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Pedini, Luca and Severini, Sabrina

Department of Economics and Social Sciences, Università Politecnica delle Marche, Department of Management, Università Politecnica delle Marche

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Luca Pedini
Department of Economics and Social Sciences, Università Politecnica delle Marche,

Piazzale Martelli, 8, Ancona, Italy

e-mail: l.pedini@univpm.it

Sabrina Severini
Department of Management, Università Politecnica delle Marche,

Piazzale Martelli, 8, Ancona, Italy

e-mail: s.severini@univpm.it

Abstract

This article proposes an empirical investigation, based on a cross-quantilogram analysis, to assess the hedge, diversifier and safe haven properties of Environmental, Social and Governance (ESG) assets in comparison to conventional investment practices (equity index, gold, commodities and cryptocurrencies). Our evidence shows that ESG assets have a weak safe haven properties but still represent an outstanding diversification and hedge asset, depending on the asset class taken as reference. Our results provide important implications for risk management suggesting that investors have started considering sustainable investing as a new measure of value maximization and risk reduction.

Keywords: cross-quantilogram, ESG investment, safe haven, portfolio allocation

JEL: C32, C52, G01, G11.

1. Introduction

In recent years, Environmental, Social, and Governance (ESG)[1] investments have grown popularity worldwide, reaching $30.7 trillion of exchanged volumes in the main markets in the solely 2018 with nearly half of these assets managed by Europe. For a long time, ESG investments have been considered a niche product that necessarily implied lower expected returns (*e.g.*, Hong and Kacperczyk, 2009). However, investors and companies have recently started to pay attention not only in accounting practices, but also in ESG aspects. Consequently, during the last decade, ESG investing has been increasingly valued by investors, especially, for its capability to lower downside risk and to be resilient during volatile market conditions (Nofsinger and Varma, 2014; Lins et al., 2017; Albuquerque et al., 2020; Broadstock et al., 2021). Several potential explanations have been proposed for such resiliency. Some studies claim that ESG factors create brand equity and brand loyalty for responsible businesses (see, *e.g.*, Flammer, 2015; Albuquerque et al. 2019; Albuquerque et al. 2020). Furthermore, ESG aspects attract loyal investors (see, *e.g.*, Heinkel et al., 2001; Renneboog et al., 2011; Ferriani and Natoli, 2020) and managers. The formers are motivated by nonfinancial reasons to invest and less likely to engage in selloffs even during crisis; the latter have desirable values in terms of how to conduct business, treat employees, and relate to customers that might leads to a higher productivity and profitability.

Motivated by the growing trend in the use of sustainable ESG investments in portfolio allocations, several existing studies have showed that especially green bonds display significant co-movement with other financial assets (Pham, 2016; Reboredo, 2018). However, little is known about the relative performance of other green asset vis-`a-vis conventional investments especially during different economic downturns, and the results are mixed (Omura et al., 2020; Folger-Laronde et al. 2020; Díaz et al., 2021).

To address these gaps, in this paper, we empirically analyze the potential safe haven, hedge and diversifier properties of different ESG assets relative to conventional investment practices (equity index, gold, commodities and cryptocurrencies) using the bivariate cross-quantilogram by Han et al., (2016), which has proven to be a powerful tool for analyzing asset co-movements in extreme quantiles avoiding any distributional

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[1] ESG investment/investing enriches the evaluation of issuers with considerations regarding sustainability aspects on the Enviromental, Social and Governace sphere. We use the espression ESG investment/investing or sustainable investment/investing og green investment/investing interchangeably.

or parametrical assumption (Baumöhl and Lyócsa, 2017; Shahzad et al., 2019; Uddin et al. 2019; Ji et al., 2020).

Our paper reveals important findings. First, despite no ESG asset among those considered can be deemed as safe haven over the entire sample period, when the observation horizon is restricted interesting, but still weak, safe haven properties emerge for few ESG assets. Second, our analysis shows that over the entire time span, all ESG assets considered represent an outstanding diversification and hedge asset, depending on the asset class taken as reference.

The present paper contributes to the literature in several ways. First, it extends the literature by providing novel insights into ongoing debate of sustainable investing by analyzing and comparing the unexplored safe haven, hedge and diversifier capabilities of different ESG asset (namely, green bond and ESG equity index). Second, despite an increasing number of academic studies have examined the impact of the Covid-19 pandemic on different financial assets, the safe haven properties of green assets are largely understudied. Third, as Ji et al. (2020) point out, a large volume of literature that empirically investigates whether an asset can act as a safe haven has achieved mixed results. Indeed, depending on the market studied or on the fundamental characteristics of the market turmoil, the safe haven properties of an asset might not be universal. By examining the period 2007-2021 and using a well-suited methodology to capture the spillover effect between assets, this is perhaps the first study that comprehensively examines the validity of various potential diversifier, hedge and safe haven of different assets with comparable evidence.

This paper has both practical and theoretical implications. As an academic contribution, it enriches the literature that explores sustainable investments from various aspects by analysing the understudied safe haven hedging and diversification benefits of these assets; from a practical point of view, it provides interesting evidence for investors to improve their portfolio diversification strategies and asset allocation process according to the market condition.

The paper is structured as follows: the review of the related literature is discussed in Section 2. Data and the methodology used are explained in Section 3; Section 4 provides the main results; finally, Section 4 concludes.

2. Literature review

Despite no common definitions of safe haven exist within the literature, a quite comprehensive one considers strong (weak) safe havens those assets which are negative correlated (uncorrelated) with other ones in extreme market conditions (Baur and Lucey, 2010). While the search for safe haven assets are mainly relevant during the market downturn, the need to hedge or diversify an investment portfolio applies at all times (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 a weak positive correlation with another asset on average, while a weak (strong) hedge is an asset that is uncorrelated (negatively correlated) with another asset on average.

As a consequence, this study lies in the growing literature dealing with the diversifier, hedging and safe haven properties of different assets classes; being aligned, at the same time, with the thread of literature that focuses on the risk-return characteristics of green investments.

In line with the first strand of studies, huge empirical evidence has analysed the diversifier, hedging and safe haven properties of assets such as gold, cryptocurrencies, and commodities, suggesting that these attributes might change over time, according to the empirical methodology and sample countries under study (see, among others, Lucey and Li, 2015; Bekiros, et al., 2017; Klein, 2017). Indeed, before the 2008 global financial crisis (GFC), gold and some currencies (especially the US dollar and Swiss franc) were conventionally used as a hedge and safe haven asset (Beckmann et al., 2015; Grisse & Nitschka, 2015). However, over the last decades, cryptocurrency drawn investors' attention as an effective hedge and a strong safe haven, due to its independence from monetary policy, its role as a store of value, and limited correlation with other financial assets (Baur et al., 2018; Bouri et al., 2017; Stensås et al., 2019). However, the recent Covid-19 pandemic has revived the debate on the role of these assets resulting in mixed evidence (*e.g.*, Ji et al., 2020; Salisu et al., 2021; Umar and Gubareva, 2021; Cheema et al., 2020; Corbet et al., 2020; Mariana et al.,2020; Disli et al., 2021). While empirical findings have showed significant co-movement of green bonds with other financial assets (Reboredo, 2018; Nguyen et al.,2020), the hedging, diversification or safe haven benefits of these assets are largely understudied, leaving the door open for the present study.

