. (2021), "Reconsidering systematic factors during the COVID-19 pandemic–the rising importance of ESG", *Finance Research Letters*, Vol. 38, p. 101870, doi: 10.1016/j.frl.2020.101870.

Dickey, D.A. and Fuller, W.A. (1979), "Distribution of the estimators for autoregressive time series with a unit root", *Journal of the American Statistical Association*, Vol. 74 No. 366, pp. 427-431.

Disli, M., Nagayev, R., Salim, K., Rizkiah, S.K. and Aysan, A.F. (2021), "In search of safe haven assets during COVID-19 pandemic: an empirical analysis of different investor types", *Research in International Business and Finance*, Vol. 58, p. 101461.

Doornik, J.A. and Hansen, H. (2008), "An omnibus test for univariate and multivariate normality", *Oxford Bulletin of Economics and Statistics*, Vol. 70 No. s1, pp. 927-939.

Eisenkopf, J., Juranek, S. and Walz, U. (2022), "Responsible investment and stock market shocks: short-term insurance without persistence", *British Journal of Management*, Vol. 34 No. 3, pp. 1420-1439.

Engle, R.F. (1982), "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation", *Econometrica*, Vol. 50 No. 4, pp. 987-1007.

Engle, R. (2002), "Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models", *Journal of Business and Economic Statistics*, Vol. 20 No. 3, pp. 339-350.

Falck, O. and Heblich, S. (2007), "Corporate social responsibility: doing well by doing good", *Business Horizons*, Vol. 50 No. 3, pp. 247-254, doi: 10.1016/j.bushor.2006.12.002.

Ferrer, R., Benítez, R. and Bolós, V.J. (2021), "Interdependence between green financial instruments and major conventional assets: a wavelet-based network analysis", *Mathematics*, Vol. 9 No. 8, p. 900.

Ferriani, F. and Natoli, F. (2020), "ESG risks in times of COVID-19", *Applied Economics Letters*, Vol. 28 No. 18, pp. 1-5, doi: 10.1080/13504851.2020.1830932.

Flammer, C. (2015), "Does product market competition foster corporate social responsibility? Evidence from trade liberalization", *Strategic Management Journal*, Vol. 36 No. 10, pp. 1469-1485.

Folger-Laronde, Z., Pashang, S., Feor, L. and ElAlfy, A. (2020), "ESG ratings and financial performance of exchange–traded funds during the covid-19 pandemic", *Journal of Sustainable Finance and Investment*, Vol. 12 No. 2, pp. 1-7.

Freeman, R.E. (1984), *Strategic Management: A Stakeholder Approach*, Pitman, Boston, MA.

Friedman, M. (1962), *Capitalism and Freedom*, University of Chicago Press, Chicago, IL.

Gao, Y., Li, Y., Zhao, C. and Wang, Y. (2022), "Risk spillover analysis across worldwide ESG stock markets: new evidence from the frequency-domain", *The North American Journal of Economics and Finance*, Vol. 59, p. 101619, doi: 10.1016/j.najef.2021.101619.

Gil-Bazo, J., Ruiz-Verdú, P. and Santos, A.A. (2010), "The performance of socially responsible mutual funds: the role of fees and management companies", *Journal of Business Ethics*, Vol. 94 No. 2, pp. 243-263.

Graham, M., Kiviaho, J. and Nikkinen, J. (2022), "Short-term and long-term dependencies of the S&P 500 index and commodity prices", *Commodities*, Chapman and Hall/CRC, New York, pp. 423-438.

Han, H., Linton, O., Oka, T. and Whang, Y.J. (2016), "The cross-quantilogram: measuring quantile dependence and testing directional predictability between time series", *Journal of Econometrics*, Vol. 193 No. 1, pp. 251-270.

Heinkel, R., Kraus, A. and Zechner, J. (2001), "The effect of green investment on corporate behavior", *The Journal of Financial and Quantitative Analysis*, Vol. 36 No. 4, pp. 431-449.

Ji, Q., Zhang, D. and Zhao, Y. (2020), "Searching for safe haven assets during the COVID-19 pandemic", *International Review of Financial Analysis*, Vol. 71, p. 101526, doi: 10.1016/j.irfa.2020.101526.

Kwiatkowski, D., Phillips, P.C., Schmidt, P. and Shin, Y. (1992), "Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root? ", *Journal of Econometrics*, Vol. 54 Nos 1/3, pp. 159-178.

