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ASSET ALLOCATION WITH ESG CONCERNS: EXPLORING ENVIRONMENTAL, SOCIAL, AND GOVERNANCE INVESTMENT STRATEGIES IN PORTFOLIO MANAGEMENT

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Abstract

This research explores different ESG investment strategies in portfolio management, analyzing their performance and risk variances for optimal risk-return outcomes. Using MSCI ESG indexes, the study reveals a slight decrease in financial returns with higher screening intensity. Well-diversified ESG indexes showed no reduced returns compared to a non-restricted index. Surprisingly, monthly variance across indexes remained equal regardless of the screening intensity. Jensen's alpha estimation found no significant differences in risk-adjusted returns among the observed ESG indexes. These findings build on previous literature and shed light on the complexities of ESG strategies within investment landscapes.

Keywords

ESG (Environmental, social, governance); Investment Strategies; Investment Performance; ESG Screenings; Investment Criteria, Risk, Return

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1 Introduction

1.1 Relevance

As the world is dealing with increasing threats caused by climate change, such as rising temperatures, severe weather occurrences, and ecological disruptions, the need to address these issues has reached a breaking point. It has become clear that environmental, social, and governance (ESG) concerns are not only a moral obligation anymore, but also a basic economic requirement. In addition, the prevailing economic challenges, as well as current public health and social justice concerns, have amplified and magnified the increased emphasis on ESG components. With the Paris Agreement in 2015, investors' involvement in climate action has spurred the expansion of sustainable investments. As a result, the total assets under management (AUM) committed to sustainable investments reached $35.3 trillion on a worldwide scale in 2020, which is a 15% increase from 2018 to 2020 and a 55% increase from 2016 to 2020. Given that the total global sustainable AUM makes up a total of 35,9% of all AUM (GSIA 2020), retail investors must understand what is meant by sustainable investments and how they can incorporate ESG concerns in their investment process.

1.2 Scientific question

The primary objective of this research project is to understand how various methods of integrating ESG factors affect the performance of investments. This aim seeks to advance current knowledge in sustainable investment research for both academic application and practical application among retail and institutional investors. The research project addresses the following questions:

What are different strategies to incorporate ESG concerns in the investment process? How do their performance and risk differ, and which approach provides the best risk-return trade-off?

Prior studies within this field have predominantly concentrated on the comparative analysis of returns achieved by socially responsible mutual funds against those of unrestricted benchmark portfolios (Jain, Sharma, and Srivastava 2019). The challenge of using the performance of mutual funds is that their performance is not solely indicative of the returns generated by their underlying securities. Instead, their performance depends on varying management fees, and transaction costs across providers, alongside a fund manager's ability in executing asset allocation, sector preferences, and securities selection. These circumstances make it difficult to use differences in mutual fund performance as a credible metric for determining the impact of implementing social responsibility screening on investment performance (Sauer 1997). Unlike previous studies, this research project investigates the performance differences of socially screened portfolios by using stock market indexes. Indexes measure the price performance of a basket of securities and are therefore unaffected by confounding effects that can affect the performance of actively managed, socially responsible investment funds (Sauer 1997). The selected indexes, each reflecting a different ESG investment strategy, are then compared to one another and an unrestricted benchmark index.

1.3 Approach in the thesis

To explore in depth the integration of ESG criteria into the investment process, the background of ESG is first discussed and then a definition of ESG is provided. This is followed by the theoretical basis of how ESG criteria are integrated into the practical investment process according to the principles of the Global Sustainable Investment Alliance (GSIA). This model provides the framework from which the various investment strategies examined are derived. The methodological section first derives the hypotheses that will be tested in this research project. In addition, insights into the data collection and data analysis procedures are provided. In the following section, the results of the inferential statistical tests performed are presented and analyzed. This involves an analysis that examines both the return and the variance of each index with one another as well as a risk-adjusted return measure. Subsequently, these results are discussed, and possible implications are pointed out to provide deeper insight into the study's significance. Lastly, the research paper presents limitations and concludes with a final summary.

2 Theoretical background

2.1 Evolution and definition of ESG and sustainable investments

In the 1960s and 1970s, the rise of antiwar sentiment and the sociopolitical movements supporting racial equity, gender equality, consumer protection, and environmental preservation changed traditional investment approaches. These global social and cultural trends resulted in socially responsible investing (SRI) (Townsend 2020). During the 1970s, "ethical investment" referred to religious investors from the UK, the US, and Australia who integrated ethical and social criteria in their portfolio selection (Sparkes and Cowton 2004). Their strategy excluded "sin stocks", referring to unethical companies operating in alcohol, tobacco, gambling, and defense industries (Wilkie 1992). In the late 1970s, the environmental movement drove the inclusion of concerns regarding toxicity, pollution, water, air quality, planetary, human welfare, and animals (Townsend 2020). Simultaneously, employee satisfaction, transparency, and corporate citizenship also gained recognition in investment practices (Moscowitz 1973), shaping the framework for corporate social responsibility (CSR) (Townsend 2020). By the late 1990s, the term "ethical investment" evolved into “socially responsible investment” or “ESG investing”. Nevertheless, the core approach of excluding sin stocks during the investment process remained unchanged (Sparkes and Cowton 2004).

The publication of “Who Cares Wins” by the United Nations (UN) in 2004 established the first unified definition of ESG and a strategy for incorporating ESG factors into capital markets. In collaboration with 18 major financial institutions, the paper outlined a comprehensive framework for incorporating ESG factors into financial analysis and investment practices. It segmented ESG into pillars, each focusing on specific subject domains, serving as assessment criteria (UN 2004). The environmental pillar focuses on climate change, deforestation, air and water pollution, land use, and the decline in biodiversity (Billio et al. 2021), evaluating companies based on energy efficiency, greenhouse gas emissions, waste and water management, and resource conservation. Multiple studies demonstrate a positive relationship between environmental practices and companies' financial performance. Research by Manrique and Martí-Ballester (2017) and Ma et al. (2023) confirms, in both developing and developed countries, that embracing environmental practices and CSR activities correlates positively with financial performance. The social pillar encompasses gender policies, human rights safeguarding, labor standard adherence, workplace and product safety, public health promotion, and income distribution, influencing employee contentment within organizations (Billio et al. 2021). Research by Luo, Zhou, and Shon (2016) establishes a positive link between employee satisfaction and corporate performance through Glassdoor.com data, while Ferreira (2010) and Horak and Cui (2017) underscore the benefits of gender-balanced boards, citing increased creativity, diverse perspectives, resource access, mentoring, public relations, and legitimacy. Lastly, the government pillar refers to board autonomy, shareholder rights, executive compensation, control systems, anti-competitive measures, and regulatory compliance (Billio et al. 2021). Studies by Alareeni and Hamdan (2020) and Wahyudin and Solikhah (2017) emphasize the notable positive impact of these approaches on accounting-based financial performance. Additionally, Darweesh (2015) highlights a statistically significant link between corporate governance mechanisms and the financial performance and market value of firms in the Saudi stock market.

2.2 Incorporation of ESG factors in the investment process

Several independent organizations have outlined distinct classifications of sustainable investment strategies. Appendix A displays different sustainable investment strategies outlined by GSIA, the European Sustainable Investment Forum (Eurosif), Principles of Responsible Investment (PRI), and the European Fund and Asset Management Association (EFAMA). These institutions focus on sustainable and responsible investment practices and aim to promote approaches that consider ESG factors in investment decisions. Given the overlapping investment approaches among those organizations, this research project primarily focuses on GSIA's seven investment strategies established in 2020 (GSIA 2020). The investment approaches observed and defined by the GSIA encompass the following strategies. **ESG Integration** systematically merges ESG factors into financial analyses, anchoring them in investment decisions. **Corporate Engagement & Shareholder Action** involve shareholders actively influencing company behavior via direct engagement, recommendations, and ESG-guided proxy voting. **Norms-Based Screening** assesses investments against global standards from bodies like the UN, OECD, and NGOs. **Negative/Exclusionary Screening** excludes sectors, companies, or countries not aligned with ethical/sustainable principles. **Best-in-Class/Positive Screening** targets top ESG performers in industries. **Sustainability Themed/Thematic Investing** directs funds into sustainable themes like agriculture and gender equity projects. **Impact Investing** quantifies social/environmental effects and engages investors actively and **Community Investing** helps historically underserved communities (GSIA 2020). These investment strategies cover various sustainable investment criteria (comparison in Appendix B). ESG investment strategies have various effects on sustainability, ranging from large to small contributions depending on their depth and scope. While strategies such as Corporate Engagement & Shareholder Action aim for long-term sustainability, simpler exclusionary approaches provide immediate benefits. The prevailing discussion about the effectiveness of these ESG strategies is primarily caused by the lack of uniformity in implementation methods and the limited systematic integration of ESG assessments into investment decisions. These factors give rise to skepticism regarding the actual effectiveness of existing integration strategies (Wagemans, Koppen, and Mol 2013).

3 Methodology

3.1 Hypotheses

Even though previous research has investigated ESG integration strategies and their financial impacts, further validation, and examination, especially regarding retail investors' choices among these strategies, remain necessary. Prior research on the performance of socially responsible investments primarily focused on the performance of SRI funds due to their longer history compared to sustainable indexes (Fowler and Hope 2007). These studies focus on comparing ESG investments to their non-ESG counterparts. So far, limited research has explored the performance difference among various sustainable investment approaches for indexes. With the rising interest of retail investors in ESG investments, further exploration into ESG integration's impact on investment returns and risk is essential (In, Rook, and Monk 2019). Therefore, this study contributes to deepening the existing knowledge of the return and volatility linkages by analyzing ESG investment strategies within the GSIA framework and comparing five sustainable indexes to one another as well as to a general market index. To explore variations among these ESG investment strategies, hypotheses are now being formulated, drawing from previous research findings.

Friede et al. (2015) conduced a meta-study of over 2,000 empirical studies and several review studies on the relationship between ESG and corporate financial performance (CFP). They found that 90% of studies reported a non-negative ESG-CFP link, with most of these studies showing positive findings. Nevertheless, Dumitrescu, Järvinen, and Zakriya (2023) observed that SRI ETF portfolios underperformed their non-restricted benchmarks between 2010 and 2020, although these statistical differences could not be observed in the second half of their sample period from 2015 to 2020 and the SRI ETFs even showed a significant outperformance in the last two years of the observation period, from 2018 to 2020. This performance shift can be explained by several factors such as industry development or increased awareness and acceptance of sustainable investing among investors. In line with these findings, the following hypothesis can be put forward:

> H1a: Incorporating ESG criteria into index investment without reducing diversification does not affect financial returns compared to an unrestricted index.

According to Statman (2002) the ideal number of individual stocks in a diversified portfolio, as assessed by the mean-variance portfolio theory, is larger than 120. As the *MSCI-CR* includes only 80 constituents, it is not seen as well-diversified in the analysis while the other indexes with over 120 constituents are considered well-diversified. Capelle-Blancard and Monjon (2014) studied French SRI funds' financial performance with different screening processes. Their findings indicate that higher screening intensity decreases financial performance. Additionally, exclusionary screening, like avoiding sin stocks, leads to a lower in financial performance while a norm-based screening method does not impact financial performance. According to these findings, the following hypothesis can be formulated:

> H1b: ESG strategies with strong ESG criteria, reducing diversification, yield lower financial returns compared to strategies lacking stringent ESG criteria.

Whenever analyzing returns, risks associated with these returns need to be considered. In literature, risk is defined as the unexpected deviation from an anticipated value (Woll 1999). Therefore, variance or standard deviation of returns is a common measure of risk in financial analysis (Cox 2008). Modern portfolio theory uses variance as a metric within mean-variance analysis to distinguish between efficient and inefficient portfolios. According to this theory, investors should maintain well-diversified portfolios to minimize idiosyncratic risk (Markowitz 1959). Idiosyncratic risk refers to risk specific to individual assets and diminishes through diversification. Systematic risk on the other hand impacts the entire market and cannot be diversified (Hill and Stone 1980). Therefore, adding constraints to portfolio selection leads to fewer assets and reduced diversification. Thus, the following hypothesis emerges:

H2: Incorporating ESG criteria in index construction, reducing diversification, results in significant variance disparities compared to more diversified indexes.

