A Factor-Tilt Approach to ESG Investing

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Abstract

This research examines the incorporation of Environmental, Social, and Governance (ESG) factors into portfolio construction, focusing on identifying companies with strong ESG practices and their relationship with financial performance. Drawing on a US sample of companies and timely ESG data provided by RepRisk, the research proposes a relative approach for constructing a portfolio with a desired exposure to traditional risk premia while tilting the final portfolio towards a quantitative ESG objective. The methodology combines bottom-up and top-down approaches to identify a potential ESG alpha while neutralizing the relative exposure to risk premia associated with traditional factors. The findings indicate a significant and positive ESG premium in the US market while addressing criticisms regarding the lack of forward-looking ESG data. The study makes a novel contribution to the literature on ESG investing by demonstrating the potential of a more flexible and nuanced approach to portfolio construction that incorporates timely ESG information. The results have general implications for investors seeking to align their investments with ESG principles, achieve better risk-adjusted returns, and generate sustainable and resilient portfolios.

1. Introduction

Environmental, Social, and Governance (ESG) investing has gained significant popularity in recent years, with increasing academic and practitioner research in the field. This trend reflects the increasing interest among investors and regulators in companies that align with their values and positively impact society and the environment. Investors typically look for companies with solid records in employee relations, sustainable practices, and ethical leadership. The importance of ESG in investment is based on the belief that these factors can significantly impact a company's long-term financial performance. Therefore, investors need to consider them when making investment decisions. Incorporating ESG considerations into portfolio construction can help investors diversify their

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portfolios and potentially identify companies with solid growth prospects, leading to better risk-adjusted returns than cap-weighted indices.

Integrating ESG factors into portfolio construction has received increasing attention in recent years. Studies have found a positive relationship between ESG integration and the financial performance of companies. For example, [1] found that portfolios constructed using ESG criteria outperformed comparable portfolios that did not consider ESG factors. Similarly, [2] used a global sample of companies to show that those with strong ESG practices tend to have lower volatility and are less likely to experience negative returns. Another study by [3] found that portfolios constructed with higher ESG scores had similar returns but lower volatility and downside risk compared to portfolios with lower ESG scores, using a large sample of companies from different countries. Although the results of studies on the relationship between ESG integration and financial performance are mixed, most have found a positive relationship between the two. In addition, ESG integration seems to lead to more sustainable and resilient portfolios. Our research aims to contribute to the body of research on ESG in finance, particularly in portfolio construction.

As investor expectations for ESG integration into investment decision-making grow, asset managers seek to develop their ESG capabilities to meet investor and regulator demands. However, the debate for practitioners is no longer about proving the existence of ESG factors but rather about developing tools to capture these different aspects without giving up a target exposure to other factors. Historical analysis has shown that an intelligent combination of factors can beat the market in both the contraction and expansion phases over the long term. Portfolio construction methods range from a top-down approach, where the portfolio manager excludes certain stocks based on quantitative or qualitative ESG criteria, to a bottom-up approach, where the portfolio is constructed from the best-in-class constituents according to the same criteria.

In this research paper, we propose a relative approach to ESG investing that allows for constructing a long-only portfolio with a desired exposure to traditional risk premia or replication of a particular index while incorporating a quantitative objective linked to an ESG risk factor. Our study incorporates timely ESG data provided by RepRisk, a global leader in ESG and business conduct research. Our methodology departs from the typical approach in the literature on ESG portfolio tilting, which involves implementing overweighting and underweighting schemes for leading and laggard ESG companies within the portfolio. Instead, our approach is based on the relative factor exposure of our portfolio to a benchmark, aiming for a specified relative exposure to the ESG factor.

To demonstrate the flexibility of the approach, we first replicate a market capitalization-weighted index and tilt our portfolio towards higher relative ESG exposure that is kept constant over time. We then neutralize the relative exposure to the risk premia associated with traditional factors identified in the literature while aiming for a higher relative ESG score than the benchmark. By doing so, we identify a potential ESG alpha through the regression of portfolio excess returns. The proposed methodology is based on a long-only approach, making it more practical for a wide range of investors. It combines the strengths of bottom-up and top-down approaches, contributing to the existing literature on ESG investing. Specifically, we respond to the criticism about the lack of forward-looking ESG data expressed in the industry. We also demonstrate the potential of ESG integration for better risk-adjusted returns than cap-weighted indices. Our findings show a statistically significant and positive ESG premium in the US market, and the proposed approach exhibited a persistent outperformance relative to the US S&P500 index from 2013 to 2022.

Overall, our research makes a novel contribution to the literature on ESG investing by demonstrating the potential of a more flexible and nuanced approach to portfolio construction that incorporates timely ESG information. This approach has important implications for investors seeking to align their investments with ESG principles while balancing risk premia.

2. Methodology

Factor tilting has been a long-standing approach to drive portfolio returns, leveraging the cyclicality of various factors that tend to outperform at different times. This approach seeks to balance enhanced returns with the long-term benefits of a diversified factor portfolio. Investors can adjust the degree of factor tilting based on their conviction and risk tolerance. Moreover, factor tilting can offer diversification benefits for investors holding a multi-factor portfolio, especially if the returns of the tilted portfolio have a low correlation with the multi-factor portfolio.

Numerous empirical studies have shown that active managers tend to tilt their portfolios towards factors such as size and value, which account for a significant portion of their returns compared to cap-weighted benchmarks. For instance, [4] found that mutual funds underperformed the Fama-French factor benchmarks due to trading costs. Meanwhile, [5] observed that traditional Fama-French factors explained about 50% of the average alpha in US institutional fund returns. Recent research by [6] showed that concentration and value factors drove pension fund performance by investing in concentrated portfolios with undervalued assets.

Active portfolio managers typically build their portfolios by selecting stocks that meet all the criteria of their investment philosophy, thereby reducing the number of investable stocks in the initial universe. Qualitative or quantitative criteria are added to this process, resulting in a sort of classification of stocks to be overweighted or underweighted. The portfolio is periodically rebalanced to maintain the desired factor exposures. Investors can use different portfolio construction techniques depending on their sustainability goals to achieve their objectives. For example, [7] found that ESG-focused investors preferred risk management over divestment to address ESG risks like climate change.

ESG considerations have been increasingly integrated into portfolio construction through optimization methods. [8] used objective programming to select socially responsible portfolios, while [9] proposed a three-stage framework that outperformed traditional investment strategies in the US market. Recently, [10] developed a 2-step optimization approach that combined temperature adaptation with carbon intensity reduction, refined through active management of factor exposures. [11] proposed a multi-objective minimax-based optimization model that incorporated investors' ESG preferences to deliver higher returns without implying higher volatility risk performance.

The factor tilt methodology, also known as smart or beta, scientific beta, and style or factor investing, has been extensively studied in the literature ([12], [13], [14]). Asset managers may use single-factor portfolios to exploit factor cyclicality or correct the factor bias of an existing allocation. Still, this approach may not be consistent with investors seeking high exposure to a single factor. For example, [15] found that score-weighting resulted in unintended factor exposures, while market-cap and score-tilt schemes had little exposure to non-target factors. Meanwhile, [16] extended the methodology of [17] to control for the ESG factor and calculate a zero-investment long-short portfolio without excluding stocks to achieve an ESG target.

