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Risk Management Opportunities between Socially Responsible Investments and Selected Commodities

Daniel Cupriak, Katarzyna Kuziak * and Tomasz Popczyk

Department of Financial Investments and Risk Management, Wroclaw University of Economics and Business, 53-345 Wroclaw, Poland; 165524@student.ue.wroc.pl (D.C.), 165660@student.ue.wroc.pl (T.P.)

* Correspondence: katarzyna.kuziak@ue.wroc.pl

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Abstract: Socially responsible investing (SRI) or sustainable, responsible, and impact investing is growing fast. The net total of SRI assets at the beginning of 2018 was USD 12.0 trillion [1]. There is extensive literature on SRI, but very little of it relates to portfolio construction and risk management combining SRI and commodities. In this paper, the authors pay attention to model volatility and dynamic conditional correlations between SRI investment and selected representative of commodities. We state the following hypothesis: the potential to create portfolio and risk management opportunities exists between SRI and commodities such as grain, precious metals, and industrial metals. To verify this, modeling of volatility and dynamic conditional correlation (DCC) between pair of elements is necessary. Empirical research conducted for the global market based on selected indices for SRI and commodities confirms this hypothesis. These results can improve asset selection in portfolio construction and allow investors to make more reasonable decisions.

Keywords: socially responsible investing (SRI), sustainable; responsible and impact (SRI) investing; DCC; GARCH; risk diversification

1. Introduction

Socially responsible investing (SRI) has become increasingly popular over the past decade. Sustainable and impact investing in the United States continues to grow and to make a difference. Investors now consider environmental, social, and governance (ESG) factors across USD 12 trillion worth of professionally managed assets. Compared to value of USD 639 billion in 1995 (when the US SIF Foundation first measured the size of the US sustainable and responsible investment universe), these assets have increased more than 18-times with a compound annual growth rate of 13.6 percent [1].

Socially responsible investing started to grow during the 1960s among the rising concerns about equality and the ongoing war. Within the next decades, as new social problems arose, the definition of social responsibility has been expanded to include human rights, global warming, working conditions, and environmental protection [2]. The selection of SRI assets may occur either through positive or negative screening [3]. The first is based on rating stocks by various criteria (e.g., CDP emission, energy reduction target, percentage of women on the board, percentage of independent directors, strict policies against child labor), and then selecting companies with the highest scores. Investors may also apply a balance across sectors. Contrastingly, negative screening simply excludes controversial sectors (e.g., coal mining, alcohol, tobacco, gambling, military).

The theoretical approach shows that although socially responsible behavior does not maximize the present value of cash flows, it maximizes the market value of the firm. This phenomenon occurs with investors having maximization interests other than wealth, causing an imbalance in demand and supply of SRI. Incorrect timing of employing SRI might also reduce market value [4]. Market-based research leads to the opposite conclusions. Applying an ESG screen to a stock portfolio provides high returns of up to 8.7% yearly. The best effect is obtained by avoiding both extremely high and extremely low ESG scores while applying various screens and the best-in-class approach [3]. Another paper investigating the influence of ESG screens on investment performance shows that in the United States and Asia-Pacific region, choosing companies with high or low ESG scores does not affect the rates of return, whereas in Europe, picking socially responsible companies leads to lower rates of return [5].

In this paper, SRI is classified as a traditional investment (like investing in common stocks), as opposed to alternative ones. Such investments may include, e.g., private equity or venture capital, real estate, commodities, art and antiques, distressed securities, and hedge funds. Despite the unique risks, alternative investments can be useful tools to improve the risk-return characteristics of an investment portfolio. Generally, alternative investments may have higher volatility than traditional investments, and they typically have low correlations with conventional asset classes. Furthermore, the specific benefit of investing in alternatives is the increased portfolio diversification and enhanced returns. However alternative investments do not have some of the same investment constraints and they have the potential for higher long-term performance compared to traditional investments. Therefore, including them in an investment portfolio results in lower volatility and a higher rate of return. In this sense, alternative investments are important in risk management, especially in the area of risk reduction.

Some authors take socially responsible investment as part of portfolio construction [6,7]. Markowitz [8] developed the mean-variance framework, which is used in calculation of a portfolio's risk, but also in its risk optimization. To calculate the risk of a portfolio, standard deviations and pairwise correlations are necessary (they are the elements of covariance construction). Nonetheless, unconditional standard deviations and constant correlations used to estimate the covariance matrix are questionable. Yet, the time-varying variances and correlations proposed by Engle [9] and GARCH(1,1), introduced by Bollerslev [10], solve this problem. The problem of constant correlation was also solved by the dynamic conditional correlation—GARCH (DCC–GARCH) proposed by Engle [11].

Because commodities have shown low or even negative correlation with equities, they are useful in hedging and portfolio diversification. Ibbotson Associates [12] found that including commodities in the portfolio opportunity set results in an increased efficient frontier. This supports the hypothesis that investing in different asset classes is desirable to diversify risk and finally leads to its reduction. This brings up an interesting question regarding what risk management opportunities exist between the SRI and popular commodities like metals and grain. Answers to this can help investors make more informed investment decisions.

The remainder of the paper is organized as follows: Section 2 presents the literature review and develops the research hypothesis, Section 3 outlines the methods and data, Section 4 discusses the findings, and the last section comprises the conclusions.

2. Literature Review

This section presents a short literature review of papers that focus directly on the volatility dynamics between SRI and other commodities like grain and metals.

Typical investors focus on the optimal risk-return portfolio through constantly analyzing information and using diversification, finally making the market more efficient. However, there has been little attention paid to the impact of their behavior on society. For a sustainable economy, there is a need to invest in assets that compromise social and environmental stability. Sustainable investment means the integration of environmental, social, and governance factors in the investment decision-making process [13]. Markowitz portfolio theory does not take into consideration the role played by the investment community in managing global risks. It uses risk and return as sole criteria, with the assumption that investors are rational and seek the highest return at the lowest level of risk [8]. However, research has shown that ethical (socially responsible) investors are willing to give up a portion of their financial returns for the increased utility provided by investments in assets that increase the social and environmental stability [14,15]. Moreover, various studies have highlighted better rates of return and reduced risk for socially responsible investments [16–19]. SRI aims at long-term rates of return by investing in companies that meet certain baseline standards of ESG responsibilities. Beal, Goyen, and Phillips consider three potential motives for SRI—superior financial returns, non-wealth returns, and social change. These motivations are neither exclusive nor exhaustive. In their proposal, an additional argument called the 'degree of ethicalness' must be inserted into the utility function of the investment [20]. Therefore, the classical portfolio theory may be inadequate for making socially responsible investments, and there is a need to search for other solutions.

There is a lot of literature which compares SRI and conventional investments. Some researchers confirmed no statistically significant difference [21–23] between the risk-adjusted return of SRI and conventional investments, while others proved similarities [24]. The correlations between SRI indices and conventional indices are high [25].

On the other hand, many authors study whether including commodities in a portfolio really improves the diversification effect and, finally, the risk-return performance. Some papers, such as Skiadopoulos [26], investigate this topic. Most papers empirically confirmed the existence of diversification benefit [27–29], while others drew different conclusions [30–33].

There is very little research on the volatility dynamics of socially responsible investments and correlations between the stock prices of socially responsible companies and commodities like grain, precious metals, and industrial metals. Sadorsky [34] investigated volatility and correlations between DJSI, S&P 500, and two commodities: gold and oil. His findings indicate, from a risk management perspective, that SRI offers very similar results in terms of dynamic correlations, hedge ratios, and optimal portfolio weights as investing in the S&P 500.

Hoti et al. [35,36] empirically analyze the conditional volatility (conditional variance) associated with investing in ESG companies. They estimate univariate GARCH(1,1) models to model time-varying risks for a number of different ESG indices and find that GARCH(1,1) models adequately capture the volatility dynamics in ESG indices. They find strong evidence of volatility clustering, with both short- and long-run persistence of shocks to the index rates of return. However, they do not investigate the dynamic correlation between the ESG indices and other assets.

In this paper, the following hypothesis was tested: risk management opportunities exist between the SRI and commodities such as grain, precious metals, and industrial metals.

