Integrating ESG Criteria into the Swiss Real Estate Index: Methods and Impacts

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Integrating ESG Criteria into the Swiss Real Estate Index: Methods and Impacts*

Fabio Alessandrini† Nathan Delacrétaz‡ Eric Jondeau §

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Abstract

In this note, we delve into diverse methodologies for constructing an ESG index comprising Swiss real estate funds, using data sourced from Alessandrini et al. (2023). This data, derived from textual analysis of publicly available fund reports, provides an ESG score for each constituent of the SXI Real Estate Funds Broad index. Our exploration spans best-in-class, reweighting, and optimization approaches. We observe a fundamental trade-off between elevating the ESG score of the portfolio and the resultant tracking error against the benchmark index. Specifically, greater ESG score improvements are accompanied by increased portfolio's tracking errors. Our analysis further highlights that this trade-off is significantly influenced by the correlation between the ESG scores and their respective portfolio weights. In our dataset, a size bias is apparent, with larger funds generally having higher ESG scores, indicating that substantial ESG enhancements could be feasible with minimal tracking error. Interestingly, we also find that the risk-return profile of the portfolios remains largely unaffected by the ESG score improvements, suggesting that responsible investing can be pursued without compromising financial performance.

Keywords: ESG, real estate, index construction.

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†Center for Risk Management at Lausanne (CRML), University of Lausanne, Enterprise for Society (E4S) Center, Banque Cantonale Vaudoise

‡Center for Risk Management at Lausanne (CRML), University of Lausanne

§Center for Risk Management at Lausanne (CRML), University of Lausanne, Enterprise for Society (E4S) Center, Swiss Finance Institute

1 Introduction

This note explores the integration of Environmental, Social, and Governance (ESG) information into the construction of a real estate fund index. We use the well-established SXI Real Estate Funds Broad (SWIIT) index as our benchmark, which includes approximately 40 real estate funds traded on the Swiss exchange. The ESG data is derived from scores calculated by the Center for Risk Management - Lausanne (CRML), based on the textual analysis of publicly available documents such as annual reports and sustainability reports.

Our investigation encompasses various methodologies for incorporating sustainability scores into the index construction. The first method is a simple exclusion strategy, equivalent to a best-in-class approach. The second method retains all funds but adjusts the weight of each constituent according to its ESG score. Lastly, we investigate methodologies centered on portfolio optimization.

Our research reveals distinct outcomes for each methodology in terms of portfolio performance and ESG score impact. The best-in-class method leads to portfolios with higher concentration, raising concerns about diversification. Though straightforward, it consistently achieves higher ESG scores compared to other methods. The reweighting method, balancing ESG integration and portfolio diversification, results in moderately improved ESG scores while maintaining operational simplicity. The most complex methods, based on score maximization or tracking error minimization, present a nuanced balance between portfolio performance and ESG score enhancement. While these portfolios generally fall short of the best-in-class approach in terms of ESG score elevation, they offer a more sophisticated balance of ESG integration, tracking error, and portfolio turnover.

The rest of this note is structured as follows: Section 2 provides an overview of the utilized data. Section 3 explains the various methodologies, presenting results for each. A comprehensive comparison of these methodologies is detailed in Section 4. Section 5 examines the sensitivity of portfolios to the correlation between weights and ESG scores.

The note concludes with Section 6, offering final thoughts and implications of our findings.

2 Data

2.1 Market data

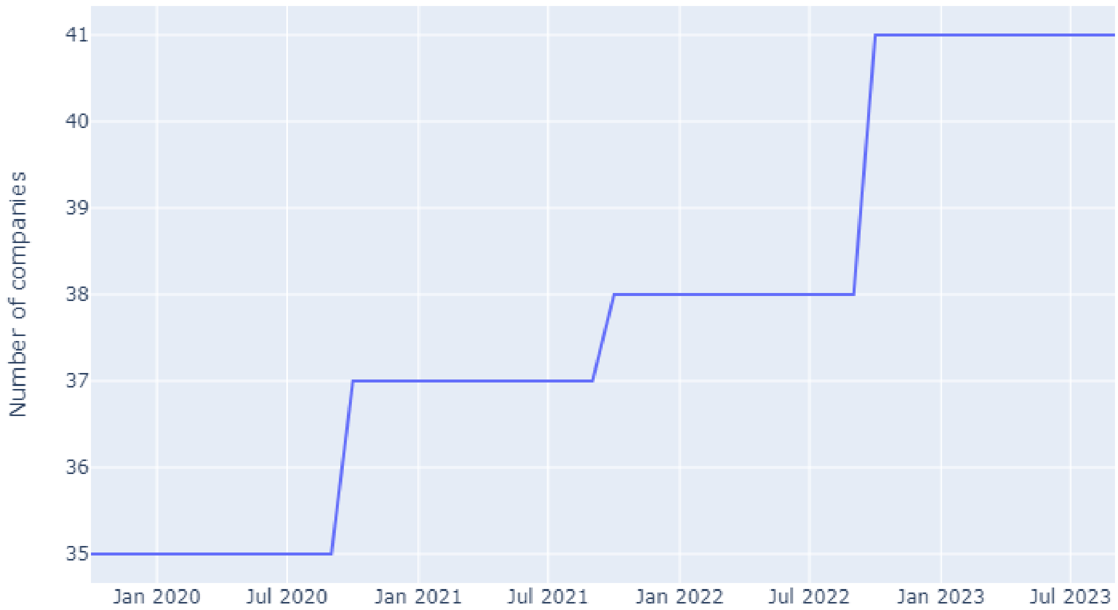
The benchmark of this paper, the SWIIT index, predominantly includes funds that invest at least 75% of their assets within Switzerland, with a focus on free-float market capitalizations. The composition of the index is dynamic, consisting of 41 funds at the end of our sample period.

The annual rebalancing of the index is scheduled for the third Friday of September, with its detailed methodology documented in SIX (2023). Our analysis replicates the SWIIT index over a period from October 2019 to October 2023, utilizing daily total return prices and market capitalizations sourced from Datastream. The market capitalization data points are used for recalculating index weights, based on the assumption that each fund's free-float is equivalent to its total market capitalization. The constituents at each rebalancing date are obtained directly from the Swiss exchange.

Figure 1 captures the evolving composition of the index, highlighting its expansion from 35 funds in October 2019 to 41 in September 2023. As shown in Figures 2a and 2b, the distribution of weights within the index emphasizes the concentration of the index. Notably, the largest fund alone comprises nearly 17% of the total index weight, with the combined weight of the top five funds exceeding 37%.

Further, Figure 3 corroborates the tight correlation between the value-weighted portfolio and the SWIIT index. The performance metrics of the index are outlined in Table 1. Beyond traditional risk and return statistics, we include concentration and turnover metrics. In particular, we report the Herfindahl index as a measure of concentration. The

Figure 1: Number of funds in the SWIIT index



Herfindahl index is measured as:

$$H = \sum_{i=1}^{N} w_i^2$$

where N is the number of constituents. This index ranges from $1/N$ for a fully diversified portfolio to 1 for a fully concentrated portfolio. We also compute the turnover of the portfolio. Monthly turnover is defined as follows:

$$Turnover_t = \sum_{i=1}^{N} \left| w_{i,t} - w_{i,t-1} \left(\frac{1 + R_{i,t}}{1 + R_{P,t}} \right) \right|$$

where $R_{i,t}$ is the return over month t of the ith constituent and $R_{P,t}$ is the return of the overall portfolio over the same month. Consequently, the measure account for weight changes due to introduction or deletion of constituents and is therefore illustrative of how much trading is implied by any portfolio.

The numbers in Table 1 reveal a modest overall growth within the analyzed period, characterized by an initial increase until the end of 2022 followed by a decrease. The index also shows a low turnover rate of 3%, underscoring its compositional stability.