In line with the second stream of literature, some studies document a relative over-performance of green mutual funds compared to their traditional counterparts (Nofsinger and Varma, 2014; Muñoz et al., 2014; Silva and Cortez, 2016) while other evidence challenges these findings showing that green bonds offer inferior risk-adjusted returns for investors (Pham, 2016; Hachenberg and Schiereck, 2018; Bachelet et al., 2019). Moreover, emerging evidence suggests that the recent Covid-19 crisis has accelerated the trend for a more sustainable approach to investing. Indeed, in the first quarter of 2020, when the virus spread globally, financial markets turned extremely volatile and investors have demanded low-ESG risk funds (Ferriani and Natoli, 2020), finding refuge in the ESG investment strategies (Singh, 2020). Therefore, with the circulation of the Covid-19, the observable over-performance of ESG investments (Díaz et al., 2021; Folger-Laronde et al. 2020; Omura et al., 2020) as well as their lower volatility, might have induced investors to consider sustainable investment as comparable alternatives to conventional safe havens (*i.e.*, gold, cryptocurrency or commodities). Put differently, investors might have started valuing nonfinancial reasons such as ESG concerns, sticking with responsible companies even during crisis periods thus support the share price during downturns. However, whether investors can protect their wealth during the downturn through selecting responsible companies requires further investigation.

3. Methodology: the cross-quantilogram

To perform our analysis we employ the cross-quantilogram apparatus, firstly introduced by Han et al. (2016), which allows to explore the dependence across different quantiles at different lag order for two series. Formally, given two stationary time series (*e.g.*, asset returns), $y_{1,t}$ and $y_{2,t}$, a quantile hit event is firstly defined as $\mathbf{1}[y_{i,t} < q_{i,t}(\alpha_i)]$ for $i = 1, 2$, where $q_{i,t}(\alpha_i)$ is the $\alpha_i \in (0,1)$ quantile of $y_{i,t}$ and $\mathbf{1}[\cdot]$ is the indicator function. In other words, a quantile hit process reports those observations which fall below the range of a given quantile, potentially signaling outliers with suitable choices of α_i. The correlation between two quantile hits, one for y_{1t} and another for y_{2t}, for an arbitrary couple (α_1, α_2) and $(t,\ t-k)$ with $k = 0, 1, \ldots.$, is referred as cross-quantilogram, which is computed as

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

where $\psi_\alpha(x) = \mathbf{1}[x < 0] - \alpha$ is the quantile hit function.

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

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

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

Clearly, $\hat{\rho}_{(\alpha_1,\alpha_2)}(k) \in [-1,1]$, with the limiting values for perfect positive and negative correlation: positive values of $\hat{\rho}_{(\alpha_1,\alpha_2)}(k)$ indicate a co-movement in the same direction for $y_{1,t}$ and $y_{2,t-k}$ on the quantiles under analysis; negative values, on the other hand, show an opposite behaviour for the series: for $k > 0$, the information pertaining $y_{2,t-k}$ obviously predates $y_{1,t}$, implying the so-called directional predictability, meaning that a quantile hit $\mathbf{1}[y_{2,t-k} < q_{2,t-k}(\alpha_2)]$ will 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 $\hat{\rho}_{(\alpha_1,\alpha_2)}(k) < 0$.

Notice, however, that the asymptotic distribution for $\hat{\rho}_{(\alpha_1,\alpha_2)}(k)$ requires the stationary bootstrap method (Politis & Romano, 1994), so for example the $(1-\gamma)$ confidence interval for $\rho_{(\alpha_1,\alpha_2)}(k)$ can be computed as $[\hat{\rho}_{(\alpha_1,\alpha_2)}(k) + T^{-1/2}c_{1,k,\gamma}, \hat{\rho}_{(\alpha_1,\alpha_2)}(k) + T^{-1/2}c_{2,k,\gamma}]$ where $c_{1,k,\gamma}$ and $c_{2,k,\gamma}$ are the critical values obtained as percentiles of the bootstrapped distribution.

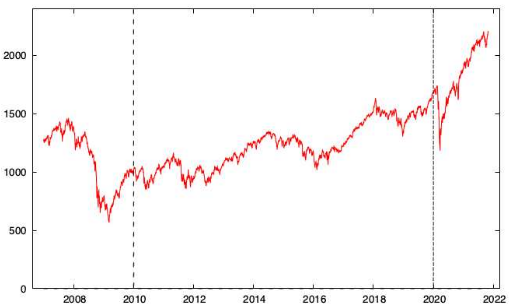
The cross-quantilogram analysis is here exploited to label a series as a safe haven, hedge or diversifier using exactly cross-quantile dependence: a safe haven investment, for instance, is assumed to be either uncorrelated or negative correlated with other assets in extreme market conditions (Baur and Lucey, 2010); as a consequence the correlation at the solely lower or upper quantiles should capture this behavior (if any). As for diversifier or hedge assets a wider perspective is required, which can be recovered by analyzing a larger set of quantiles, from the lower to the upper ones.

4 Data

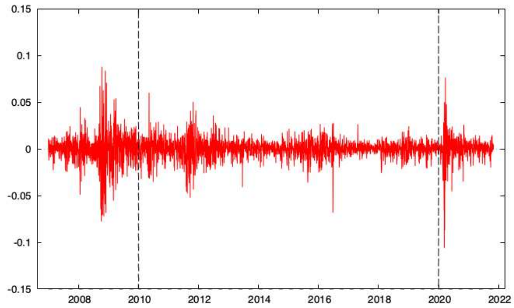
To investigate the role of ESG investments, we use daily data from 1st January 2007 to 1st November 2021. The ESG indices here employed are respectively the Dow Jones Sustainability World Index ("DJSI"), the Standard & Poor Global Clean Energy Index ("SPClean") and the Standard & Poor Green Bond Index ("SPGreenBond"). The former comprises the top 10% of the largest 2,500 companies in the SP Global BMI whose performance in terms of sustainability is defined via the SP Global ESG Score which weights both the environmental and the socio-political dimensions of the constituent. The SPClean Index, instead, includes 100 stocks from companies which either derive at least the 25% of their revenues from Clean-Energy related businesses or that exploit renewable energy for their production activity. Finally, the SPGreenBond Index, refers to global bonds labelled "green" by Climate Bonds Initiative (CBI) and subject to eligibility criteria Clearly, these indicators represent different aspect of the ESG ecosystem, with the DJSI as the more comprehensive in terms of ESG standards, while the SPClean and the SPGreenBond more environmental-oriented.

To represent the other assets, we consider the Dow Jones Global for the equity market; the SP GSCI Commodity Index and the SP GSCI Gold for the commodity one and finally the Bitcoin as leader cryptocurrency. Each series is expressed in terms of daily returns, computed as logarithmic difference between price at time t and t-1. All data are collected from Datastream except for the Bitcoin series available from Coindesk.

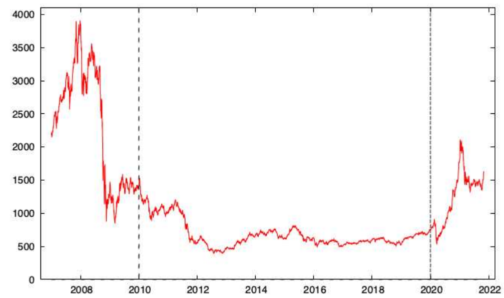
Figures 1-2 report graphically both the price and the return series, with dotted lines as separators for the main financial turmoil periods, namely the Global Financial Crisis, *i.e.*, GFC (2007-2008) and the Covid-19 pandemics (2020-ongoing).