The paper contributes to the literature in two areas. Firstly, it provides an extension to a number of indices—regional, global socially responsible, and commodity indices (grain, precious and industrial metals)—by taking into account current events in modeling volatility and dynamic conditional correlations. Table A1 (Appendix A) describes the indices selected for empirical investigation. Secondly, the paper fills the existing gap in the studies combining SRI and grain or industrial metals. To refine our analysis, we show how correlations evolved during the observed period. To this effect, we use the dynamic conditional correlation method (DCC–GARCH) developed by Engle [11] and its extension, the copula–DCC–GARCH approach.

Analysis of the states of the sustainable investments and commodity market based on the conditional dependence structure using DCC–GARCH and the copula–DCC–GARCH methodology allows addressing the question of whether the dependence between sustainable investments and commodity market is stable or if it undergoes changes.

3. Materials and Methods

In this paper, a GARCH model is used to model volatility and dynamic conditional correlations between a stock price index comprised of socially responsible companies and the grain index, precious metals index, and industrial metals index. Following the research of Sadorsky [34], who found that the dynamic conditional correlation model fits the data best, this model is also used in this paper to verify the potential of portfolio diversification.

Two-stage empirical research was necessary to verify the research hypothesis. The DCC model is a dynamic specification based on conditional correlations within such models as, e.g., GARCH (developed by Engle [11], Engle and Sheppard [37], and Tse and Tsui [38]). It allows simultaneous modeling of the variances and conditional correlations of several series. The estimation consists of two steps. Firstly, the conditional variance of each variable using, e.g., GARCH procedure is estimated. Secondly, the time-varying correlations are modeled relying on lagged values of residuals and covariance matrices. After that, conditional covariance matrix is found by using conditional standard deviations and dynamic correlations.

The conditional variances for an individual asset can be obtained from the univariate GARCH(1,1) model.

$$r_t = \mu + \varepsilon_t = \mu + \sqrt{h_t} z_t \ldots z_t \sim N(0,1) \tag{1}$$

Under GARCH specification, the time-varying conditional volatility is a function of its own past lag: one term plus the past innovations, and using GARCH(1,1) it can be modeled as

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \ldots \tag{2}$$

$$V_L = \frac{\omega}{1 - \alpha - \beta} \tag{3}$$

$$\omega > 0, \quad \alpha \geq 0, \quad \beta \geq 0, \quad \alpha + \beta < 1. \tag{4}$$

In Equation (1), r_t is the return and z_t is the random error term with conditional variance h_t. Equation (2) specifies the GARCH(1,1) process. In Equation (3), the long-term variance (V_L) is defined. The usual GARCH restrictions of non-negativity and imposed stationarity, such as non-negativity of variances (Equation (4)) are applied. The sum of α and β coefficients is a measure of persistence of volatility shocks and is expected to be less than 1. A sum of coefficients higher than 1 means the shock has an explosive effect.

$$\ldots X_t = \mu + \varepsilon_t \ldots\ldots\ldots \varepsilon_t \mid F_{t-1} \sim N(0, D_t R_t D_t) \tag{5}$$

$$\ldots D_t^2 = diag\{H_t\} \tag{6}$$

$$H_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i H_{i,t-1} \tag{7}$$

$$z_t = D_t^{-1} \varepsilon_t \tag{8}$$

$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2} \tag{9}$$

$$Q_t = \Omega + \alpha z_{t-1} z'_{t-1} + \beta Q_{t-1}, \qquad \Omega = \bar{R}(1 - \alpha - \beta) \tag{10}$$

where D_t = diag{} in Equation (6), diag{} is a matrix operator creating a diagonal matrix with the vector along the main diagonal, and R_t in Equation (5) is a dynamic correlation matrix. R in Equation (10) is the unconditional covariance of the standardized residuals resulting from the univariate GARCH equation. The parameters α and β are non-negative with a sum of less than unity.

In this study, the authors considered GARCH(2,1); GARCH(1,2) and GARCH(1,1) with normal and Student's *t*-distributions; and the DCC with multivariate normal, Laplace and Student's *t*-distributions. The following combinations were analyzed:

- normal—multivariate Student's *t*,
- Student's *t*—multivariate normal,
- Student's *t*—multivariate Student's *t*,

- normal—multivariate Laplace,
- Student's t—multivariate Laplace.

Since the differences in results were not significant, we decided to present only the results of the standard model DCC(1,1)–GARCH model with normal and multivariate normal distribution.

However, this assumption is still unrealistic because we observed that asset returns are skewed, leptokurtic, and asymmetrically dependent. These difficulties can be treated as a problem of copulas. The copula functions were introduced for the first time by Sklar in 1959 in the article Fonctions de repartition à n dimensions et leurs marges. A copula is a function that links univariate marginals to their multivariate distribution.

The process of identifying the states of financial and commodity market and analyzing their temporal evolution was based also on the conditional dependence structure using a copula–DCC–GARCH methodology with normal and Student's t-distributions. In this approach, multivariate joint distributions of the return vector $\mathbf{r}$ conditional on the information set available at time $t - 1$ are modeled using the conditional copulas introduced by Patton [39,40]. The model parameters were estimated through maximum likelihood method in two steps. In the first step, univariate rates of return $\mathbf{r}_t$ are modeled using a GARCH process, and the conditional variance is estimated. The dependence structure of the margins is then assumed to follow a Gaussian and Student's t copula with conditional correlation matrix R_t. In the second step, the dynamics of R_t are modeled with the use of the dynamic conditional correlation model DCC, and the parameters for the conditional correlation, given by the parameters of the first stage, are estimated. The copula–DCC–GARCH approach allows flexibility in the choice of marginal distributions and dependence structures. To validate the model, we used the Jarque Bera test statistic for residuals and squared residuals in order to test the null hypothesis that the data are normal against the alternative of non-normality.

Estimation of the parameters of the DCC–GARCH and copula–DCC–GARCH models was executed using the maximum likelihood method. All calculations were completed using R environment with the rmgarch package (cran.r-project.org/web/packages/rmgarch).

4. Results

4.1. Dataset

The data used in this study comprise weekly logarithmic rates of return of selected indices from 12 October 2012, through 4 October 2019. It is a compromise between the availability of data (some ESG indices were introduced to the market only recently) and the requirements of the estimation procedure. To eliminate any errors in daily data, weekly returns were used. The weekly rate of return was calculated as a logarithmic rate by comparison of the Friday–Friday values. The following indices were analyzed (for a description, see Table A1 (Appendix A)):

- 2 ESG indices for the global market—Stoxx Global ESG Impact, Dow Jones Sustainability World Index;
- 3 ESG indices for the European market—Stoxx Europe Industry Neutral, Stoxx Europe ESG Leaders Select 30, Dow Jones Sustainability Europe;
- 2 ESG indices for the US market—Dow Jones Sustainability US Composite Index, S&P 500 ESG Index;
- 2 non-ESG indices—Euro Stoxx Select Dividend 30, SP 500;
- 3 commodity indices (Dow Jones Commodity Index Industrial Metals, Dow Jones Precious Metals Index, Dow Jones Commodity Grains Index).

The data for ESG indices and the Stoxx Europe Leaders Index was obtained from Reuters Datastream (datastream.thomsonreuters.com/). The data for commodity indices was gathered from S&P Dow Jones Indices website (us.spindices.com) and the time series for SP 500 was downloaded from stooq.pl.

The descriptive analysis and graphics of the used data based on the results presented in Table 1 show that standard deviations of commodity indices are higher than these of the stock indices and the mean rate of return for commodities is negative. It is observed that skewness is negative for almost all the analyzed indices except for the industrial metal index and positive excess kurtosis values, which are generally higher than 0. This suggests that the distributions of the index returns are leptokurtic (the presence of fat tails). Since skewness is different from zero and there is high excess kurtosis, the data distribution shows the characteristics of non-normality. This is supported by the results of the Jarque–Bera test. Since the probability values of Jarque–Bera test are lower than 0.01 (99%, confidence level) for almost all the indices except the industrial metals index, it shows non-normality. The results indicate the varying volatility (higher for commodities, lower for stock indices) and the non-normality of weekly logarithmic rates of return of the indices selected for the study.

Table 1. Descriptive statistics.