Our research paper follows a tilt methodology described by FTSE Russell in [18], designed to preserve the investment philosophy and exposure to specific risk premia. This approach utilizes a long-only strategy, which is more feasible for all types of investors and employs a multiplicative weighting scheme (sequential tilt) to achieve multi-factor exposure objectives with high diversification. As demonstrated in [19], the tilt methodology is efficient regarding exposure and diversification trade-offs. Our contribution to the literature on ESG investing is a general framework that incorporates forward-looking ESG data using the sequential tilt methodology of FTSE Russell while maintaining exposure to other factors in the initial portfolio.

2.1. Factor Scores

We start from a given portfolio with known weightings w_i in each of the $i = 1, \dots, n$ securities. We consider $k = 1, \dots, K$ factors and form a factor matrix for all stocks $\Psi \in \mathbb{R}^{n \times K}$. The columns of Ψ, denoted ψ_k contain the factor scores for each of the K factors and the n stocks. For each stock and each time t, the value (score) of the factor f_k, t is known.

2.1.1. Normalization

Since the factors are generally expressed in different units, for the sake of interpretation, it is necessary [4] to proceed in the first step to a normalization, which is often done by using the well-established z-score. In this research, however, we normalize each factor at date t in percentiles, thus allowing an unequivocal interpretation and comparing stocks and factors. The rank-based normalization is performed as follows:

$$S(\Psi) = \frac{rank(\Psi) - \frac{1}{2}\mathbb{1}_n}{n} \tag{1}$$

[4] It is not strictly needed to proceed in this way.

where the *rank* operator ranges from 0 to n, corresponding to the smallest and largest factor score respectively and $\mathbb{1}$ stands for the indicator function. The normalized rank (S) lies between 0 for the worst factor value and 1 for the best one. Unlike the z-score methodology, the rank-based normalization does not consider the distribution of factor values.

2.1.2. Mapping Function

The next step is to transform each percentile value (normalized rank) with a function M that maps the values of each percentile S to a real positive number. The choice of this function is not innocuous, as it affects the final portfolio weights and, thus, the deviation from the initial portfolio (relative weights) in the final portfolio.

Several functions have been used in the factor tilting literature. In principle, any non-decreasing function can be used, so stocks with high factor scores do not receive a lower weight in the portfolio than stocks with lower scores. Step functions and the inverse cumulative normal distribution function are the most popular, as they limit the weight of stocks with extreme scores, which are often just outliers. In this paper, we adopt the exponential function, as suggested in [18], to emphasize stocks with high ESG scores, thereby improving the convergence speed of the algorithm for multiple exposure objectives. Unlike the traditional S-shaped function, the exponential function allows for more pronounced differentiation between stocks with different ESG scores. Specifically, each factor score is mapped onto the exponential function as follows:

$$M(S_k) = exp(S_k), \quad k = 1, \cdots, K \tag{2}$$

where S_k corresponds to a given factor's normalized rank.

2.1.3. Factor Tilting

Following [18], we introduce the concept of factor's power or strength, which is closely linked to the principle of score multiplicativity.[5].Specifically, we apply a tilt strength, denoted by p_k, for each mapped factor score S_k in the following way:

$$F_k = F(S_k) = M(S_k)^{p_k} = M(p_k \cdot S_k) \tag{3}$$

where p, the power of the factor, is any positive real number. Using the exponential tilt function here, we know the risk of weights' concentration as the power p increases. The stocks with a high factor value take a predominant place in the portfolio (concentration issue). It might thus be necessary to apply lower/upper bounds when implementing the portfolio or to lower the targeted relative exposure.

[5]Multiple factor objectives can be incorporated by tilting an initial set of portfolio weights towards each factor in a multiplicative manner.

To increase or decrease exposure to a particular factor, a factor tilt is applied to an initial set of portfolio weights to create a tilted portfolio. The level of factor exposure is determined by the strength of the tilt, with stronger tilts resulting in higher exposure to the factor and weaker tilts resulting in lower exposure. The tilted portfolio weights can be obtained by using the formula:

$$\mathrm{W}_{\text{tilted}} = \mathrm{W}_{\text{initial}} \prod_{k=1}^{K} F_k = \mathrm{W}_{\text{initial}} \prod_{k=1}^{K} M(p_k \cdot S_k) \tag{4}$$

where $\mathrm{W}_{\text{initial}}$ represents the initial portfolio weights, F_k and p_k are the mapped score and tilt power of factor $k = 1, \ldots, K$ respectively.

The target exposure methodology can neutralize any undesired factor exposures relative to a benchmark or initial portfolio by applying a set of corrective tilts to the initial portfolio weights at each rebalancing date. This is equivalent to solving the system of linear equations:

$$(\mathrm{W}_{\text{tilted}} - \mathrm{W}_{\text{initial}}) \cdot S(\psi) = \mathrm{E}_{\text{relative}} \tag{5}$$

where $\mathrm{W}_{\text{tilted}} \in \mathbb{R}^{1\times n}$ represents the tilted portfolio as computed in (4), $\mathrm{W}_{\text{initial}} \in \mathbb{R}^{\times n}$ is the initial portfolio, $S(\psi) \in \mathbb{R}^{n\times K}$ is the rank-based factor scores matrix defined above, and $E_{relative} \in \mathbb{R}^{k}$ is a vector with the target relative exposures to the K factors.

Solving Equation 5 numerically gives the tilt strength for each factor, and the portfolio weights that generate the target level of factor exposure are obtained from Equation 4.

The resulting vector $\mathrm{W}_{\text{tilted}}$ obtained from Equation 4 must be rescaled, to sum up to one. A normalization scheme is used to obtain a fully invested portfolio without the need to integrate a constraint while solving the linear system of equations in 5:

$$W_p = \mathrm{W}_{\text{tilted}} - W_{EW} \cdot (\mathbb{1}^T \mathrm{W}_{\text{tilted}} - 1) \tag{6}$$

where $\mathrm{W}_{\text{tilted}} \in \mathbb{R}^{1\times n}$ represents the (unscaled) tilted portfolio, $\mathrm{W}_{\text{EW}} \in \mathbb{R}^{1\times n}$ is an equally-weighted portfolio, and $\mathbb{1}$ is the indicator function.

2.2. Relative ESG Factor Exposure

The target factor exposure methodology allows for reducing or eliminating exposure to traditional style factors. It can be extended to target specific factor exposures, such as those related to ESG criteria. This section applies this approach to meet a given ESG objective while simultaneously neutralizing remaining active factor exposures.

For example, we can start with an initial portfolio (benchmark) $\mathrm{W}_{\text{initial}}$ that aims to replicate a given market index with fewer stocks. We incorporate two traditional factors, value, and momentum, into the portfolio construction and an ESG factor. The general tilt equation is as follows:

$$\mathrm{W}_{\text{tilted}} = \mathrm{W}_{\text{initial}} \times F_{\text{value}}^{p_{\text{v}}} \times F_{\text{mom}}^{p_{\text{m}}} \times F_{\text{esg}}^{p_{\text{e}}} \tag{7}$$

where $\mathrm{W}_{\text{initial}}$ is the vector of initial portfolio weights, $F_{\text{value}}, F_{\text{mom}}, F_{\text{esg}}$ and $p_{\text{v}}, p_{\text{m}}, p_{\text{e}}$ are the mapped scores and tilt powers of the two traditional factors and the ESG factor respectively.