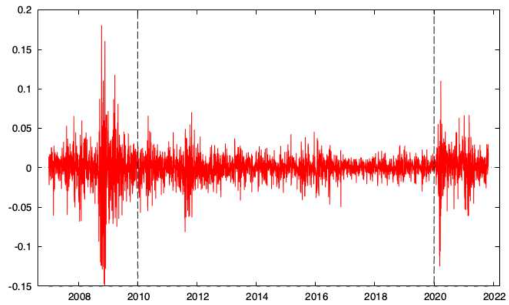
DJSI - price



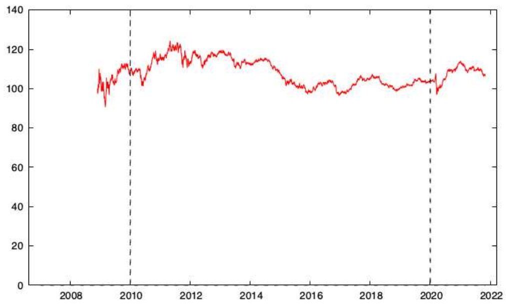
DJSI - return



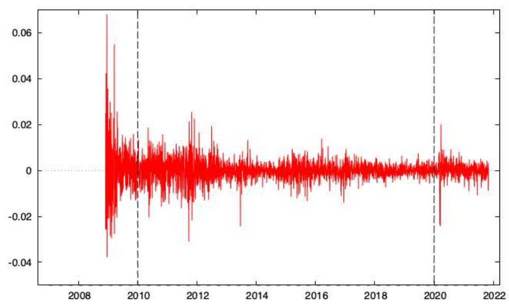
SPClean - price



SPClean - return

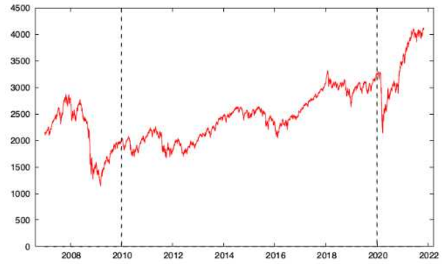


SPGreenBond - price

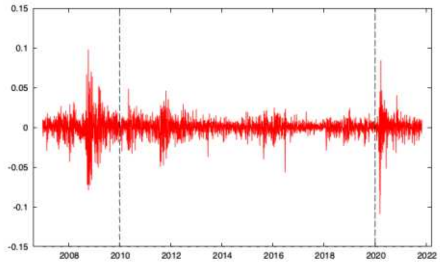


SPGreenBond - return

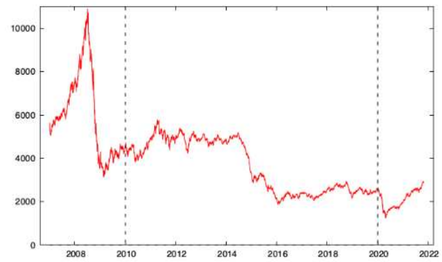
Figure 1 – ESG price (left) and return (right) series. Dotted vertical lines denote the subsample repartition, with GFC from 2007 to 2009; after crisis periord in 2010-2019 and Covid-19 timespan ranging from 2020 to 2021.



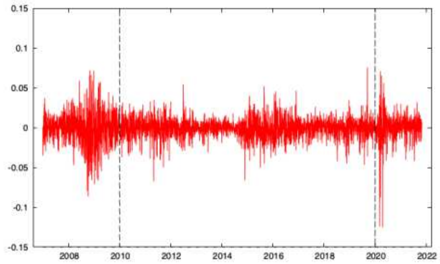
DJ Global - price



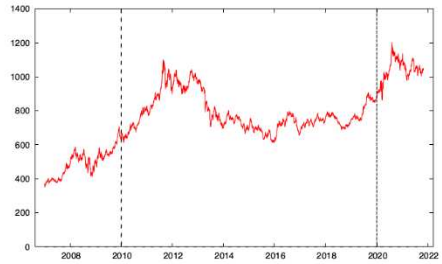
DJ Global - return



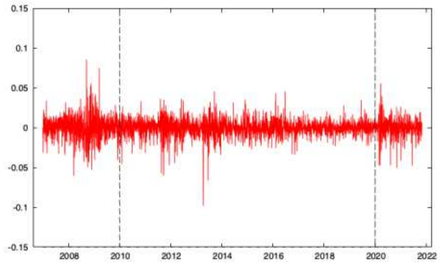
SPGSCICommodity - price



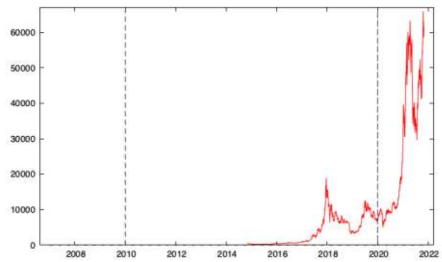
SPGSCICommodity - return



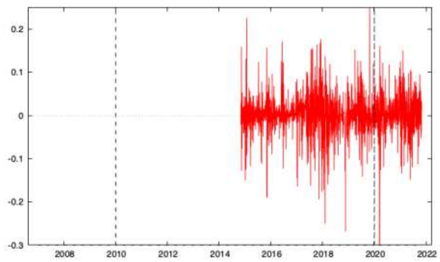
SPGold - price



SPGold - return



Bitcoin - price



Bitcoin - return

Figure 2 – Non ESG price (left) and return (right) plots.

As it can be noticed, both the DJSI and the SPClean prices show a declining trend during most part of the GFC (more evident for the latter) with a negative peak around 2008-2009, which turns into high volatility in the returns. The after-crisis period is instead characterized by a positive trend for the DJSI prices, while SPClean ones manifest a not unique pattern: the series tends to decline up to 2012-2013 and then it maintains this level with some fluctuations. Covid-19 outbreaks leads to a sharp fall of both ESG index prices, immediately followed by a steady rise for the DJSI and a less pronounced one for the SPClean. SPGreenBond prices show, instead, stable behavior during the whole sample span, with some fluctuation as reported in the return plot.

Non-ESG investments show some similarities: the equity index reflects quite accurately the DJSI behavior, with a declining trend during the GFC, followed by un upward pattern till the Covid-19 pandemic. The commodity index, instead, falls sharply during the GFC, then maintains a constant trend (with some fluctuation) until late 2014 where it declines suddenly. The Covid-19 impact introduces a new negative shock, which however is followed by an increasing trend.

As for the Gold price series, the impact of the financial crisis seems quite moderate, with an overall increasing trend up to 2012-2013. A slightly decline is then spotted with a subsequent steady but moderate rise till the Covid-19 subperiod, where a "peculiar" attitude is displayed. The negative impact seems to be delayed with respect to the other series and the magnitude is small, leading to the potential conclusion of safe haven properties.

Finally, for the Bitcoin price we refer to the only available periods which dates back from its institution (2014) up to the end of the time span here considered. In the pre-Covid period and increasing trend till 2018 can be identified, after this period the series declines. In the Covid-19 sample, the price rises quickly up to a peak at the end of 2020, followed by a sudden fall at the beginning of 2021.

Table 1 presents the main summary statistics for the return series under investigation: notably all series apart from SPGreenBond exhibit negative skewness. As for the excess of kurtosis, all series appear as leptokurtic, with the ESG ones and the DJ equity index with quite remarkable results.

Table 2 reports the main diagnostic test for the return series: 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). P-values are shown for the sake of simplicity. All series appear to be stationary, with ARCH/GARCH effects and are non-normal.