So far, only index returns and variances have been considered when formulating the above hypotheses. Nevertheless, analyzing portfolios with risk-adjusted measures is crucial for diversified investors focused on systematic risk, as return and variance alone do not account for risk-adjusted returns. Jensen's alpha is one of the most common financial metrics for showcasing an asset's systematic risk. It measures the risk-adjusted performance of an asset in relation to its systematic exposure (Jensen 1968). Recent research by Bekaert et al. (2023) showed that an ESG portfolio using MSCI's ESG momentum scores has a higher alpha than the MSCI US index. Meanwhile, Billio et al. (2021) found no significant difference between ESG and non-ESG portfolio alphas, suggesting they perform similarly in terms of risk-adjusted returns. As a result, the following hypothesis is formulated:

H3: ESG index alphas are not statistically different from zero and therefore neither underperform nor outperform the market index.

3.2 Data

The research project examines risk-return profiles among different investment strategies outlined by GSIA (2020) by analyzing secondary index data from Morgan Stanley Capital International (MSCI). Secondary data analysis involves the re-utilization of information initially gathered for alternate purposes (Swart et al.

2015). The required dataset can be retrieved from MSCI's website using the end-of-day index data query tool. MSCI emerged as a market leader in global equity indexes after Morgan Stanley acquired Capital International's index business rights. In 2010, MSCI ESG Research was launched after acquiring Kinder, Lydenberg, Domini & Co. (KLD), and Innovest Strategic Value Advisor, Inc. As of today, MSCI ESG Research rates over 6,000 companies and 40,000+ securities, making it the largest ESG rating agency globally (Eccles and Stroehle 2018). The analyzed index data, updated monthly, is reported in USD at a net return index level. The used equity indexes derive from the *MSCI World Index (MSCI-W)*, which covers 1,510 large and mid-cap companies in 23 developed markets (MSCI 2023e) (Appendix E). The following analysis employs the *MSCI-W* as both an unrestrained benchmark portfolio and the market portfolio for evaluation. The *MSCI World ESG Leaders Index (MSCI-ESGL)* replicates the ESG inclusion investment approach by selecting companies based on MSCI's ESG ratings, rating trends, controversies, and industry-adjusted ESG scores (MSCI 2023b) (Appendix F). The *MSCI World Climate Paris Aligned Index (MSCI-CP)* reflects the norms-based screening investment approach because it is designed to surpass EU Delegated Act benchmarks and align with Task Force on Climate-Related Financial Disclosures (TCFD) guidelines (MSCI 2023a) (Appendix G). The *MSCI ESG Screened Index (MSCI-ESGS)* adopts a negative/exclusionary screening approach since it excludes companies linked to controversial weapons, civilian firearms, nuclear weapons, tobacco, palm oil, arctic oil & gas, revenue from thermal coal, oil sands extraction, and those that do not comply with the United Nations Global Compact principles (MSCI 2023c) (Appendix H). The *MSCI World SRI Index (MSCI-SRI)* applies a best-in-class method and selects companies with the best ESG rating, representing 25% of the market capitalization in each sector (MSCI 2023f) (Appendix I). The *MSCI World Impact ESG Select Children's Rights Index (MSCI-CR)* follows a thematic investment approach by filtering out companies with poor labor rights for children (MSCI 2023d) (Appendix J). The investment approaches "Impact Investing & Community Investing" and "Corporate Engagement & Shareholder Action" follow a managerial approach and cannot be replicated using an index. Hence, these approaches are excluded from the analysis.

3.3 Data analysis

The descriptive and inferential statistical analyses are carried out using the statistical software R Studio® version 2023.09.1 for Windows. According to the guidelines of Cohen (1992), correlations are considered statistically significant if the probability of error is less than or equal to 5% ($p \leq 0.05$). If the p-value is less than or equal to 1%, the test result is considered very significant. A p-value less than or equal to 0.1% ($p \leq 0.001$) is considered a highly significant result.

3.3.1 Test for differences in returns

First, a Shapiro-Wilk test is employed to verify the assumption of normal distribution. The null hypothesis presumes that the sample is drawn from a normally distributed population. A non-significant p-value implies a normal distribution assumption, whereas a significant p-value indicates a deviation from the assumption of normal distribution (Shapiro and Wilk 1965). Concerning the data sample, this is intended to determine if the returns originate from a normally distributed population. The test showed that the distribution of the *MSCI-CR* return departed from normality ($W = 0.967$, p-value $= 0.00493$). Based on this outcome, the Friedman test, a non-parametric equivalent to the analysis of variance (ANOVA) for dependent samples, was employed to test H1a and H1b, aiming to identify significant differences in the monthly returns across the six indexes. Chi-squared is the test statistic employed in this analysis (Field, Miles, and Field 2012).

In order to confirm H1a, the monthly returns of the well-diversified ESG indexes must not significantly differ from the unrestricted index. To confirm H1b, the ESG index, which is the least diversified, needs to have a significant difference in monthly returns compared to other ESG indexes which are more diversified. An initial descriptive analysis is followed by a Friedman test, aiming to identify any significant discrepancies among the indexes' returns. This test evaluates whether at least one index significantly differs from the rest, operating under the null hypothesis that there are no significant differences between the returns of the six indexes. No special assumptions beyond the necessity for an ordinally scaled dependent variable are required for this test (Field, Miles, and Field 2012). If the Friedman test rejects the null hypothesis, the effect strength of the Friedman test is calculated using Kendall's coefficient of concordance (Kendall's ω). The subsequent non-parametric Dunn-Bonferroni post-hoc analysis, employing pairwise comparisons, identifies between which of the returns significant differences exist. Adjusting the p-value using the conservative Bonferroni method mitigates alpha error accumulation in multiple tests. Upon completion of the group comparison, the effect sizes are computed by transforming p-values from pairwise comparisons into standardized test statistics, quantifying the strength of the observed differences between each index (Field, Miles, and Field 2012).

3.3.2 Test for equality of variance

A Brown-Forsythe Levene-type test (B-F test) is used to test H2, which examines the differences in variances between the different indexes. This test, a version of the Levene test (Levene 1960), determines if variances between groups are statistically different or reflect homogeneity, especially when normality assumptions are violated. Unlike the Levene test, which uses deviations from group means and can lead to skewed data that violates normality assumptions, the B-F test corrects for skewness by using deviations from group medians. This modification makes the test more robust and less prone to incorrectly identifying uneven variances. Therefore, the B-F test was used to test for homogeneity due to the non-normal distribution of the *MSCI-CR*'s return. The null hypothesis of the B-F test states that the variances across the indexes are homogenous. If the B-F test shows significance, a Tukey-Kramer post-hoc test is used to identify the specific variances with significant differences (Brown and Forsythe 1974).

3.3.3 Estimation of Jensen's alpha

As previously discussed in section 3.1, Jensen's alpha reflects the mean risk premium per unit of systematic risk. A statistically significant positive alpha indicates an outperformance of the index, whereas a negative alpha indicates underperformance relative to the market. Under the assumption that the capital asset pricing model (CAPM) represents the accurate equilibrium pricing model, Jensen's alpha can be calculated as follows:

[1] $$\alpha_{\mathrm{P}} = \left(R_{P,t} - R_{f,t}\right) - \beta_{\mathrm{P}} * (R_{M,t} - R_{f,t})$$

where $R_{P,t}$ is the monthly return of the different ESG indexes, $R_{f,t}$ the monthly return of the three-month U.S. treasury bill reported by the Federal Reserve (FED), $R_{M,t}$

the monthly return of the market index, and β_p the measure of systematic risk (Jensen 1968). To test H3, which examines if the Jensen alphas differ from zero, α_P and β_P need to be estimated using the CAPM. For this, the excess return of the five ESG indexes and the excess return of the market index or the market risk premium (MRP), which is represented by the *MSCI-W*, need to be calculated. Then the index excess returns are regressed on the MRP using the following estimation model:

[2] $$\left(R_{P,t} - R_{f,t}\right) = \alpha_P + \beta_P * \left(R_{M,t} - R_{f,t}\right) + \varepsilon_{P,t}$$

where $\left(R_{P,t} - R_{f,t}\right)$ represents the monthly excess return of the ESG indexes and $\left(R_{M,t} - R_{f,t}\right)$ the MRP. The constant α_P within the model signifies Jensen's alpha, representing the average excess monthly return of the index compared to the market portfolio. The coefficient β_p indicates the sensitivity of the index's returns in relation to the returns of the overall market. Therefore, the excess return of ESG indexes can be explained by Jensen's alpha, the market sensitivity of these indexes multiplied by the MRP, and a residual term $\varepsilon_{P,t}$. This residual, with an expected value of $E(\varepsilon_P) = 0$, follows an identical and independent distribution (i.i.d.), i.e., $var(\varepsilon) = \sigma^2$ for all t and $cov(\varepsilon_{P,t}, \varepsilon_{P,\, t+x}) = 0$ for all $x \neq 0$. As the market portfolio fully reflects systematic risks, ε_P is independent of the MRP. Consequently, the covariances between the specific risks of the different indexes are $cov(\varepsilon_{P1}, \varepsilon_{P2}) = 0$ for all $P1 \neq P2$. Thus, the residual fulfills the Gauss-Markov conditions and allows the parameters α_P and β_P to be estimated using the ordinary least squares (OLS) approach within the linear regression model (Dodge 2008). The standard errors of the regression model are corrected for autocorrelation using the Newey-West correction method, ensuring robust estimations of α_P and β_P (Newey and West 1987).

4 Empirical evidence

4.1 Sample description

Over the period from December 2013 to September 2023, 118 observations were gathered for the six indexes and the three-month treasury bills. Appendix K contains detailed information about the sample used in the empirical analysis. The descriptive analysis reveals that for each index, the median is higher than the mean, indicating left-skewed returns with a long tail of low returns significantly impacting the mean more than the median. Moreover, the mean monthly returns of the *MSCI-W* (0.718%), *MSCI-ESGL* (0.720%), *MSCI-CP* (0.770%), MSCI-ESGS (0.741%), and *MSCI-SRI* (0.780%) are notably higher than the mean of the *MSCI-CR* (0.539%). All indexes show a monthly standard deviation ranging from 4.209% to 4.297%, except for *MSCI-CR*, which has a deviation of 3.290%. *MSCI-CR*'s lower return and standard deviation are consistent with the CAPM, implying that assets positioned lower on the capital market line exhibit lower risk (Markowitz 1959).

4.2 Friedman Test

The sample described in 4.1 was used for the analysis of H1a and H1b, which investigates the effects of incorporating ESG criteria on the monthly return. As shown above, the *MSCI-CR* demonstrates slightly lower median and mean returns ($Mdn = 1.095$, $M = 0.539$) compared to other indexes, such as the *MSCI-W* ($Mdn = 1.333$, $M = 0.718$) (Appendix K). Additionally, the boxplot in Appendix L indicates fewer outliers in the monthly returns for *MSCI-CR* compared to other indexes. The *MSCI-CP* showed the highest median ($Mdn = 1.461$) and the *MSCI-SRI* the highest mean ($M = 0.780$). The indexes *MSCI-ESGL*, *MSCI-ESGS*, *MSCI-SRI*, and *MSCI-W* exhibit similar monthly medians (between 1.197 and 1.349) and means (between 0.718 and 0.780).