Table 1: Descriptive statistics for the SWIIT index

	Index
Ann. return	0.86 %
Ann. volatility	9.69 %
Sharpe ratio	0.09
Weight of largest position	16.89 %
Sum of 5 largest positions	37.49 %
Herfindahl index	0.054
Ann. turnover	3.00 %
Last ESG score	7.02
Mean ESG score	6.43

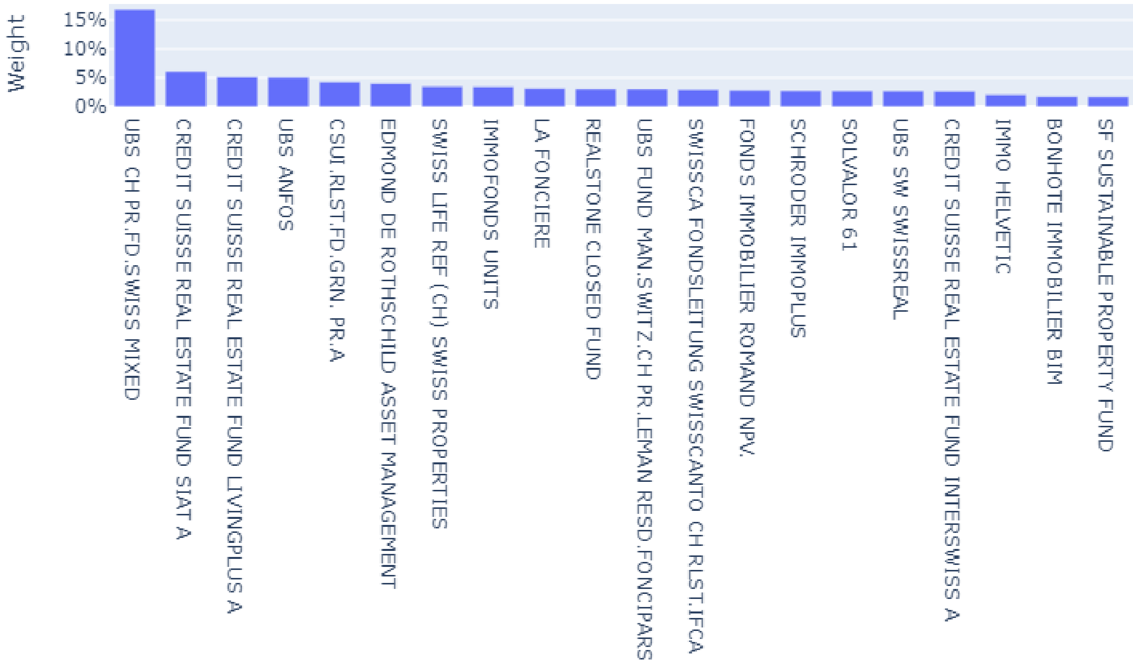
2.2 ESG scores

The ESG scores used in our analysis are derived from the textual analysis methodology detailed in Alessandrini et al. (2023). These scores are a component of the broader PRESS scores, which integrate various metrics from publicly accessible data sources. For this study, we focus solely on the textual analysis scores due to their historical comprehensiveness. These scores, ranging from 0 (lowest) to 10 (highest), are based on an analysis of public documents such as annual and sustainability reports published by the funds. We have compiled these documents since 2019, enabling us to calculate retrospective scores over a five-year period.

The foundation of our textual analysis is a meticulously improved ESG dictionary, originally based on Baier et al. (2020), and a practical bag-of-words approach. This dictionary, with 491 ESG-focused terms, has been specifically augmented for real estate relevance using the word2vec skip-gram model and is adapted for analyzing texts in multiple languages. The bag-of-words methodology simplifies the processing of texts, aiding in the effective quantification of ESG terms from a range of documents, including Swiss real es-

Figure 2: Weights of the funds in the SWIIT index as of September 2023

(a) Weights of the 20 largest funds



(b) Weights of the 21 smallest funds

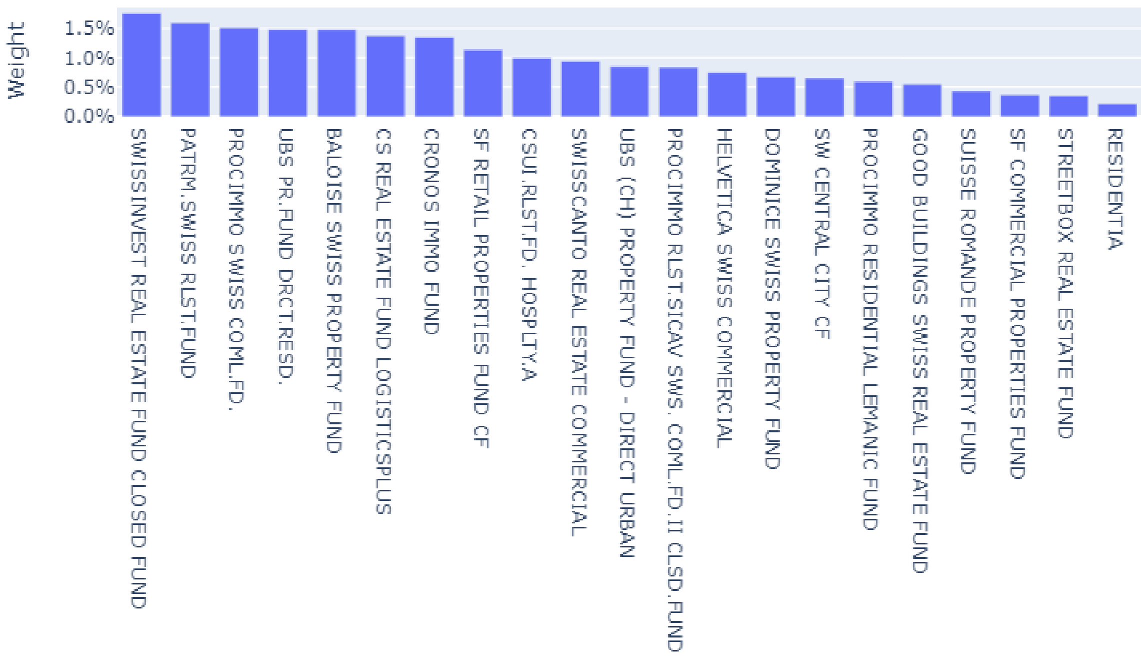
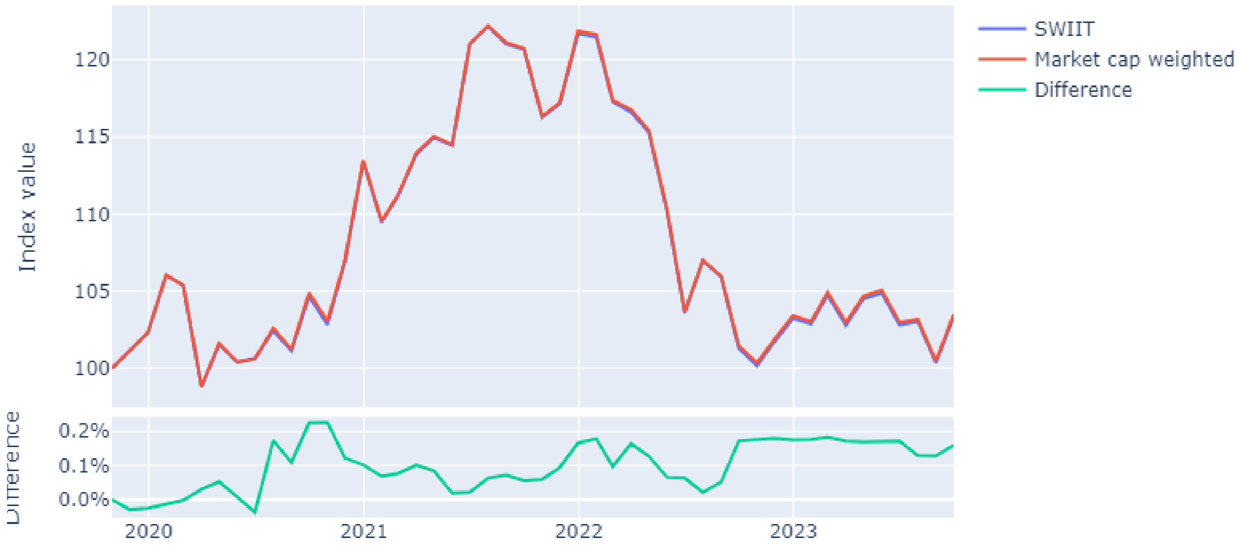