	Mean	**Std. Dev.**	**Skewness**	**Kurtosis**	**Jarque–Bera stat. (*p*-value)**
DJS Europe	0.0011	0.0206	−0.3496	2.4	96.05 (0)
DJS US	0.0019	0.0179	−0.6971	2.462	123 (0)
DJ Commodity Index Grains	−0.0015	0.0251	−0.047	1.098	18.66 (0.0025)
DJ Commodity Index Industrial Metals	−0.0005	0.0221	0.1484	0.4838	4.954 (0.0745)
DJ Commodity Index Precious Metals	−0.0017	0.0474	−0.1853	1.402	32.35 (0.0005)
GSLI	0.0012	0.0183	−0.4127	1.231	33.79 (0)
S&P500	0.0019	0.0176	−0.7726	2.619	142.2 (0)
S&P500 ESG	0.0019	0.0175	−0.7964	2.773	157.3 (0)
Stoxx Europe IN	0.0009	0.0209	−0.33	2.241	83.94 (0)
Stoxx Europe ESG Leaders	0.0006	0.0189	−0.3271	2.253	84.66 (0)
Euro Stoxx Select Dividend 30	0.0008	0.022	−0.1131	1.369	29.6 (0)
Stoxx Global ESG Impact	0.0013	0.0174	−0.6521	1.772	74.45 (0)

Before estimation of the volatility model, the stationarity, autocorrelation, and ARCH effect for the time series were tested. Testing indicated that the time series of the weekly logarithmic rates of return are (detailed results are presented in table A2 (Appendix A))

- Stationary;
- For most indices, autocorrelation exists in returns and in squared returns—only for commodity indices is the null hypothesis not rejected (there is no autocorrelation in returns and in squared returns present);
- For most indices, the ARCH effect is present—only for metals is the null hypothesis not rejected (there is no ARCH effect).

4.2. *Volatility and Dynamic Conditional Correlation*

To model volatility and persistence of selected indices, we apply the GARCH(1,1) model. Table 2 presents the estimation results.

Table 2. GARCH(1,1) parameters.

	Estimate	**Std. Error**	***t* Value**	**Pr (>|*t*|)**
		DJS Europe		
μ	0.001355	0.000923	1.4688	0.141900
ω	0.000025	0.000016	1.5587	0.119068
α	0.128621	0.052574	2.4465	0.014427
β	0.813363	0.076869	10.5812	0.000000
		DJS US		
μ	0.002344	0.000964	2.43118	0.015050
ω	0.000056	0.000075	0.75441	0.450604
α	0.186019	0.160194	1.16121	0.245556
β	0.646293	0.365139	1.76999	0.076729
		Euro Stoxx Select Dividend 30		
μ	0.000902	0.001049	0.86019	0.389684

ω	0.000024	0.000019	1.26074	0.207403
α	0.079084	0.038602	2.04869	0.040492
β	0.870998	0.068637	12.68989	0.000000
Stoxx Europe Industry Neutral				
μ	0.001219	0.000940	1.2976	0.194438
ω	0.000031	0.000020	1.4955	0.134774
α	0.138452	0.057707	2.3992	0.016431
β	0.794510	0.088570	8.9704	0.000000
Stoxx Europe ESG Leaders				
μ	0.001032	0.000890	1.1599	0.246087
ω	0.000051	0.000030	1.6804	0.092889
α	0.187059	0.071726	2.6080	0.009108
β	0.681275	0.126732	5.3757	0.000000
S&P 500 ESG				
μ	0.002266	0.000879	2.57832	0.009928
ω	0.000047	0.000044	1.07133	0.284021
α	0.154973	0.084964	1.82399	0.068154
β	0.696988	0.204795	3.40335	0.000666
Dow Jones Commodity Index Precious Metals				
μ	−0.002108	0.002130	−0.98957	19.82116
ω	0.000082	0.000058	1.40912	0.158798
α	0.079973	0.033522	2.38567	0.017048
β	0.887014	0.044751	19.82116	0.000000
Dow Jones Commodity Index Industrial Metals				
μ	−0.000455	0.001146	−0.39734	0.691118
ω	0.000024	0.000030	0.80580	0.420360
α	0.034342	0.027151	1.26486	0.205923
β	0.917218	0.072335	12.68016	0.000000
Dow Jones Commodity Index Grains				
μ	−0.001260	0.001358	−0.928406	0.353197
ω	0.000005	0.000000	182.297927	0.000000
α	0.000024	0.001117	0.021198	0.983088
β	0.992316	0.000829	1196.821063	0.000000

The estimation of the GARCH(1,1) model shows that both the ARCH term alpha (short-run persistency of shocks) and the GARCH term beta (long-run persistency of shocks) are significant for most indices, indicating the impact of shocks on volatility. This means that conditional variance has correlation with lagged conditional variance and lagged squared disturbance. The sum of ARCH and GARCH terms, $\alpha + \beta$, is less than one, indicating that the volatility shocks are quite persistent. The financial implication of these coefficients for investors is that the volatility of the index's rate of return exhibits clustering.

The alpha parameter indicates the sensitivity of the index *j* following a volatility shock of the index *i*, whereas beta indicates the persistence of the index *j* following a volatility shock of the index *i*. Interpretation of the results presented in Table 2 is as follows. The volatility of the ESG indices are, on average, close to zero (0.001–0.002), while for the commodity indices, they are also negative (−0.002 to −0.0004). In addition, the ESG indices are more sensitive to their own volatility shocks compared to the volatility shocks of the commodity indices. Regarding the persistence of shocks, we find that the impact of volatility of the commodity indices on themselves is more persistent and amounts to around 88%–99% compared to the persistence of volatility shocks of the ESG indices on themselves, which amounts to around 69%–80%.

Before we start the analysis of the evolution of conditional correlations, we removed all statistically insignificant pairs of indices (see Table A6 (Appendix B)).

In the last ten years for commodities and the financial market, three main periods may be observed:

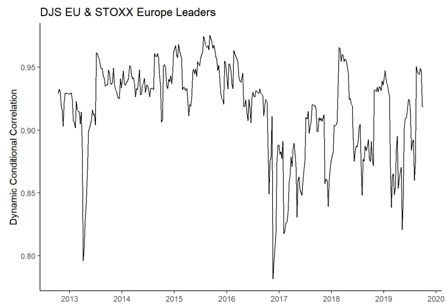
- January 2010–July 2011 (economic growth);

- August 2011–December 2015 (a collapse in the metals market);
- January 2016–December 2017 (economic growth in metals and financial markets).

Figure 1 shows the evolution of conditional correlations for statistically significant pairs of indices.

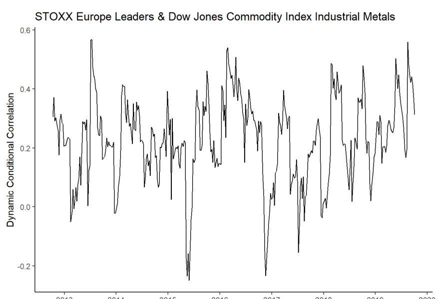
In most cases (Figure 1), we observe a statistically significant increase in correlation for a pair of indices for the first period (after 2010). A detailed analysis is as follows:

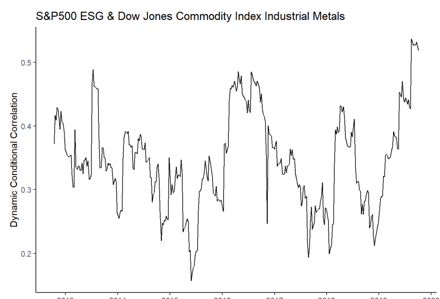
1. For the ESG–ESG relationship, one pair of indices (out of 5) showed statistically significant high conditional correlation. In the last year, this correlation has been weakening, but still remains close to 1.
2. In the case of the ESG–non-ESG relationship, two pairs of indices (out of 5) show statistically significant high conditional correlation (close to 1). For the European market, we observed two periods where the correlation was weakening considerably, mainly in the years 2013—a drop to 0.4 (the problem of the banking sector in the EU)—and in 2016/2017, a drop by −0.2 (the start of economic growth). For the American market, there were few periods where correlation was weakening but still remained high. The level of correlation is higher for the American market comparing to the European one.
3. Eight pairs of indices (out of a total of 21) for the ESG–commodities relationship showed statistically significant low and medium (lower than 0.5) conditional correlation.
    a. The ESG—precious metals relationship is characterized by low correlation (less than 0.15). Four pairs of indices (out of seven) showed a growth in correlation in 2013–2015 (the beginning and the end of the downturn period on the metals market) and also in 2018, but of not more than around 0.1. The evolution of conditional correlations for the European market as represented by three indices looks very similar. For the American market, the level of correlation is higher—even more than 0.3.
    b. For the ESG—industrial metals relationship, two pairs of indices (out of seven) behave similarly for the European and American markets, but there are substantial differences. For the European indices, we observed three periods where the correlation is higher than 0.5, mainly in 2013 (the collapse period of the metals market), 2016 (the economic growth period in the metals and financial markets), and 2019, and also lower than 0 (−0.5) in 2015 and 2016–2017 (two drops). For the American indices, we observed one period where the correlation is higher than 0.5, mainly in 2019. Moreover, the volatility is higher in the case of European market.
    c. The ESG—grains relationship is weaker compared to two earlier described relationships, around 0.06. Two pairs of indices out of seven behave similarly for the European and American markets, but there are substantial differences in some subperiods. For both markets, we observed one period where the correlation is higher than 0.06, mainly in 2013 (one pick) and 2016–2017 (the economic growth period on metals market and financial markets), and also lower than 0.02 in 2015 (the collapse period on metals market). Moreover, volatility is considerably lower in the case of the American market.

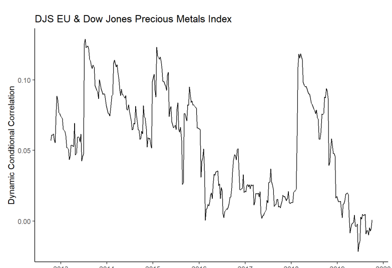

DJS EU & STOXX Europe Leaders
Dynamic Conditional Correlation
0.80
0.85
0.90
0.95
2013 2014 2015 2016 2017 2018 2019 2020


STOXX Europe Leaders & Euro Stoxx Select Dividend 30
Dynamic Conditional Correlation
0.80
0.85
0.90
0.95
2013 2014 2015 2016 2017 2018 2019 2020


DJS US & S&P500
Dynamic Conditional Correlation
0.976
0.980
0.984
0.988
2013 2014 2015 2016 2017 2018 2019 2020


STOXX Europe Leaders & Dow Jones Commodity Index Industrial Metals
Dynamic Conditional Correlation
-0.2
0.0
0.2
0.4
0.6
2013 2014 2015 2016 2017 2018 2019 2020


S&P500 ESG & Dow Jones Commodity Index Industrial Metals
Dynamic Conditional Correlation
0.2
0.3
0.4
0.5
2013 2014 2015 2016 2017 2018 2019 2020


DJS EU & Dow Jones Precious Metals Index
Dynamic Conditional Correlation
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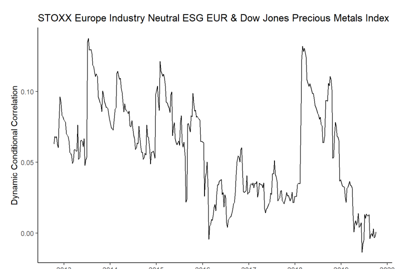
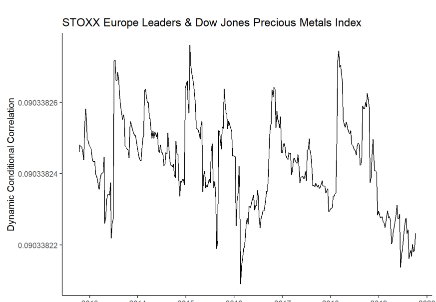
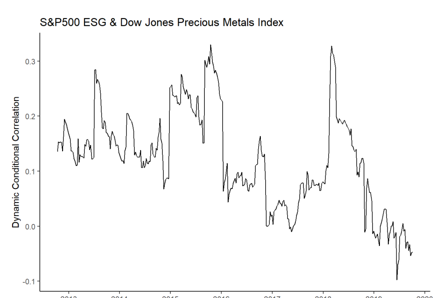
0.05
0.10
2013 2014 2015 2016 2017 2018 2019 2020


STOXX Europe Industry Neutral ESG EUR & Dow Jones Precious Metals Index
Dynamic Conditional Correlation
0.00
0.05
0.10
2013 2014 2015 2016 2017 2018 2019 2020


STOXX Europe Leaders & Dow Jones Precious Metals Index
Dynamic Conditional Correlation
0.09033822
0.09033824
0.09033826
2013 2014 2015 2016 2017 2018 2019 2020


S&P500 ESG & Dow Jones Precious Metals Index
Dynamic Conditional Correlation
-0.1
0.0
0.1
0.2
0.3
2013 2014 2015 2016 2017 2018 2019 2020

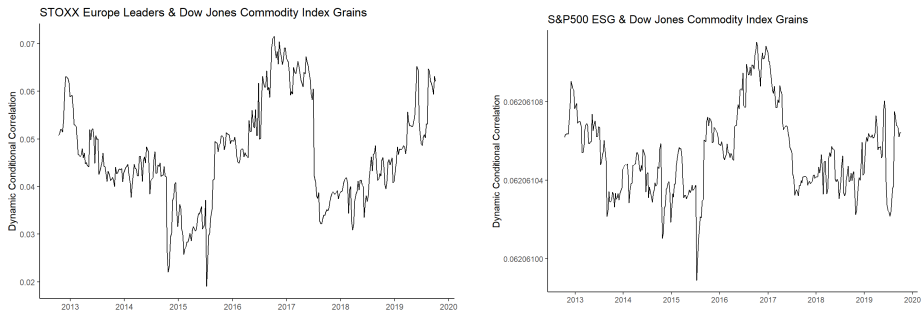


Figure 1. Dynamic conditional correlation (DCC) evolution results.

Detailed results of DCC estimation are presented in Tables 3–5.

Table 3. DCC estimation results.

	Estimate	Std. Error	*t* Value	Pr (>|*t*|)
DJS Europe and Stoxx Europe ESG Leaders				
Dcca	0.092053	0.024236	3.7982	0.000146
Dccb	0.820905	0.046229	17.7574	0.000000
Stoxx Europe ESG Leaders and Euro Stoxx Select Dividend 30				
Dcca	0.060171	0.018470	3.25775	0.001123
Dccb	0.849697	0.039364	21.58559	0.000000
DJS US and S&P 500				
Dcca	0.013889	0.006376	2.1782	0.029388
Dccb	0.974591	0.017620	55.3116	0.000000
Stoxx Europe ESG Leaders and DJ Commodity Index Industrial Metals				
Dcca	0.098396	0.033519	2.93555	0.003330
Dccb	0.713455	0.067294	10.60204	0.000000
S&P500 ESG and DJ Commodity Index Industrial Metals				
Dcca	0.030847	0.022086	1.39668	0.162511
Dccb	0.929136	0.033460	27.76848	0.000000
DJS Europe and DJ Commodity Index Precious Metals				
Dcca	0.008395	0.019347	0.43394	0.664332
Dccb	0.958185	0.063344	15.12664	0.000000
Stoxx Europe Industry Neutral and DJ Index Precious Metals				
Dcca	0.008955	0.021058	0.42525	0.670653
Dccb	0.948135	0.061708	15.36486	0.000000
Stoxx Europe Leaders and DJ Index Precious Metals				
Dcca	0.000000	0.000059	0.000075	0.999940
Dccb	0.918458	0.357601	2.568391	0.010217
S&P500 ESG and DJ Index Precious Metals				
Dcca	0.022400	0.017380	1.28885	0.197449
Dccb	0.932937	0.065525	14.23785	0.000000
Stoxx Europe Leaders and DJ Commodity Index Grains				
Dcca	0.003321	0.018948	0.175273	0.860865
Dccb	0.953796	0.020143	47.351902	0.000000
S&P500 ESG and DJ Commodity Index Grains				
Dcca	0.000000	0.000202	0.000043	0.999966
Dccb	0.946848	0.759758	1.246250	0.212673

The results in Table 3 indicate that the values of Dccb parameters generally range from 0.94 to 0.97, which indicates high volatility of conditional correlation. With slightly lower Dccb values in the range 0.71–0.85, a lower volatility of conditional correlation may be noticed compared to the previous case, but it seems that a relationship between the correlation values in different periods still exists.