In consideration of the non-normal distribution of the *MSCI-CR* returns, a Friedman test was conducted to determine significant variations in monthly returns among the indexes. The result shows a significant difference between the six indexes' monthly returns ($\chi^2 = 11.191$, p-value = 0.048). Consequently, the null hypothesis, which states that there are no differences in monthly returns, is rejected. The calculated effect size of the Friedman test using Kendall's ω is 0.0190. According to Cohen (1992), the difference observed in the Friedman test indicates a small effect size. A post-hoc analysis was conducted using Eisinga's et al. (2017) exact p-value method, which was chosen for its lower beta error probability. The alpha error probability was adjusted with the Bonferroni correction. The results show a statistically significant difference between *MSCI-CP* and *MSCI-CR* (p-value = 0.043) with an effect size of $r = 0.274$, also indicating a small effect size (Cohen 1992). There are no statistically significant differences among the other indexes. The detailed results of the Friedman test and the post-hoc analysis can be found in Appendix M and Appendix N. Hence, the Friedman test validates H1a and provides partial confirmation for H1b.

4.3 Brown-Forsythe Levene-type test

Upon testing H2, which examines the differences in variance among the six indexes, a B-F test is carried out. This test aims to determine if the indexes display homogeneity in variance based on the F-distribution. Initial observations unveil similar standard deviations across the indexes, with *MSCI-CP*, *MSCI-ESGL*, *MSCI-ESGS*, *MSCI-SRI*, and *MSCI-W* registering standard deviations ranging from

0.042 to 0.043, except for *MSCI-CR* which deviates slightly with a lower value of 0.033 (Appendix K). However, the obtained B-F test shows a *p*-value of 0.303 with an *F*-value of 1.209 (Appendix O). This implies that the null hypothesis cannot be rejected, indicating equality in variances across the indexes. Consequently, H2 cannot be confirmed.

4.4 Estimation of Jensen's alpha

To evaluate the risk-adjusted returns of ESG indexes, Jensen's alphas are going to be estimated with a single-index model using the OLS method. If the alphas are significantly different from zero, an out- or underperformance can be assumed. An initial analysis of excess returns reflects similar findings from sections 4.1 and 4.2. Similar to prior observations, the *MSCI-CR* exhibits a consistently lower excess return compared to all other indexes. Additionally, while the *MSCI-SRI* displays comparable mean and median excess returns to the other indexes (excluding *MSCI-CR*), its excess return demonstrates fewer extreme outliers. The lowest excess return of the *MSCI-SRI* is -10.969 and the highest is 11.933, while the other indexes have minimum values between -12.782 and -13.361 and maximum values between 12.451 and 12.778 (Appendix P). If the CAPM represents the correct equilibrium pricing model, then α_P and β_P can be estimated using OLS in a single linear regression model (Section 3.3.3). Each ESG index's excess return is regressed against the MRP, as shown by the scatter plots in Appendices Q to U. While almost all points in each scatter plot of the different indexes lay in an almost perfect line, the *MSCI-CR*'s scatter plot shows notably greater dispersion around the regression line, indicating a comparatively lower correlation with the MRP.

Appendix V presents the outcome of the regression models. All models exhibit a strong goodness of fit, with the lowest R^2 standing at $R^2 = 0.777$ (adjusted $R^2 = 0.775$) for the *MSCI-CR*. Despite this lower R^2 compared to the other indexes (R^2 around 0.99), the model remains highly significant, $F(1,116) = 404.8$, $p < 0.001$ (Cohen 1988). The high R^2 values are unsurprising given that some of the indexes closely resemble the market index, such as the *MSCI-ESGS*, and therefore their returns show a high correlation with the market returns. The alpha coefficients indicate marginal positive monthly alphas across all indexes. However, the lack of statistical significance invalidates the assumption that these ESG indexes outperform the market, confirming H3. Furthermore, all estimated betas are highly statistically significant and have a value of around one. The only expectation is the *MSCI-CP*, which has a highly statistically significant beta of $\beta_{\text{MSCI-CP}} = 0.682$. A lower beta implies a lower volatility compared to the market.

In the above analysis, it is assumed that the CAPM represents the correct equilibrium pricing model. However, Fama and French (1993) suggest that relying solely on the market return might overlook other return-influencing factors. To validate the shown results, alpha is re-estimated using the Carhart-Fama-French four-factor model (CFF4FM). The model analyzes the portfolio performance by considering market risk, company size impact, book-to-market ratios, and the momentum factor (Carhart 1997). Appendix W offers a detailed model description, while Appendix X provides a descriptive analysis of the utilized data. The result of the CFF4FM is shown in Appendix Y. Generally, the multiple regression models of each index exhibit slightly higher R^2 values than the previous single linear regression model, except from the *MSCI-ESGL*, suggesting a slightly better fit. Additionally, all multiple regressions demonstrate high significance ($p < 0.001$). Diverging from earlier observations, *MSCI-ESGL*, *MSCI-ESGS*, and *MSCI-CR* display minor negative monthly alphas. However, all alphas lack statistical significance and therefore H3 can also be confirmed according to the four-factor model.

5 Discussion

5.1 Discussion of the results

The comprehensive findings derived from the Friedman test outlined in section 4.2 highlight significant variations in the returns across diverse indexes. The subsequent post-hoc examination unveils statistical significance solely between the returns of *MSCI-CP* and *MSCI-CR*. Conversely, among the remaining indexes, no statistically significant differences in median returns are evident. Considering that the *MSCI-CR* is not well-diversified, it can be concluded that there is no statistically significant difference in median returns between a well-diversified ESG index and the market portfolio, represented by the *MSCI-W*. This outcome effectively validates H1a. In line with Friede, Busch, and Bassen's (2015) meta-analysis highlighted in section 3.1, the results of this study are consistent with most studies in the meta-analysis, suggesting a non-negative ESG-CFP relationship. However, contrary to the meta-study's findings that highlight a positive link between ESG and CFP in some examined studies, this research project does not reach this conclusion due to the absence of statistically significantly higher median returns. The statistically significant lower median monthly return of the *MSCI-CR* compared to the *MSCI-CP* suggests that stricter ESG strategies underperform due to reduced diversification. Therefore, H1b can be confirmed in this scenario. However, as the other indexes are also regarded as well-diversified and show no statistically significant distinction from the *MSCI-CR*'s median return, H1b confirmation remains elusive. To clarify this, further research that compares indexes with varying levels of diversification is needed.

The B-F test yields non-significant results despite the *MSCI-CR* exhibiting a visibly lower variance than other indexes. This insignificance suggests equal variances among indexes, indicating similar risk levels. Consequently, H2, proposing significant variance differences for stricter ESG criteria integration approaches, cannot be confirmed. This result indicates that the *MSCI-CR* does not align with the characteristics of an efficient portfolio on the capital market line, because *MSCI-CR*'s significantly lower return, compared to *MSCI-CP*, contradicts expectations for reduced risk levels (Markowitz 1959). Nevertheless, when considering the estimated betas from the CAPM, they all show betas around one (Appendix V), except for *MSCI-CR*'s beta ($\beta_{\text{MSCI-CR}} = 0.682^{***}$), which displays a beta below one, indicating that the asset's volatility is lower compared to the market. Based on this observation, it can be concluded that the *MSCI-CR* has a lower risk compared to the market. Nevertheless, this difference remains unapparent when considering variance independently. Therefore, the absence of different variances could be attributable to other factors, such as the limited historical data available for ESG indexes (Jain, Sharma, and Srivastava 2019). Given the short lifespan of ESG indexes, the observed ten-year period does not cover various economic cycles, making it difficult to monitor these ESG indexes over time. In financial research, understanding market behavior, asset performance, and economic trends usually requires observing multiple market cycles (Y. Ma and Zhang 2016).

Lastly, the estimation of Jensen's alphas with both the CAPM and the CFF4FM yields non-significant alphas for all ESG indexes, confirming H3. This observation aligns with prior literature, indicating that ESG indexes demonstrate comparable risk-adjusted returns to their non-restricted counterparts (Sauer 1997; Capelle-Blancard and Monjon 2014; Albuquerque et al. 2020; Guimarães and Malaquias 2023). Until now, limited research has delved into the performance differences among various ESG investment strategies. This study specifically examines these differences. The noticeably higher median return of *MSCI-CP* compared to *MSCI-CR* suggests that the norm-based investment approach achieves a significantly higher average monthly return compared to the thematic investment approach. However, Jensen’s alpha estimation regressions indicate no significant differences between alphas, making it inconclusive to assume substantial variations in risk-adjusted returns among all the observed ESG investment strategies. In a separate study conducted by Naffa and Fain (2020), an examination was made of the risk-adjusted financial performance metrics of ESG-themed megatrends. Their analysis spanned nine ESG themes from 2015 to 2019 (Appendix Z), revealing that most of these megatrend factors generated non-negative excess returns in comparison to the market portfolio. Nevertheless, the study could also derive no statistically significant conclusions regarding the superior or inferior performance of specific ESG investment strategies.

The finding that ESG indexes do not notably outperform or underperform broader market indexes, implies that investing in diversified ESG-aligned indexes does not drastically alter portfolio performance compared to traditional investments. This has multiple implications. Firstly, it suggests that the inclusion of ESG metrics in investment strategies does not distinctly enhance or worsen financial performance. This does not necessarily suggest that ESG metrics provide no additional information and therefore have no direct impact on investment returns. Rather, it indicates that this information might already be factored into general market pricing or that other dominant factors influence performance more significantly. For example, factors such as the level of diversification of portfolios, other market dynamics, or macroeconomic factors could dilute the influence of more specific factors like ESG criteria. Secondly, ESG metrics could hold long-term value due to improved resilience and risk management (Orlitzky and Benjamin 2001) in companies despite the limited immediate financial impact. Therefore, for institutional investors, this research project indicates that there is no significant risk-adjusted return difference between well-diversified ESG indexes and their non-restricted counterparts over the last decade. Thus, choosing between well-diversified ESG indexes and their parent indexes does not significantly affect risk-adjusted returns. As there is no statistically significant difference in risk-adjusted returns among various well-diversified ESG investment strategies, investors can invest in their preferred diversified ESG investment approach without sacrificing lower risk-adjusted returns.

5.2 Critical review

As outlined in section 5.1, a significant shortcoming in the financial analysis of ESG investments is the absence of long-term observation. The constrained timeline of sustainable investment strategies poses a limitation in forming definitive conclusions within financial research. Comprehensive analyses across multiple economic cycles are imperative to derive conclusive findings, surpassing the constraints of a limited duration for robust and reliable assessments (Ashe and Egan

2023; Dinh 2023). Only through long-term observations can conclusive, long-term insights be drawn regarding the efficacy and implications of the investment strategy. Moreover, to date, a unified definition of ESG concepts remains elusive. Although the UN (2004) has published guidelines regarding ESG investments, ESG developed into a non-financial “index” for enterprises, which summarizes an enterprise's practices and performance concerning ESG factors (Li et al. 2021). Despite ongoing efforts to quantify and define this “index” with ESG-compliant guidelines (European Parliament 2020), a standardized global concept remains elusive. Consequently, various rating agencies often show significant disparities between company’s ESG ratings (Chatterji et al. 2016; Charles Yonts, Jamie Allen, and Miriam Zhou 2018; Allen 2018; Semenova and Hassel 2015; Dorfleitner, Halbritter, and Nguyen 2015). Therefore, a significant drawback of this research paper is also, that the investigated indexes are chosen based on their ESG investment strategy but without considering ESG scores. Within this context, the integration of a standardized ESG score into future analyses would be an interesting approach to explore. Consequently, a comprehensive data analysis would clarify the consistency of results across indexes sharing identical ESG scores. Another notable limitation of this study is that it focuses solely on analyses of return, variance, and Jensen's alpha. Other financial ratios, such as the Sharpe and Treynor ratios, should be examined in further scientific studies to validate the observed results and therefore gain further insights into risk-adjusted measures of ESG indexes. Unfortunately, this research project could not carry out an analysis of the Sharpe or Treynor ratios. These metrics are limited in their ability to evaluate statistical significance in portfolio performance disparities (Sauer 1997; Jobson and Korkie 1981). To enable a comparative analysis with these metrics, modifications of their methodologies are required. However, such an undertaking exceeds the scope of this project.