Figure 3: SWIIT index vs. Market capitalization portfolio

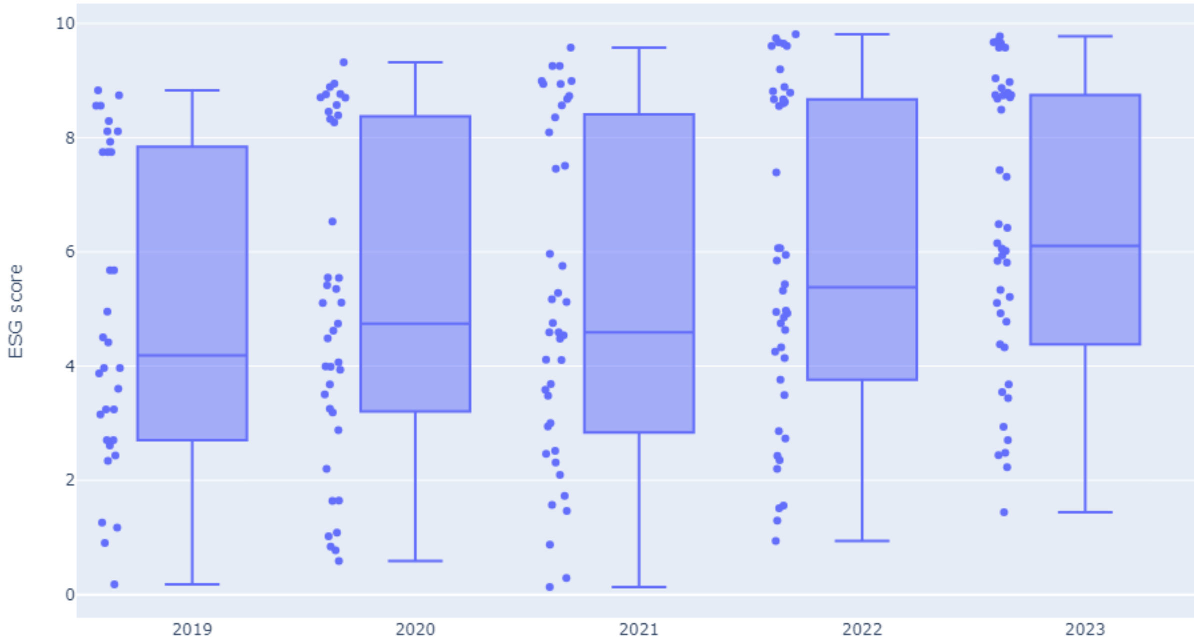


tate funds' annual and sustainability reports. This approach, centered on term frequency analysis, diverges from traditional sentiment analysis, providing a more straightforward path to assess ESG performance.

Figure 4 presents the evolution of individual fund scores, indicating a gradual increase in the median score from around 4 in 2019 to approximately 6 in 2023. This figure highlights an upward trend in ESG performance, while also revealing significant heterogeneity among the funds in each year. The scores reflect the year of computation, which is based on documents available up to mid-year, usually representing the previous year's performance.

The ESG score of the index itself has shown a positive trend, progressing from an initial average of 5.8 to around 7 by the end of the period, as shown in Figure 5. Notably, the index score consistently exceeds the median score across funds, reflecting a tendency for larger funds to achieve higher ESG scores. This phenomenon is further illustrated by Figures 6a and 6b, which depict a positive correlation between fund sizes and ESG scores. This correlation, quantified as 0.37 for all funds and 0.44 excluding the largest fund, highlights the significant influence of fund size on ESG performance.

Figure 4: Box plot of the ESG scores



3 Methodology

The methodologies explored in this section integrate the ESG scores discussed in Section 2.2. Given the monthly data framework, rebalancing is set to occur annually on October 1st. This timing aligns closely with the annual rebalancing schedule of the SWIIT Index, which occurs in the third week of September. At each rebalancing time, we utilize the ESG scores corresponding to the current year.[1]

To facilitate the interpretation of the subsequent analysis, we introduce the ESG

[1] Typically, annual reports are published between March and June and cover the preceding year's activities. Therefore, we can reasonably expect that all critical data necessary for calculating the ESG scores is available by the time of rebalancing in October.

Figure 5: Temporal evolution of the ESG score of the SWIIT index

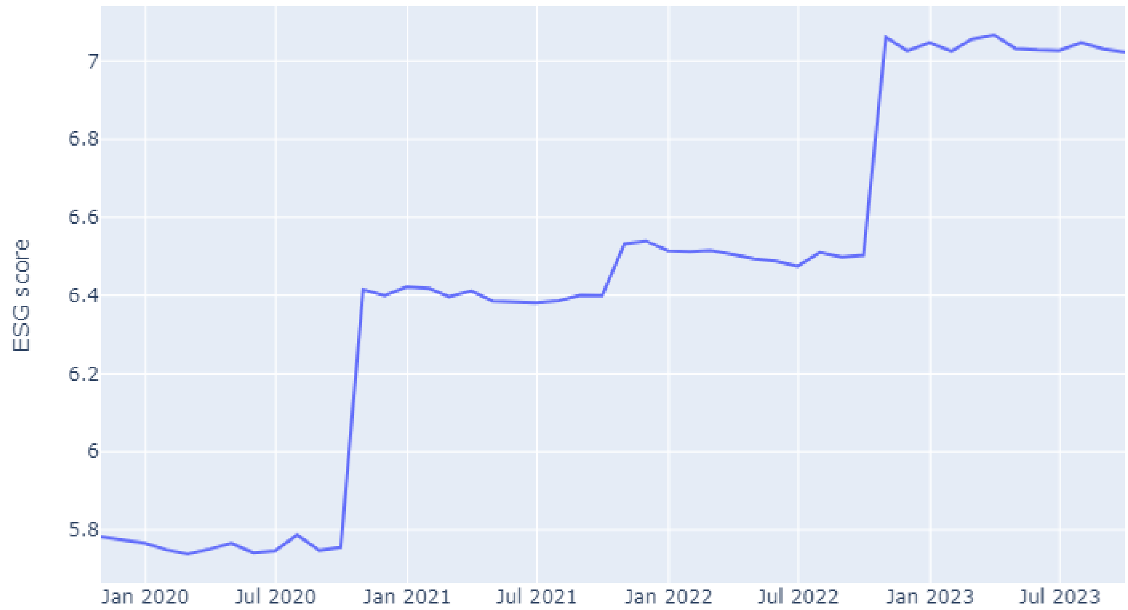
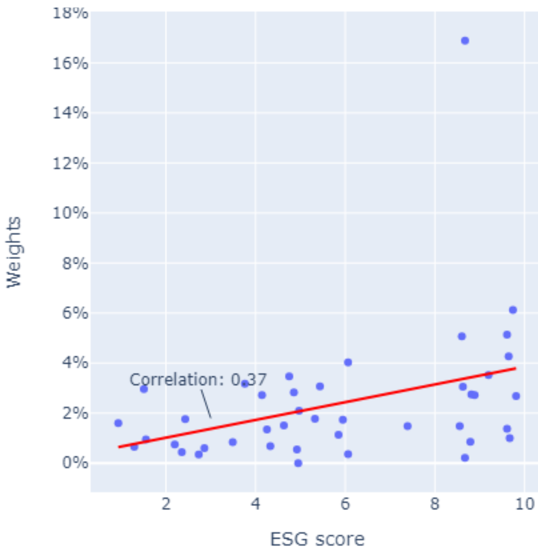
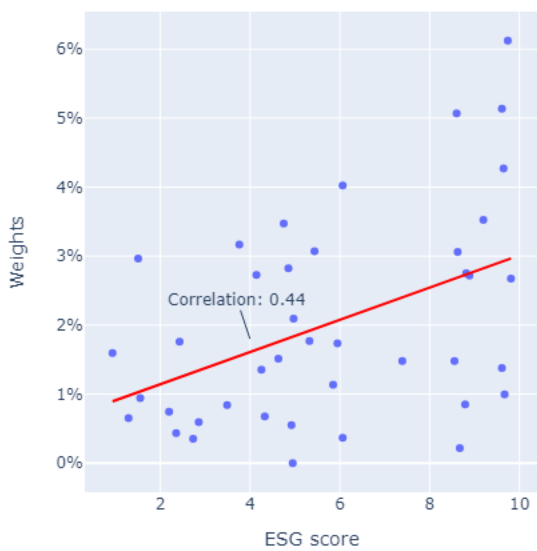