These estimated Dcca and Dccb parameters to sum to a value which is less than 1, indicating that the dynamic conditional correlations are undergoing mean reversion process.

In order to test the validity of the GARCH model, we ensured that the standardized residuals and squared standardized residuals were normally distributed. Tables A4–A6 of the residual normality Jarque–Bera test were included in the Appendix.

Results of the copula–DCC–GARCH (Gaussian distribution) in Table 4 are similar to DCC–GARCH. The results of copula–DCC–GARCH (Student's *t*-distribution) in Table 5 are more promising—they need further deep investigation. Residual diagnostic tests on the standardized residuals and squared standardized residuals for the DCC models presented in Tables A5 and A6 show no statistically significant evidence of normality in most cases.

Table 4. Copula–DCC–GARCH (Gaussian) estimation results.

	Estimate	Std. Error	*t* Value	Pr (>|*t*|)
DJS Europe and Stoxx Europe ESG Leaders				
Dcca	0.092053	0.024227	3.7996	0.000145
Dccb	0.820905	0.046120	17.7992	0.000000
Stoxx Europe ESG Leaders and Euro Stoxx Select Dividend 30				
Dcca	0.060171	0.018632	3.22950	0.001240
Dccb	0.849697	0.039899	21.29618	0.000000
DJS US and S&P 500				
Dcca	0.013889	0.006312	2.20026	0.027789
Dccb	0.974591	0.017345	56.18803	0.000000
Stoxx Europe ESG Leaders and DJ Commodity Index Industrial Metals				
Dcca	0.098396	0.033597	2.92869	0.003404
Dccb	0.713455	0.067675	10.54240	0.000000
S&P500 ESG and DJ Commodity Index Industrial Metals				
Dcca	0.030847	0.022175	1.39109	0.164198
Dccb	0.929136	0.033097	28.07300	0.000000
DJS Europe and DJ Commodity Index Precious Metals				
Dcca	0.008395	0.020666	0.40625	0.684559
Dccb	0.958185	0.058471	16.38735	0.000000
Stoxx Europe Industry Neutral and DJ Index Precious Metals				
Dcca	0.008955	0.021913	0.40866	0.682792
Dccb	0.948135	0.055833	16.98148	0.000000
Stoxx Europe Leaders and DJ Index Precious Metals				
Dcca	0.000000	0.000000	0.39360	0.693875
Dccb	0.918457	0.350274	2.62211	0.008739
S&P500 ESG and DJ Index Precious Metals				
Dcca	0.022400	0.017505	1.27968	0.200658
Dccb	0.932936	0.063356	14.72519	0.000000
Stoxx Europe Leaders and DJ Commodity Index Grains				
Dcca	0.003321	0.018598	0.178575	0.858271
Dccb	0.953796	0.019704	48.405075	0.000000
S&P500 ESG and DJ Commodity Index Grains				
Dcca	0.000000	0.000059	0.000003	0.999997
Dccb	0.946849	0.597310	1.585190	0.112923

Table 3. Copula DCC GARCH (Student's *t*) estimation results.

	Estimate	Std. Error	*t* Value	Pr (>|*t*|)
DJS Europe and Stoxx Europe ESG Leaders				
Dcca	0.089614	0.028287	3.1680	0.001535
Dccb	0.833153	0.064187	12.9802	0.000000
shape	10.291252	7.848614	1.3112	0.189784
Stoxx Europe ESG Leaders and Euro Stoxx Select Dividend 30				
Dcca	0.060536	0.020564	2.94381	0.003242
Dccb	0.851205	0.046137	18.44954	0.000000
shape	21.961475	16.823304	1.30542	0.191750
DJS US and S&P 500				
Dcca	0.012786	0.005962	2.14477	0.031971
Dccb	0.981967	0.012947	75.84782	0.000000
shape	21.060808	8.035996	2.62081	0.008772
Stoxx Europe ESG Leaders and DJ Commodity Index Industrial Metals				
Dcca	0.102885	0.035039	2.93633	0.003321
Dccb	0.720513	0.064630	11.14828	0.000000
shape	14.396227	7.333689	1.96303	0.049643
S&P500 ESG and DJ Commodity Index Industrial Metals				
Dcca	0.034528	0.023747	1.45402	0.145942
Dccb	0.924289	0.036495	25.32642	0.000000
shape	49.999997	39.914116	1.25269	0.210319
DJS Europe and DJ Commodity Index Precious Metals				
Dcca	0.016588	0.020351	30.93940	0.415015
Dccb	0.955769	0.030892	2.57255	0.000000
shape	7.765412	3.018562	2.57255	0.010095
Stoxx Europe Industry Neutral and DJ Index Precious Metals				
Dcca	0.016491	0.022330	0.73851	0.460207
Dccb	0.948290	0.034365	27.59473	0.000000
shape	7.833953	3.175421	2.46706	0.013623
Stoxx Europe Leaders and DJ Index Precious Metals				
Dcca	0.000604	0.025593	0.023594	0.981176
Dccb	0.935939	0.072982	12.824212	0.000000
shape	7.547719	2.674170	2.822453	0.004766
S&P500 ESG and DJ Index Precious Metals				
Dcca	0.029924	0.018557	1.61250	0.106854
Dccb	0.940486	0.025153	37.39083	0.000000
shape	8.268864	3.516566	2.35140	0.018703
S&P500 ESG and DJ Commodity Index Grains				
Dcca	0.000000	0.000000	0.040853	0.967413
Dccb	0.998961	0.010566	94.546781	0.000000
shape	49.999924	6.762795	7.393381	0.000000

5. Discussion

Most financial time series exhibit autocorrelation and volatility clustering. In this study, a standard GARCH model was used to analyze the volatility of the rates of return of the selected indices. This model captures symmetric dynamics and the volatility clustering of the return series.

The results show that indices' returns exhibit volatility clustering with time-varying variance in the residuals. These findings show the nonlinear structure in the conditional variance of the returns. This dynamic may be modeled with the GARCH(1,1) model which is consistent with the literature.

Regarding the financial market, changing correlations are not a new phenomenon. Indeed, correlations among the asset classes have never been fixed; however, the pace of change varies over time for different reasons. Globalization and market integration is one key factor.

As the IMF shoved, the correlations between the US equities (S&P 500) and other asset classes were growing in the post-crisis era: from a pre-crisis (1988–2007) cross-asset median correlation of 0.44 to a post-crisis (2010–2015) median of 0.702 [41].

There are several possible factors that have contributed to the change of the correlation between the assets:

- Synchronized monetary policy: the evidence suggests elevated correlations [42,43];
- Financial innovation: the analysis shows increased correlations between commodities and equities [44,45];
- Market trading strategies: the research suggests increased cross-asset correlations [46,47].

The results of this study are not surprising in the case of conditional correlation between ESG indices, which are high. From the point of view of risk reduction, including the same type of assets in a portfolio is not effective. Since only one pair of indices showed statistically significant correlation, the results are difficult to generalize in terms of evolution of the conditional correlation in time, and further studies are necessary.

Combining the ESG assets and the non-ESG assets in one portfolio is also not effective from a risk reduction perspective as the conditional correlation is also high (close to 1). Likewise, in this case, we find only two pairs of indices with statistically significant correlation, therefore further studies are necessary.

Even if the correlation between commodities and equities is growing over time, it is still possible to use commodities as diversifiers in a portfolio. This study confirmed that there exists an opportunity for socially responsible investments to include precious and industrial metals and grains in order to reduce the risk of the portfolio.

6. Conclusions

This study focused on the modeling of volatility and conditional correlation in order to find opportunities of risk reduction in the case of socially responsible investing. The hypothesis that there is a potential to create a portfolio by adding to SRI commodities and that risk management opportunities exist between SRI and commodities like grain, precious metals, and industrial metals was positively verified. The results show that all the considered commodity indices had low correlation with the ESG indices. Including particular commodities (e.g., gold, silver, copper, wheat) in a portfolio of particular ESG assets could be developed with further studies.