6 Conclusion

Throughout this work, various analyses were carried out to answer the research questions: What are different strategies to incorporate ESG concerns in the investment process? How do their performance and risk differ, and which approach provides the best risk-return trade-off? This research project analyzes diverse ESG investment approaches within GSIA's sustainable investment strategies, using MSCI ESG indexes as the primary analytical framework. The results of the Friedman test indicate a small but statistically significant difference in return between the *MSCI-CP* and the *MSCI-CR*, suggesting that higher screening intensity lowers financial return (H1b). Additionally, no significant differences in monthly returns can be observed between diversified ESG indexes and the market index, supporting previous research that diversified ESG portfolios do not yield lower returns compared to their non-restricted counterparts (H1a). Nevertheless, the shown results do not confirm a positive relationship between ESG and financial performance. The analysis of variance unexpectedly reveals uniform variances between the indexes (H2). This observation's absence might be attributed to the limited historical data available for sustainable indexes, emphasizing the need for broader observations across multiple economic cycles to draw more robust conclusions. Yet, Jensen's alpha estimations using both the CAPM and the CFF4FM show no out- or underperformance across ESG indexes and the market index, indicating comparable risk-adjusted returns among them. Hence, determining superior performance among the sustainable investment strategies based on these indexes is not possible.

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List of Annexes

Appendix A: Sustainable investment methods across various organizations

GSIA	Eurosif-equivalent	PRI-equivalent*	EFAMA-equivalent
Negative/exclusionary screening	Exclusion of holdings from the investment universe	Negative/exclusionary screening	Negative screening or exclusion
Norms-based screening	Norms-based screening	Norms-based screening	Norms based approach (type of screening)
Positive / best-in-class screening	Best-in-class investment selection	Positive / best-in-class screening	Best-in-class policy (type of screening)
Sustainability-themed investing	Sustainability-themed investment	Sustainability themed investing	Thematic investment (type of screening)
ESG integration	ESG integration	Integration of ESG issues	-
Corporate engagement and shareholder action	Engagement and voting on sustainability matters	Active ownership and engagement	Engagement (voting)
Impact/community investing	Impact investing	-	-

* Detailed information of the Principles of Responsible Investment is shown in Appendix C

Source: European Sri Study 2018 (Eurosif 2018)

Appendix B: GSIA’s sustainable investment strategies

	Strategies	Description	Example
Portfolio selection	*ESG Integration*	Incorporating ESG factors into traditional financial analysis	In-house research of many institutional investors
	Norms-based Screening	Examination of investments against internationally recognized standards and norms	Only firms with ISO 14001
	Negative/exclusionary screening	Exclusion of certain sectors, companies, or countries from the investment portfolio	No weapons, nuclear, and/or tobacco
	Best-in-class / positive screening	Selection of sectors, companies, or projects that exceed their industry counterparts in terms of their ESG performance	Only the 10% best regarding ESG criteria
	Sustainability themed/ thematic investing	Specific sustainability-themed investment	Clean-tech funds
Management approach	*Impact investing and community investing*	Includes quantifying and reporting on the ESG impact of investment activities (impact comes first)	Microfinance to help farmers in India
	Corporate Engagement & Shareholder Action	Shareholders’ proactive impact in shaping company behavior	Direct engagement with senior management

Source: Own representation based on GSIA (2020) and Busch, Bauer, and Orlitzky (2016)

Appendix C: PRI framework for possible actions to incorporate ESG issues

Principles of Responsible Investment (PRI)					
Incorporate ESG issues into investment analysis	Commitment to active ownership and ESG integration in ownership policies	Promoting ESG disclosure among invested entities	Promoting Principles' acceptance and implementation in investment industry	Collaborative efforts to strengthen Principles implementation	Commitment to transparent reporting
Actions: • Consideration of ESG criteria in investment policy • Promote the development of ESG-related tools • Evaluate asset managers on the integration of ESG issues • Involvement of financial service providers in ESG analysis • Stimulating academic research on ESG issues • ESG training for investment professionals	Actions: • Create and disclose active ownership policy • Contribute to policy, regulation, and standards development • Propose shareholder resolutions in line with ESG factors • Engage with companies on ESG matters • Request investment managers to conduct and report ESG-related engagement	Actions: • Demand standardized ESG reporting • Integrate ESG matters into annual financial reports • Request information on companies adopting relevant norms and standards • Back shareholder initiatives promoting ESG disclosure	Actions: • Integration of Principles in requests for proposals (RFPs) • Align mandates, monitoring, indicators, and incentives with Principles • Communicate ESG expectations to service providers • Reevaluate non-compliant provider relationships • Back development of ESG benchmarking tools • Support ESG-friendly regulatory changes	Actions: • Engage in networks and information platforms for resource-sharing • Collaboratively address emerging issues • Support and participate in relevant initiatives	Actions: • Disclose ESG integration in the investment process • Disclose active ownership actions • Specify the conditions under which service providers must comply with the Principles • Engage with beneficiaries on ESG issues • Report progress • Assess the Principles' impact • Use reporting for broader stakeholder awareness

Source: Own representation based on UNEP Finance Initiative and UN Global Impact (2021)

Appendix D: Characteristics of the studied indexes

	MSCI-ESGL	MSCI-CP	MSCI-ESGS	MSCI-SRI	MSCI-CR	MSCI-W
Investment approach	ESG inclusion	Norms-based screening	Negative/exclusionary screening	Best-in-class / positive screening	Sustainability themed / thematic investing	No ESG
Number of constituents	717	604	1,391	403	80	1,510
Launched in	Sep. 2008	Nov. 2013	May 2012	Sep. 2008	Jan. 2013	Mar. 1986
Country weights	US: 70.2% Japan: 6.6% UK: 3.9% France: 3.6% Canada: 3.3% Other: 12.4%	US: 69.3% Japan: 5.0% Canada: 4.8% France: 4.0% Switzerland: 3.9% Other: 13.0%	US: 70.1% Japan: 6.6% UK: 3.9% France: 3.2 % Canada: 2.9% Other: 13.3%	US: 68.9% Japan: 6.6% Canada: 3.9% UK: 3.5% France: 3.1% Other: 14.0%	US: 36.5% Japan: 11.0% Switzerland: 7.7% Germany: 7.6% Spain: 6.6% Other: 30.6%	US: 69.7% Japan: 6.2% UK: 4.1% France: 3.3% Canada: 3.2% Other: 13.5%
Sector weights	IT: 22.4% Consumer goods: 18.3% Financials: 14.8% Health: 12.9% Industrials: 11.2% Other: 20.4%	IT: 26.5% Financials: 18.1% Health: 14.5% Industrials: 12.7% Consumer goods: 12.3% Other: 15.9%	IT: 24.0% Financials: 16.4% Consumer goods: 15.9% Health: 14.0% Industrials: 10.2% Other: 19.5%	IT: 24.9% Consumer goods: 20.8% Financials: 15.3% Health: 12.6% Industrials: 11.2% Other: 15.2%	Consumer goods: 22.4% Health: 20.0% Utilities: 12.9% Industrials: 11.0% Financials: 8.6% Other: 25.1%	IT: 21.7% Consumer goods: 18.1% Financials: 15.0% Health: 12.8% Industrials: 10.9% Other: 21.5%

Source: Own representation based on MSCI (2023a, 2023b, 2023c, 2023d, 2023e, 2023f)

Appendix E: Overview MSCI World Index

Description:

The MSCI World Index encompasses large and mid-cap companies from 23 Developed Markets, totaling 1,510 constituents. This represents about 85% of each country's free float-adjusted market capitalization. As of September 29th, 2023, the index's market capitalization stands at 54,508,310.80 million USD.

Annual performance:

Year	MSCI World (%)
2022	-17.73
2021	22.35
2020	16.50
2019	28.40
2018	-8.20
2017	23.07
2016	8.15
2015	-0.32
2014	5.50
2013	27.37

Top ten constituents:

	Adj Mkt Cap (USD Billions)	Index weight (%)	Sector
Apple	2,692.91	4.94	Info Tech
Microsoft Corp	2,230.37	4.09	Info Tech
Amazon.com	1,173.87	2.15	Cons Discr
Nvidia	1,074.43	1.97	Info Tech
Alphabet A	777.44	1.43	Comm Srvcs
Tesla	713.77	1.31	Cons Discr
Alphabet C	697.04	1.28	Comm Srvcs
Meta Platforms A	664.11	1.22	Comm Srvcs
Exxon Mobil Corp	475.30	0.87	Energy
UnitedHealth Group	469.42	0.86	Health Care
Total	10,968.64	20.12	

Note: Info Tech = Information Technology; Cons Discr = Consumer Discretionary; Comm Srvcs = Communication Services

Source: Own representation based on MSCI(2023e)

Appendix F: Overview MSCI World ESG Leaders Index

Description:

The MSCI World ESG Leaders Index is a free float-adjusted market capitalization-weighted index representing companies chosen from the MSCI World Index using ESG criteria. These criteria screen out companies based on specific business activities, ESG ratings, and controversies. Comprising large and mid-cap companies across 23 Developed Markets, it targets 50% coverage of each GICS® sector by selecting constituents primarily on ESG rating trends and industry-adjusted scores. It is part of the MSCI ESG Leaders Index series, designed to mirror sector weights of the corresponding Parent Indexes based on ESG criteria.

Annual performance:

Year	MSCI World ESG Leaders Index (%)
2022	-19.17
2021	25.29
2020	15.90
2019	28.91
2018	-7.22
2017	21.69
2016	7.93
2015	-0.55
2014	5.42
2013	28.22

Top ten constituents:

	Index weight (%)	Sector
Microsoft Corp	8.10	Info Tech
Nvidia	3.90	Info Tech
Alphabet A	2.82	Comm Srvcs
Tesla	2.59	Cons Discr
Alphabet C	2.53	Comm Srvcs
Lilly (Eli) & Company	1.57	Health Care
Johnson & Johnson	1.36	Health Care
Visa A	1.35	Financials
Procter & Gamble Co	1.25	Cons Staples
Mastercard A	1.22	Financials
Total	26.71	

Note: Info Tech = Information Technology; Comm Srvcs = Communication Services; Cons Discr = Consumer Discretionary; Cons Staples = Consumer Staples

Source: Own representation based on MSCI (2023b)

Appendix G: Overview MSCI World Climate Paris Aligned Index

Description:

The MSCI World Climate Paris Aligned Index, a subset of the MSCI World Index, includes large and midcap securities across 23 Developed Markets. It is tailored for investors aiming to mitigate climate risks and seize opportunities linked to a lower-carbon economy, aligning with Paris Agreement guidelines. These indexes exceed EU standards, adhering to TCFD recommendations and the 1.5°C climate scenario. They aim to cut exposure to extreme weather events, shift towards environmentally friendly assets, bolster companies poised for climate opportunities, and diminish risks. Additionally, they reduce weight on high carbon emitters while favoring firms with credible carbon reduction targets, aiming for modest tracking errors and low turnover. Rebalancing semi-annually, these changes coincide with MSCI Global Investable Market Indexes' May and November reviews.

Annual performance:

Year	MSCI World Climate Paris Aligned (%)
2022	-21.57
2021	21.86
2020	18.18
2019	29.37
2018	-7.50
2017	23.78
2016	8.14
2015	1.47
2014	6.94

Top ten constituents:

	Index weight (%)	Sector
Apple	5.50	Info Tech
Microsoft Corp	4.59	Info Tech
Nvidia	2.34	Info Tech
Amazon.com	2.11	Cons Discr
Alphabet C	1.92	Comm Srvcs
Tesla	1.58	Cons Discr
Meta Platforms A	1.33	Comm Srvcs
Lilly (Eli) & Company	1.18	Health Care
Schneider Electric	1.05	Industrials
Alphabet A	1.00	Comm Srvcs
Total	22.60	

Note: Info Tech = Information Technology; Cons Discr = Consumer Discretionary; Comm Srvcs = Communication Services

Source: Own representation based on MSCI (2023a)

Appendix H: Overview MSCI World ESG Screened Index

Description:

The MSCI World ESG Screened Index, a subset of the MSCI World Index, includes large and mid-cap securities across 23 Developed Markets. It excludes companies involved in controversial activities like weapons, tobacco, and specific oil extraction, along with those not compliant with the UN Global Compact principles or embroiled in severe controversies. The index aims for a 30% reduction in carbon intensity compared to its parent index. It adheres to the MSCI Global Investable Indexes Methodology, ensuring comprehensive coverage, liquidity, and replicability across market segments.