Figure 6: Scatter plot of weights vs ESG scores

(a) Including largest fund



(b) Excluding the largest fund



Efficiency ratio, formulated as:

$$ESG\ Efficency\ ratio_p = \frac{ESG_p - ESG_{SWIIT}}{\sigma_p}$$

This ratio effectively measures ESG score enhancements relative to tracking error. ESG_{SWIIT} and ESG_p denote the 5-year average ESG scores of the SWIIT index and portfolio p, respectively, highlighting the comparative ESG performance of portfolio p. The denominator, σ_p, denotes the tracking error of portfolio p relative to the SWIIT index. This metric, rooted in the efficiency ratio concept from Alessandrini and Jondeau (2021), is utilized across all portfolios, serving as a key indicator of the efficacy of ESG integration in relation to the ability of the portfolio to track the market index. It allows to summarize in a single metric the trade-off the investor is facing between improving the ESG profile of the portfolio and adding financial risk with respect to the benchmark.

3.1 Best-in-class

The best-in-class method involves creating a sub-set of the universe by selecting top-performing funds above a specified threshold or excluding the lowest performers. This corresponds to either a best-in-class or an exclusion strategy. We consider different levels of portfolio concentration, ranging from a highly concentrated group of the top 10 funds to a more diverse selection of the top 30 funds, increasing in increments of 5. For each portfolio, initial fund weights are based on market capitalization and then normalized so their total sum equals 1.

The performance and ESG profiles of the portfolios are detailed in Table 2, with their values depicted in Figure 7 and ESG scores shown in Figure 8. The ESG score improvements range from 37% in the Best 10 portfolio to 12% in the Best 30 portfolio. Tracking errors also show an increase, ranging from 2.6% in the Best 10 to 0.7% in the Best 30. This analysis delineates a balance between improving ESG scores and moderating tracking error. Corresponding to these insights, the evaluation of the ESG Efficiency ratio shows that portfolios within the Best 15 to 20 range realize the most effective combination of enhanced ESG scores and minimal tracking error. While the overall portfolio performance is relatively stable, as indicated by consistent Sharpe ratios, a notable limitation is the concentration risk, particularly in the Best 10 portfolio where the top five funds represent over 70% of the portfolio, with the largest fund representing more than a third of the index.

Turnover rates, a crucial factor for index replication, also vary significantly. In highly concentrated portfolios like the Best 10 portfolio, turnover rates can reach almost 50%, whereas they decrease to around 11% in the less concentrated options. This variation is an important consideration for investors in terms of rebalancing costs and operational efforts.

The correlation between the fund size and the ESG score significantly influences these results. The sample indicates that larger funds generally have higher ESG scores (as shown in Figures 6a and 6b), leading best-in-class indices to favor larger funds and consequently lower tracking errors. Section 5 delves into the implications of a potential negative correlation between fund size and ESG scores.

As an alternative method, equal weighting is applied to each fund within the same best-in-class criteria, promoting simplicity and diversification. This method tends to favor smaller funds, a typical feature of equally-weighted portfolios. The outcomes of this approach are summarized in Table 3.

While the equally-weighted method achieves greater diversification, with larger funds typically staying below the 10% threshold, it tends to yield less significant ESG score improvements. In some cases, like the Best 30, it may even result in a performance decline relative to the index, as it allocates higher weights to median or below-median funds. This underperformance is reflected in the ESG Efficiency ratio, which is lower in equally-weighted portfolios compared to value-weighted ones. Additionally, this approach

Table 2: Best-in-class strategy, value-weighted

	Index	Best 10	Best 15	Best 20	Best 25	Best 30
Ann. return	0.86%	0.34%	0.58%	0.57%	0.55%	0.67%
Ann. volatility	9.69%	9.94%	9.95%	9.77%	9.75%	9.91%
Sharpe ratio	0.09	0.03	0.06	0.06	0.06	0.07
Tracking Error	-	2.65%	1.70%	1.46%	1.11%	0.73%
Largest weight	16.9%	20.1%	29.6%	25.6%	23.0%	20.3%
Sum 5 largest	37.5%	71.7%	65.6%	56.9%	51.1%	45.0%
Herfindahl index	0.05	0.13	0.14	0.11	0.09	0.07
Turnover	3.0%	48.5%	29.0%	27.4%	21.7%	11.6%
Last ESG score	7.02	9.45	9.08	8.70	8.35	7.91
Change vs index	-	*34.58%*	*29.22%*	*23.85%*	*18.83%*	*12.63%*
Mean ESG score	6.43	8.82	8.50	8.24	7.74	7.22
Change vs index	-	*37.30%*	*32.31%*	*28.17%*	*20.43%*	*12.41%*
ESG Efficiency ratio		0.90	1.22	1.24	1.18	1.08

Figure 7: Best-in-class strategies, value-weighted

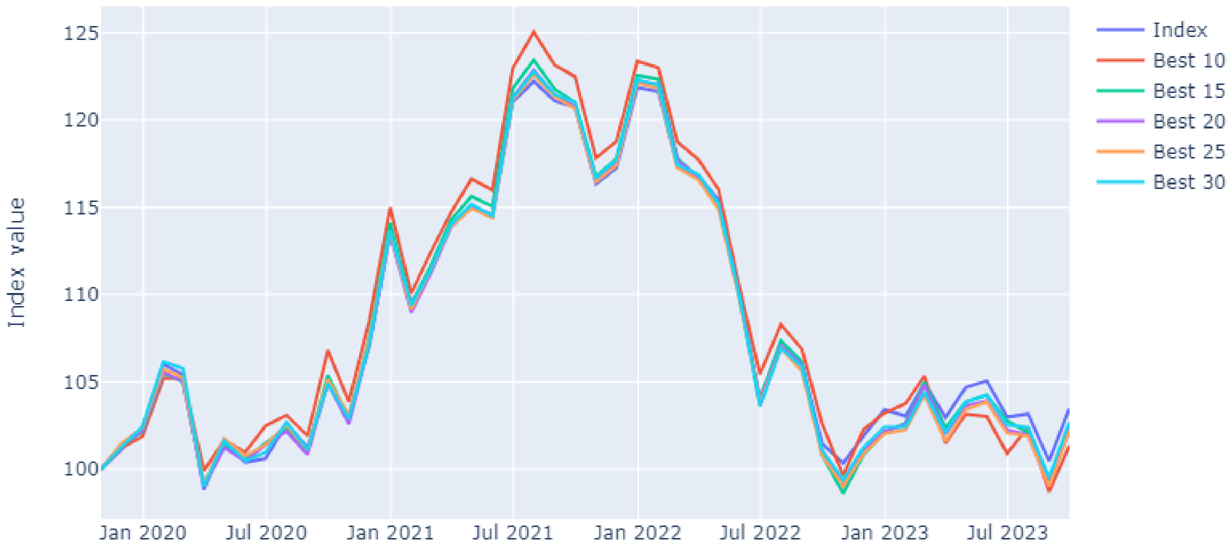
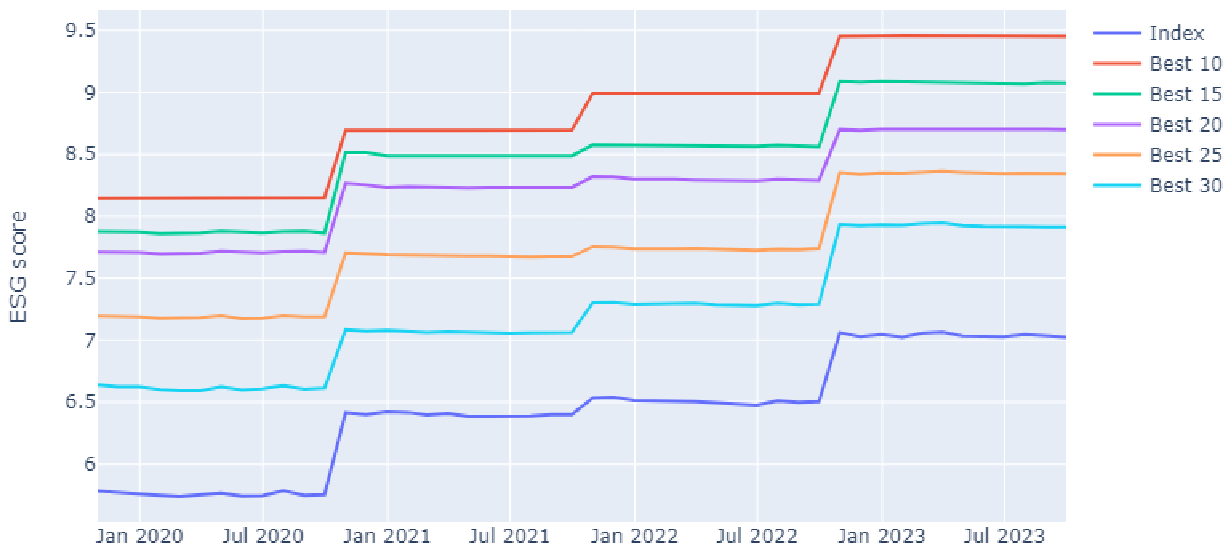