	Mean	Median	Min	Max	Std. Dev.	Skewness	Ex.Kurtosis
DJSI	0.00014344	0.00051038	-0.10604	0.088379	0.011468	-0.59014	10.924
SPClean	-7.4641e-05	0.00062229	-0.14973	0.18093	0.019111	-0.58228	12.526
SPGreenBond	1.9243e-05	2.2878e-05	-0.037822	0.068154	0.0051451	0.95112	19.957
DJ Global	0.00017002	0.00057717	-0.10907	0.098835	0.01118	-0.72044	12.493
SPGSCI Comm	-0.00017016	8.0703e-05	-0.12522	0.076166	0.014624	-0.58991	6.2028
SPGSCI Gold	0.00026734	0.00012561	-0.098112	0.085901	0.011202	-0.27619	6.1138
Bitcoin	0.0028650	0.0023295	-0.31595	0.24987	0.045749	-0.40370	5.1963

Table 1 Main summary statistics for the return series – Full sample (from 2007-01-01 to 2021-11-01)

	ADF p-value	KPSS p-value	PP p-value	ARCH p-value	DH p-value
DJSI	0	>0.10	0	0	0
SPClean	0	>0.10	0	0	0
SPGreenBond	0	>0.10	0	0	0
DJ Global	0	>0.10	0	0	0
SPGSCI Comm	0	>0.10	0	0	0
SPGSCI Gold	0	>0.10	0	0	0
Bitcoin	0	>0.10	0	0	0

Table 2 Main diagnostic tests for the return series – p-value reported.

5 Empirical results

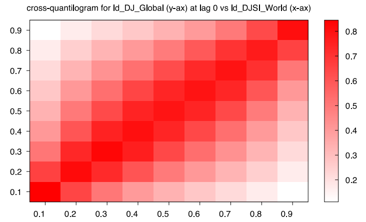
5.1 Cross-quantilogram analysis

We report the results of the cross-quantilogram approach in form of heatmaps, where quantile-hits in all combinations of deciles for the two series are considered. On the y-axis the quantiles for the non-ESG indices with a lag $k = 0, 1$ (representing, respectively, simultaneity and one-day lag effect) are reported, while on the x-axis the ESG indices ones are shown. The color scale from blue (negative correlation) through white (uncorrelation) to red (positive) is used to represent the magnitude of such spillover effect. Moreover, each cross-quantilogram is reported after a preliminary significance test: using the critical values obtained from the stationary bootstrap procedure with 1000 iterations and a size of 0.05, the correlation in Equation (2) is tested for significance (null hypothesis H0: $\hat{\rho}$=0), and only in case of no rejection the value of the cross-quantilogram is set to zero. We deem a series on the x-axis to be a safe haven with respect to the y-axis series, if for different time lags, null or negative correlation across the quantile combinations in the bottom left and on the right corner of the heatmaps is detected; similarly, we define a hedge or diversifier asset when, respectively, *light red* or white/blue shades appear as dominant in the heatmap.

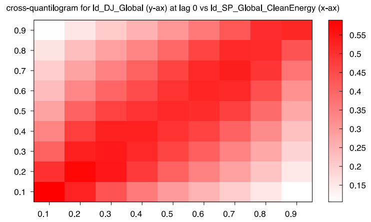
In Figure 3, in particular, the quantile cross-correlation considering *k=0* for the non-ESG asset is displayed: the DJSI shows a high positive correlation along the main diagonal with respect to the equity index, suggesting a strong co-movement not only in adverse market conditions (bottom left corner), but also in normal and favourable time. In this sense, the DJSI does not seem to belong to any category previously defined. The comparison with the SP GSCI Commodity Index still reports an overall positive correlation (more marked on the bottom left corner), but smaller in magnitude, opening the possibility for classifying the DJSI as a diversifier for the commodity index. The same line of reasoning is even more evident when considering DJSI versus the SP GSCI Gold series. Finally, DJSI appears to be uncorrelated with Bitcoin along most quantiles.

The SPClean follows a similar pattern, acting as a diversifier for the solely commodity market. The high positive correlation shown with DJ Global, especially on the main diagonal, does not allow for such categorization, which is instead guaranteed with respect to the SP GSCI Commodity Index and the SP GSCI Gold. The SP GreenBond shows, instead, a more peculiar tendency: the heatmap with respect to the DJ Global Index displays a weaker tone for positive correlation, which is here particularly marked on the lower quantiles. The same diversifier nature appears considering the quantile dependency with the SP GSCI Commodity Index. The comparison with respect to gold goes in this direction too; however, it is worth mentioning that the Green Bond index manifests a more marked positive correlation with gold than the other two ESG assets. Null correlation is instead detected with respect to Bitcoin for both SPClean and SPGreenBond.

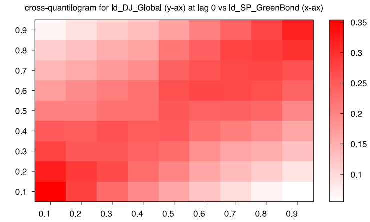
Coming to the cross-quantilogram with *k=1* for the non-ESG series, Figure 4 reports how most ESG assets still appear to be diversifier: the DJSI shows a small positive correlation over most quantile combinations with respect to the DJ Global. The same is still true for the SPClean, while the SPGreenBond shows positive correlation on the lower quantile combinations ($\alpha_{ESG} \in [0.1;\ 0.5]$; $\alpha_{Not\ ESG} \in [0.1;\ 0.3]$) and on the upper right corner, while the rest of the heatmap mostly indicates null correlation. The comparison with SP GSCI Commodity Index reveals again a similar pattern, confirming the potential nature of ESG indeces as diversifier.



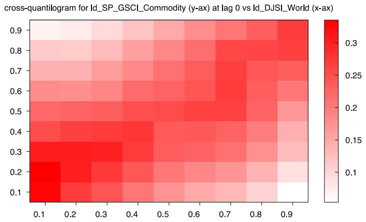
DJSI vs DJ Global (k=0)



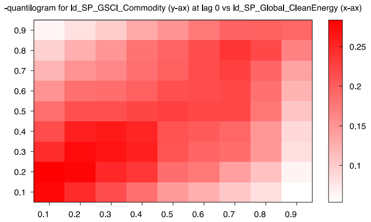
SPClean vs DJ Global (k=0)



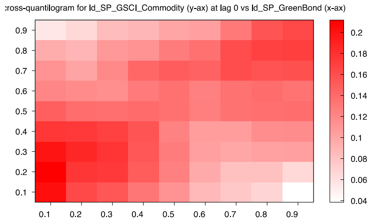
SPGreenBond vs DJ Global (k=0)



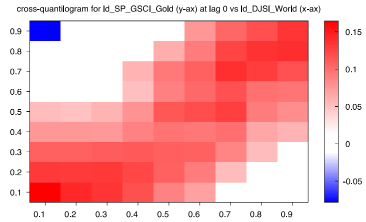
DJSI vs SP GSCI Commodity (k=0)



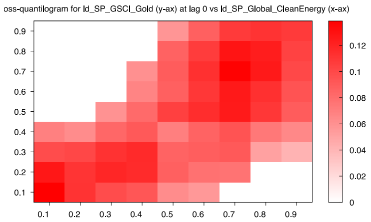
SpClean vs SP GSCI Commodity (k=0)



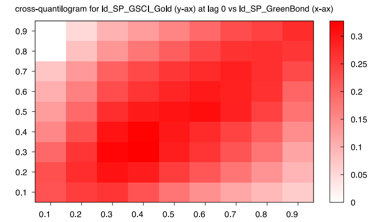
SPGreenBond vs SP GSCI Commodity (k=0)



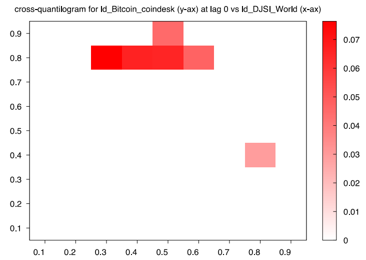
DJSI vs SP Gold (k=0)