Lei, H., Xue, M., Liu, H. and Ye, J. (2023), "Precious metal as a safe haven for global ESG stocks: portfolio implications for socially responsible investing", *Resources Policy*, Vol. 80, p. 103170.

Ling, S. and McAleer, M. (2002), "Stationarity and the existence of moments of a family of GARCH processes", *Journal of Econometrics*, Vol. 106 No. 1, pp. 109-117.

Lins, K.V., Servaes, H. and Tamayo, A. (2017), "Social capital, trust, and firm performance: the value of corporate social responsibility during the financial crisis", *The Journal of Finance*, Vol. 72 No. 4, pp. 1785-1824, doi: 10.1111/jofi.12505.

Liu, J.C. (2006), "On the tail behaviors of a family of GARCH processes", *Econometric Theory*, Vol. 22 No. 5, pp. 852-862.

Mariana, C.D., Ekaputra, I.A. and Husodo, Z.A. (2021), "Are Bitcoin and Ethereum safe havens for stocks during the COVID-19 pandemic? ", *Finance Research Letters*, Vol. 38, p. 101798, doi: 10.1016/j.frl.2020.101798.

Mousa, M., Saleem, A. and Sági, J. (2021), "Are ESG shares a safe haven during COVID-19? Evidence from the Arab region", *Sustainability*, Vol. 14 No. 1, p. 208.

Nguyen, T.T.H., Naeem, M.A., Balli, F., Balli, H.O. and Vo, X.V. (2021), "Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds", *Finance Research Letters*, Vol. 40, p. 101739.

Nofsinger, J. and Varma, A. (2014), "Socially responsible funds and market crises", *Journal of Banking and Finance*, Vol. 48, pp. 180-193, doi: 10.1016/j.jbankfin.2013.12.016.

Omura, A., Roca, E. and Nakai, M. (2020), "Does responsible investing pay during economic downturns: evidence from the COVID-19 pandemic", *Finance Research Letters*, Vol. 42, p. 101914, doi: 10.1016/j.frl.2020.101914.

Pham, L. and Nguyen, C.P. (2021), "Asymmetric tail dependence between green bonds and other asset classes", *Global Finance Journal*, Vol. 50, p. 100669.

Phillips, P.C.B. and Perron, P. (1988), "Testing for a unit root in time series regression", *Biometrika*, Vol. 75 No. 2, pp. 335-346.

Piserà, S. and Chiappini, H. (2022), "Are ESG indexes a safe-haven or hedging asset? Evidence from the COVID-19 pandemic in China", *International Journal of Emerging Markets*, Vol. 19 No. 1, pp. 56-75, doi: 10.1108/IJOEM-07-2021-1018.

Politis, D.N. and Romano, J.P. (1994), "The stationary bootstrap", *Journal of the American Statistical Association*, Vol. 89 No. 428, pp. 1303-1313.

Pollard, J.L., Sherwood, M.W. and Klobus, R.G. (2018), "Establishing ESG as risk Premia", *Journal of Investment Management*, Vol. 16 No. 1, pp. 32-43.

Ratner, M. and Chiu, C. (2013), "Hedging stock sector risk with credit default swaps", *International Reviews Finance Analysis*, Vol. 30, pp. 18-25, doi: 10.1016/j.irfa.2013.05.001.

Reboredo, J.C. (2018), "Green bond and financial markets: co-movement, diversification and price spillover effects", *Energy Economics*, Vol. 74, pp. 38-50.

Renneboog, L., Ter Horst, J. and Zhang, C. (2008), "The price of ethics and stakeholder governance: the performance of socially responsible mutual funds", *Journal of Corporate Finance*, Vol. 14 No. 3, pp. 302-322.

Renneboog, L., ter Horst, J. and Zhang, C. (2011), "Is ethical money financially smart? Nonfinancial attributes and money flows of socially responsible investment funds", *Journal of Financial Intermediation*, Vol. 20 No. 4, pp. 562-588.

Rubbaniy, G., Khalid, A.A., Rizwan, M.F. and Ali, S. (2022), "Are ESG stocks safe-haven during COVID-19?", *Studies in Economics and Finance*, Vol. 39 No. 2, pp. 239-255, doi: 10.1108/SEF-08-2021-0320.