Figure 8: ESG scores of the best-in-class strategies, values-weighted



tends to negatively impact financial performance and tracking errors while increasing turnover.

3.2 Reweighting

The reweighting method modifies the weights of all constituents in a portfolio in accordance with their ESG scores. This process begins by ranking the funds based on their ESG scores and dividing them into n percentiles. The degree of reweighting depends on the chosen percentile value n and an over- or under-weighting adjustment factor k.

For $n = 3$, the methodology involves increasing the weights of the top percentile by a factor of $1 + k$ and decreasing the weights of the bottom percentile by $1/(1 + k)$. For instance, with $n = 3$ and $k = 1$, the weights of the top tercile are doubled, while the weights of the bottom tercile are halved. The weights of the middle tercile remain unchanged. These weights are then normalized to ensure their sum equals 1.

In scenarios where $n = 4$, the reweighting is more granular. The weights of the top quartile are increased by $1 + k$, while those in the bottom quartile are decreased by

Table 3: Best-in-class strategy, equally-weighted

	Index	Best 10 EW	Best 15 EW	Best 20 EW	Best 25 EW	Best 30 EW
Ann. return	0.86%	0.37%	-0.17%	-0.17%	-0.09%	0.24%
Ann. volatility	9.69%	10.25%	10.22%	10.03%	10.12%	9.95%
Sharpe ratio	0.09	0.04	-0.02	-0.02	-0.01	0.02
Tracking Error	-	2.87%	2.01%	2.05%	2.06%	1.83%
Largest weight	16.9%	11.3%	7.4%	5.6%	4.5%	4.0%
Sum 5 largest	37.5%	52.9%	35.9%	27.1%	21.6%	18.4%
Herfindahl index	0.05	0.10	0.07	0.05	0.04	0.03
Turnover	3.0%	50.2%	42.8%	43.8%	38.7%	29.3%
Last ESG score	7.02	9.36	9.11	8.41	7.73	7.15
Change vs index	-	*33.34%*	*29.74%*	*19.81%*	*10.06%*	*1.75%*
Mean ESG score	6.43	8.84	8.31	7.50	6.82	6.22
Change vs index	-	*37.49%*	*29.37%*	*16.64%*	*6.16%*	*-3.23%*
ESG Efficiency ratio		0.84	0.94	0.52	0.19	-0.11

$1/(1+k)$. The second-best quartile undergoes a moderate increase by $1+k/2$, and the weights of the second-worst quartile are decreased by $1/(1+k/2)$. After these adjustments, weights are normalized to sum to 1. The adjustment factors for $n = 3$ and $n = 4$ with $k = 1$ and $k = 0.5$ are outlined in Table 4.

Tables 5 and 6 present the outcomes of the reweighting method for the three tertile and four quartile approaches, respectively. This method exhibits a balance between enhancing ESG scores and controlling tracking error, although the trade-off is less pronounced compared to the best-in-class method as shown by the more uniform ESG Efficiency ratio values observed among the portfolios. Including all funds in this method means significant ESG score improvements are limited, with increases ranging from 3% to 17% in the $n = 3$ configuration. However, the method benefits from lower tracking errors and turnover rates, and it maintains financial performance closely in line with the index, positioning it as a more conservative choice.

The correlation between the fund size and the ESG score affects this reweighting

Table 4: Adjustment factors for the case of tertiles and quartiles

	Adjustment factor	
	$k = 1$	$k = 0.5$
$n = 3$		
Tertile T1 (best)	2	1.5
Tertile T2	1.0	1.0
Tertile T3 (worst)	0.5	0.66
$n = 4$		
Quartile Q1 (best)	2	1.5
Quartile Q2	1.5	1.25
Quartile Q3	0.66	0.8
Quartile Q4 (worst)	0.5	0.66

Figure 9: Index value for reweighting with $n = 3$

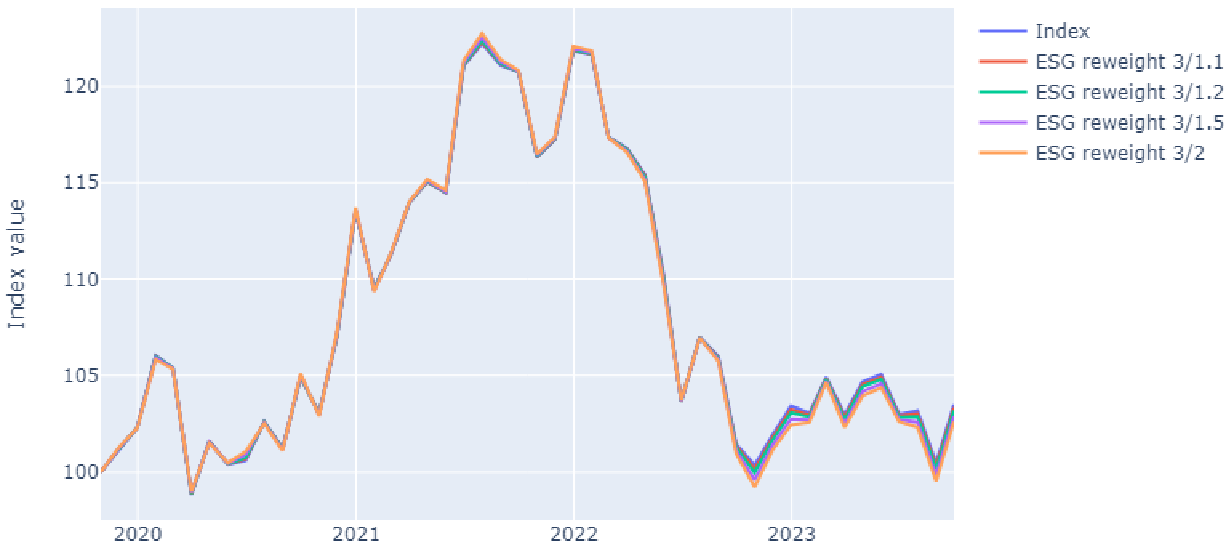
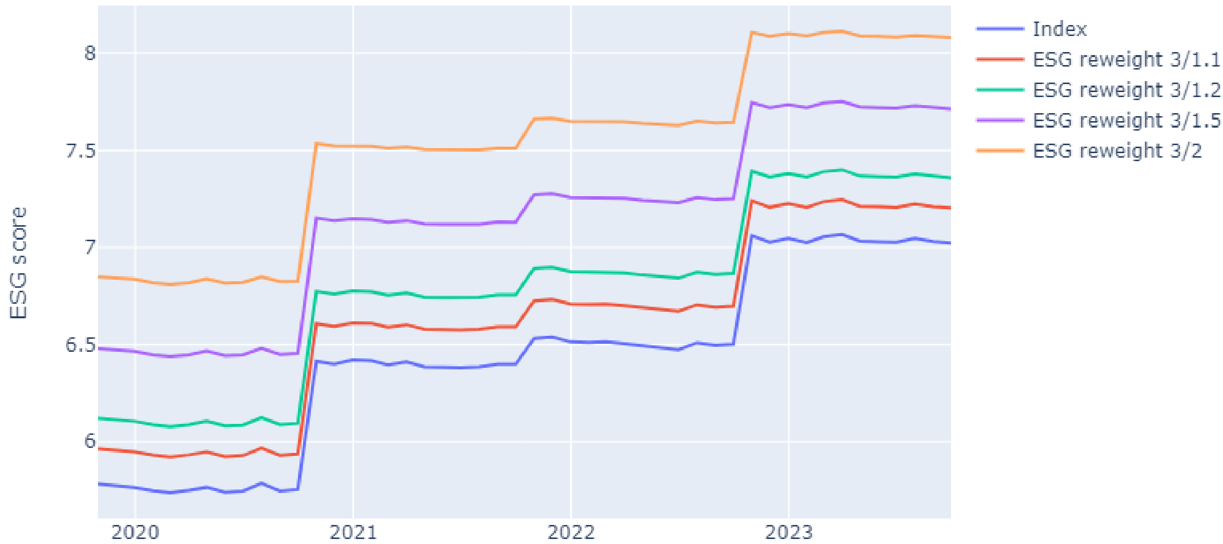