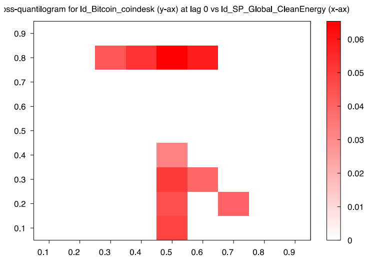
SPClean vs SP Gold (k=0)



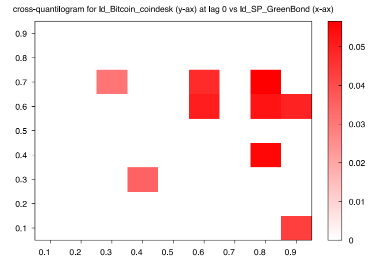
SPGreenBond vs SP Gold (k=0)



DJSI vs Bitcoin (k=0)



SPClean vs Bitcoin (k=0)

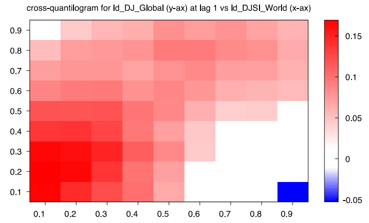


SPGreenBond vs Bitcoin (k=0)

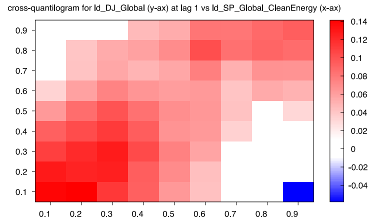
Figure 3 – Cross-quantilogram between ESG assets (DJSI first column, SP Clean Energy secon column, SP Green Bond third column) versus DJ Global, SP GSCI Commodity Index, SP GSCI Gold and Bitcoin at lag 0. Correlations are tested for significance at size 0.05, if insignificant these are set to zero. Stationary bootstrap with 1000 iterations is used.

Interestingly, some negative correlation is detected too, especially on the bottom right corner. Notice that this result is not at odds with the possible positive correlation on the opposite corner. Finally, null quantile correlation (with both positive and negative peaks) appears with respect to gold and Bitcoin, with the exception of Green Bond which exhibits an overall positive correlation with gold.

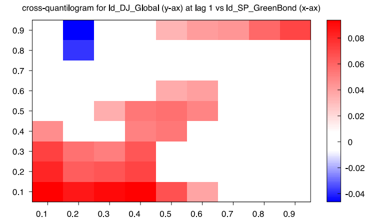
In sum, ESGs seem to exihibits diversifier properties with respect to equity and commodity markets, especially relevant when considering a day lag; in other words, equity or commodity indeces have a small positive influence on ESGs both instantaneously and after a day (the directionality goes from non-ESGs to ESGs).



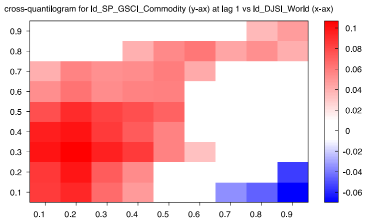
DJSI vs DJ Global (k=1)



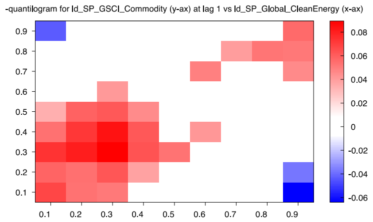
SPClean vs DJ Global (k=1)



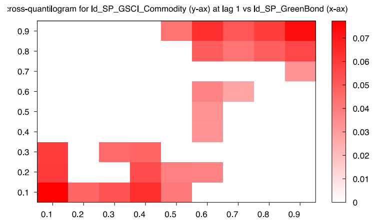
SPGreenBond vs DJ Global (k=1)



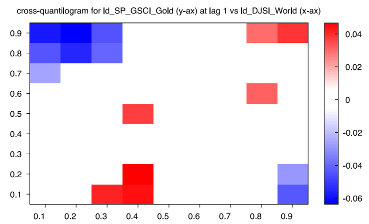
DJSI vs SP GSCI Commodity (k=1)



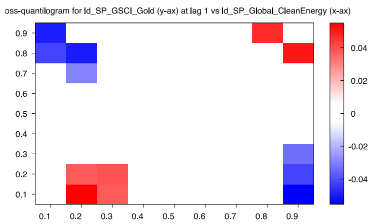
SPClean vs SP GSCI Commodity (k=1)



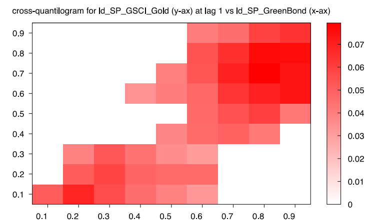
SPGreenBond vs SP GSCI Commodity (k=1)



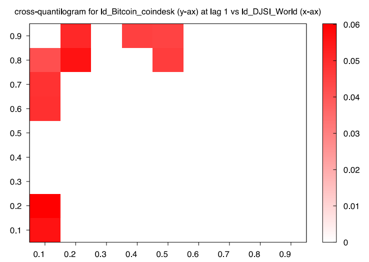
DJSI vs SP Gold (k=1)



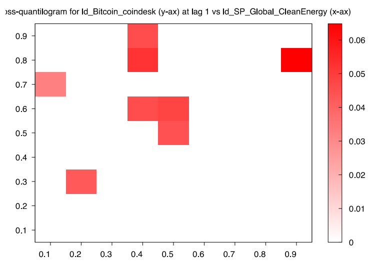
SPClean vs SP Gold (k=1)



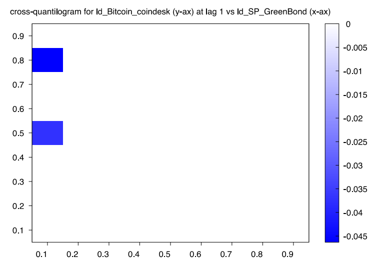
SPGreenBond vs SP Gold (k=1)



DJSI vs Bitcoin (k=1)



SPClean vs Bitcoin (k=1)



SPGreenBond vs Bitcoin (k=1)

Figure 4 – Cross-quantilogram between ESG assets (DJSI first column, SP Clean Energy secon column, SP Green Bond third column) versus DJ Global, SP GSCI Commodity Index, SP GSCI Gold and Bitcoin at lag 1. Correlations are tested for significance at size 0.05, if insignifant these are set to zero. Stationary bootstrap with 1000 iterations is used.

5.2 Quantile cross-correlation using rolling windows

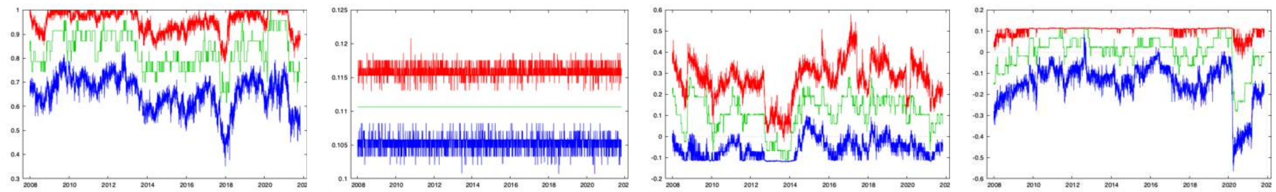
As pointed out among the others by Shazad et al. (2019) or Uddin et al. (2019), the cross-quantilogram analysis over a whole time span is a static picture of the reality which does not account for time-varying dynamics, *i.e.*, the cross-quantile dependence may be affected by the sample selected. To overcome this issue we provide a rolling window exercise: the cross-quantilogram is computed for selected quantile combinations over recursive samples of 261 days (a single year), obtained by simple shifting the window by a single day ahead till the end of the sample (01-11-2021).