Equation 4 can be applied with a tilt strength p consistent with a given ESG target relative to the benchmark while neutralizing active exposure to the two traditional factors. We rewrite Equation 5, set the targeted relative exposure to the ESG factor to 0.2, and, for illustration purposes, reduce the active exposure to momentum and quality to 0.01. We thus solve the following linear system of equations:

$$\begin{aligned} (\mathrm{W}_{\text{tilted}} - \mathrm{W}_{\text{initial}}) \cdot S_{\text{esg}} &= 0.2 \\ (\mathrm{W}_{\text{tilted}} - \mathrm{W}_{\text{initial}}) \cdot S_{\text{val}} &= 0.01 \\ (\mathrm{W}_{\text{tilted}} - \mathrm{W}_{\text{initial}}) \cdot S_{\text{mom}} &= 0.01 \end{aligned} \tag{8}$$

where $\mathrm{W}_{\text{initial}}$ is the vector of initial portfolio weights, $S_{\text{esg}}, S_{\text{value}}, S_{\text{mom}}$ are the ESG, Value, and Momentum rank-based factor scores (not mapped) respectively.

Figure 1 displays the average active exposures of the ESG-tilted portfolio relative to the benchmark. It is observed that the active exposures to Value and Momentum have been nearly neutralized, while the ESG exposure exhibits the desired relative exposure.

[Figure 1 about here.]

2.3. Pure Style Factors

The seminal paper by [20] introduced the concept of multi-factor models, leading to numerous publications on the topic. In their three-factor model explaining US stock market returns, Fama and French proposed the market factor based on the traditional Capital Asset Pricing Model (CAPM), as well as the size factor (large vs. small capitalization stocks) and the value factor (low vs. high book-to-market).

[21] expanded on this framework by introducing the momentum factor, while recent literature has focused on identifying additional factors that show high abnormal returns. [22] extended their three-factor model to include qualitative aspects such as profitability and investment, and [23] proposed a protocol for constructing Environmental, Social, and Governance (ESG) factors, accounting for the different scales of ESG companies and considering other stylized facts such as book-to-market and size effects.

Our research has identified the most relevant and widespread stylized facts in empirical and academic papers, including momentum, size, growth, value, quality, low volatility, investment, and dividend. Appendix 6 summarizes these factors, which have generated excess returns above the market in empirical studies.

To construct the traditional factors, we follow the same methodology described in Equation 7, which allows us to achieve a target exposure to a specific factor while neutralizing exposure to other factors. Our approach is market-neutral, and we construct pure factor portfolios that aim for the top 90th percentile exposure in the long leg and the bottom 10th percentile exposure in the short leg of the long-short factor portfolio.

2.4. Portfolio Construction

We rebalance our monthly portfolio using the index's constituents at that date. We limit our investment universe to the 100 most representative stocks to streamline the implementation. First, we construct a market-cap-weighted benchmark to replicate the overall market. Then, we compute the tilted portfolio by targeting a 50 percent increase in ESG exposure relative to our benchmark while maintaining neutral relative exposure to the style factors we consider.

To further analyze the performance of our approach, we constructed pure long (short) portfolios for each traditional and ESG factor. These portfolios are invested in the same 100 stocks and aim to have a 90th (10th) percentile exposure to the factor of interest while maintaining zero exposure to other factors.

To evaluate our tilting approach's performance and ex-post exposure, we apply a nine-factor model using OLS regression, as detailed in the previous section. This model takes into account the returns of the nine pure factors, including both the eight traditional and the ESG factors, using the following equation:

$$R_{p,t} - Rf_t = b_0 + \sum_{k=1}^{K} b_k \mathrm{F}_{k,t} + e_t, \quad k = 1, \cdots, 9 \tag{9}$$

Here, $R_{p,t}$ denotes the portfolio return at time t, Rf_t is the risk-free return, b_0 is the intercept of the regression, $F_{k,t}$ and b_k represent the returns and estimated coefficients for the nine pure factors at time t, respectively, and e_t denotes a zero-mean residual. In order to account for potential issues of heteroskedasticity and autocorrelation, we applied a Newey-West correction to calculate the standard errors of the coefficients ([24]). Our analysis revealed evidence of heteroskedasticity, detected through the Breusch-Pagan test ([25]), as well as autocorrelation, detected through the Breusch-Godfrey test ([26]; [27]).

2.5. Significance Test

We evaluate the significance of a portfolio's information ratio (IR) relative to its benchmark using a methodology adapted from [28] for the Sharpe ratio. This approach accounts for non-normal returns by testing whether the information ratio deviates significantly from zero, equivalent to testing the Sharpe ratio of an overlay portfolio (Portfolio - Benchmark) against zero.

[28] show that Sharpe ratios are asymptotically normally distributed, even if the returns are not. Using this property, they derive the Probabilistic Sharpe Ratio (PSR) to test the significance of the Sharpe ratio. We adapt their methodology to compute the Probabilistic Information Ratio (PIR), which is used to test the significance of the information ratio.

The PIR is computed as follows:

$$\widehat{PIR}(IR^\star) = \mathrm{Z}\Big[\frac{(\widehat{IR} - IR^\star)\sqrt{n-1}}{\sqrt{1 - \hat{\gamma_3}\widehat{IR} + \frac{\hat{\gamma_4}-1}{4}\widehat{IR}^2}}\Big] \tag{10}$$

Here, $\widehat{IR}$ is the estimated information ratio of the portfolio relative to the benchmark, $IR^\star$ is the value of the information ratio under the null hypothesis (i.e., 0), Z denotes the cumulative distribution function of the standard normal distribution, and $\hat{\gamma_3}$ and $\hat{\gamma_4}$ are the sample skewness and excess kurtosis of the relative returns, respectively.

The PIR increases with larger $\widehat{IR}$, longer track records n and positively skewed relative returns, but it decreases with fatter tails of the relative returns. For example, at a 5% significance level, an information ratio is significantly greater than zero if the estimated PIR is larger than 0.95.

Overall, this approach provides a robust methodology for testing the significance of the information ratio in portfolios with non-normal returns.

3. Data

This section presents the ESG and input data used in portfolio construction and subsequent performance analysis. The stock universe consists of all S&P 500 stocks from 2013 to 2022, totaling an average of 504 stocks, with the universe representing the largest companies in the index constitution of that time. Our backtest period spans ten years, starting in January 2013 and ending in December 2022. We consider delisted or insolvent companies until the last day of their membership in the reference index, mitigating potential survivorship bias. The Refinitiv dataset allows building the eight style factors identified in academic research and detailed in 6.

3.1. ESG Data

Index providers such as Dow Jones, MSCI and FTSE Russell have been at the forefront of developing ESG factor indices, which were first launched over a decade ago ([29], [30], [31]). These indices incorporate ESG factors alongside traditional financial metrics to create investment products that aim to deliver improved risk-adjusted returns while aligning with investors' ESG goals. Despite their growing popularity among investors, ESG indices have been criticized by academics and industry experts. One of the main concerns is that these indices may not fully capture the complexity of ESG issues and may rely too heavily on self-reported data from companies. In addition, ESG indexes may not be comprehensive enough, as they often exclude entire industries or companies without considering their unique ESG characteristics or potential for improvement. Finally, some experts argue that ESG indices may not provide sufficient differentiation between companies, grouping companies with very different ESG profiles under a single label such as "ESG leader" or "ESG laggard".

Implementing ESG portfolios in practice has proven challenging, as asset managers often struggle to obtain reliable and forward-looking ESG information to inform their investment decision-making. A study conducted by [32] found that about 50% of asset managers complain about the lack of real-time information and forward-looking disclosure related to ESG matters, rendering ESG data of little use for investment purposes. The ESG dataset used in this research addresses this industry need by providing reliable, real-time, and incident-based ESG data.