Conditional correlations evolve in time, but we were not able to find any tendencies of correspondence to observed market cycles (periods of growth and collapse).

Many studies analyze socially responsible investments as a potential diversifier of a traditional portfolio, e.g., stocks portfolio. In this paper, a different approach was adopted—SRI are treated as traditional investments and commodities as a diversifier. There is little research on portfolio construction using SRI. Mostly, mutual funds invested in ESG companies are analyzed. The existing selective studies concern the indices of ESG stocks or commodities like gold and oil (there is no research considering grain). Thus, the paper fills an existing gap in the current research.

This study provides robust evidence on socially responsible investments and commodities as portfolio diversifiers (based on the indices), which might be a starting point for a discussion on the practical application of a set of ESG companies and selected representatives of commodities.

From an investor's point of view, it seems important to notice that the correlation between the two securities can change, sometimes in a rather violent way. Considering this fact seems necessary, e.g., when constructing a portfolio. For ethical (socially responsible) investors, modified utility function is also essential. Therefore, the aim of further research will be to use the DCC model in portfolio construction and risk analysis assuming a modified utility function.

Investors in sustainable investment funds generally have a long-term investment horizon [45]. It was found by Talan and Deep Sharma [48] that only around 8% of the reviewed papers considered a period of more than 10 years in their research [46]. The authors of this paper studied SRIs over a period of 8 years, which is longer compared to most of the other studies.

This study is not free of limitations. Firstly, we used indices, while a more detailed analysis would be advantageous, including ESG companies from different markets (developed and developing) and particular commodities (e.g., gold, silver, copper, corn). Secondly, we analyzed diversification possibilities by using commodities, and deeper studies would be beneficial (e.g., involving hedge ratio calculations, optimal weights).

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Description of selected indices.

Index	Ticker	Number of Constituents	Criteria	Sectors	Weights	First Value
Stoxx Global ESG Impact	SXEIMGGR	889	Stoxx Global 1800 without excluded sectors and high ESG score in every sector	1. Technology 2. Banks 3. Health Care	Free-float	Sep 17, 2010
Stoxx Europe Industry Neutral	SXESEN	471	Stoxx Global 1800 without excluded sectors, and Sustainability score above 50	1. Health Care 2. Industrial Goods and Services 3. Banks	Free-float	Sep 24, 2012
Stoxx Europe ESG Leaders Select 30	SEESGSEG	30	Dividend-paying, high liquidity European companies included in Global ESG Index	1. Utilities 2. Insurance 3. Telecommunications	Inverted volatility	Jun 21, 2004
Euro Stoxx Select Dividend 30	SD3E	30	High-dividend-yielding companies across the 11 Eurozone countries	Insurance Banks	Annual net dividend yield	Dec 30, 1998
Global Sustainability Leader Index	GSLI	Top 100 representative group of companies	Companies selected on the basis of their ESG performance. excluding companies involved in tobacco	x	Free Float Market Cap	Oct 1st, 2012

Dow Jones Sustainability US Composite Index	AASGI	126	The top 20% of 600 largest in the Dow Jones Sustainability North America Index	x	Modified market cap	Dec 31, 1998
Dow Jones Sustainability Europe	DJSEUR	126	The top 20% of the largest 600 European companies in the S&P Global BMI based on long-term economic, environmental and social criteria	Health care Consumer staples Financials	float-adjusted market capitalization	Aug 4, 2010
S&P 500 ESG Index	SPXESUP	315	S&P 500 companies without excluded sectors, without low 5% in terms of UNCG score and without 25% of ESG score	1. Information technology 2. Health Care 3. Financials	Float-adjusted market cap	April 30, 2010
Dow Jones Commodity Index Industrial Metals	DJCIIM	x	Industrial Metals based through futures contracts	x	Capped	July 1, 2014
Dow Jones Precious Metals Index	DJGSP	30	US companies engaged in the exploration and production of gold, silver and platinum-group metals	x	Float-adjusted market cap	December 30, 2000
Dow Jones Commodity Index Grains	DJCIGR	-	Grains sector through futures contracts	x	Capped	Jan 17, 2006

Table A2. Time series tests results.

Index	ADF Stat and (p-Value)	Ljung–Box r Stat and (p-Value)	Ljung–Box r^2 Stat and (p-Value)	ARCH-LM Test and (p-Value)
DJS Europe	−7.564 (0.01)	6.979 (0.0082)	14.32 (0.0002)	45.09 (0)
DJS US	−7.495 (0.01)	8.532 (0.0035)	7.559 (0.006)	27.44 (0.0067)
DJ Commodity Index Grains	−7.423 (0.01)	0.1851 (0.6671)	1.141 (0.2855)	26.47 (0.0092)
DJ Commodity Index Industrial Metals	−6.892 (0.01)	1.114 (0.2911)	2.011 (0.1562)	18.29 (0.1071)
DJ Commodity Index Precious Metals	−6.629 (0.01)	0 (0.9975)	1.28 (0.258)	30.98 (0.002)
GSLI	−7.74 (0.01)	6.436 (0.0112)	3.468 (0.0626)	17.88 (0.1193
S&P500	−7.738 (0.01)	6.78 8 (0.0092)	7.72 (0.0055)	25.3 (0.0135
S&P500 ESG	−7.605 (0.01)	7.7 (0.0055)	7.578 (0.0059)	24.52 (0.0173
Stoxx Europe IN	−7.7 (0.01)	6.415 (0.0113)	16.05 (0.0001)	42.16 (0)
Stoxx Europe ESG Leaders	−8.135 (0.01)	−4.619 (0.0316)	18.97 (0)	38.41 (0.0001)
Euro Stoxx Select Dividend 30	−8.297 (0.0)1	7.859 (0.0051)	18.01 (0)	37.02 (0.0002)
Stoxx Global ESG Impact	−7.828 (0.01)	6.796 (0.0091)	5.492 (0.0191)	22.62 (0.0311)

Table A3. Test results for residuals from DCC–GARCH.

	JB Test Stat	JB Test p-value	JB Test Stat (Squared Residuals)	JB Test p-VALUE (Squared Residuals)
DJS Europe and Stoxx Europe ESG Leaders				
DJS Europe	8.715	0.0175	1212	0
Stoxx Europe ESG Leaders	25.14	0.002	14,072	0
Stoxx Europe ESG Leaders and Euro Stoxx Select Dividend 30				
Stoxx Europe ESG Leaders	44.22	0	26,708	0
Euro Stoxx Select Dividend 30	0.4084	0.81	1399	0
DJS US and S&P 500				
DJS US	3.611	0.142	2386	0
S&P 500	27.83	0.0005	5921	0
Stoxx Europe ESG Leaders and DJ Commodity Index Industrial Metals				
Stoxx Europe ESG Leaders	45	0	6131	0
DJ Commodity Index Industrial Metals	4.912	0.0805	6465	0
S&P500 ESG and DJ Commodity Index Industrial Metals				
S&P500 ESG	157.6	0	38,957	0
DJ Commodity Index Industrial Metals	4.316	0.0975	4121	0
DJS Europe and DJ Commodity Index Precious Metals				
DJS Europe	40.66	0	3628	0
DJ Commodity Index Precious Metals	38.42	0	8879	0
Stoxx Europe Industry Neutral and DJ Index Precious Metals				
Stoxx Europe Industry Neutral	41.13	0.0005	5657	0
DJ Index Precious Metals	38.26	0	8919	0
Stoxx Europe Leaders and DJ Index Precious Metals				
Stoxx Europe Leaders	37.59	0	7340	0
DJ Index Precious Metals	29.23	0.0005	9142	0
S&P500 ESG and DJ Index Precious Metals				
S&P500 ESG	184.1	0	23,099	0
DJ Index Precious Metals	37.51	0.0005	8839	0
Stoxx Europe Leaders and DJ Commodity Index Grains				

Stoxx Europe Leaders	48.51	0	6892	0
DJ Commodity Index Grains	16.53	0.0025	9747	0
S&P500 ESG and DJ Commodity Index Grains				
S&P500 ESG	184.4	0	30,952	0
DJ Commodity Index Grains	17.1	0.002	9933	0

Table A4. Test results for residuals from copula–DCC–GARCH (Gaussian).