Instead of considering the whole quantilogram, we will consider for simplicity the bottom left and right corner denoted by the combinations ($\alpha_{ESG} = 0.1$; $\alpha_{Not\ ESG} = 0.1$) and ($\alpha_{ESG} = 0.9$; $\alpha_{Not\ ESG} = 0.1$) respectively, using again lag $k = 0$, 1. Such choice reflects firstly the interest in discovering potential safe haven properties which may be even more hidden when considering the "static" representation in a considerably large time span; secondly it may be worthy of consideration to identify a peculiar time period where also the static representation may display such conditions. Moroever, we will consider only equity (Figure 5) and commodity index (Figure 6) as non-ESG ones since more suitable for a wider perspective of the phenomenon.

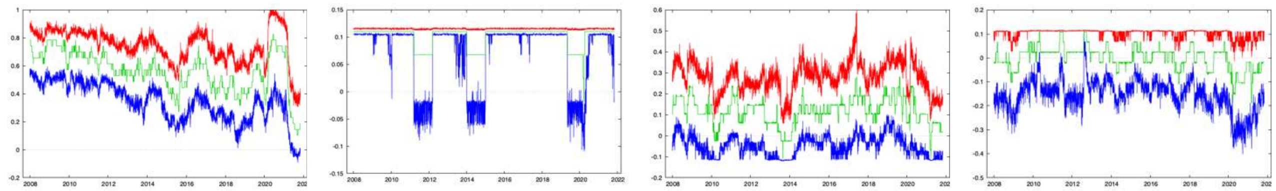
In particular, Figure 5 and Figure 6 display the dynamic cross-quantilogram for the related quantile combinations under the green line; the blue and red ones represent instead the 95% confidence interval limits under the hypothesis of null correlation. These value are derived using the stationary bootstrap with 1000 replications. The first column of Figure 5 shows how the cross-correlation along the bottom left corner with *k* = 0, maintain a positive value for both DJSI and SPClean versus the DJ Global series for the whole sample with some marked fluctuation during major financial turmoil events (*e.g.*, Covid-19 pandemics); the SPGreenBond instead crosses the zero axis of non correlation several times after 2014, with again some peaks spread across the sample. In the second column the bottom right corner of the heatmap is instead reported, with again null or negative correlation reached by the Green Bond after 2014, with outliers during both the sovereign debt crisis and the Covid-19 one. The third and the fourth columns report the result with *k* = 1, where a more distinct pattern emerges: all ESG indeces shows null or negative quantile cross-correlation in both quantile couples, with again some remarkable peak during 2020.

In Figure 6 the same analysis is reported with respect to the SP GSCI Commodity Index: this time the instantaneous response at ($\alpha_{ESG} = 0.1$; $\alpha_{Not\ ESG} = 0.1$) shows null or even negative correlation events even

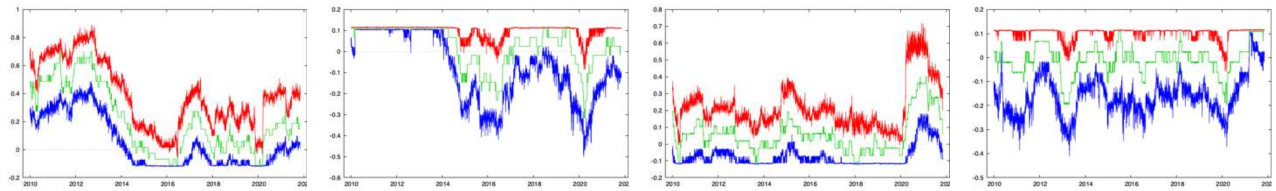
$(\alpha_{ESG} = 0.1;\ \alpha_{Not\ ESG} = 0.1)$; k=0 $(\alpha_{ESG} = 0.9;\ \alpha_{Not\ ESG} = 0.1)$; k=0 $(\alpha_{ESG} = 0.1;\ \alpha_{Not\ ESG} = 0.1)$; k=1 $(\alpha_{ESG} = 0.9;\ \alpha_{Not\ ESG} = 0.1)$; k=1



DJSI vs DJ Global



SP_CleanEnergy vs DJ Global



SP_GreenBond vs DJ Global

Figure 5 – Cross-quantilogram (green line) between ESG assets (DJSI first row, SP Clean Energy secon row, SP Green Bond third row) versus DJ Global at lag 0 and 1. A rolling window of 261 days is employed (a year), which advances on a daily bases. The red and blue lines represent respectively the upper and the lower limits of a 95% confidence interval built with 1000 replications stationary bootstrap. The first and third column report quantile combiations $(\alpha_{ESG} = 0.1;\ \alpha_{Not\ ESG} = 0.1)$, while the second and the fourth $(\alpha_{ESG} = 0.9;\ \alpha_{Not\ ESG} = 0.1)$.

for the DJSI and the SPClean . The same is even clearer for $(\alpha_{ESG} = 0.9;\ \alpha_{Not\ ESG} = 0.1)$. With $k = 1$, the ESGs tend to float around the zero value especially on the fourth column with negative correlation during 2020.

The time dynamics of the cross-quantilogram seems to suggest that quantile dependence is actually affected by the time span, with *plausible* safe haven conditions for Green Bond versus DJ Global or SP GSCI Commodity Index at $k = 0$ since both $(\alpha_{ESG} = 0.1;\ \alpha_{Not\ ESG} = 0.1)$ and $(\alpha_{ESG} = 0.9;\ \alpha_{Not\ ESG} = 0.1)$ simultaneously experience null or negative correlation; while DJSI and SP Clean Energy only at lag $k = 1$ of the non-ESG series.

To further investigate this possibility we reuse the static heatmap approach changing the reference sample: since the Covid-19 outbreak seems to be from the previous rolling window analysis a time span where negative correlation appear and, implicitly, corresponds to a well-motivated market turmoil event, we choose to restrict the series from 01-01-2020 to 01-11-2021.