Annual performance:

Year	MSCI World ESG Screened Index (%)
2022	-19.61
2021	22.16
2020	17.56
2019	28.15
2018	-8.60
2017	22.49
2016	7.02
2015	0.08
2014	5.39
2013	27.58

Top ten constituents:

	Index weight (%)	Sector
Apple	5.45	Info Tech
Microsoft Corp	4.52	Info Tech
Amazon.com	2.38	Cons Discr
Nvidia	2.18	Info Tech
Alphabet A	1.57	Comm Srvcs
Tesla	1.45	Cons Discr
Alphabet C	1.41	Comm Srvcs
Meta Platforms A	1.34	Comm Srvcs
Exxon Mobil Corp	0.96	Energy
UnitedHealth Group	0.95	Health Care
Total	22.60	

Note: Info Tech = Information Technology; Cons Discr = Consumer Discretionary; Comm Srvcs = Communication Services

Source: Own representation based on MSCI (2023c)

Appendix I: Overview MSCI World SRI Index

Description:

The MSCI World SRI Index comprises large and mid-cap stocks across 23 Developed Markets. It is a capitalization-weighted index emphasizing companies with robust Environmental, Social, and Governance (ESG) ratings while excluding those with negative societal or environmental impacts. Intended for socially responsible investors, it employs value-based exclusions and a Best-in-Class selection process based on MSCI ESG Research. After excluding specific industries, the remaining eligible securities undergo the Best-in-Class selection. It aligns sector and region weights with underlying indexes to mitigate systematic risk and aims to include top-rated ESG companies, constituting 25% of sector and region market capitalization in the parent indexes. Eligibility criteria demand high ESG ratings for inclusion or retention in the index, with constituents selected from the MSCI Global Investable Market Indexes.

Annual performance:

Year	MSCI World SRI Index (%)
2022	-22.50
2021	27.04
2020	19.86
2019	29.76
2018	-6.72
2017	23.64
2016	7.69
2015	-1.58
2014	3.91
2013	27.39

Top ten constituents:

	Index weight (%)	Sector
Microsoft Corp	15.74	Info Tech
Tesla	5.04	Cons Discr
Home Depot	2.14	Cons Discr
Novo Nordisk B	2.11	Health Care
ASML HLDG	1.68	Info Tech
PepsiCo	1.65	Cons Staples
Adobe	1.64	Info Tech
Coca Cola (THE)	1.62	Cons Staples
Linde (NEW)	1.29	Materials
Danaher Corp	1.23	Health Care
Total	34.14	

Note: Info Tech = Information Technology; Cons Discr = Consumer Discretionary; Cons Staples = Consumer Staples

Source: Own representation based on MSCI (2023f)

Appendix J: Overview MSCI World Impact ESG Select Children’s Rights Index

Description:

The MSCI World Impact ESG Select Children’s Rights Index, part of the MSCI World Index, includes large and mid-cap securities across 23 Developed Markets. It seeks to mirror the performance of stocks generating higher revenue from Sustainable Impact activities. Employing an ESG screen excludes companies with low ESG performance and Child Labor Rights Scores below 5, adhering to MSCI ESG Research metrics. The index focuses on diversification within country and sector limits, applying constraints aligned with UCITS III investment guidelines and MSCI's 10/40 Index Methodology.

Annual performance:

Year	MSCI World Impact ESG Selected Children’s Rights Index (%)
2022	-4.72
2021	19.07
2020	-5.81
2019	24.99
2018	-1.96
2017	8.20
2016	7.33
2015	19.31
2014	23.50

Top ten constituents:

	Index weight (%)	Sector
Softbank Corp	3.49	Comm Srvcs
Marathon Petroleum	3.17	Energy
Novartis	2.36	Health Care
Colgate-Palmolive	2.18	Cons Staples
Ferrovial	2.07	Industrials
Johnson & Johnson	2.01	Health Care
Beiersdorf	1.95	Cons Staples
Roche Holding Genuss	1.82	Health Care
Kellogg Co	1.75	Cons Staple
Redeia Corp	1.73	Utilities
Total	22.53	

Note: Comm Srvcs = Communication Services; Cons Staples = Consumer Staples

Source: Own representation based on MSCI (2023d)

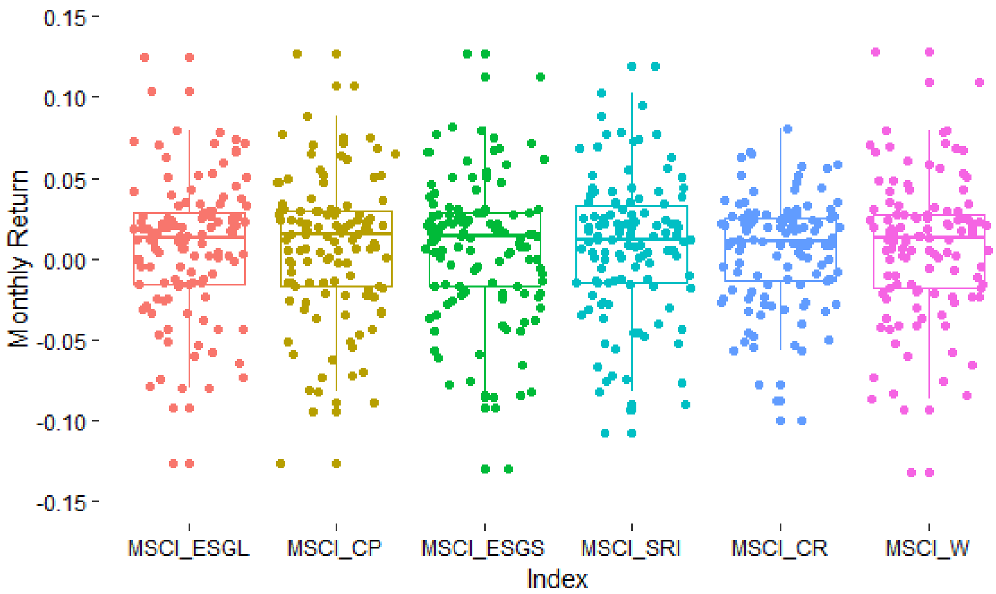
Appendix K: Descriptive analysis of the return

	MSCI-ESGL	MSCI-CP	MSCI-ESGS	MSCI-SRI	MSCI-CR	MSCI-W
Mdn	1.3009%	1.4606%	1.3490%	1.1966%	1.0950%	1.3329%
M	0.7201%	0.7696%	0.7414%	0.7802%	0.5385%	0.7179%
Min	-12.7311%	-12.6553%	-13.0455%	-10.8419%	-10.0220%	-13.2343%
Q1	-1.5465%	-1.6579%	-1.6663%	-1.4656%	-1.3862%	-1.7978%
Q3	2.8944%	2.9586%	2.8092%	3.2785%	2.4799%	2.7825%
Max	12.4594%	12.6966%	12.6713%	11.9413%	8.0438%	12.7859%
Var	0.001772	0.001839	0.001846	0.001832	0.001082	0.001815
SD	4.2091%	4.2887%	4.2968%	4.2797%	3.2898%	4.2601%

Note: N =118. *Mdn* = Median, *M* = Mean, *Q1* = 25th percentile, *Q3* = 75th percentile, *Var* = Variance, *SD* = Standard Deviation

Source: Own representation

Appendix L: Boxplot monthly return



Source: Own representation

Appendix M: Results Friedman test

	chi-squared	df	*p*-value
Returns	11.191	5	0.04772

Source: Own representation

Appendix N: Results Eisinga et al. (2017) all-pair test

	MSCI-CP	MSCI-CR	MSCI-ESGL	MSCI-ESGS	MSCI-SRI
MSCI-CR	0.043	-	-	-	-
MSCI-ESGL	0.443	1.000	-	-	-
MSCI-ESGS	1.000	0.868	1.000	-	-
MSCI-SRI	1.000	0.484	1.000	1.000	-
MSCI-W	1.000	1.000	1.000	1.000	1.000

Source: Own representation

Appendix O: Result of the Brown-Forsythe Levene-type test

	n	df	***F*-value**	***p*-value**
Indexes	702	5	1.2086	0.3033

Source: Own representation

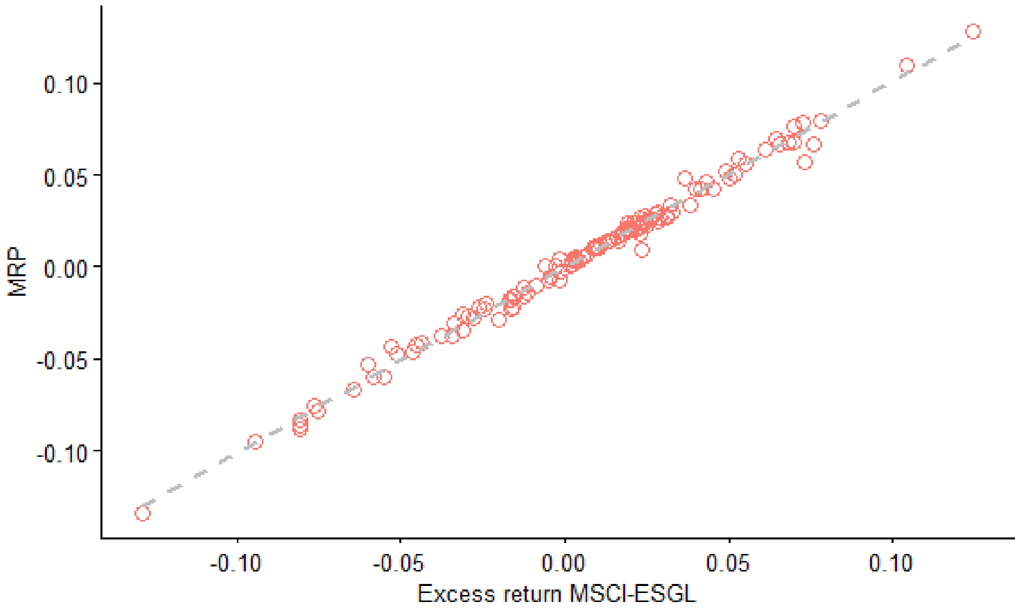
Appendix P: Descriptive analysis of the excess return

	MSCI-ESGL	MSCI-CP	MSCI-ESGS	MSCI-SRI	MSCI-CR	MSCI-W
Mdn	1.2056%	1.3003%	1.2317%	1.1301%	1.0821%	1.1821%
M	0.6262%	0.6757%	0.6475%	0.6863%	0.4446%	0.6240%
Min	-12.8577%	-12.7819%	-13.1722%	-10.9685%	-10.1487%	-13.3610%
Q1	-1.6120%	-1.6744%	-1.6706%	-1.5885%	-1.4380%	-1.8022%
Q3	2.8065%	2.9063%	2.7317%	3.1776%	2.4398%	2.7132%
Max	12.4511%	12.6883%	12.6630%	11.9330%	8.0354%	12.7775%

Note: N =118. *Mdn* = Median, *M* = Mean, *Q1* = 25th percentile, *Q3* = 75th percentile