	JB Test Stat	**JB Test *p*-value**	**JB test Stat (Squared Residuals)**	**JB Test *p*-value (Squared Residuals)**
DJS Europe and Stoxx Europe ESG Leaders				
DJS Europe	8.752	0.018	1216	0
Stoxx Europe ESG Leaders	25.16	0	14,128	0
Stoxx Europe ESG Leaders and Euro Stoxx Select Dividend 30				
Stoxx Europe ESG Leaders	44.26	0.001	26,716	0
Euro Stoxx Select Dividend 30	0.4151	0.7995	1402	0
DJS US and S&P 500				
DJS US	3.643	0.148	2396	0
S&P 500	27.99	0.0005	5954	0
Stoxx Europe ESG Leaders and DJ Commodity Index Industrial Metals				
Stoxx Europe ESG Leaders	44.89	0.0005	6135	0
DJ Commodity Index Industrial Metals	4.924	0.072	6463	0
S&P500 ESG and DJ Commodity Index Industrial Metals				
S&P500 ESG	157.8	0	38975	0
DJ Commodity Index Industrial Metals	4.321	0.0905	4123	0
DJS Europe and DJ Commodity Index Precious Metals				
DJS Europe	40.7	0	3637	0
DJ Commodity Index Precious Metals	38.41	0	8865	0
Stoxx Europe Industry Neutral and DJ Index Precious Metals				
Stoxx Europe Industry Neutral	41.15	0	5660	0
DJ Index Precious Metals	38.25	0	8906	0
Stoxx Europe Leaders and DJ Index Precious Metals				
Stoxx Europe Leaders	74.35	0	13,870	0
DJ Index Precious Metals	29.23	0.0005	2673	0
S&P500 ESG and DJ Index Precious Metals				
S&P500 ESG	184.1	0	23,089	0
DJ Index Precious Metals	37.5	0.0005	8832	0
Stoxx Europe Leaders and DJ Commodity Index Grains				
Stoxx Europe Leaders	48.5	0	6891	0
DJ Commodity Index Grains	16.52	0.0055	9748	0
S&P500 ESG and DJ Commodity Index Grains				
S&P500 ESG	184.4	0	30,952	0
DJ Commodity Index Grains	17.1	0.0035	9933	0

Table A5. Test results for residuals from copula–DCC–GARCH (Student's t).

	JB Test Stat	**JB Test *p*-Value**	**JB Test Stat (Squared Residuals)**	**JB Test *p*-Value (Squared Residuals)**
DJS Europe and Stoxx Europe ESG Leaders				
DJS Europe	8.607	0.019	1192	0
Stoxx Europe ESG Leaders	24.24	0	14,448	0
Stoxx Europe ESG Leaders and Euro Stoxx Select Dividend 30				
Stoxx Europe ESG Leaders	43.69	0	27,212	0
Euro Stoxx Select Dividend 30	0.4202	0.8155	1437	0

DJS US and S&P 500				
DJS US	2.998	0.1885	2058	0
S&P 500	25.56	0	5475	0
Stoxx Europe ESG Leaders and DJ Commodity Index Industrial Metals				
Stoxx Europe ESG Leaders	44.99	0	6143	0
DJ Commodity Index Industrial Metals	5.004	0.081	6429	0
S&P500 ESG and DJ Commodity Index Industrial Metals				
S&P500 ESG	157.8	0	38,991	0
DJ Commodity Index Industrial Metals	4.39	0.097	4160	0
DJS Europe and DJ Commodity Index Precious Metals				
DJS Europe	41.47	0	3692	0
DJ Commodity Index Precious Metals	38.32	0	9018	0
Stoxx Europe Industry Neutral and DJ Index Precious Metals				
Stoxx Europe Industry Neutral	41.75	0	5617	0
DJ Index Precious Metals	38.13	0.0005	9050	0
Stoxx Europe Leaders and DJ Index Precious Metals				
Stoxx Europe Leaders	46.19	0	7400	0
DJ Index Precious Metals	37.42	0.0005	9218	0
S&P500 ESG and DJ Index Precious Metals				
S&P500 ESG	191.1	0	22,555	0
DJ Index Precious Metals	37.36	0	8814	0
S&P500 ESG and DJ Commodity Index Grains				
S&P500 ESG	184.5	0	30,978	0
DJ Commodity Index Grains	17.08	0.0035	9927	0

Appendix B

Table 6. Statistical significance/insignificance of dynamic conditional correlations for pair of indices.

Europe—ESG Indices		
DJS Europe	Stoxx Europe ESG Leaders	Insignificant
DJS Europe	Stoxx Europe IN	Significant
Stoxx Europe IN	Stoxx Europe ESG Leaders	Insignificant
ESG indices and non-ESG indices		
DJS Europe	Euro Stoxx Select Dividend 30	Insignificant
Stoxx Europe IN	Euro Stoxx Select Dividend 30	Insignificant
Stoxx Europe ESG Leaders	Euro Stoxx Select Dividend 30	Significant
ESG Indices and Commodity indices		
DJS Europe	Dow Jones Commodity Index Industrial Metals	Insignificant
DJS Europe	Dow Jones Commodity Index Precious Metals	Significant
DJS Europe	Dow Jones Commodity Index Grains	Insignificant
Stoxx Europe IN	Dow Jones Commodity Index Industrial Metals	Insignificant
Stoxx Europe IN	Dow Jones Commodity Index Precious Metals	Significant at 0.1
Stoxx Europe IN	Dow Jones Commodity Index Grains	Insignificant
Stoxx Europe ESG Leaders	Dow Jones Commodity Industrial Index Metals	Significant
Stoxx Europe ESG Leaders	Dow Jones Commodity Index Precious Metals	Significant
Stoxx Europe ESG Leaders	Dow Jones Commodity Index Grains	Significant
USA—ESG indices		
DJS US	S&P 500 ESG	Insignificant
ESG indices and non-ESG indices		
DJS US	S&P 500	Significant
S&P 500 ESG	S&P 500	Insignificant
ESG Indices and Commodity indices		
DJS US	Dow Jones Commodity Index Industrial Metals	Insignificant
DJS US	Dow Jones Commodity Index Precious Metals	Insignificant

DJS US	Dow Jones Commodity Index Grains	Insignificant
SP 500 ESG	Dow Jones Commodity Index Industrial Metals	Significant
SP 500 ESG	Dow Jones Commodity Index Precious Metals	Significant at 0.06
SP 500 ESG	Dow Jones Commodity Index Grains	Significant
	Global—ESG indices	
GSLI	Stoxx Global ESG Impact	Insignificant
	ESG Indices and Commodity indices	
Stoxx Global ESG Impact	Dow Jones Commodity Index Industrial Metals	Insignificant
Stoxx Global ESG Impact	Dow Jones Commodity Index Precious Metals	Insignificant
Stoxx Global ESG Impact	Dow Jones Commodity Index Grains	Insignificant
GSLI	Dow Jones Commodity Index Industrial Metals	Insignificant
GSLI	Dow Jones Commodity Index Precious Metals	Insignificant
GSLI	Dow Jones Commodity Index Grains	Insignificant