Figure 10: ESG scores for reweighting with $n = 3$



method. However, the impact is less pronounced compared to best-in-class portfolios due to the greater diversification achieved with reweighting.

3.3 Optimization

3.3.1 Score maximization

This subsection delves into optimization methods, with a specific focus on balancing ESG score maximization against tracking error control. The objective here is to enhance the ESG score of the index, while keeping the tracking error under a predetermined threshold. The optimization model is defined as follows:

$$w^* = arg \ \max \ w'S$$

$$s.t. \quad \sqrt{(w - w_B)' \, \Sigma \, (w - w_B)} \leq \sigma^*$$

Table 5: Reweighting portfolios for $n = 3$

	Index	$(n = 3, k = 0.1)$	$(n = 3, k = 0.2)$	$(n = 3, k = 0.5)$	$(n = 3, k = 1)$
Ann. return	0.86%	0.82%	0.79%	0.72%	0.65%
Ann. volatility	9.69%	9.71%	9.72%	9.77%	9.81%
Sharpe ratio	0.09	0.08	0.08	0.07	0.07
Tracking Error	-	0.15%	0.28%	0.58%	0.89%
Largest weight	16.9%	17.9%	18.8%	20.8%	23.1%
Sum 5 largest	37.5%	39.7%	41.7%	46.3%	51.3%
Herfindahl index	0.05	0.06	0.06	0.07	0.09
Turnover	3.0%	4.8%	6.9%	11.4%	15.9%
Last ESG score	7.02	7.20	7.36	7.71	8.08
Change vs index	-	*2.57%*	*4.78%*	*9.83%*	*15.06%*
Mean ESG score	6.43	6.61	6.78	7.14	7.52
Change vs index	-	*2.92%*	*5.43%*	*11.16%*	*17.03%*
ESG Efficiency ratio		1.20	1.25	1.22	1.22

Figure 11: Index value for reweighting with $n = 4$

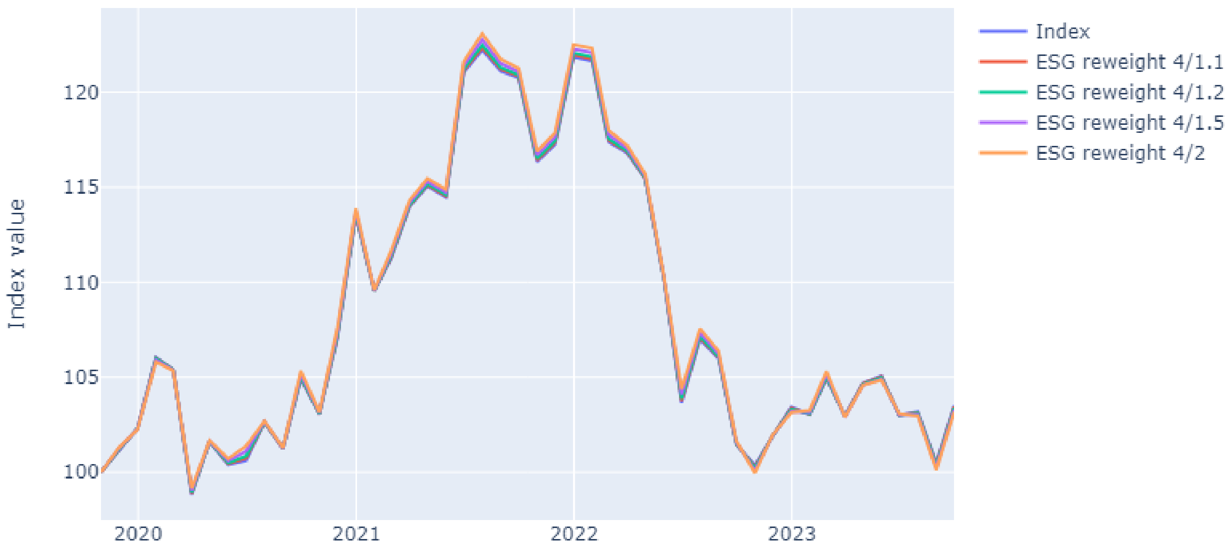


Figure 12: ESG scores for reweighting with $n = 4$

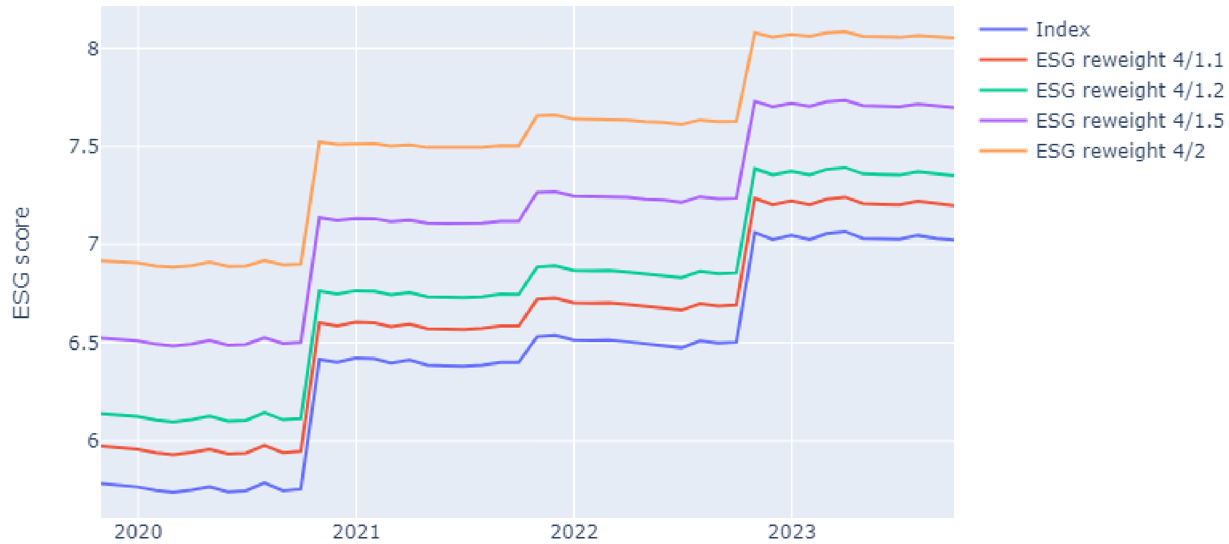


Table 6: Reweighting portfolios for $n = 4$

	Index	$(n = 4, k = 0.1)$	$(n = 4, k = 0.2)$	$(n = 4, k = 0.5)$	$(n = 4, k = 1)$
Ann. return	0.86%	0.85%	0.83%	0.81%	0.78%
Ann. volatility	9.69%	9.69%	9.69%	9.69%	9.70%
Sharpe ratio	0.09	0.09	0.09	0.08	0.08
Tracking Error	-	0.16%	0.29%	0.61%	0.93%
Largest weight	16.9%	17.9%	18.8%	20.9%	23.2%
Sum 5 largest	37.5%	39.5%	41.3%	45.4%	49.8%
Herfindahl index	0.05	0.06	0.06	0.07	0.09
Turnover	3.0%	4.9%	7.1%	12.4%	17.9%
Last ESG score	7.02	7.20	7.35	7.70	8.05
Change vs index	-	*2.50%*	*4.67%*	*9.62%*	*14.66%*
Mean ESG score	6.43	6.61	6.77	7.14	7.53
Change vs index	-	*2.89%*	*5.40%*	*11.18%*	*17.12%*
ESG Efficiency ratio		1.13	1.17	1.16	1.18