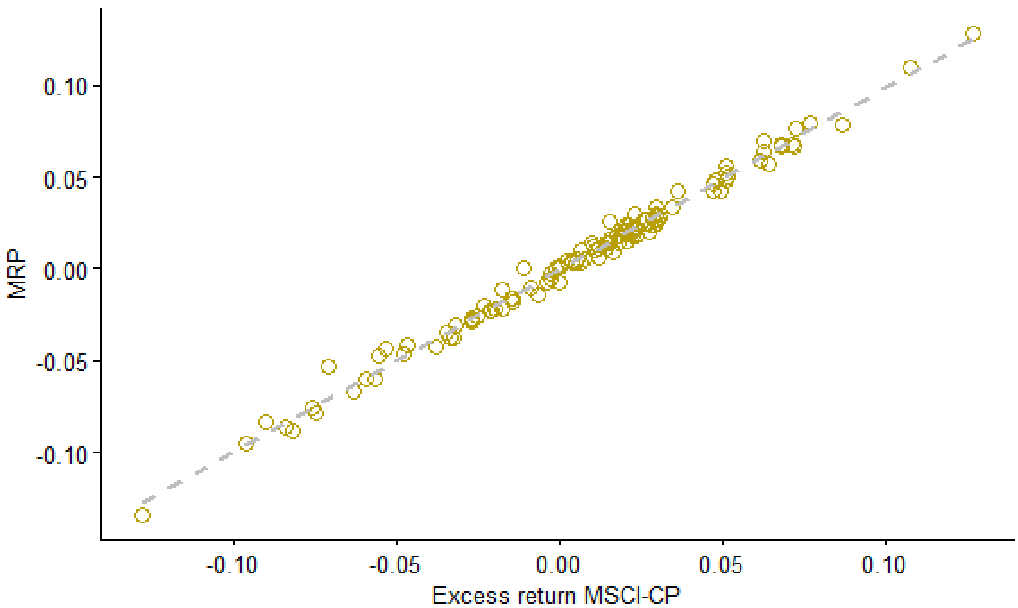
Source: Own representation

Appendix Q: Scatter plot of MSCI-ESGL's excess return against the MRP



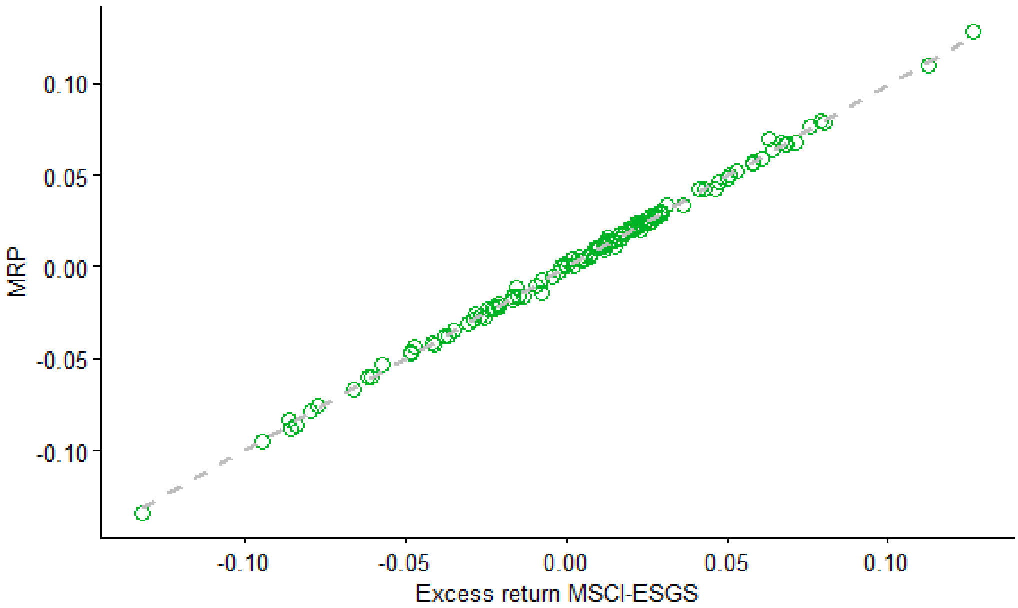
Source: Own representation

Appendix R: Scatter plot of MSCI-CP's excess return against the MRP



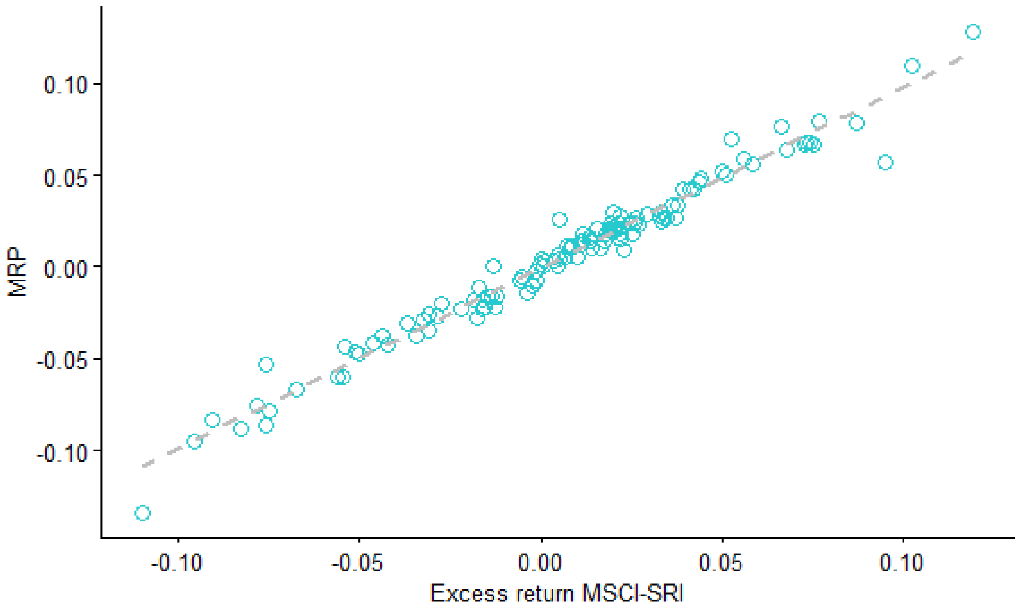
Source: Own representation

Appendix S: Scatter plot of MSCI-ESGS's excess return against the MRP



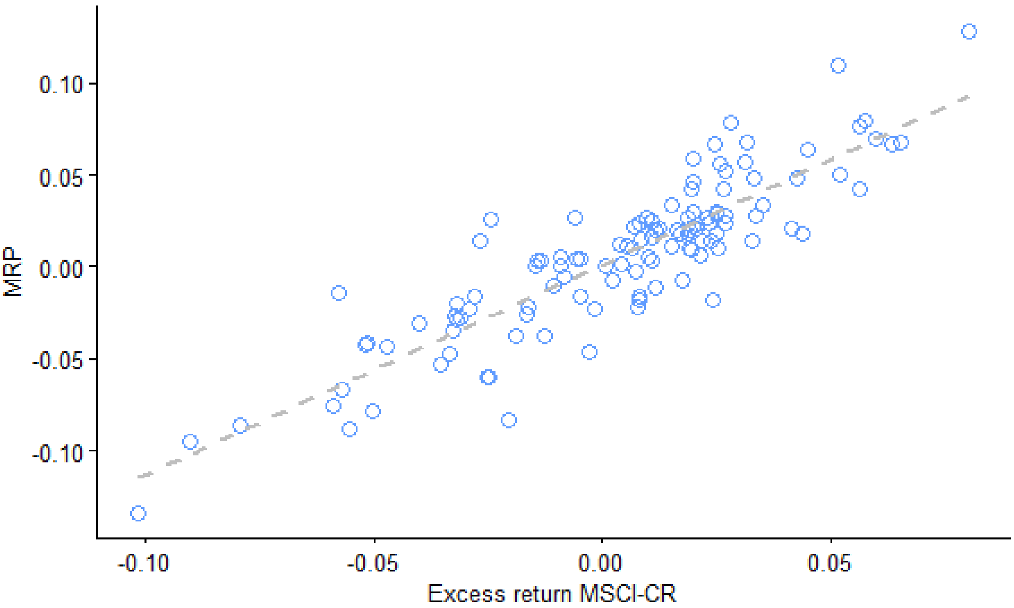
Source: Own representation

Appendix T: Scatter plot of MSCI-SRI's excess return against the MRP



Source: Own representation

Appendix U: Scatter plot of MSCI-CR's excess return against the MRP



Source: Own representation

Appendix V: Estimates of the CAPM model for the ESG indexes

	MSCI-ESGL	**MSCI-CP**	**MSCI-ESGS**	**MSCI-SRI**	**MSCI-CR**
Alpha	0.0001234 (0.0002976)	0.0005034 (0.0004375)	0.0001868 (0.0001563)	0.0006869 (0.0006788)	0.000191 (0.0013855)
Beta	0.9836142*** (0.0114335)	1.0020525*** (0.0111736)	1.0076387*** (0.0022139)	0.9897127*** (0.0274554)	0.681809*** (0.0338730)
F-statistic (df=1;116)	1.379e+04***	1.193e+04***	6.796e+04***	3928***	404.8***
Residual Std. Error (df=116)	0.00387	0.00423	0.00178	0.00729	0.01564
Multiple R^2	0.9917	0.9904	0.9983	0.9713	0.7773
Adjusted R^2	0.9916	0.9903	0.9983	0.9711	0.7753
Obs.	118	118	118	118	118

Note: Newey-West's (HAC) standard errors are reported with brackets; Statistical significance is denoted by ***, **, and * at the 0.1%, 1%, and 5% level

Source: Own representation

Appendix W: Description of the Carhart four-factor model

The Carhart four-factor model, an extension of the Fama-French three-factor model, evaluates stock return by considering a market (MKT), size (SMB), value (HML), and momentum (MOM) factor. The MKT factor is determined by the excess return of the market portfolio over the risk-free rate. SMB is determined by the difference in returns between small and large firms. HML is assessed through the returns of portfolios with high book-to-market ratios compared to those with low ratios. Lastly, MOM captures the returns from recent winners versus recent losers in the market. Therefore, the return of an asset with the Carhart-Fama-French model can be calculated as follows:

[3] $R_P = r_f + \beta_{\mathrm{P,MKT}} * r_{MKT} + \beta_{\mathrm{P,SMB}} * r_{SMB} + \beta_{\mathrm{P,HML}} * r_{HML} + \beta_{\mathrm{P,MOM}} * r_{MOM}$

R_P represents the monthly return of the portfolios, r_f is the risk-free rate, r_{MKT} is the monthly return of the market portfolio, r_{SMB} is the return difference between small and large firms, r_{HML} is the return difference between companies with high book-to-market ratios compared to those with low book-to-market ratios, r_{MOM} the return difference between recent winners and recent losers of the market, and β_{P} represents the exposure of the portfolio to each of the four factors (Fama and French 1993; Carhart 1997). If the Carhart-Fama-French four-factor model represents the correct equilibrium pricing models for assets, then Jensen's alpha can be estimated using the following model:

[4] $\alpha_{\mathrm{P}} = (R_p - r_f) + \beta_{\mathrm{P,MKT}} * r_{MKT} + \beta_{\mathrm{P,SMB}} * r_{SMB} + \beta_{\mathrm{P,HML}} * r_{HML} + \beta_{\mathrm{P,MOM}} * r_{MOM}$

$(R_p - r_f)$ represents the excess return of each index calculated with the monthly return of three-month U.S. treasury bills reported by the FED and the factor returns were obtained through Fama-French's website for developed countries (Fama and French 2023). A descriptive analysis of the different market factors can be obtained in Appendix X and results of the Jensen Alpha estimation based on the Carhart-Fama-French four-factor model can be obtained in Appendix Y.

