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Risk Management Opportunities between Socially Responsible Investments and Selected Commodities

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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. Contrarily, 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.

Hotti 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 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.

\[ r_t = \mu + \varepsilon_t = \mu + \sqrt{h_t} z_t, \quad z_t \sim N(0, 1) \]  

(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

\[ h_t = \omega + \alpha \varepsilon^2_{t-1} + \beta h_{t-1} \]  

(2)

\[ V_L = \frac{\omega}{1 - \alpha - \beta} \]  

(3)

\( \omega > 0, \quad \alpha \geq 0, \quad \beta \geq 0, \quad \alpha + \beta < 1. \)  

(4)

In Equation (1), \( r \) is the return and \( z \) is the random error term with conditional variance \( h \). 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 \( \alpha \) and \( \beta \) 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.

\[ \ldots \chi_t = \mu + \varepsilon_t, \quad \ldots | F_{t-1} \sim N(0, D_t R_t D_t) \]  

(5)

\[ \ldots D_t^2 = diag\{H_t\} \]  

(6)

\[ H_{i,t} = \omega_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i H_{i,t-1} \]  

(7)

\[ z_t = D_t^{-1} \varepsilon_t \]  

(8)

\[ R_i = diag\{Q_i\}^{-1/2} Q_i diag\{Q_i\}^{-1/2} \]  

(9)

\[ \Omega + \alpha z_{t-1} \varepsilon^2_{t-1} + \beta Q_{i-1}, \quad \Omega = R(1 - \alpha - \beta) \]  

(10)

where \( D_t = diag[\varepsilon_t] \) in Equation (6), \( diag[\cdot] \) is a matrix operator creating a diagonal matrix with the vector along the main diagonal, and \( R_i \) 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 \( \alpha \) and \( \beta \) 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 \( t \),
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- 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 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 r 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. In the second step, the dynamics of R 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 Datasync (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.

| Index                                  | 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 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 | 0.001355   | 0.000923 | 1.4688 | 0.141900 |
| DJS US    | 0.000025   | 0.000016 | 1.5587 | 0.119068 |
| S&P500    | 0.128621   | 0.052574 | 2.4465 | 0.014427 |
| S&P500 ESG| 0.813363   | 0.076869 | 10.5812| 0.000000 |
| Stoxx Europe IN | 0.0009  | 0.000056 | 1.5587 | 0.119068 |
| Stoxx Europe ESG Leaders               | 0.186019  | 0.160194 | 1.1612 | 0.245556 |
| Euro Stoxx Select Dividend 30          | 0.646293  | 0.365139 | 1.7699 | 0.076729 |
| Euro Stoxx Select Dividend 30          | 0.000902  | 0.001049 | 0.8601 | 0.389684 |
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 persistency 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 persistency 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.
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 | 3.2577 | 0.001123 |
| Dccb | 0.849697 | 0.039364 | 21.5856 | 0.000000 |
| DJS US and S&P 500 | | |
| Dcca | 0.013889 | 0.018470 | 0.7578 | 0.442552 |
| Dccb | 0.974591 | 0.017620 | 55.3116 | 0.000000 |
| Stoxx Europe ESG Leaders and DJ Commodity Index Industrial Metals | | |
| Dcca | 0.098396 | 0.033519 | 2.9355 | 0.003330 |
| Dccb | 0.713455 | 0.067294 | 10.6020 | 0.000000 |
| S&P500 ESG and DJ Commodity Index Industrial Metals | | |
| Dcca | 0.030847 | 0.022086 | 1.3966 | 0.162511 |
| Dccb | 0.929136 | 0.03460 | 27.7648 | 0.000000 |
| DJS Europe and DJ Commodity Index Precious Metals | | |
| Dcca | 0.008395 | 0.019347 | 0.4339 | 0.664332 |
| Dccb | 0.958185 | 0.063344 | 15.1266 | 0.000000 |
| Stoxx Europe Industry Neutral and DJ Index Precious Metals | | |
| Dcca | 0.008955 | 0.021058 | 0.4232 | 0.670653 |
| Dccb | 0.948135 | 0.061708 | 15.3486 | 0.000000 |
| Stoxx Europe Leaders and DJ Index Precious Metals | | |
| Dcca | 0.000000 | 0.000009 | 0.0000 | 0.999990 |
| Dccb | 0.918488 | 0.357601 | 2.568391 | 0.010217 |
| S&P500 ESG and DJ Index Precious Metals | | |
| Dcca | 0.022400 | 0.017380 | 1.2888 | 0.197449 |
| Dccb | 0.932937 | 0.065525 | 14.2378 | 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 | 0.000020 | 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.