In this model, w represents the weight vector of the portfolio, and w_B denotes the weight vector of the benchmark. S is the vector of ESG scores, Σ is the covariance matrix of returns, calculated from daily returns over the previous 250 days, and σ^* is the tracking error threshold. To avoid over-concentration in any single fund, we impose a cap of 30% on each portfolio weight.

The outcomes of this optimization are presented in Table 7, where tracking error thresholds range from 0.5% to 2%. It is crucial to understand that the tracking errors reported in the table are ex-post measurements, whereas the optimization problem uses ex-ante tracking error. Our findings show that the ex-post tracking errors consistently exceed the set ex-ante limits.[2] Moreover, these variations in tracking error are paralleled by a notably low and unstable ESG Efficiency ratio.

Table 7: Score maximization with varying levels of tracking error

	Index	$\sigma^* = 0.5\%$	$\sigma^* = 1.0\%$	$\sigma^* = 1.5\%$	$\sigma^* = 2.0\%$
Ann. return	0.86%	0.39%	0.37%	0.57%	0.80%
Ann. volatility	9.69%	9.63%	9.77%	9.81%	9.99%
Sharpe ratio	0.09	0.04	0.04	0.06	0.08
Tracking Error	-	1.14%	1.66%	2.20%	2.31%
Largest weight	16.9%	17.8%	17.8%	16.5%	15.3%
Sum 5 largest	37.5%	47.3%	50.4%	53.6%	57.1%
Herfindahl index	0.05	0.07	0.08	0.08	0.09
Turnover	3.0%	43.5%	55.4%	61.3%	63.3%
Last ESG score	7.02	7.94	8.49	8.86	9.13
Change vs index	-	*13.04%*	*20.93%*	*26.11%*	*29.95%*
Mean ESG score	6.43	7.68	8.29	8.62	8.82
Change vs index	-	*19.47%*	*29.06%*	*34.13%*	*37.22%*
ESG Efficiency ratio		1.10	1.12	1.00	1.03

[2] This discrepancy between ex-post and ex-ante tracking errors is not unique to our sample but is a recognized characteristic in tracking error analysis. It suggests a need to consider this difference when targeting an ex-post tracking error.

3.3.2 Tracking error minimization

This method presents an alternate variation of the optimization problem, focusing on minimizing tracking error, while ensuring a specified level of improvement in the ESG score. The optimization model is stated as follows:

$$w^* = arg\ \min\ (w - w_B)'\, \Sigma\, (w - w_B)$$

$$s.t. \quad w'S \geq \theta^* \cdot w_B' S$$

In this model, θ^* is a factor set to target a desired improvement in the ESG score. We analyze results with θ^* values ranging from 1.1 to 1.25, corresponding to ESG score improvements between 10% and 25%, as detailed in Table 8.

Our analysis reveals that an average ESG score improvement of 10% is attainable with a tracking error of 0.5%. Conversely, aiming for a 25% increase in the ESG score results in a higher tracking error of approximately 1.28%. Yet, these enhancements result in consistently high ESG Efficiency ratios, indicating a favorable and uniform trade-off between ESG score improvement and tracking error increase across all portfolios. It is critical to note that achieving these improvements comes at the cost of increasing turnover, which ranges from 19% to 37% for the least ambitious and the most aggressive targets, respectively. However, this strategy offers an advantage in terms of portfolio diversification, outperforming best-in-class portfolios in this regard. The Herfindahl index in the optimization portfolios stays below 0.1, and the largest portfolio position is maintained under 20%.

4 Summary and comparative analysis

To compare the various methods, we select in each method the portfolio that yields an ex-post tracking error closest to 1%. We end up with the best 25 value weighted, the

Table 8: Tracking error minimization with varying levels of ESG score improvement

	Index	$\theta^* = 10\%$	$\theta^* = 15\%$	$\theta^* = 20\%$	$\theta^* = 25\%$
Ann. return	0.86%	0.71%	0.61%	0.51%	0.37%
Ann. volatility	9.69%	9.77%	9.82%	9.88%	9.94%
Sharpe ratio	0.09	0.07	0.06	0.05	0.04
Tracking Error	-	0.50%	0.76%	1.01%	1.28%
Largest weight	16.9%	16.2%	16.5%	16.7%	16.9%
Sum 5 largest	37.5%	39.6%	41.8%	45.0%	49.8%
Herfindahl index	0.05	0.06	0.06	0.07	0.08
Turnover	3.0%	19.0%	26.5%	33.1%	37.1%
Last ESG score	7.02	7.73	8.09	8.45	8.82
Change vs index	-	*10.00%*	*15.16%*	*20.33%*	*25.63%*
Mean ESG score	6.43	7.07	7.40	7.72	8.05
Change vs index	-	*10.04%*	*15.08%*	*20.13%*	*25.21%*
ESG Efficiency ratio		1.28	1.28	1.28	1.27

reweighting with $n = 4$ and $k = 1$, score maximization with $\sigma^* = 0.5\%$ and tracking error minimization with $\theta^* = 20\%$. In Table 9 we observe notable differences and trade-offs unique to each methodology.

The best-in-class method is relatively straightforward in implementation, focusing on selecting top-performing funds based on the ESG criterion. This method, while simpler to execute and easier to understand, tends to result in higher portfolio concentration, as indicated by the largest weight being 23%. This could pose diversification risks, but it also allows for considerable ESG score improvement, while preserving a relatively favorable ESG Efficiency ratio in portfolios within the Best 15 or 20.

Conversely, the reweighting method, which adjusts weights based on ESG scores, introduces moderate complexity in its implementation. It necessitates ongoing data analysis and rebalancing, which can be resource-intensive. However, this method offers a more balanced portfolio. In addition to achieving a favorable balance between tracking error and ESG score improvement, reflected in the ESG Efficiency ratios, this method also successfully manages to limit portfolio turnover to 17.9%.

Optimization-based methods, comprising score maximization and tracking error minimization, are the most complex in terms of implementation. They require sophisticated mathematical modeling to balance objectives such as ESG score maximization and tracking error minimization. This complexity is evident in the higher portfolio turnover, with the score maximization index showing a turnover of more than 40%, the highest among the strategies. Although these methods offer great diversification, as seen in with the largest weights under 18%, they can also lead to increased tracking errors, as high as 1.14% for the score maximization strategy. Nonetheless, the tracking error minimization portfolios consistently achieve the highest and most stable ESG Efficiency ratios.

The selection of a strategy for constructing an ESG index for the Swiss real estate market should consider not only the ESG score improvements and tracking errors but also the complexity of implementation. While the best-in-class method offers simplicity, it comes with diversification risks. The reweighting method provides a middle ground, balancing performance with moderate operational complexity. In contrast, optimization-based methods deliver nuanced performance advantages but at the cost of high complexity and operational demands. This understanding is crucial for investors to align their strategy choice with their capability to manage such strategies effectively.