To address these criticisms, this study uses an independent provider, RepRisk, to incorporate timely ESG data into a more flexible and nuanced approach to portfolio construction. This addresses asset managers' challenges in obtaining reliable and forward-looking ESG information to inform their investment decisions. The ESG dataset used in this research provides reliable, real-time, and incident-based ESG data critical to addressing the industry's need for better information.

3.1.1. RepRisk Data

RepRisk, one of the world-renowned ESG data providers, was founded in 1998 and offers a global ESG data service collected from various public sources, such as news websites, blogs, social media, and print media. The data is collected through machine learning technology and human power, enabling RepRisk to cover numerous sources and update its database daily. This high update frequency lets investors detect changes in a company's ESG profile immediately after publishing negative ESG-related news and integrate this information into their portfolio construction.

RepRisk's ESG data provides advantages such as its point-in-time aspect, consistent methodology, and resulting unbroken time series with a history of 15+ years, allowing investors and researchers to backtest their ESG strategies. Moreover, RepRisk is one of the few data providers to offer detailed methodology and source code of their indicators.

The flagship RepRisk Index (RRI) is a proprietary algorithm developed by RepRisk that quantifies reputational risk exposure to environmental, social, and governance (ESG) issues. The RRI provides an initial assessment of ESG risks, facilitates a comparison of a company's exposure with its peers, and tracks risk trends over time. The RRI is calibrated on a scale of zero to 100, where a higher value indicates higher risk exposure. The scale is divided into four categories: low-risk exposure (0-25), medium-risk exposure (26-49), high-risk exposure (50-59), and very high/extremely high-risk exposure (60-100). The RRI is calibrated such that only a handful of companies with extremely high-risk exposure ever reach the maximum threshold of 100, allowing clients to identify these companies quickly.

The RRI is calculated based on the reach, frequency, and timing of ESG risk incidents and the severity and novelty of the issues addressed. The methodology does not depend on the sequence of ESG risk incidents, and ESG issues are not weighted by sector or country. The RRI emphasizes companies or projects that are newly exposed or have had less exposure in the past, making them more sensitive to new risk incidents.

The RRI provides three values: the current RRI reflects the current level of media and stakeholder attention given to a company's ESG issues, the peak RRI is the highest level of the RRI over the past two years, and the RRI change or trend shows the increase or decrease of the RRI within the past 30 days. This research focuses on Trend RRI, which considers the dynamics of change of the flagship indicator (RRI). Appendix 6.2 provides details of the index construction methodology.

3.1.2. Stock characteristics

The study uses monthly stock returns and fundamental data from Refinitiv between January 2006 and December 2022 to examine the relationship between ESG scores and stock returns. The investment universe is highly liquid and tradeable with relatively low transaction costs. The research exclusively relies on RepRisk ESG scores (RRI), and the analysis considers only returns starting from December 2012 to mitigate a potential selection bias. Table 1 presents descriptive statistics based on an average of approximately 761 companies. The complete stock universe has an annualized average excess return of 11.02% and an annualized standard deviation of 27.9%. The financial sector has the highest annualized return (+25.3%), while the energy sector has a negative annualized return (-4.7%) over the period. The real estate and utilities sectors have the lowest volatilities, while the energy sector has the highest volatility. The financial sector's performance is due to the catch-up effect after its underperformance following the financial crisis of 2008. The real estate sector has the lowest RRI, while consumer non-cyclical exhibits the highest RRI. The consumer, financial, and technology sectors have the highest volatility in the RRI scores.

[Table 1 about here.]

3.2. Style Factors

The Fama-French factors and their associated returns are typically estimated by sorting stocks to construct factor-mimicking portfolios. This results in long-short portfolios without additional constraints that would make them investable in practice. However, as this research focuses on practical applications, we adopt the same methodology for constructing the ESG-tilted portfolio, as detailed in section 2.3, enabling us to create investable portfolios. We compute our pure factor portfolios every month using the same 100 most representative stocks as in the ESG-tilted portfolio, based on the arguments presented by [33], which suggest that companies of different sizes are less likely to participate in corporate social responsibility initiatives. We use the 30-day Treasury Bill return as the risk-free return to calculate excess returns.

[Table 2 about here.]

Table 2 presents descriptive statistics for the pure factor portfolios, including an ESG factor. Both the Growth and Value factors exhibit a positive annualized return of around 4%, resulting in a Sharpe Ratio of 0.5. The RepRisk ESG factor portfolio displays a 1.5% annualized return, which translates to a Sharpe Ratio of 0.4. On the downside, both the Low Vola and the Dividend pure factor portfolio exhibit an annualized return of -4.3%, resulting in a significant negative Sharpe Ratio of -0.26 and -0.50, respectively.

To avoid potential multicollinearity issues within our factor universe, we calculate in figure 2 the variance inflation factor (VIF) in the diagonal. We observe that the VIF stays below two, far below the threshold of 10 suggested by ([34]). Our factor set thus does not present any concern about linear dependency.

[Figure 2 about here.]

4. Results

Using the methodologies described in Equation 8, we conducted a monthly rebalancing of the ESG-tilted portfolio and its benchmark between January 2013 and December 2022. As shown on the left side of Figure 3, we maintain a constant ex-ante relative exposure to the ESG factor of +0.25 while fully neutralizing the relative exposure to the eight style factors. We selected a moderate exposure to the ESG factor to remain close to the benchmark and avoid significant deviations in relative weights. On the right chart of Figure 3, we observed that during 2021, the relative weights remained within a narrow range of around 0 with only a few outliers.[6]

[Figure 3 about here.]

We compare the Sharpe ratios of the resulting strategies and then consider various risk and performance metrics. We also compare the relative risk-adjusted performance to the benchmark and the official index, namely the information ratio and tracking error. To further investigate whether the ESG-tilted portfolio is not significantly exposed ex-post to any of the eight traditional factors considered in this research, we present the results of the eight-factor regression.

It is important to highlight that the resulting portfolio, which is computed using Equation 6, may not adhere strictly to a long-only approach and may include small short positions, depending on the specific tilt level chosen. The adjustment made to address these short positions could result in minor deviations from achieving complete neutralization of the portfolio with respect to common factors.

4.1. Performance

In this section, we analyze the performance and risk profile of the ESG-tilted portfolio compared to the initial portfolio replicating the market benchmark and the official benchmark used in the replication.

[Figure 4 about here.]

Figure 4 displays the historical performance of the ESG-tilted portfolio, the replicating benchmark, and the S&P500 between 2013-2022. The portfolio consistently outperformed its benchmark and the official index throughout the period. We show that the replicating benchmark closely tracks the official benchmark, demonstrating the effectiveness of the replication method employed. Table 3 compares the portfolio's key performance and risk figures, benchmark, and official index. The ESG-tilted portfolio achieved an annualized return of 11.01% compared to 9.38% for the replicating benchmark and 9.79% for the S&P500. Despite the slightly higher volatility of the portfolio (13.19%) compared to its benchmark (13.06%) but below the official index (13.68%), it achieved a

[6] The same observation can be made throughout the period covered.

higher Sharpe ratio (0.84) than both the benchmark (0.72) and the index (0.72). We also observe a low tracking error between the portfolio and the benchmark and a similar maximum drawdown for the three portfolios.

[Table 3 about here.]

4.1.1. Information ratio

We assess the significance of the information ratio (IR) for the ESG-tilted portfolio in comparison to both the replicating benchmark and the official index by employing Equation 10. This evaluation aims to determine the probability of a significant deviation from zero.

[Table 4 about here.]