References

1. Report on US Sustainable Responsible and Impact Investing Trends 2018, US SIF Foundation. Available online: https://www.ussif.org/files/Trends/Trends%202018%20executive%20summary%20FINAL.pdf (accessed on 3 November 2019).
2. Schueth, S. Socially Responsible Investing in the United States. *J. Bus. Ethics* **2003**, *43*, 189–194.
3. Kempf, A.; Osthoff, P. The Effect of Socially Responsible Investing on Portfolio Performance. Centre for Financial Research (CFR), Working Paper, No. 06-10, University of Cologne. 2007. Available online: http://hdl.handle.net/10419/57725 (accessed on 3 November 2019).
4. Mackey, A.; Mackey, T.B.; Barney, J.B. Corporate Social Responsibility and Firm Performance: Investor Preferences and Corporate Strategies. *Acad. Manag. Rev.* **2007**, *32*, 817–835.
5. Auer, B.R.; Schuhmacher, F. Do socially (ir)responsible investments pay? New evidence from international ESG data. *Q. Rev. Econ. Financ.* **2016**, *59*, 51–62.
6. Fritz, T.M.; von Schnurbein, G. Beyond Socially Responsible Investing: Effects of Mission-Driven Portfolio Selection. *Sustainability* **2019**, *11*, 6812.
7. Biasin, M.; Cerqueti, R.; Giacomini, E.; Marinelli, N.; Quaranta, A.G.; Riccetti, L. Macro Asset Allocation with Social Impact Investments. *Sustainability* **2019**, *11*, 3140.
8. Markowitz, H. Portfolio Selection. *J. Financ.* **1952**, *7*, 77–91.
9. Engle, R.F. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica* **1982**, *50*, 987–1007, doi:10.2307/1912773.
10. Bollerslev, T. Generalized autoregressive conditional heteroscedasticity. *J. Econom.* **1986**, *31*, 307–327.
11. Engle, R.F. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J. Bus. Econ. Stat.* **2002**, *20*, 339–350.
12. Ibbotson Associates. *Strategic Asset Allocation and Commodities*; Ibbotson Associates Chicago, IL, USA, 2006.
13. Global Sustainable Investment Alliance. *Global Sustainable Investment Review*; Global Sustainable Investment Alliance: Washington, DC, USA, 2014.
14. Webley, P.; Lewis, A.; Mackenzie, C. Commitment among Ethical Investors: An Experimental Approach. *J. Econ. Psychol.* **2001**, *22*, 27–42.
15. Ariely, D.; Bracha, A.; Meier, S. Doing Good or Doing Well? Image Motivation and Monetary Incentives in Behaving Prosocially. *Am. Econ. Rev.* **2009**, *99*, 544–555.
16. Ortas, E.; Burritt, R.L.; Moneva, J.M. Socially responsible investment and cleaner production in the Asia Pacific: Does it pay to be good? *J. Clean. Prod.* **2013**, *52*, 272–280.
17. Goyal, M.M.; Aggarwal, K. ESG Index is Good for Socially Responsible Investor in India. *Asian J. Multidiscip. Stud.* **2014**, *2*, 92–96.
18. Sudha, S. Risk-Return and Volatility Analysis of Sustainability Index in India. *Environ. Dev. Sustain.* **2015**, *17*, 1329–1342.
19. Fatemi, A.; Glaum, M.; Kaiser, S. ESG Performance and Firm Value: The Moderating Role of Disclosure. *Glob. Financ. J.* **2017**, *38*, 45–64.
20. Beal, D.J.; Goyen, M.; Phillips, P. Why Do We Invest Ethically? *J. Invest*. **2005**, *14*, 66–77.
21. Bello, Z. Socially responsible investing and portfolio diversification. *J. Financ. Res*. **2005**, *28*, 41–57.
22. Benson, K.L.; Brailsford, T.J.; Humphrey, J.E. Do socially responsible fund managers really invest differently? *J. Bus. Ethics* **2006**, *65*, 337–357.

23. Cortez, M.C.; Silva, F.; Areal, N. Socially responsible investing in the global market: The performance of US and European funds. *Int. J. Financ. Econ*. **2012**, *17*, 254–271.
24. Bauer, R.; Otten, R.; Rad, A. Ethical investing in Australia: Is there a financial penalty? *Pac. Basin Financ. J.* **2006**, *14*, 33–48.
25. Statman, M. Socially responsible indexes: Composition, performance, and tracking error. *J. Portf. Manag*. **2006**, *32*, 100–109.
26. Skiadopoulos, G. Advances in the commodity futures literature: A review. *J. Deriv*. **2013**, *20*, 85–96.
27. Cheung, C.S.; Miu, P. Diversification benefits of commodity futures. *J. Int. Financ. Mark. Inst. Money* **2010**, *20*, 451–474.
28. Belousova, J.; Dorfleitner, G. On the diversification benefits of commodities from the perspective of euro investors. *J. Bank. Financ*. **2012**, *36*, 2455–2472.
29. Daskalaki, C.; Skiadopoulos, G.; Topaloglou, N. Diversification benefits of commodities: A stochastic dominance efficiency approach. *J. Empir. Financ*. **2017**, *44*, 250–269.
30. Cao, B.; Jayasuriya, S.; Shambora, W. Holding a commodity futures index fund in a globally diversified portfolio: A place effect? *Econ. Bull*. **2010**, *30*, 1842–1851.
31. Daskalaki, C.; Skiadopoulos, G. Should investors include commodities in their portfolios after all? New evidence. *J. Bank. Financ*. **2011**, *25*, 2606–2626.
32. Bessler, W.; Wolff, D. Do Commodities add Value in Multi-Asset Portfolios? An Out-of-Sample Analysis for different Investment Strategies. *J. Bank. Financ*. **2015**, *60*, 1–20.
33. Lombardi, M.J.; Ravazzolo, F. On the correlation between commodity and equity returns: Implications for portfolio allocation. *J. Commod. Market*. **2016**, *2*, 45–57.
34. Sadorsky, P. Modeling volatility and conditional correlations between socially responsible investments, gold and oil. *Econ. Model.* **2014**, *38*, 609–618.
35. Hoti, S.; McAleer, M.; Pauwels, L. Modelling environmental risk. *Environ. Model. Softw.* **2005**, *20*, 1289–1298.
36. Hoti, S.; McAleer, M.; Pauwels, L.L. Measuring risk in environmental finance. *J. Econ. Surv.* **2007**, *21*, 970–998.
37. Engle, R.F.; Sheppard, K. Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH. NBER Working Paper No. 8554. 2001. Available online: https://www.researchgate.net/publication/46441088_Theoretical_and_Empirical_Properties_of_Dynamic_Conditional_Correlation_Multivariate_GARCH (accessed on 3 November 2019).
38. Tse, Y.K.; Tsui, A. A Multivariate Generalized Autoregressive Conditional Heteroscedasticity Model with Time-Varying Correlations*. J. Bus. Econ. Stat*. **2002**, *20*, 351–62.
39. Patton, A.J. Modelling Asymmetric Exchange Rate. *Int. Econ. Rev.* **2006**, *47*, 527–556.
40. Patton, A.J. A Review of Copula Models for Economic Time Series. *J. Multivar. Anal*. **2012**, *110*, 4–18.
41. IMF. Global Financial Stability Report. 2015. Available online: https://www.imf.org/en/Publications/GFSR/Issues/2016/12/31/Global-Financial-Stability-Report-April-2015-Navigating-Monetary-Policy-Challenges-and-42422 (accessed on 3 November 2019).
42. Rogers, J.; Scotti, C.; Wright, J. Evaluating Asset Market Effects of Unconventional Market Policy: A Cross Country Comparison, Board of Governors of the Federal Reserve System. International Finance Discussion Papers No 1101. 2014. Available online: https://www.federalreserve.gov/PUBS/ifdp/2014/1101/ifdp1101.pdf (accessed on 3 November 2019).
43. Bank of International Settlements. Available online: https://www.bis.org/publ/arpdf/ar2017e.pdf (accessed on 15 February 2020).
44. Tang, K.; Xiong, W. Index investment and the financialization of commodities. *Financ. Anal. J.* **2012**, *68*, 54–74.
45. Lombardi, M.; Ravazzolo, F. On the correlation between commodity and equity returns: Implications for portfolio allocation. BIS Working Papers No 420. 2013 Available online: https://www.bis.org/publ/work420.pdf (accessed on 3 November 2019).
46. Bicchetti, D.; Maystre, N. The Synchronized and Long-Lasting Structural Change on Commodity Markets: Evidence from High-Frequency Data. United Nations Conference on Trade and Development (UNCTAD). 2012. Available online: https://unctad.org/en/PublicationsLibrary/osgdp2012d2_en.pdf (accessed on 3 November 2019).

47. Paul, K. The effect of business cycle, market return and momentum on financial performance of socially responsible investing mutual funds. *Soc. Responsib. J.* **2017**, *13*, 513–528.
48. Talan, G.; Deep Sharma, G. Doing Well by Doing Good: A Systematic Review and Research Agenda for Sustainable Investment. *Sustainability* **2019**, *11*, 353.