5 Accounting for the correlation between size and score

Previous sections have highlighted a size bias in our sample, where larger funds tend to have better ESG scores. This bias implies that portfolios favoring top ESG performers will automatically put more weight into larger funds. Such portfolios then naturally exhibit limited tracking error, as these larger funds are, by definition, the most heavily weighted in the benchmark.

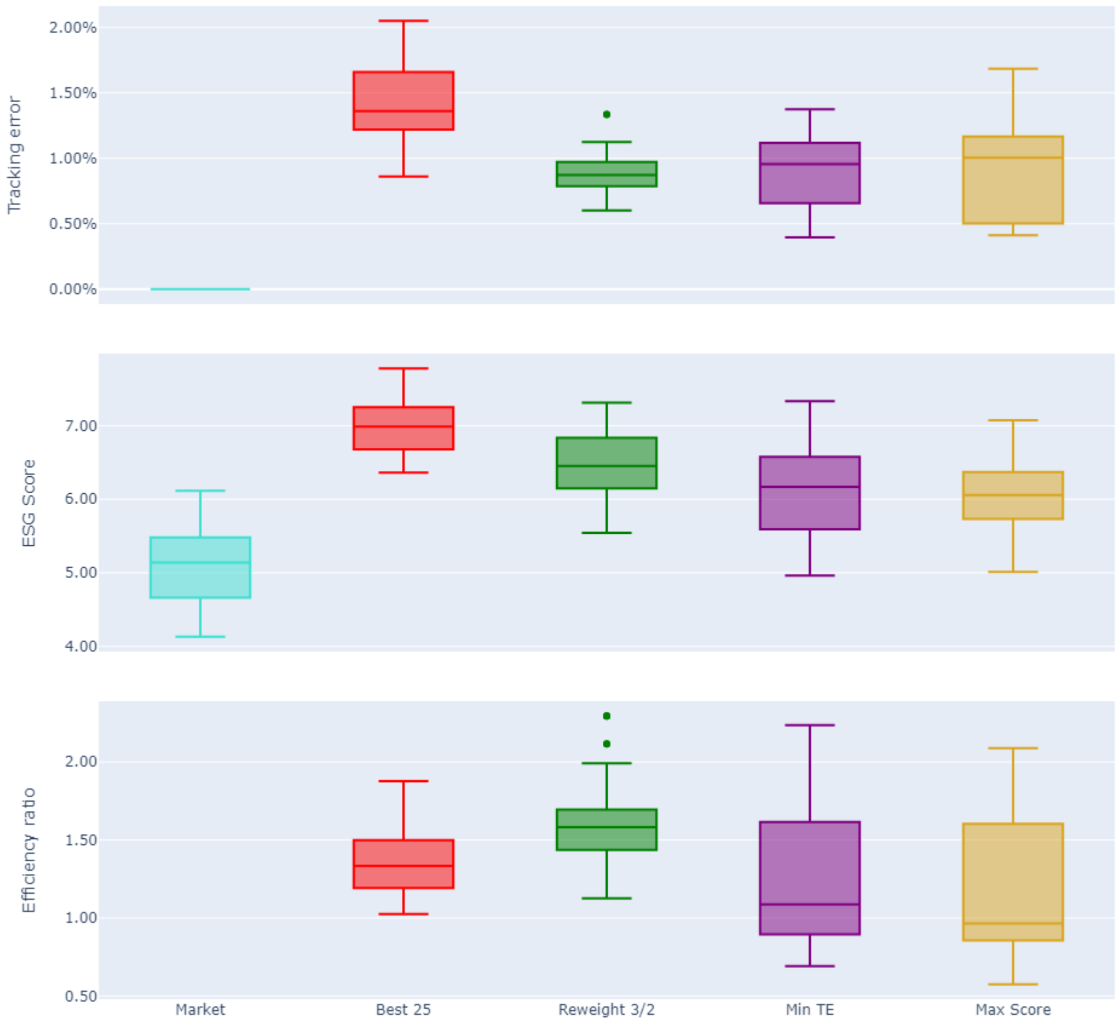
Table 9: Various strategies with tracking error levels close to 1.0% and ESG score improvement of about 20%

	Index	Best 25 VW	Reweighting (4/1)	Max score, $\sigma^* = 0.5\%$	Min TE $\theta^* = 20\%$
Ann. return	0.86%	0.55%	0.78%	0.39%	0.51%
Ann. volatility	9.69%	9.75%	9.70%	9.63%	9.88%
Sharpe ratio	0.09	0.06	0.06	0.04	0.05
Tracking Error	-	1.11%	0.93%	1.14%	1.01%
Largest weight	16.9%	23.0%	23.2%	17.8%	16.7%
Sum 5 largest	37.5%	51.1%	49.8%	47.3%	45.0%
Herfindahl index	0.05	0.09	0.09	0.07	0.07
Turnover	3.0%	21.7%	17.9%	43.5%	33.1%
Last ESG score	7.02	8.35	8.05	7.94	8.45
Change vs index	-	*18.83%*	*14.66%*	*13.04%*	*20.33%*
Mean ESG score	6.43	7.74	7.53	7.68	7.72
Change vs index	-	*20.43%*	*17.12%*	*19.47%*	*20.13%*
ESG Efficiency ratio		1.18	1.18	1.10	1.28

However, a contrasting scenario may arise if smaller funds had better than average scores. In this case, giving more weight to small funds would significantly deviate from the benchmark, resulting in a much higher tracking error. To quantify this effect, we conducted an experiment by randomly reshuffling ESG scores among the funds. Each fund received a complete time-series from another fund selected at random. We then recalculated our strategies with this modified data set, repeating this process 100 times.

Figure 13 shows the distribution in tracking errors, ESG scores and efficiency across the four methodologies outlined in Section 4. The best-in-class method is particularly sensitive to the score distribution, with its tracking error often exceeding the levels indicated in Table 9. The median tracking error for this method is equal to 1.4%, with values sometimes above 2%. While the optimization portfolios also exhibit variations, their median values align more closely with those found in the real sample. Conversely, the reweighting method demonstrates the most stable distribution.

Figure 13: Various methodologies with randomly attributed ESG scores



Regarding ESG scores, the dispersion across methodologies is relatively uniform. However, the best-in-class method consistently achieves higher scores. In contrast, optimization methods generally fall short in this aspect. The reweighting method emerges as a balanced option, offering a stable compromise between tracking error and ESG score performance. The distribtion of efficiency ratios highlights the best overall trade-off that is achieved with the reweigthing method.

6 Discussion and conclusion

Our exploration of various methodologies for integrating ESG criteria into the construction of a real estate fund index provides valuable insights for investors looking to balance sustainability considerations with financial objectives.

For investors prioritizing ESG score improvement while accepting some level of portfolio concentration, the best-in-class method is recommended. This strategy is especially well-suited for investors who favor a method that is both transparent and straightforward, directly aligning with elevated ESG standards. However, it is important to note that this method may accentuate the size bias, favoring larger funds with potentially higher ESG scores.

Investors seeking a balance between ESG integration and operational simplicity may find the reweighting strategy more appropriate. This method offers a moderate improvement in ESG scores and a more diversified portfolio compared to the best-in-class method, making it a viable option for investors seeking a middle ground between ESG performance and portfolio management practicality. Additionally, it addresses the size bias more effectively by distributing weights across a broader range of funds.

For investors with access to more sophisticated analytical tools and a preference for a nuanced investment strategy, the optimization methods, including both score maximization and tracking error minimization, provide a complex yet potentially rewarding approach. These methods are well-suited for investors willing to navigate the intricacies of portfolio optimization to achieve a tailored balance between ESG enhancement, tracking error, and turnover. They also offer a nuanced way to manage the size bias through their complex optimization algorithms.

In conclusion, our research into the integration of ESG criteria into real estate fund index construction offers a multifaceted view of sustainable investing. Beyond the immediate realm of investors, these findings contribute to the broader discourse on sustainable finance, highlighting the complexities and trade-offs involved in integrating ESG considerations into investment strategies. As the financial world increasingly recognizes the importance of sustainability, the methodologies explored in this paper provide a foundation for future research and development in this dynamic field.

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