Salisu, A.A., Vo, X.V. and Lawal, A. (2021), "Hedging oil price risk with gold during COVID-19 pandemic", *Resources Policy*, Vol. 70, p. 101897.

Shahzad, S.J.H., Bouri, E., Roubaud, D., Kristoufek, L. and Lucey, B. (2019), "Is bitcoin a better safe-haven investment than gold and commodities?", *International Review of Financial Analysis*, Vol. 63, pp. 322-330, doi: 10.1016/j.irfa.2019.01.002.

Singh, A. (2020), "COVID-19 and safer investment bets", *Finance Research Letters*, Vol. 36, p. 101729, doi: 10.1016/j.frl.2020.101729.

Uddin, G.S., Rahman, M.L., Hedström, A. and Ahmed, A. (2019), "Cross-quantilogram-based correlation and dependence between renewable energy stock and other asset classes", *Energy Economics*, Vol. 80, pp. 743-759.

Umar, Z., Kenourgios, D. and Papathanasiou, S. (2020), "The static and dynamic connectedness of environmental, social, and governance investments: international evidence", *Economic Modelling*, Vol. 93, pp. 112-124, doi: 10.1016/j.econmod.2020.08.007.

Umar, Z., Gubareva, M. and Teplova, T. (2021), "The impact of covid-19 on commodity markets volatility: analyzing time-frequency relations between commodity prices and coronavirus panic levels", *Resources Policy*, Vol. 73, p. 102164.

Verheyden, T., Eccles, R.G. and Feiner, A. (2016), "ESG for all? The impact of ESG screening on return, risk, and diversification", *Journal of Applied Corporate Finance*, Vol. 28 No. 2, pp. 47-55, doi: 10.1111/jacf.12174.

Yousaf, I., Suleman, M.T. and Demirer, R. (2022), "Green investments: a luxury good or a financial necessity?", *Energy Economics*, Vol. 105, p. 105745.

Appendix 1. The role of gold

To better understand the role of ESG investing as a diversification or hedging tool, we conduct the CQG analysis using as benchmark variable (on the *x*-axis of the heatmap) the GLD return series versus the DJ and the SPCM (*y*-axis). This experiment aims to unravel the gold properties: despite the fact that it is universally considered as hedging/safe-haven asset, from an empirical perspective, divergent results have been documented.

Figure A1 displays the heatmaps: the CQG for lag 0 of both DJ and SP GSCI commodity reveals a diversifying property. Moreover, the magnitude of the correlations suggests a better performance in both markets with respect to the ESGs.

Coming to lag 1, positive correlations decrease substantially and become uncorrelations; as a consequence, gold can clearly be considered a superior diversifier than ESGs. Notice that according to our definitions, safe haven indications are lightly shown for lag 1.

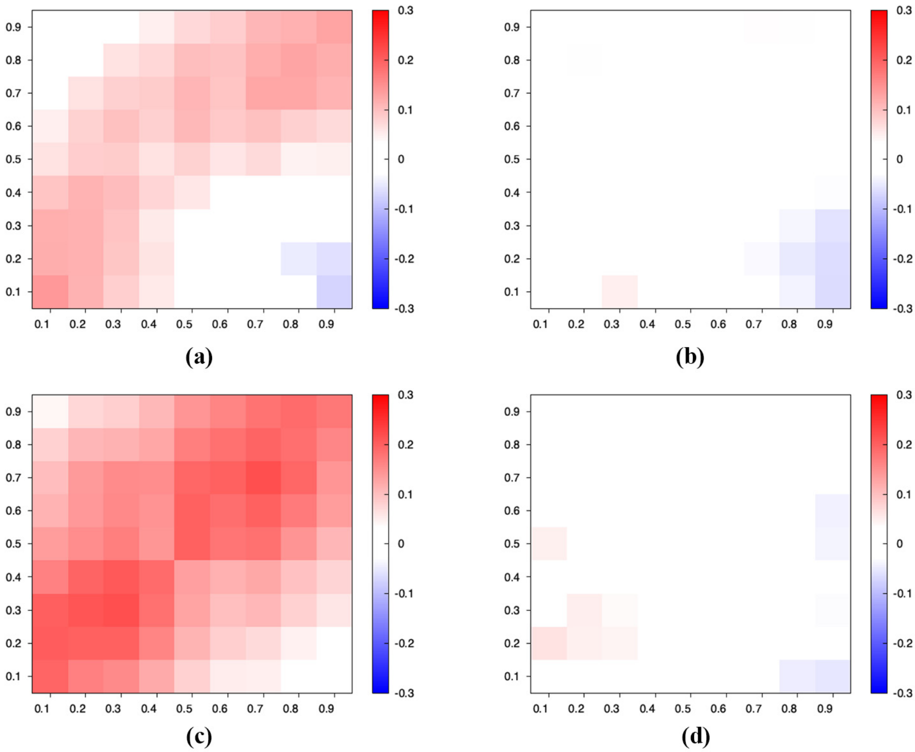
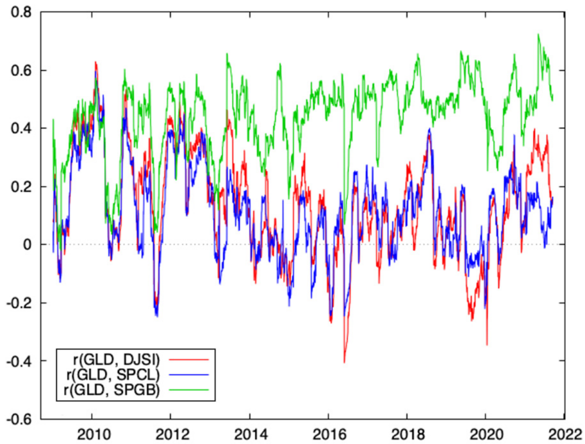