Table 4 presents the test results for the relative returns of the ESG-tilted portfolio compared to the replicating benchmark and the official index, respectively. Based on our analysis, the information ratio (IR) of the ESG-tilted portfolio computed against the replicating benchmark is found to be significantly greater than 0 at a 5% significance level. As for the information ratio against the official index, it is deemed significant at the 10% level.

[Table 5 about here.]

4.2. Ex-post Analysis

In this section, we analyze the ex-post exposure of the ESG-tilted portfolio, the replicating benchmark, and an overlay portfolio to traditional style factors and the ESG factor. The overlay portfolio represents the difference between the ESG-tilted and the replicating benchmark and is a long-short portfolio with relative exposures.

[Figure 5 about here.]

Table 5 presents a summary of the regression analysis results obtained from estimating Equation 9, which captures the relationship between the excess returns of the tilted portfolio and the eight style factors, as well as the ESG factor. We find that the excess returns of the replicating benchmark have a positive relationship with the size, growth, value, low volatility, and investment style factors and a negative association with the momentum, quality, and dividend style factors. The coefficients for the momentum, value, quality, and investment style factors are statistically insignificant at the 5% level. In contrast, the coefficients of growth, low volatility, and dividend style factors are statistically significant at the 1% level. As expected, the overlay portfolio has no significant exposure to any of the eight traditional factors but shows a significant exposure to the ESG factor at the 1% level.

In summary, the overlay portfolio exhibited no significant alpha, indicating that it could not produce excess returns beyond those the ESG and style factors accounted for. This further supports the notion that incorporating ESG considerations into portfolio construction does not necessarily lead to a trade-off between sustainability and financial performance.

[Table 6 about here.]

4.3. Robustness

Our research also shows that the outperformance of the ESG-tilted portfolio was consistent across different sub-periods and robust to different levels of ESG tilts, suggesting that the ESG integration has a positive impact on the portfolio's relative performance over time.

Table 6 displays the tilted portfolio's monthly and annualized active returns relative to the replicating benchmark throughout 2013-2022. Except for 2013, during which the ESG-tilted portfolio slightly underperformed the benchmark (-0.04%), the strategy consistently outperformed the benchmark. The active monthly returns ranged from -1.35% to +2.01% over the period, which can be attributed to the conservative relative ESG tilt chosen (+0.25).

Furthermore, Figure 5 demonstrates that the sectors over and underweight positions of the ESG-tilted portfolio, as compared to the replicating benchmark, vary over the analyzed period and fluctuate within a reasonable range. These results suggest that the portfolio's sector tilts are dynamic and responsive to market conditions. Notably, during the technology sector sell-off in 2022, the portfolio maintained an underweight position in the sector, while it was overweighted in the sector during the period of technology sector growth in 2017. However, the adaptivity to market conditions is beyond the scope of this article, and further research is necessary to investigate the extent to which the portfolio's sector tilts contribute to its overall performance and risk characteristics.

5. Conclusion

Incorporating ESG criteria into portfolio construction is becoming increasingly important for asset managers. The proposed relative tilt methodology, which utilizes timely ESG data, provides a forward-looking and practical solution for capturing various ESG issues without compromising exposure to traditional style factors. The method consistently generates gross alpha on the US market index. Still, a practical implementation must be considered, as high portfolio turnover and transaction costs could erode much of the alpha generated by the ESG tilts. To address this, reducing rebalancing frequency or imposing weight constraints could help mitigate these concerns.

The study presents a novel contribution to the literature on ESG investing by demonstrating the potential benefits of a flexible and nuanced approach to portfolio construction that integrates timely ESG information. These findings provide compelling evidence that including ESG considerations in investment decision-making can lead to superior risk-adjusted returns compared to a market benchmark, as demonstrated in the US market. These results hold significant implications for asset managers and investors seeking to align their investments with ESG principles. However, it is essential to acknowledge the limitations of this study, including the focus on a single market and a relatively short period. Additionally, other factors beyond ESG considerations, such as relative sector exposures, could impact performance. Future research should explore the potential trade-offs between portfolio performance and additional costs associated with ESG integration, such as high portfolio turnover and transaction costs, and investigate the impact of ESG integration on investment decision-making in different markets and asset classes.

In conclusion, our study supports the idea that ESG integration can enhance risk-adjusted returns in the US market. However, further research is needed to (1) address the limitations of this study, (2) explore the potential impact of ESG integration on investment decision-making in different markets and asset classes, and (3) inform portfolio construction for investors seeking to integrate ESG criteria into their investment strategies.

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6. Appendix

6.1. Factor Definitions

Table 7 presents the definitions of the traditional and ESG factors used in this research. The table includes the names of the factors, a brief description of each factor, and the specific definition or calculation used for each factor. The traditional factors include Momentum, Size, Growth, Value, Quality, Low Volatility, Investment, and Dividend, while the ESG factor is measured using the Trend RepRisk Index detailed in Appendix 6.2.

[Table 7 about here.]

6.2. Calculation of the RepRisk Index

The RepRisk ESG Incident Data consists of incident data, each of which is linked to one or more issues and one or more companies. Each incident is rated by analysts based on Severity, Reach, and Novelty using a scale of 1-3 for Severity (with 3 denoting very severe incidents), Reach (with 3 denoting high Reach), and 1-2 for Novelty (with 1 representing the first time a company is exposed to an issue). The reported date of the incident is also included.

6.3. Methodology of Current RRI at Company Level

The Current RRI (Reputation Risk Index) is an ESG (Environmental, Social, and Governance) indicator that measures a company's reputational risk related to ESG issues. The RRI is calculated by aggregating incident scores related to the target company over the last two years. The methodology for calculating the Current RRI, along with further details, has been published on the official RepRisk website to enhance the transparency of ESG data (see [35]).

The RRI is calculated in four steps, as follows:

1. Calculation of Average Incident Value
   The Incident Value for each incident i is calculated using the incident's Severity, Reach, and Novelty. Severity measures the potential harm caused by the incident, Reach measures the number of people affected, and Novelty measures how unique or unexpected the incident is. These three measures are combined to calculate the incident value using the formula:

$$\text{Incident Value}_i = \frac{1}{3}\sqrt[3]{\text{Severity}_i \times \text{Reach}_i \times \text{Novelty}_i}.$$

   The Average Incident Value is a metric used to estimate the impact of risk incidents on the corporate reputation of an organization c. It is calculated as a time-weighted average of the individual incident scores for all incidents in the past 730 days (approximately two years). The weight assigned to each incident is determined based on the time elapsed between the date of the incident and the calculation date t, with incidents that occurred more recently receiving a higher weight. The formula for calculating the weighted average is:

$$\text{Incident Value}_{c,t} = \frac{\sum_i \in I^{2y}_{c,t} \text{Incident Value}_i \times w_{i,t}}{\# I^{2y}_{c,t}},$$
$$w_{i,t} = 1 - \frac{1}{2} \times \frac{\Delta T_{i,t}}{730}$$

   where $I^{2y}c, t$ is the set of incidents that occurred within the past two years for company c at time t and $\# I^{2y}_{c,t}$ is the total number of incidents in the set. The weight assigned to each incident is calculated as follows:

$$w_{i,t} = 1 - \frac{1}{2} \times \frac{\Delta T_{i,t}}{730}$$

   where $\Delta T_{i,t}$ is the time elapsed in days since the incident occurred. The weight decreases linearly over time, with a weight of 1 assigned to incidents that happened on the calculation date t and a weight of 0.5 given to incidents that occurred 730 days before the calculation date. This methodology ensures that recent incidents are given more weight in the calculation, reflecting their more significant impact on the organization's current reputation.