| Estimate                                      | Std. Error | t Value | Pr (>|t|) |
|-----------------------------------------------|------------|---------|-----------|
| **DJS Europe and Stoxx Europe ESG Leaders**   |            |         |           |
| Dcca                                          | 0.92053    | 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                                          | 0.008995   | 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| 0.17857    | 0.858217  |
| Dccb                                          | 0.953796   | 0.019704| 48.405075  | 0.000000  |
| **S&P500 ESG and DJ Commodity Index Grains** | | | |
| Dcca                                          | 0.000000   | 0.000000| 0.00003   | 0.999997  |
| Dccb                                          | 0.946849   | 0.597310| 1.585190  | 0.112923  |
Table 3. Copula DCC GARCH (Student’s t) estimation results.

| Estimation Model                                                                 | Estimate  | Std. Error | t Value | Pr (>|t|) |
|---------------------------------------------------------------------------------|-----------|------------|---------|-----------|
| DCC: DJS Europe and Stoxx Europe ESG Leaders                                    | 0.089614  | 0.028287   | 3.1680  | 0.001535  |
| DCC: Stoxx Europe ESG Leaders and Euro Stoxx Select Dividend 30                 | 0.060536  | 0.020564   | 2.94381 | 0.003242  |
| DCC: Stoxx Europe ESG Leaders and DJ Commodity Index Industrial Metals         | 0.102885  | 0.035039   | 2.93633 | 0.003321  |
| DCC: S&P500 ESG and DJ Commodity Index Industrial Metals                       | 0.034528  | 0.023747   | 1.45402 | 0.145942  |
| DCC: DJS Europe and DJ Commodity Index Precious Metals                         | 0.016588  | 0.020351   | 30.93940| 0.415015  |
| DCC: Stoxx Europe Industry Neutral and DJ Index Precious Metals                | 0.016491  | 0.022330   | 0.73851 | 0.460207  |
| DCC: S&P500 ESG and DJ Commodity Index Grains                                  | 0.000000  | 0.000000   | 0.040853| 0.967413  |

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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**Appendix A**

**Table A1.** Description of selected indices.

| Index                      | Ticker | Number of Constituents | Criteria                                                                                                                                                                                                 | Sectors                              | Weights       | First Value |
|----------------------------|--------|------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------|---------------|-------------|
| Stoxx Global ESG Impact    | SXEIMGG | 889                    | Stoxx Global 1800 without excluded sectors and high ESG score in every sector of the index                                                                                                                    | 1. Technology                       | 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                      | Free-float    | Sep 24, 2012 |
| Stoxx Europe ESG Leaders Select 30 | SEESGSE | 30                     | Dividend-paying, high liquidity European companies included in Global ESG Index                                                                                                                           | 1. Utilities                        | Inverted volatility | Jun 21, 2004 |
|                            |        |                        | High-dividend-yielding companies across the 11 Eurozone countries Companies selected on the basis of performance of their global ESG indices                                                                 | 2. Insurance                        |               |             |
|                            |        |                        | excluding companies involved in tobacco                                                                                                                                                                 | 3. Telecommunications               |               |             |
|                            |        |                        |                                                                                                                                           | Insurance Banks                     | Annual net dividend yield | Dec 30, 1998 |
|                            |        |                        |                                                                                                                                           | Free Float                          | Market Cap    | Oct 1st, 2012 |
The top 20% of 600 largest companies in the Dow Jones Sustainability North America Index.