Figure A1. Cross-quantilograms between GLD and other non-ESG assets at lag 0 and 1

Notes: Correlations are tested for significance at size 0.05 by means of the stationary bootstrap with 10,000 iterations; (a) GLD vs DJ (k = 0); (b) GLD vs DJ (k = 1); (c) GLD vs SPCM (k = 0); (d) GLD vs SPCM (k = 1)

Source: Authors' own creation

To further investigate this result, we also propose the DCC analysis via dynamic correlations. In Figure A2, we find the comparison between ESG assets and GLD: both the DJSI and the SPCL manifest a mild positive correlation, while the SPGB has a more pronounced positive correlation. In Figure A3, the dynamic correlations between gold and the equity and commodity indices are reported: a marked diversifying nature with some hedging/safe haven tendency is clearly spotted. These results have to be interpreted, again, in light of the role of gold as a superior diversifier. This evidence is in line with Lei *et al.* (2023) that confirms the usefulness of gold in gaining diversification benefits and reducing downside risks. Interestingly, the more marked correlation between GLD and SPGB can be seen as a consequence of the better-diversifying qualities of SPGB than those of DJSI and SPCL.



Source: Authors' own creation

Figure A2. Conditional correlation between ESGs and GLD

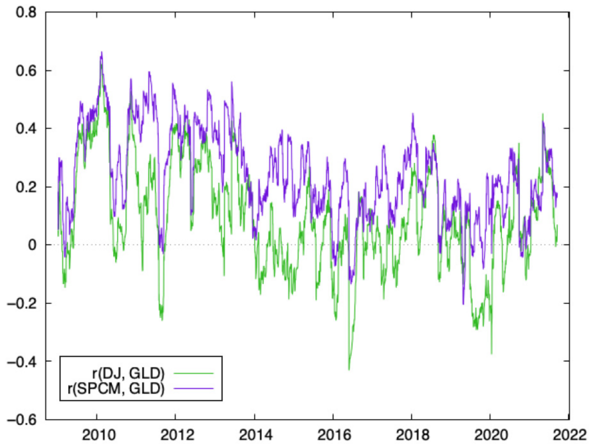


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Figure A3. Conditional correlation between GLD and DJ/SPCM

Appendix 2. Partial cross-quantilogram analysis

Following Han *et al.* (2016), we extend our framework to include the partial CQG analysis to control for the effects of external variables on cross-quantile dependence. Let $y_{3,t}, \ldots, y_{l,t}$, with $l \geq 3$, be the controlling variables and define $z_t \equiv \left[\psi_{\alpha_3}(y_{3,t} - q_{3,t}(\alpha_3)), \ldots, \psi_{\alpha_l}(y_{l,t} - q_{l,t}(\alpha_l))\right]$ as the related quantile hit processes [9].