2. Calculation of Incident Intensity
The incident intensity is calculated based on the number of incidents that occurred during the past two months. The incident intensity measures how frequently incidents have happened for the company in recent months and is calculated using a piece-wise linear function that assigns a different weight to the number of incidents depending on the range in which the number falls. The formula for calculating the incident intensity is:

$$\text{Incident Intensity}_{c,t} = \begin{cases} 0.5 + \#I_{c,t}^{2m}/10, & \#I_{c,t}^{2m} \leq 8 \\ 1.3 + (\#I_{c,t}^{2m} - 8)/20, & 8 \leq \#I_{c,t}^{2m} \leq 12 \\ 1.5 + (\#I_{c,t}^{2m} - 12)/50, & 12 \leq \#I_{c,t}^{2m} \leq 20 \\ 1.66, & 20 \leq \#I_{c,t}^{2m} \end{cases}$$

where $\#I^{2m}c, t$ is the number of incidents in the past two months for company c at time t.

3. Calculation of raw RRI
The raw RRI is calculated by multiplying the average incident value and the incident intensity and then multiplying the result by 100. The average incident value reflects the impact of risk incidents on the organization's reputation, which is calculated as a time-weighted average of the individual incident scores. The incident intensity is a measure of the frequency of risk incidents. The formula for the raw RRI is:

$$\text{RRI}_{c,t}^{\text{raw}} = \text{Incident Value}_{c,t} \times \text{Incident Intensity}_{c,t} \times 100$$

where Incident Valuec, t is the average incident value and Incident Intensityc, t is the incident intensity for a company c at time t.

4. Smoothing of raw RRI
In the final step of the RRI methodology, a decay function is applied to the raw RRI to smooth out fluctuations over time. The decay function detailed in [35] gradually reduces the RRI to zero over two years if no incidents occur during that time. The resulting smoothed RRI is then used as the final measure for the company and period of interest. To compute the smoothed RRI, the decay function is applied as follows: In the final step, the raw RRI is smoothed using a decay function that gradually reduces the RRI to zero over two years if no incidents occur. The smoothed RRI is then used as the final RRI for the company and period of interest and is computed as follows:

$$\text{RRI}_{c,t} = \begin{cases} \text{RRI}_{c,t}^{\text{raw}}, & \text{RRI}_{c,t}^{\text{raw}} \geq \text{RRI}_{c,t-1} \\ Decay(\text{RRI}_{c,t-1}), & \text{otherwise} \end{cases}$$

The RRI methodology is standardized by scaling the raw RRI with a factor of 100, converting it into a percentage. This approach enables straightforward comparisons across various companies and periods. By offering a valuable tool for evaluating the impact of risk incidents on an organization's reputation, the RRI methodology can inform decision-making and support risk management efforts. Notably, the present method highlights that the average incident value and intensity represent the primary determinants of the Current RRI.

Table 1: Summary Statistics and ESG Factor Scores for S&P 500 stocks by sector.
This table summarizes S&P 500 stock universe by sector, including returns, volatilities, and the Current RepRisk Index (Current RRI), whose corresponding changes over 30 days serve as the ESG factor in this study. The data covers the period from January 2013 to December 2022 and is presented annually. All Current RRIs are scored on a scale of 0 to 100, and the table shows the minimum and maximum values and the 25th and 75th percentiles for each metric.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Sector: Academic & Educational Services							
Return (p.a.)	3	-0.006	0.135	-0.158	-0.059	0.07	0.101
Volatility (p.a.)	3	0.347	0.107	0.235	0.297	0.403	0.447
Current RRI	3	10.905	3.469	7.606	9.096	12.554	14.522
Sector: Basic Materials							
Return (p.a.)	43	0.073	0.092	-0.165	0.01	0.125	0.311
Volatility (p.a.)	43	0.334	0.137	0.166	0.233	0.389	0.678
Current RRI	42	15.52	7.554	0	12.439	19.307	39.629
Sector: Consumer Cyclicals							
Return (p.a.)	132	0.052	0.149	-0.727	-0.024	0.135	0.455
Volatility (p.a.)	132	0.386	0.225	0.159	0.266	0.443	2.06
Current RRI	127	18.194	11.152	0	11.257	22.887	55.117
Sector: Consumer Non-Cyclicals							
Return (p.a.)	56	0.114	0.147	-0.296	0.049	0.143	0.655
Volatility (p.a.)	56	0.262	0.162	0.13	0.175	0.264	1.116
Current RRI	55	24.107	10.921	5.924	17.148	31.272	55.277
Sector: Energy							
Return (p.a.)	55	-0.047	0.273	-0.709	-0.113	0.059	0.906
Volatility (p.a.)	55	0.554	0.376	0.215	0.388	0.595	2.756
Current RRI	52	17.219	9.569	0	10.983	22.498	51.676
Sector: Financials							
Return (p.a.)	89	0.253	1.477	-0.108	0.053	0.144	14.016
Volatility (p.a.)	89	0.355	0.563	0.145	0.216	0.328	5.448
Current RRI	84	14.902	11.774	0	8.059	18.442	55.815
Sector: Healthcare							
Return (p.a.)	87	0.154	0.206	-0.791	0.084	0.214	0.956
Volatility (p.a.)	87	0.305	0.179	0.076	0.218	0.321	1.432
Current RRI	86	14.774	10.299	0	6.812	20.004	54.511
Sector: Industrials							
Return (p.a.)	93	0.12	0.088	-0.127	0.083	0.167	0.417
Volatility (p.a.)	93	0.29	0.11	0.154	0.222	0.326	0.736
Current RRI	92	13.75	9.075	0	6.321	20.33	48.656
Sector: Real Estate							
Return (p.a.)	37	0.031	0.074	-0.139	-0.021	0.087	0.143
Volatility (p.a.)	37	0.249	0.068	0.183	0.198	0.278	0.492
Current RRI	36	4.304	4.238	0	1.471	5.62	17.379
Sector: Technology							
Return (p.a.)	130	0.149	0.34	-0.569	0.061	0.204	3.482
Volatility (p.a.)	129	0.33	0.163	0.141	0.234	0.359	1.338
Current RRI	128	11.889	12.056	0	2.574	16.9	57.219
Sector: Utilities							
Return (p.a.)	36	0.066	0.053	-0.087	0.043	0.096	0.161
Volatility (p.a.)	36	0.211	0.08	0.153	0.171	0.211	0.547
Current RRI	34	18.546	6.973	4.17	15.802	22.421	34.72

Table 2: Summary statistics for the pure (long-short) style and the ESG factors.
This table presents summary statistics for the pure (long-short) style and ESG factors used in an ex-post factor exposure analysis conducted from January 2013 to December 2022. A pure (long-short) style factor is a portfolio that targets the 90th percentile in the long leg and the 10th percentile in the short leg for a specific factor.

	Return (p.a.)	Volatility (p.a.)	Sharpe Ratio	Max. Drawdown
Momentum	-0.004	0.138	-0.031	0.421
Size	0.013	0.062	-0.205	0.235
Growth	0.035	0.067	0.523	0.095
Value	0.041	0.082	0.503	0.144
Quality	0.07	0.054	0.135	0.175
Lowvola	-0.043	0.164	-0.260	0.588
Investment	-0.013	0.051	-0.249	0.244
Dividend	-0.043	0.086	-0.499	0.560
ESG	0.015	0.037	0.400	0.109

Table 3: Key Performance Figures.
This table provides a performance comparison of the ESG-tilted portfolio with the replicating benchmark and the S&P 500 index over the sample period from January 2013 to December 2022. The table includes key performance measures, such as annualized returns, volatilities, Sharpe ratio, VaR, ES, maximum drawdown, alpha, tracking error, information ratio, and beta, reported in percentage (except beta and ratios).