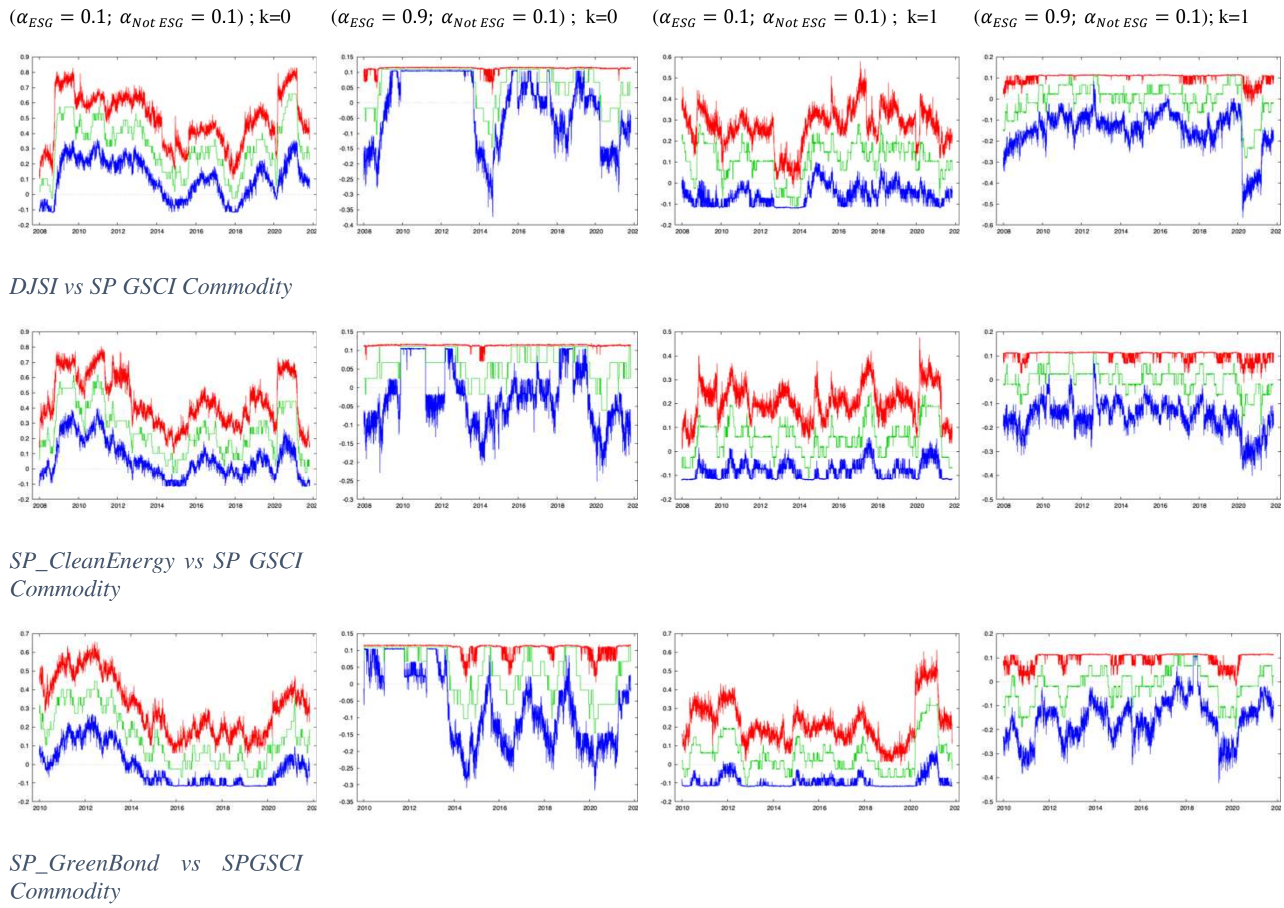
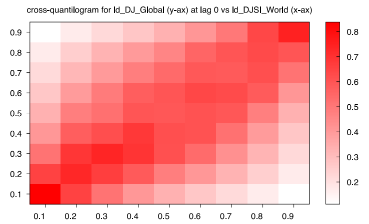


Figure 6 – Cross-quantilogram (green line) between ESG assets (DJSI first row, SP Clean Energy secon row, SP Green Bond third row) versus SP GSCI Commodity Index at lag 0 and 1. A rolling window of 261 days is employed (a year), which advances on a daily bases. The red and blue lines represent respectively the upper and the lower limits of a 95% confidence interval built with 1000 replications stationary bootstrap. The first and third column report quantile combiations ($\alpha_{ESG} = 0.1;\ \alpha_{Not\ ESG} = 0.1$), while the second and the fourth ($\alpha_{ESG} = 0.9;\ \alpha_{Not\ ESG} = 0.1$).

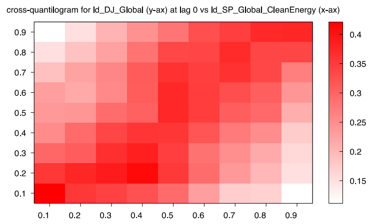
In Figure 7 we find the cross-quantilogram for the ESG versus the non-ESG assets at $k = 0$: the DJSI results are mostly in line with the previous heatmap analysis in Section 5.1; SPClean shows instead less correlation with respect the commodity index and gold; the SPGreenBond plots introduce some major changes. The comparison with DJ shows a small positive correlation on the bottom left and upper right corner opposite to small negative correlation on the bottom right corner and null correlation on the remaining quantile combinations. Even though this is not compatible with a safe haven good, this can potentially be seen as an hint for hedge properties. This becomes more evident when compared to the SP GSCI Commodity Index. On the other hand, positive correlation is detected when analyzing the directional predicatability with gold over the whole heatmap.

The main differences with the analysis in Section 5.1 appear however at $k = 1$: the plots in Figure 8 exhibit overall null correlation for the SPClean and DJSI. The latter presents, moreover, positive and negative correlation on the bottom left and right corner respectively. SP Greenbond this time has a mild positive correlation with DJ, while becomes mostly uncorrelated with the commodity market proxies.

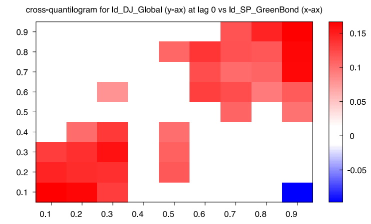
The cross-quantilogram heatmaps of ESGs versus Bitcoin report mainly null correlation, with some red or blue shade as in the case of SPGreenBond at lag 1.



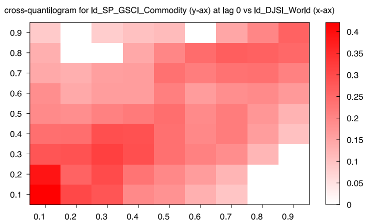
DJSI vs DJ Global (k=0)



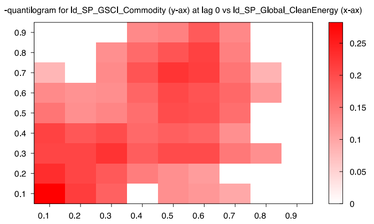
SPClean vs DJ Global (k=0)



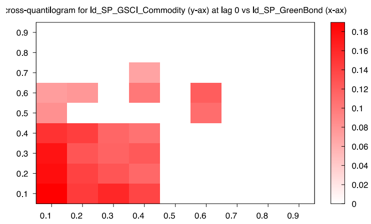
SPGreenBond vs DJ Global (k=0)



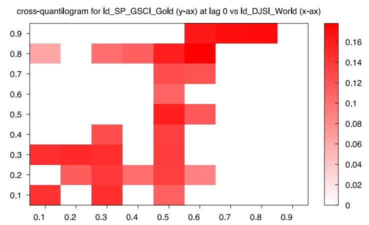
DJSI vs SP GSCI Commodity (k=0)



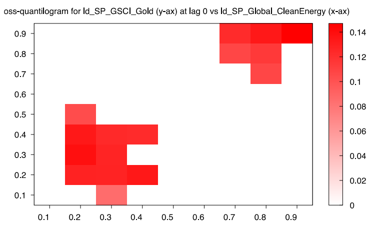
SpClean vs SP GSCI Commodity (k=0)



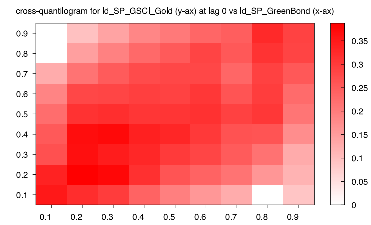
SPGreenBond vs SP GSCI Commodity (k=0)



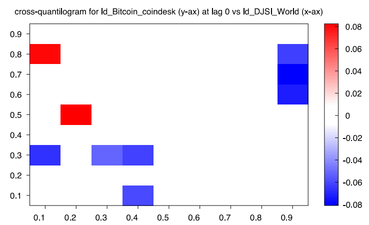
DJSI vs SP Gold (k=0)



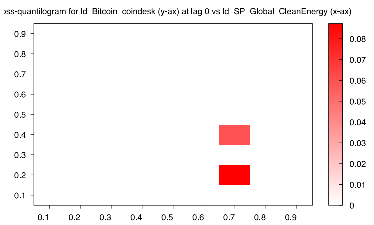
SPClean vs SP Gold (k=0)



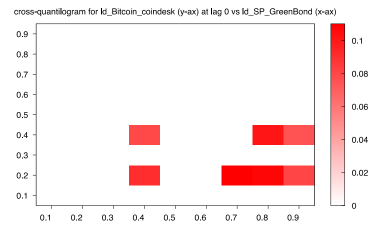
SPGreenBond vs SP Gold (k=0)