The correlation matrix of the quantile hits is:

$$R = E\left[h_t(\alpha)h_t(\alpha)^{\top}\right]$$

where $\alpha = (\alpha_1, \alpha_2, \alpha_3, \ldots, \alpha_l)$ and $h_t(\alpha) = \left[\psi_{\alpha_1}(y_{1,t} - q_{1,t}(\alpha_1)), \psi_{\alpha_2}(y_{2,t} - q_{2,t}(\alpha_2)), \psi_{\alpha_3}(y_{3,t} - q_{3,t}(\alpha_3)), \ldots, \psi_{\alpha_l}(y_{l,t} - q_{l,t}(\alpha_l))\right]$.

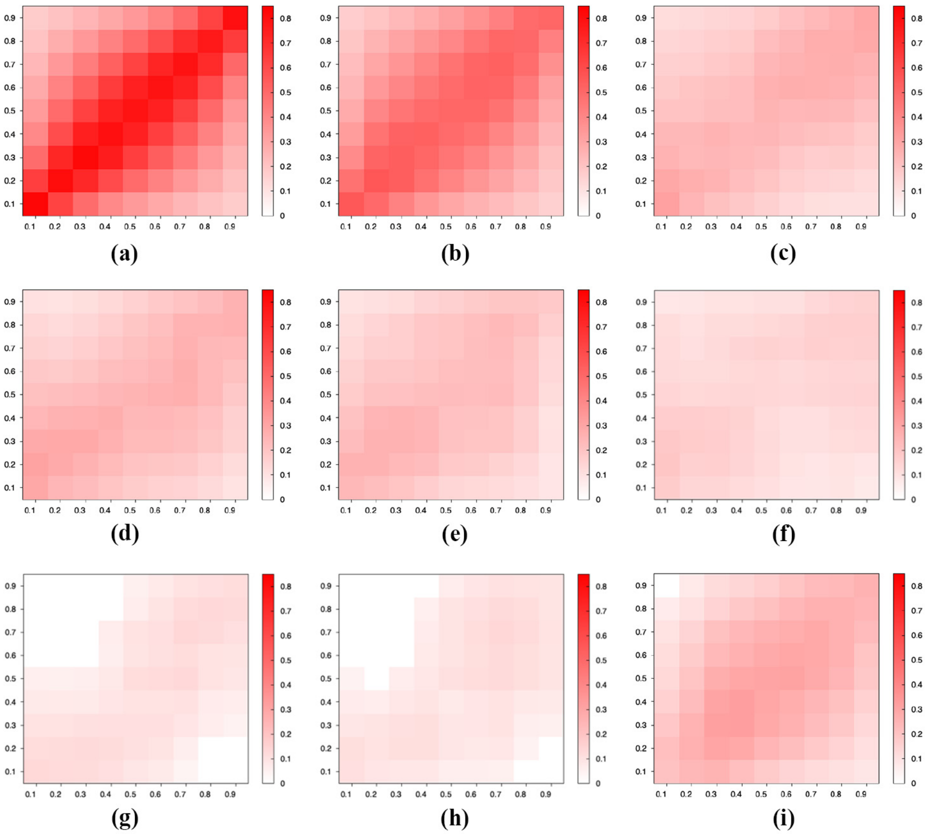


Figure A4. Partial cross-quantilograms between ESG assets and non-ESGs at lag 0: a 0.90-quantile hit on the VIX index (lag 0) is used as conditioning variable