The top 20% of the largest 600 European companies in the S&P Global BMI based on long-term economic, environmental, and social criteria.

S&P 500 companies without excluded sectors, without low 5% in terms of UNCG score and without 25% of ESG score.

US companies engaged in the exploration and production of gold, silver, and platinum-group metals.

US companies in the Grains sector through futures contracts.

Information technology, Health Care, and Financials sectors.

 float-adjusted market capitalization.
Table A2. Time series tests results.

| Index                                      | ADF Stat (p-value) | Ljung–Box r Stat (p-value) | Ljung–Box r² Stat (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)      | 6.788 (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 (0.00173)            |
| 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 (0.01)      | 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| 8.715        | 0.0175          | 1212                             | 0                                   |
| DJ Commodity Index Industrial Metals    | 4.912        | 0.0805          | 6465                             | 0                                   |
| S&P500 ESG and DJ Commodity Index Metals| 157.6       | 0               | 38,957                           | 0                                   |
| DJ Commodity Index Precious Metals      | 4.316        | 0.0975          | 4121                             | 0                                   |
| DJ Commodity Index Industry Neutral     | 38.42        | 0               | 8879                             | 0                                   |
| Stoxx Europe Industry Neutral and DJ Index Precious Metals | 41.13 | 0.0005 | 5657 | 0 |
| DJ Index Precious Metals                | 38.26        | 0               | 8919                             | 0                                   |
| Stoxx Europe Leaders and DJ Index Precious Metals | 37.59 | 0 | 7340 | 0 |
| DJ Index Precious Metals                | 29.23        | 0.0005          | 9142                             | 0                                   |
| S&P500 ESG and DJ Index Precious Metals | 184.1       | 0               | 23,099                           | 0                                   |
| DJ Index Precious Metals                | 37.51        | 0.0005          | 8839                             | 0                                   |
| Stoxx Europe Leaders and DJ Commodity Index Grains | 37.51 | 0 | 8839 | 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 | 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 | 44.26        | 0.001          | 26,716                            | 0                                   |
| Euro Stoxx Select Dividend 30  | 0.4151       | 0.7995         | 1402                              | 0                                   |
| DJS US and S&P 500             | 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 | 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 | 157.8        | 0              | 38975                             | 0                                   |
| DJ Commodity Index Industrial Metals | 4.321       | 0.0905         | 4123                              | 0                                   |
| DJS Europe and DJ Commodity Index Precious Metals | 40.7         | 0              | 3637                              | 0                                   |
| DJ Commodity Index Precious Metals | 38.41       | 0              | 8865                              | 0                                   |
| Stoxx Europe Industry Neutral and DJ Index Precious Metals | 41.15        | 0              | 5660                              | 0                                   |
| DJ Index Precious Metals       | 38.25        | 0              | 8906                              | 0                                   |
| Stoxx Europe Leaders and DJ Index Precious Metals | 74.35        | 0              | 13,870                            | 0                                   |
| DJ Index Precious Metals       | 29.23        | 0.0005         | 2673                              | 0                                   |
| S&P500 ESG and DJ Index Precious Metals | 184.1       | 0              | 23,089                            | 0                                   |
| DJ Index Precious Metals       | 37.5         | 0.0005         | 8832                              | 0                                   |
| Stoxx Europe Leaders and DJ Commodity Index Grains | 48.5         | 0              | 6891                              | 0                                   |
| DJ Commodity Index Grains      | 16.52        | 0.0055         | 9748                              | 0                                   |
| S&P500 ESG and DJ Commodity Index Grains | 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 | 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 | 43.69        | 0              | 27,212                            | 0                                   |
| Euro Stoxx Select Dividend 30  | 0.4202       | 0.8155         | 1437                              | 0                                   |
### Appendix B

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

|                      | 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 |

**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 |
|                      | Stoxx Europe IN | 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 | 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 |
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