	Portfolio	Benchmark	S&P500
Performance (eff.)	196.89	154.41	164.53
Return (p.a.)	11.01	9.38	9.79
Volatility (p.a.)	13.19	13.06	13.68
Sharpe Ratio	0.84	0.72	0.72
VaR	-5.90	-5.95	-6.24
ES	-8.63	-8.33	-9.06
Max. Drawdown	23.68	23.79	22.76
Alpha		1.63	1.22
Tracking Error		1.82	2.71
Information Ratio		0.90	0.45
Beta		0.991	0.945

Table 4: Probabilistic Information Ratio test (PIR).
This table shows the results of the Probabilistic Information Ratio (PIR) test on the relative returns of the ESG-tilted portfolio compared to the replicating benchmark and the S&P 500 index. The PIR is a statistical test that assesses the probability that the information ratio of a portfolio is positive, given its relative historical performance. The table reports the monthly Information Ratio for each reference portfolio and the PIR. The test is performed on non-annualized relative returns, and the sample period covers January 2013 to December 2022.

Benchmark	Information Ratio	PIR
Replicating Benchmark	0.241	0.998
S&P500	0.112	0.913

Table 5: Regression on the 8 style and the ESG factors.
This table shows the results of the nine-factor regression for the overlay portfolio (ESG-tilted - Benchmark), the ESG-tilted long-only portfolio, and the replicating benchmark respectively from 2013 to 2022 on a monthly basis. The regressions are calculated individually for each portfolio. For each factor, we compute a long-short portfolio, that targets the 90th percentile in the long leg and the 10th percentile in the short leg. Monthly alphas and adj. R^2 are reported upon. Standard error estimates are computed using the Newey and West procedure.

	Overlay	ESG-tilted Portfolio	Replicating Benchmark
Constant	0.001	0.007^{***}	0.006^{**}
	(0.000)	(0.003)	(0.003)
Momentum	0.005	-0.020	-0.025
	(0.013)	(0.077)	(0.076)
Size	0.029	0.358^{**}	0.329^{**}
	(0.027)	(0.162)	(0.160)
Growth	-0.039	0.355^{**}	0.393^{***}
	(0.024)	(0.144)	(0.142)
Value	0.018	0.194^{*}	0.176
	(0.019)	(0.115)	(0.114)
Quality	0.025	-0.0158	-0.183
	(0.029)	(0.175)	(0.173)
Lowvola	0.024	0.439^{***}	0.415^{***}
	(0.011)	(0.065)	(0.065)
Investment	-0.036	0.265	0.301
	(0.031)	(0.189)	(0.187)
Dividend	0.003	-0.301^{**}	-0.305^{***}
	(0.021)	(0.125)	(0.123)
ESG	0.179^{***}	-0.234	-0.413^{**}
	(0.040)	(0.244)	(0.241)
Observations	150	150	150
R^2	0.192	0.425	0.424
Adjusted R^2	0.140	0.388	0.387
Residual Std. Error (df = 140)	0.005	0.031	0.030
F Statistic (df = 9; 140)	3.700^{***}	11.500^{***}	11.400^{***}
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Table 6: Calendar Returns.
The table shows the calendar relative returns for the ESG-tilted portfolio vs. the replicating benchmark between January 2013 and December 2022. The monthly and annual relative returns are expressed in percentage and reported for each month of the year. The last column represents the difference between the ESG-tilted portfolio returns and the benchmark returns for each year.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	YTD
2013	-0.31	-0.37	-0.08	-1.28	0.92	-0.26	-0.23	0.56	0.69	0.02	0.65	-0.33	-0.04
2014	0.21	0.14	0.03	-0.03	-0.22	-0.47	0.20	0.96	0.58	0.59	0.41	0.52	2.94
2015	0.93	0.28	-1.25	0.33	-0.76	0.42	0.54	0.92	0.62	0.09	-1.35	0.28	1.03
2016	-0.72	0.84	0.49	0.92	-0.82	0.45	-0.05	0.02	-0.09	0.01	0.04	-0.83	0.25
2017	0.05	0.00	0.25	-0.33	-0.05	-0.22	0.63	-0.29	0.85	0.96	0.19	-0.03	2.02
2018	0.80	0.77	-0.35	1.09	-1.17	0.45	0.27	0.34	0.49	-1.12	0.57	0.96	3.11
2019	-0.14	1.21	0.70	-0.12	-0.29	-0.23	0.09	-0.11	-1.17	0.89	0.06	0.42	1.29
2020	-0.17	-0.99	0.23	1.60	0.81	-0.09	0.35	1.08	0.42	-0.92	0.13	1.30	3.77
2021	0.45	1.53	-0.17	0.45	0.07	1.32	0.82	-0.40	-0.492	0.89	1.60	2.01	8.35
2022	0.40	0.51	0.85	-0.43	0.68	0.71	-0.62	-0.80	0.75	0.68	0.76	0.45	3.99

Table 7: Definitions of Traditional and ESG Factors.
This table presents the definitions of the eight traditional factors (Momentum, Size, Growth, Value, Quality, Low Volatility, Investment, and Dividend) and the ESG factor (measured using the RepRisk Index) used in this research.

Factor	Description	Definition
Momentum	Stocks with strong performance over the past year	Average of z-scores of 6-month momentum and 12-month momentum
Size	Stocks with small market capitalization	Minus the natural logarithm of Market Capitalization
Growth	Stocks with strong growth prospects using historical earnings and sales	Weighted average of z-scores of estimated long-term and short-term EPS as well as SPS growth
Value	Stocks with lower valuations as measured by price-earning, price-to-book and enteprise value-cash-flows from operations ratios	Average of relative z-scores of PER, PBR, and EV/CFO within each sector
Quality	Stocks with strong profitability, stability as measured by Return on Equity, Debt-Equity ratio and Earnings per Share volatility	Average of z-scores of ROE, DE ratio, and 5-year EPS volatility
Low Vola	Stocks with low volatility	Standard deviation of the daily returns in the last 5 years
Investment	Growth in total assets	Annual growth of total assets
Dividend	Dividend policy of the company	Dividend yield
ESG	Trend RepRisk Index (inverted)[7]	Change of RepRisk Index in the last 30 days