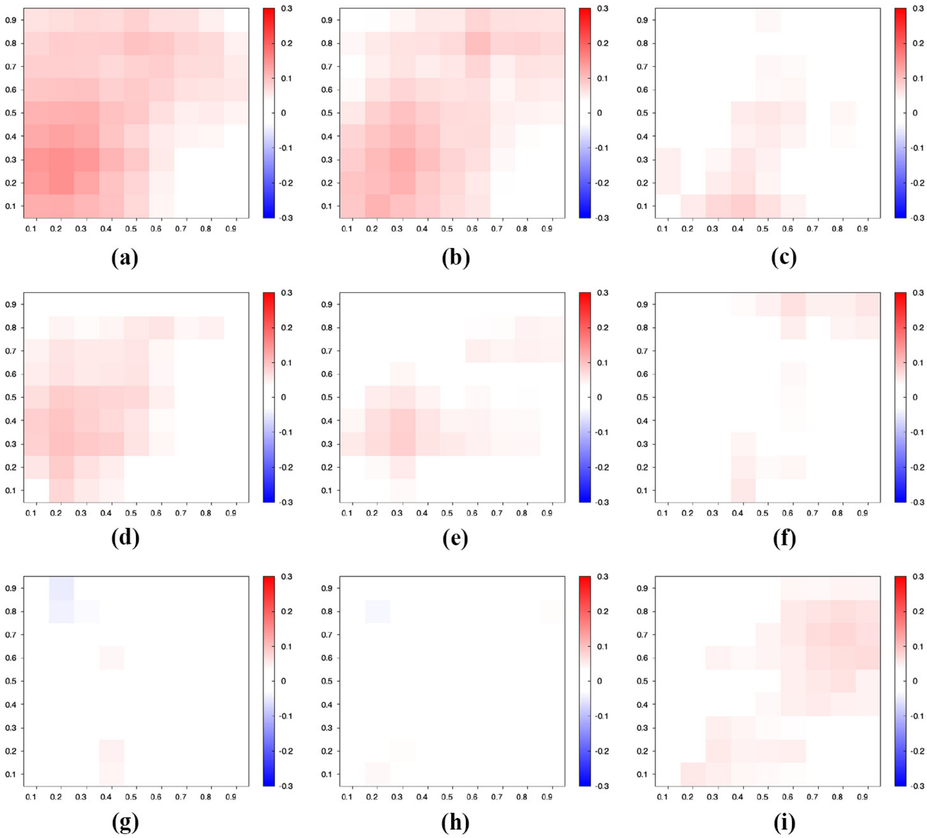
Notes: Non-significance at size 0.05 is reconducted to 0 (stationary bootstrap with 10,000 iterations); (a) DJSI vs DJ (k = 0); (b) SPCL vs DJ (k = 0); (c) SPGB vs DJ (k = 0); (d) DJSI vs SPCM (k = 0); (e) SPCL vs SPCM (k = 0); (f) SPGB vs SPCM (k = 0); (g) DJSI vs GLD (k = 0); (h) SPCL vs GLD (k = 0); (i) SPGB vs GLD (k = 0)
Source: Authors' own creation

Furthermore, let us define the inverse of R as P in symbols $P = R^{-1}$.

Finally, the partial CQG of $y_{1,t}$ and $y_{2,t}$ after having controlled for external variables $y_{3,t}, \ldots, y_{l,t}$ is given by:

$$\rho_{\alpha|z} = -\frac{p_{\alpha,12}}{\sqrt{p_{\alpha,11} p_{\alpha,22}}}$$

where p_{ij} identifies the *ij-th* element of P. The sample counterpart is immediately available by using sample statistics instead of their expected value.



Notes: Non-significance at size 0.05 is reconducted to 0 (stationary bootstrap with 10,000 iterations); (a) DJSI vs DJ (k = 1); (b) SPCL vs DJ (k = 1); (c) SPGB vs DJ (k = 1); (d) DJSI vs SPCM (k = 1); (e) SPCL vs SPCM (k = 1); (f) SPGB vs SPCM (k = 1); (g) DJSI vs GLD (k = 1); (h) SPCL vs GLD (k = 1); (i) SPGB vs GLD (k = 1)
Source: Authors' own creation

Figure A5.
Partial cross-quantilograms between ESGs and non-ESGs at lag 1: a 0.90-quantile hit on the VIX index (lag 1) is used as conditioning variable

In our example, we introduce a single controlling variable $y_{3,t}$ corresponding to the Chicago board options exchange's (CBOE) volatility index (VIX). Incorporating uncertainty measures is a common robustness check (Uddin *et al.*, 2019) since the perceived volatility may directly affect asset returns. In Figure A4, the partial CQGs for the ESG assets versus the non-ESG ones (at lag $k = 0$) are reported. The setup is identical to one reported in Section 4.1; that is, heatmaps are used considering all deciles over the time span January 1, 2007, up to November 1, 2021. The effect of a higher perceived risk is conveyed by the quantile hit for the VIX variable at the 0.9-quantile, $\psi_{0.9}[VIX_t - q_{VIX,t}(0.9)]$.

As can be noticed, the results portrayed in Figure A4 are similar to the original CQG ones: uncertainty measures seem to have limited information impact on cross-quantile dependence. The same conclusions are obtained in Figure A5, where the partial CQGs for non-ESG indices at lag $k = 1$ are displayed.

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