DJSI vs Bitcoin (k=0)

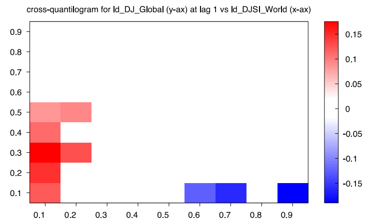


SPClean vs Bitcoin (k=0)

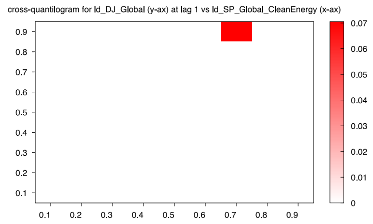


SPGreenBond vs Bitcoin (k=0)

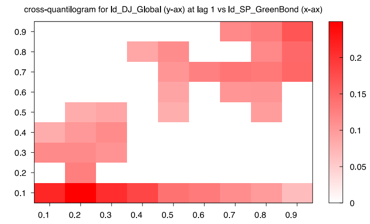
Figure 7 – Cross-quantilogram between ESG assets (DJSI first column, SP Clean Energy secon column, SP Green Bond third column) versus DJ Global, SP GSCI Commodity Index, SP GSCI Gold and Bitcoin at lag 0, during Covid-19 sub-period (from 01-01-2020 to 01-11-2021). Correlations are tested for significance at size 0.05, if insignifant these are set to zero. Stationary bootstrap with 1000 iterations is used.



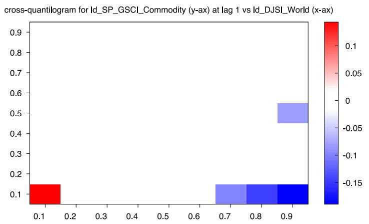
DJSI vs DJ Global (k=1)



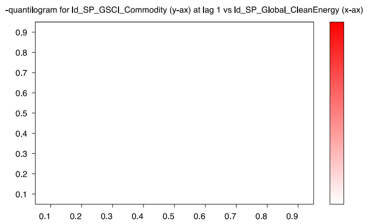
SPClean vs DJ Global (k=1)



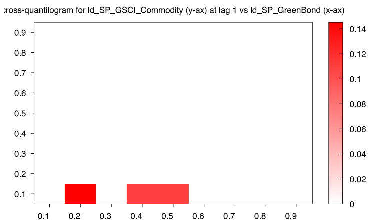
SPGreenBond vs DJ Global (k=1)



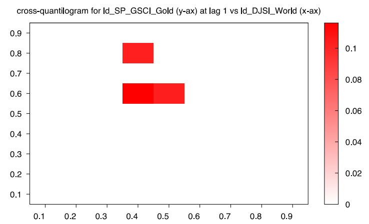
DJSI vs SP GSCI Commodity (k=1)



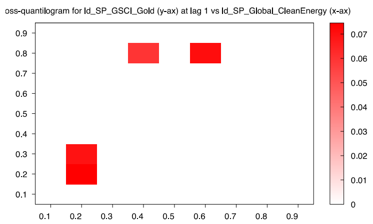
SPClean vs SP GSCI Commodity (k=1)



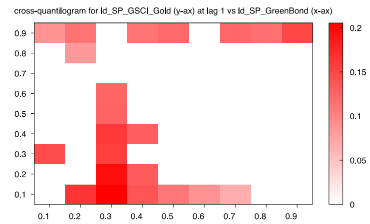
SPGreenBond vs SP GSCI Commodity (k=1)



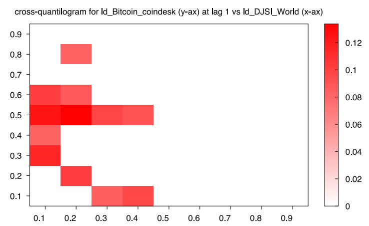
DJSI vs SP Gold (k=1)



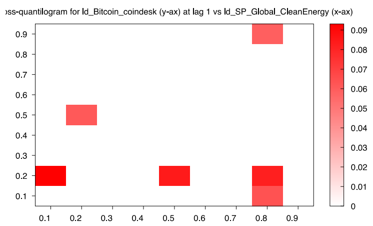
SPClean vs SP Gold (k=1)



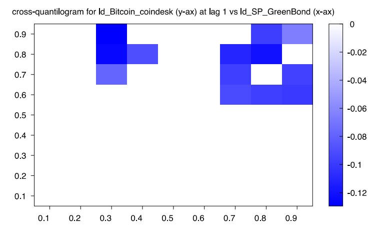
SPGreenBond vs SP Gold (k=1)



DJSI vs Bitcoin (k=1)



SPClean vs Bitcoin (k=1)



SPGreenBond vs Bitcoin (k=1)

Figure 8 – Cross-quantilogram between ESG assets (DJSI first column, SP Clean Energy secon column, SP Green Bond third column) versus DJ Global, SP GSCI Commodity Index, SP GSCI Gold and Bitcoin at lag 1, during Covid-19 sub-period (from 01-01-2020 to 01-11-2021). Correlations are tested for significance at size 0.05, if insignificant these are set to zero. Stationary bootstrap with 1000 iterations is used.

6. Discussion & Conclusion

The instability of financial markets owing to different financial crises has amplified uncertainty of international investments. Given this uncertainty, it becomes challenging for investors to accomplish diversification benefits. All these events encouraged international investors to look for different investments that would provide a potential hedging opportunity, resulting in an increased interest in the search for different safe haven assets. In this contest, sustainable investing experienced a significant growth in response to the requirements of stakeholders to achieve economic value via a reduction of the ESG risks. As a matter of the fact, the ongoing debate on sustainable investing has showed that firms with best ESG practices are more 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 pointed out the properties of ESG investments to lower downside risk and to be more resilient vis-à-vis conventional investments, especially during market turmoil. Moreover, during the recent Covid-19 pandemic, a shift in investor preferences towards sustainable investments has been documented. However, a question that remains unfold is whether investors can protect their wealth during economic downturn and/or diversificate/hedge their portfolio through selecting ESG investing.

In this paper, we address this aspect by studying the quantile correlation from conventional investment practices (equity index, gold, commodities and cryptocurrencies) to ESG ones using the cross-quantilogram approach. We find that no ESG asset, among those considered, can be deemed as safe haven during the various crises considered over the entire observation period (from 1st January 2007 to 1st November 2021). Conversely, our analysis shows that over the entire time span, all ESG assets considered represent an outstanding diversification asset. Futhermore, our findings allows us to compare the behavior of ESG assets to that of traditional safe haven assets namely, gold and Bitcoin, showing that in the period analized the ESG might be an hedge for Bitcoin.

When the observation period is narrowed down to the pandemic crisis, it emerges that with 1 day-lag the ESG investment can serve as a hedge for commodities and stock markets. Interestingly, the analysis of the quantile cross-correlation using rolling windows shows that during the period of the sovereign debt crisis, the green bond had a negative correlation exhibiting some weak safe haven properties.

Our evidence enlarges the debate on sustainable investing by providing valuable implication on how investors and portfolio managers can hedge their portfolio risks. The results provide important implications for risk management suggesting a better understanding of the type of links between assets. On the whole, investors have started considering sustainable investing as a new measure of value maximization and risk reduction. Consequently, althought some crisis, such as the pandemic ones, highlighted the importance of re-prioritizing the business agenda through a set of ESG initiations and actions, sustainale investment can no longer be considered a strategy for environmentally conscious investors, but instead, as a new hedging and diversification opportunity.

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