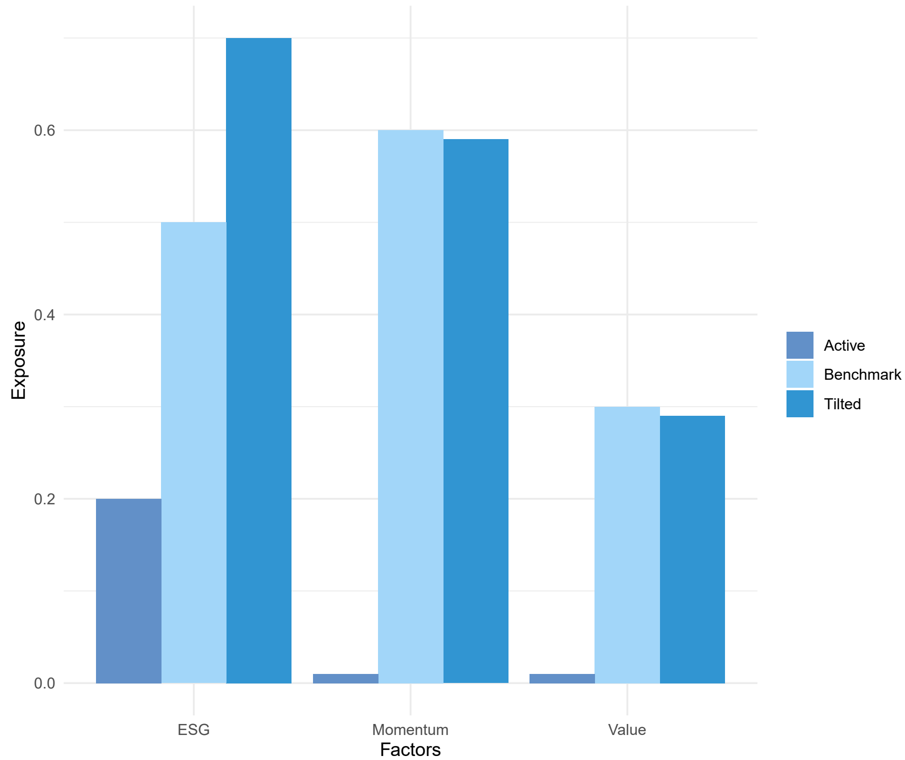

Figure 1: Illustrative example: Comparing average active exposure of tilted and benchmark portfolios.

Figure 2: Variance inflation factors.
The variance inflation factors of the eight traditional and ESG factors are shown in the diagonal. The return series of each factor is computed as the market-cap weighted return of the upper decile less the market-cap weighted return of the lower decile of each factor for the reduced investment universe of 100 stocks.

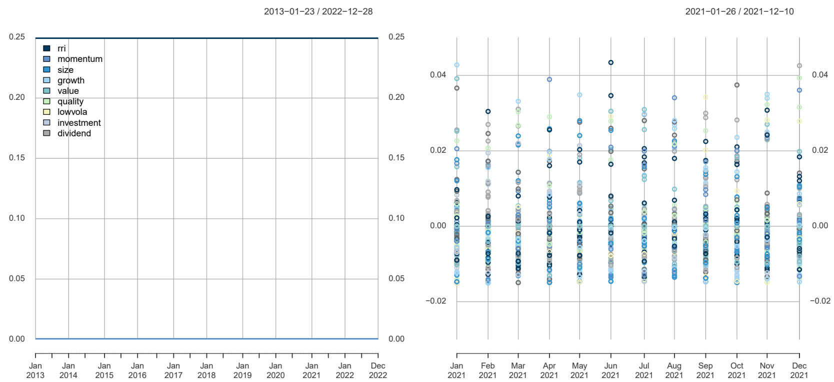

Figure 3: ESG-tilted Portfolio: Factors Exposure (ex-ante) and Relative Weights.
The left chart depicts the constant ex-ante relative target exposure to the ESG factor of +0.25 and zero exposure to the eight style factors between January 2013 and December 2022. The right chart shows the over- and underweights of the ESG-tilted portfolio relative to the S&P500 in the year 2021.

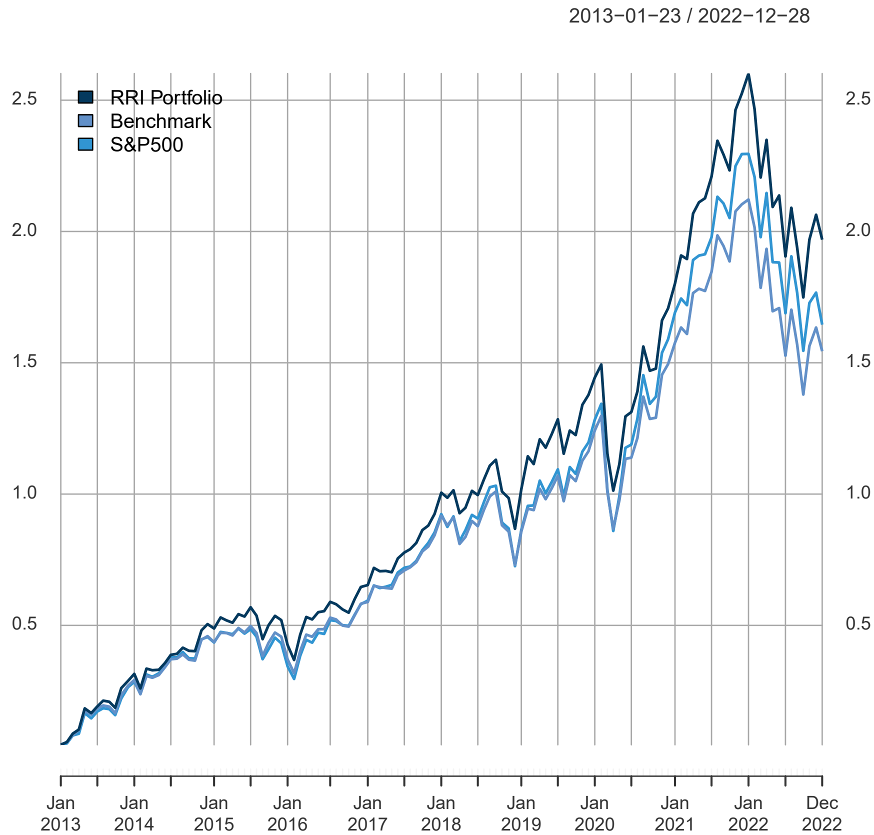

Figure 4: Comparing Performance: ESG-tilted Portfolio vs. Benchmark and S&P500. This plot compares the cumulative performance of the ESG-tilted portfolio, the replicating benchmark, and the S&P 500 index over the sample period from January 2013 to December 2022.

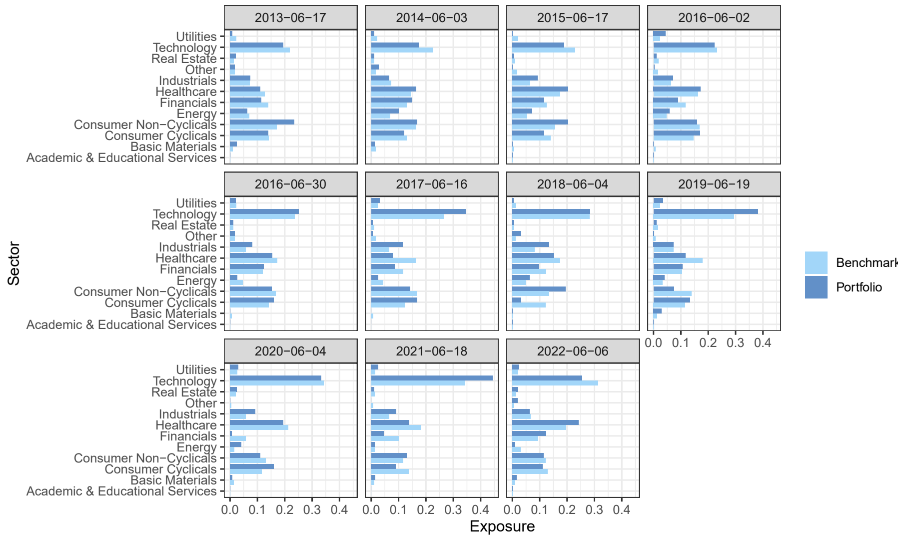

Figure 5: Sector Exposures: ESG-tilted Portfolio vs. Benchmark.
The chart depicts the sector exposure differences between the ESG-tilted portfolio and its benchmark. The tilted portfolio shows a significant overweighting in the technology sectors in 2019 and 2021, while the benchmark exhibited a higher allocation to healthcare in 2019.