Appendix X: Descriptive statistics for the model variables

	MKT	**SMB**	**HML**	**MOM**
Mdn	0.0102500	-0.0026500	-0.0045500	0.0051000
M	0.0061619	-0.0023390	-0.0015042	0.0031186
Min	-0.1377000	-0.0416000	-0.0930000	-0.1092000
Q1	-0.0175500	-0.0125750	-0.0173750	-0.0134250
Q3	0.0273500	0.0085250	0.0125000	0.0206500
Max	0.1334000	0.0331000	0.1196000	0.0668000

Note: N =118. *Mdn* = Median, *M* = Mean, *Q1* = 25th percentile, *Q3* = 75th percentile

Source: Own representation

Appendix Y: Estimates of the Carhart Four-Factor Model for the ESG indexes

	MSCI-ESGL	**MSCI-CP**	**MSCI-ESGS**	**MSCI-SRI**	**MSCI-CR**
Alpha	-0.0002499	0.0002738	-9.2827e-05	0.0001286	-0.0011750
	(0.0003038)	(0.003610)	(0.0002083)	(0.0003663)	(0.0014903)
MKT	0.9840891***	0.9918191***	1.0063000***	0.9838096***	0.7436591***
	(0.0140245)	(0.0096008)	(0.0080773)	(0.0221581)	(0.0343380)
SMB	-0.1936046***	-0.1301726***	-0.1530400***	-0.2270133***	-0.2378750**
	(0.0253118)	(0.0236244)	(0.0140810)	(0.0525594)	(0.0770744)
HML	-0.0548347***	-0.1382962***	0.0644170***	-0.1684972***	0.0510998
	(0.0113876)	(0.0196608)	(0.0087194)	(0.0214859)	(0.0514809)
MOM	-0.0060950	-0.0232130	0.0061689	-0.0138997	0.2012491***
	(0.0214158)	(0.0153125)	(0.0099782)	(0.03514412)	(0.0524320)
F-statistic (df=4;113)	3107***	4914***	1.071e+04***	1435***	110.6***
Residual Std. Error (df=113)	0.00407	0.00330	0.00225	0.00606	0.01513
Multiple R^2	0.9910	0.9943	0.9974	0.9807	0.7966
Adjusted R^2	0.9907	0.9941	0.9973	0.9800	0.7894
Obs.	118	118	118	118	118

Note: Newey-West's (HAC) standard errors are reported with brackets; Statistical significance is denoted by ***, **, and * at the 0.1%, 1%, and 5% level

Source: Own representation

Appendix Z: Megatrends and themes of Naffa and Fains's study

Megatrends	Themes
Environment (E)	Energy efficiency
	Food security
	Water scarcity
Social (S)	Aging
	Millennials
	Urbanization
Governance (G)	Disruptive technology
	Cybersecurity
	Robotics

Source: Naffa and Fain (2020)

Appendix AA: R Syntax

```
---

title: "Research project Christian Meyer"

author: "Christian Meyer"

date: "2023-12-18"

---



### Load packages ###



library(readxl) # necessary reading the data

library(car) # necessary for Levene's test

library(rstatix) # necessary for the effect size

library(ggpubr) # necessary for graphics

library(PMCMRplus) # necessary Friedman's post-hoc test

library(lawstat) # necessary for Brown-Forsythe Levene-type test

library(sandwich) # necessary for HAC

library(lmtest) # necessary for HAC

library(tidyverse) # necessary for general calculations



### Load data ###



# Specify the file path of the excel file
```

```
file_path <- "C:/Users/cmeyer/OneDrive - MTP-Marketing zwischen Theorie und Praxis e. V/03_Uni/02_Master/03_Third_semester/02_Master_Thesis/02_Data/Import_R.xlsx"

# Read the excel in R

my_data <- read_excel(file_path)


#---------------------------------------------------------------------------#


#---------------------------------------------------------------------------#


### Testing from differences in return ###


# First step: Data preparation

## Creating data set with returns from 2013 to 2023

data_return <- my_data[c("Date", "MSCI-ESGL_Return", "MSCI-CP_Return", "MSCI-ESGS_Return", "MSCI-SRI_Return", "MSCI-CR_Return", "MSCI-W_Return")]

## Renaming the column names

colnames(data_return)[colnames(data_return) == "MSCI-ESGL_Return"] <- "MSCI_ESGL"

colnames(data_return)[colnames(data_return) == "MSCI-CP_Return"] <- "MSCI_CP"

colnames(data_return)[colnames(data_return) == "MSCI-ESGS_Return"] <- "MSCI_ESGS"

colnames(data_return)[colnames(data_return) == "MSCI-SRI_Return"] <- "MSCI_SRI"

colnames(data_return)[colnames(data_return) == "MSCI-CR_Return"] <- "MSCI_CR"

colnames(data_return)[colnames(data_return) == "MSCI-W_Return"] <- "MSCI_W"
```

```
##Creating a long format for the inferential statistical test

data_return_long <- pivot_longer(data_return, MSCI_ESGL:MSCI_W)


# Second step: Testing for normal distribution

## Shapiro-Wilk Test (p-value greater than 0,05 indicates that the data is normally distributed; a p-value lower than 0,05 indicates that the data is not normally distributed)

shapiro.test(data_return$MSCI_ESGL) # normal distribution

shapiro.test(data_return$MSCI_CP) # normal distribution

shapiro.test(data_return$MSCI_ESGS) # normal distribution

shapiro.test(data_return$MSCI_SRI) # normal distribution

shapiro.test(data_return$MSCI_CR) # no normal distribution

shapiro.test(data_return$MSCI_W) # normal distribution


# Third step: Descriptive statistical evaluation

## Boxplot-Graphic

data_return_long$name <- factor(data_return_long$name, levels = unique(data_return_long$name))

graphic_1 <- ggplot(data_return_long, aes(x = name, y = value, color = name)) +
  geom_boxplot() +
  geom_jitter() +
  labs(y = "Monthly Return", x = "Index") +
  theme(legend.position = "none",
```

```
      panel.background = element_rect(fill = "white"),
      axis.text = element_text(color = "black")) +
  scale_y_continuous(
    limits = c(-0.15, 0.15),
    breaks = seq(-0.15, 0.15, by = 0.05),
    labels = function(x) sprintf("%1.2f", x)
  )
graphic_1 # exported as image in width: 580 and height:350
## Median, Mean, Q1 and Q3
data_return_long %>%
  group_by(name) %>%
  summarize(Mdn = median(value),
            M = mean(value),
            Q1 = quantile(value, probs = .25),
            Q3 = quantile(value, probs = .75),
            Min = min(value),
            Max = max(value),
            Var = var(value),
            SD = sqrt(var(value))) %>%
  as.data.frame()


# Fourth step: Friedman Test (no normal distribution, dependent, more than 2 samples)
```

result_return <- friedman.test(y=data_return_long$value, groups=data_return_long$name, blocks=data_return_long$Date)

print(result_return) # P Value is 0.04772 and therefore there is a significant difference between the groups

Fifth step: Effect size Kendall's tau

friedman_effsize(data_return_long, value ~ name | Date) # small effect size (Cohen 1992)

Interpretation: Different indexes have a significantly small effect on the return and they are not all the same

Sixth step: Post-hoc test (Pairwise comparisons using Eisinga et al.)

frdAllPairsExactTest(data_return_long$value, data_return_long$name, data_return_long$Date, p.adjust.method = "bonferroni") # Climate_Paris and Children_Impact with a significant difference

Seventh step: Effect size of post-hoc test of Friedman test

Unadjusted p-values

frdAllPairsExactTest(data_return_long$value, data_return_long$name, data_return_long$Date, p.adjust.method = "none")

Dividing significant p-value due to paired testing

z1_return <- qnorm(0.0029/2)

Number of observations

n_return <- friedman_test(data_return_long, value ~ name | Date)$n

Calculation of the effect size

```
r1_return <- z1_return/sqrt(n_return)

r1_return # 0.2741603 (minus can be ignored) in the range between 0.1 to 0.3 specifies that there is a small effect between Climate_Paris_Return and Children_Impact_Return


# Eighth step: Reporting

## The Friedman test shows a significant difference in the test scores over the different indexes (Chi² (x) = 11.191, p = 0.04772, ω = 0.0190).

## Between the Return of the index MSCI World Climate Paris Aligned (Mdn = 0.0146) and MSCI World Children Impact ESG Selected (Mdn = 0.0110), p = 0.044, r = 0.2742 is a difference observable

## According to Cohen (1992) the differences are small


#-----------------------------------------------------------------------------#


#-----------------------------------------------------------------------------#


### Testing for homogeneity ###


# First step: Descriptive statistical evaluation

## Variance and Standard Deviation

data_return_long %>%

  group_by(name) %>%

  summarize(Var = var(value),
```

```
    SD = sqrt(var(value))) %>%
  as.data.frame()


# Second step: Testing for homogeneity

## Brown-Forsythe Levene-type test

data_variance_long <- pivot_longer(data_return, MSCI_ESGL:MSCI_W)

levene.test(data_variance_long$value, data_variance_long$name, location="median", correction.method="zero.correction")

## Levene Test

data_return_long$name <- factor(data_return_long$name)

leveneTest(value ~ name, data = data_return_long)


# Third step: Post hoc analysis Tukey Kramer Test (package agricolae)

post_hoc <- lm(value ~ name, data = data_return_long)

anova <- aov(post_hoc)

summary(anova)

tukey_test <- TukeyHSD(anova)

tukey_test

# Fourth step: Reporting

## The Brown-Forsythe Levene-type test does not show a significant difference in variances between the groups
```

```
#-----------------------------------------------------------------------------#

#-----------------------------------------------------------------------------#

### Estimating Jensen's alpha using CAPM ###

# First step: Data preparation

# Creating data set with alphas from 2013 to 2023

data_alpha <- my_data[c("Date", "MSCI-ESGL_Rp_Rf", "MSCI-CP_Rp_Rf", "MSCI-ESGS_Rp_Rf", "MSCI-SRI_Rp_Rf", "MSCI-CR_Rp_Rf", "MSCI-W_Rp_Rf")]

## Renaming the column names (ER: Excess Return)

colnames(data_alpha)[colnames(data_alpha) == "MSCI-ESGL_Rp_Rf"] <- "MSCI_ESGL_ER"

colnames(data_alpha)[colnames(data_alpha) == "MSCI-CP_Rp_Rf"] <- "MSCI_CP_ER"

colnames(data_alpha)[colnames(data_alpha) == "MSCI-ESGS_Rp_Rf"] <- "MSCI_ESGS_ER"

colnames(data_alpha)[colnames(data_alpha) == "MSCI-SRI_Rp_Rf"] <- "MSCI_SRI_ER"

colnames(data_alpha)[colnames(data_alpha) == "MSCI-CR_Rp_Rf"] <- "MSCI_CR_ER"

colnames(data_alpha)[colnames(data_alpha) == "MSCI-W_Rp_Rf"] <- "MRP"

##Creating a long format for the inferential statistical test

data_alpha_long <- pivot_longer(data_alpha, MSCI_ESGL_ER:MRP)

# Second step: Descriptive statistics of Jensen's alpha

data_alpha_long %>%
```

```
  group_by(name) %>%
  summarize(Mdn = median(value),
            M = mean(value),
            Q1 = quantile(value, probs = .25),
            Q3 = quantile(value, probs = .75),
            Min = min(value),
            Max = max(value)) %>%
  as.data.frame()


# Third step: Using a single linear regression model to estimate alpha and beta
## MSCI-ESGL
### Scatter plot of the excess return of the MSCI-ESGL and the MRP
scatter_plot_1 <- ggscatter(data_alpha, x = "MSCI_ESGL_ER", y = "MRP",
                     add = "reg.line",  # Adding a regression line
                     add.params = list(color = "gray", linetype = "dashed"),
                     xlab = "Excess return MSCI-ESGL",
                     ylab = "MRP",
                     palette = "jco",
                     shape = 21,
                     fill = "transparent",
                     color = rgb(248, 118, 109, maxColorValue = 255),
                     size = 2.5,
```

```
                         stroke = 0.75
) +
  theme(plot.background = element_rect(fill = "transparent"),
        text = element_text(size = 10),
        axis.text = element_text(size = 10)
  )
scatter_plot_1 # exported as image in width: 580 and height:350
### Regressing the excess return of the MSCI-ESGL on the MRP
MSCI_ESGL_regression <- lm(MSCI_ESGL_ER ~ MRP, data = data_alpha)
summary(MSCI_ESGL_regression)
### Calculating Newey-West's (HAC) standard error
coeftest(MSCI_ESGL_regression, vcov = NeweyWest(MSCI_ESGL_regression))


## MSCI-CP
### Scatter plot of the excess return of the MSCI-CP against the market's excess return
scatter_plot_2 <- ggscatter(data_alpha, x = "MSCI_CP_ER", y = "MRP",
                      add = "reg.line",  # Adding a regression line
                      add.params = list(color = "gray", linetype = "dashed"),
                      xlab = "Excess return MSCI-CP",
                      ylab = "MRP",
                      palette = "jco",
                      shape = 21,
```

```
                    fill = "transparent",
                    color = rgb(184, 160, 4, maxColorValue = 255),
                    size = 2.5,
                    stroke = 0.75
) +
  theme(plot.background = element_rect(fill = "transparent"),
        text = element_text(size = 10),
        axis.text = element_text(size = 10)
  )
scatter_plot_2 # exported as image in width: 580 and height:350
### Regressing the excess return of the MSCi-CP against the market's excess return
MSCI_CP_regression <- lm(MSCI_CP_ER ~ MRP, data = data_alpha)
summary(MSCI_CP_regression)
### Calculating Newey-West's (HAC) standard error
coeftest(MSCI_CP_regression, vcov = NeweyWest(MSCI_CP_regression))


## MSCI-ESGS
### Scatter plot of the excess return of the MSCI-ESGS and the MRP
scatter_plot_3 <- ggscatter(data_alpha, x = "MSCI_ESGS_ER", y = "MRP",
                      add = "reg.line",  # Adding a regression line
                      add.params = list(color = "gray", linetype = "dashed"),
                      xlab = "Excess return MSCI-ESGS",
```

```
                 ylab = "MRP",
                 palette = "jco",
                 shape = 21,
                 fill = "transparent",
                 color = rgb(0, 180, 38, maxColorValue = 255),
                 size = 2.5,
                 stroke = 0.75
) +
  theme(plot.background = element_rect(fill = "transparent"),
        text = element_text(size = 10),
        axis.text = element_text(size = 10)
  )
scatter_plot_3 # exported as image in width: 580 and height:350


### Regressing the excess return of the MSCI-ESGS against the market's excess return
MSCI_ESGS_regression <- lm(MSCI_ESGS_ER ~ MRP, data = data_alpha)
summary(MSCI_ESGS_regression)
### Calculating Newey-West's (HAC) standard error
coeftest(MSCI_ESGS_regression, vcov = NeweyWest(MSCI_ESGS_regression))


## MSCI-SRI
### Scatter plot of the excess return of the MSCI-SRI and the MRP
```

```
scatter_plot_4 <- ggscatter(data_alpha, x = "MSCI_SRI_ER", y = "MRP",
                            add = "reg.line",  # Adding a regression line
                            add.params = list(color = "gray", linetype = "dashed"),
                            xlab = "Excess return MSCI-SRI",
                            ylab = "MRP",
                            palette = "jco",
                            shape = 21,
                            fill = "transparent",
                            color = rgb(38, 201, 205, maxColorValue = 255),
                            size = 2.5,
                            stroke = 0.75
) +
  theme(plot.background = element_rect(fill = "transparent"),
        text = element_text(size = 10),
        axis.text = element_text(size = 10)
  )
scatter_plot_4 # exported as image in width: 580 and height:350
### Regressing the excess return of the MSCI-SRI against the market's excess return
MSCI_SRI_regression <- lm(MSCI_SRI_ER ~ MRP, data = data_alpha)
summary(MSCI_SRI_regression)
### Calculating Newey-West's (HAC) standard error
coeftest(MSCI_SRI_regression, vcov = NeweyWest(MSCI_SRI_regression))
```

```
## MSCI-CR

### Scatter plot of the excess return of the MSCI-CR and MRP

scatter_plot_5 <- ggscatter(data_alpha, x = "MSCI_CR_ER", y = "MRP",

                           add = "reg.line",  # Adding a regression line

                           add.params = list(color = "gray", linetype = "dashed"),

                           xlab = "Excess return MSCI-CR",

                           ylab = "MRP",

                           palette = "jco",

                           shape = 21,

                           fill = "transparent",

                           color = rgb(97, 156, 255, maxColorValue = 255),

                           size = 2.5,

                           stroke = 0.75

) +

  theme(plot.background = element_rect(fill = "transparent"),

        text = element_text(size = 10),

        axis.text = element_text(size = 10)

  )

scatter_plot_5 # exported as image in width: 580 and height:350

### Regressing the excess return of the MSCI-CR against the market's excess return

MSCI_CR_regression <- lm(MSCI_CR_ER ~ MRP, data = data_alpha)
```

```
summary(MSCI_CR_regression)

### Calculating Newey-West's (HAC) standard error

coeftest(MSCI_CR_regression, vcov = NeweyWest(MSCI_CR_regression))


#----------------------------------------------------------------------------#


#----------------------------------------------------------------------------#


### Estimating Jensen's alpha using Carhart-Fama-French four-factor model ###


# First step: Data preparation

# Creating data set with alphas from 2013 to 2023

data_alpha_FF4M <- my_data[c("Date", "MSCI-ESGL_FF4M_Rp_Rf", "MSCI-CP_FF4M_Rp_Rf", "MSCI-ESGS_FF4M_Rp_Rf", "MSCI-SRI_FF4M_Rp_Rf", "MSCI-CR_FF4M_Rp_Rf", "FF4M_Rp_Rf", "FF4M_SMB", "FF4M_HML", "FF4M_WML")]

## Renaming the column names (ER: Excess Return)

colnames(data_alpha_FF4M)[colnames(data_alpha_FF4M) == "MSCI-ESGL_FF4M_Rp_Rf"] <- "MSCI_ESGL_FF4M_ER"

colnames(data_alpha_FF4M)[colnames(data_alpha_FF4M) == "MSCI-CP_FF4M_Rp_Rf"] <- "MSCI_CP_FF4M_ER"

colnames(data_alpha_FF4M)[colnames(data_alpha_FF4M) == "MSCI-ESGS_FF4M_Rp_Rf"] <- "MSCI_ESGS_FF4M_ER"
```

```
colnames(data_alpha_FF4M)[colnames(data_alpha_FF4M) == "MSCI-SRI_FF4M_Rp_Rf"] <-
"MSCI_SRI_FF4M_ER"

colnames(data_alpha_FF4M)[colnames(data_alpha_FF4M) == "MSCI-CR_FF4M_Rp_Rf"] <-
"MSCI_CR_FF4M_ER"

colnames(data_alpha_FF4M)[colnames(data_alpha_FF4M) == "FF4M_Rp_Rf"] <- "MRP_FF4M"

colnames(data_alpha_FF4M)[colnames(data_alpha_FF4M) == "FF4M_SMB"] <- "SMB"

colnames(data_alpha_FF4M)[colnames(data_alpha_FF4M) == "FF4M_HML"] <- "HML"

colnames(data_alpha_FF4M)[colnames(data_alpha_FF4M) == "FF4M_WML"] <- "WML"

## Creating a long format for the factors of the FF3M

data_alpha_FF4M_long <- pivot_longer(data_alpha_FF4M, MRP_FF4M:WML)



# Second step: Descriptive statistics of Jensen's alpha

data_alpha_FF4M_long %>%

  group_by(name) %>%

  summarize(Mdn = median(value),

            M = mean(value),

            Q1 = quantile(value, probs = .25),

            Q3 = quantile(value, probs = .75),

            Min = min(value),

            Max = max(value)) %>%

  as.data.frame()
```

```
# Third step: Using a multiple linear regression model to estimate alpha

## MSCI-ESGL

### Regressing the excess return of the MSCI-ESGL against MRP, SMB, and HML

MSCI_ESGL_FF4M_regression <- lm(MSCI_ESGL_FF4M_ER ~ MRP_FF4M + SMB + HML +
WML, data = data_alpha_FF4M)

summary(MSCI_ESGL_FF4M_regression)

### Calculating Newey-West's (HAC) standard error

coeftest(MSCI_ESGL_FF4M_regression, vcov = NeweyWest(MSCI_ESGL_FF4M_regression))


## MSCI-CP

### Regressing the excess return of the MSCI-CP against MRP, SMB, and HML

MSCI_CP_FF4M_regression <- lm(MSCI_CP_FF4M_ER ~ MRP_FF4M + SMB + HML + WML,
data = data_alpha_FF4M)

summary(MSCI_CP_FF4M_regression)

### Calculating Newey-West's (HAC) standard error

coeftest(MSCI_CP_FF4M_regression, vcov = NeweyWest(MSCI_CP_FF4M_regression))


## MSCI-ESGS

### Regressing the excess return of the MSCI-ESGS against MRP, SMB, and HML

MSCI_ESGS_FF4M_regression <- lm(MSCI_ESGS_FF4M_ER ~ MRP_FF4M + SMB + HML +
WML, data = data_alpha_FF4M)

summary(MSCI_ESGS_FF4M_regression)
```

```
### Calculating Newey-West's (HAC) standard error

coeftest(MSCI_ESGS_FF4M_regression, vcov = NeweyWest(MSCI_ESGS_FF4M_regression))


## MSCI-SRI

### Regressing the excess return of the MSCI-SRI against MRP, SMB, and HML

MSCI_SRI_FF4M_regression <- lm(MSCI_SRI_FF4M_ER ~ MRP_FF4M + SMB + HML + WML, data = data_alpha_FF4M)

summary(MSCI_SRI_FF4M_regression)

### Calculating Newey-West's (HAC) standard error

coeftest(MSCI_SRI_FF4M_regression, vcov = NeweyWest(MSCI_SRI_FF4M_regression))


## MSCI-CR

### Regressing the excess return of the MSCI-CR against MRP, SMB, and HML

MSCI_CR_FF4M_regression <- lm(MSCI_CR_FF4M_ER ~ MRP_FF4M + SMB + HML + WML, data = data_alpha_FF4M)

summary(MSCI_CR_FF4M_regression)

### Calculating Newey-West's (HAC) standard error

coeftest(MSCI_CR_FF4M_regression, vcov = NeweyWest(MSCI_CR_FF4M_regression))
```

Appendix AB: List of abbreviations

ANOVA	Analysis of Variance
AUM	Asset Under Management
B-F test	Brown-Forsythe Levene-type test
CAPM	Capital Asset Pricing Model
CFF4FM	Carhart-Fama-French four-factor model
CFP	Corporate Financial Performance
CSR	Corporate Social Responsibility
EFAMA	European Fund and Asset Management Association
ESG	Environmental, Social, and Governance
Eurosif	European Sustainable Investment Forum
FED	Federal Reserve
GSIA	Global Sustainable Investment Alliance
I.I.D.	Independent and identically distributed
KLD	Kinder, Lydenberg, and Domini & Co.
MRP	Market Risk Premium
MSCI	Morgan Stanley Capital International
MSCI-CP	MSCI World Climate Paris Aligned Index
MSCI-CR	MSIC World Impact ESG Select Children’s Rights Index
MSCI-ESGL	MSCI World ESG Leaders Index
MSCI-ESGS	MSCI World ESG Screened Index
MSCI-SRI	MSCI World SRI Index
MSCI-W	MSCI World Index
OECD	Organization for Economic Cooperation and Development

OLS	Ordinary Least Squares
PRI	Principles for Responsible Investment
S&P 500 Index	Standard & Poor 500 Index
SME	Small and medium-sized enterprises
SRI	Socially Responsible Investment
TCFD	Task Force on Climate-Related Financial Disclosure
UN	United Nations
UNEP	United Nations Environment Programme