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Environmentally Responsible Index Tracking: Maintaining Performance while Reducing Carbon Footprint of the Portfolio

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Abstract

Amid the global crisis of climate change, urgent action is imperative. In this study, we develop two types of decarbonized indices, which render a dynamic hedging approach for passive investors. Focusing on long-term returns with minimal active trading and risk exposure, we create the decarbonized indices for NIFTY-50, a benchmark index for the Indian market. Proposed methodology relies on suitable optimization techniques to choose the portfolio weights that minimize the tracking error while significantly reducing carbon footprints. These indices are shown to perform better than existing benchmarks, especially during major climate events. They are likely to offer investors a buffer to adapt to climate policies and carbon pricing. Since these indices align with the net-zero objective and foster climate-resilient advancements, they also offer actionable pathways to address climate challenges while maintaining financial objectives.

Key words: Climate change; Decarbonized index; Market index; NIFTY-50; Tracking error.

1. Introduction

Climate change, a significant challenge in recent times, not only impacts health, environment and the ecosystem, but also poses a large aggregate risk to the financial systems. This necessitates the development of analytical tools that can offer enhanced indexation of financial markets by considering Environmental, Social and Governance (ESG) factors. Such techniques are critical to solve the inefficiency of fundamental financial markets, especially in developing countries like India.

In this paper, we present methods to create two decarbonized indices from established benchmarks, and demonstrate their efficacy for the Indian economy. Specifically, we show that the resulting index significantly lowers total carbon impact, acting as a hedge against climate risks. Our method relies on tracking error (TE), a metric representing the variation

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of the difference in composition between a portfolio and its benchmark index. The relationship of TE to ESG has remained largely unexplored. The mimicking portfolio approach of Lamont (2001) is theoretically appealing but challenging to implement. In a more relevant study, Andersson *et al.* (2016) introduced decarbornized indices from the benchmark by minimizing TE subject to suitable constraints based on carbon footprints of the constituent companies. Mezali and Beasley (2013) earlier used quantile regression with a mixed-integer linear programming formulation. Li *et al.* (2022) constructed a robust model that maximizes ESG score, while minimizing the risk and maximizing the return simultaneously.

It is further important to note that the existing sustainability-themed indices in the Indian stock market, namely S&P BSE GREENEX, BSE Carbonex, and NIFTY100 Enhanced ESG Index (Patel and Kumari, 2020; C and Nishad, 2021) prioritize tracking the performance of companies based on their carbon emissions, ESG score and efforts to mitigate climate risk, without focusing on the parent index's performance. They use market capitalization for weighting, without any effort to replicate the performance of the dropped stocks. To circumvent this, we develop an optimized index by minimizing tracking error. It is more effective in capturing lost contributions from dropped stocks by compensating from other highly correlated stocks that remain in the portfolio.

We describe this methodology in Section 2. The application of the methods on Indian market is illustrated in Section 3. By utilizing real-time data for in-sample and out-of-sample calculations, we show how the index attempts to bridge the divide between theory and practice. The paper ends with a succinct summary and scopes of future work in Section 4.

2. Methodology

Throughout this article, we work with the Indian stock market index NIFTY-50, that tracks 50 largest Indian companies listed in the National Stock Exchange. To explain the method, let these $N = 50$ stocks be sorted by their carbon footprints in decreasing order. For the i^{th} stock, r_i, m_i, q_i denote the return, market capitalization and carbon footprint, respectively. Bold-faced letters $\boldsymbol{r}, \boldsymbol{m}, \boldsymbol{q}$ denote the corresponding vectors for all stocks. Following extant literature, the portfolio return of the benchmark is indicated by $R^b = (\boldsymbol{w}^b)^T\boldsymbol{r}$, where $\boldsymbol{w}^b = (w_i^b)_{1\leq i\leq N}$ is the vector of portfolio weights taken to be proportional to the market capitalization,

$$w_i^b = \frac{m_i}{\sum_{i=1}^N m_i}. \tag{1}$$

Let $\boldsymbol{w^d}$ be the vector of weights for the proposed decarbonized index, R^d being the corresponding return. Our objective is to minimize the tracking error and find (sd indicates standard deviation)

$$\boldsymbol{w^d} = \underset{\boldsymbol{w}=(w_i)_{1\leq i\leq N}}{\arg\min}\,(\text{TE}) = \underset{\boldsymbol{w}=(w_i)_{1\leq i\leq N}}{\arg\min}\left[\text{sd}\left(\sum_{i=1}^N (w_i - w_i^b) r_i\right)\right]. \tag{2}$$

To avoid computing the large dispersion matrix of returns in (2), we use the Fama and French (2012) factor model. It allows us to decompose the return into weighted sum of common factor returns and specific returns. If r_{it} and r_{ft} denote the return of the i^{th} stock and the risk-free rate at time t, then the model is

$$r_{it} - r_{ft} = \beta_{i0} + \beta_{i1}\mathrm{SMB}_t + \beta_{i1}\mathrm{HML}_t + \beta_{i3}\mathrm{WML}_t + \beta_{i4}\mathrm{MF}_t + e_{it}, \tag{3}$$

where e_{it} is the error, β_{ij} denotes the factor loading; SMB, HML, WML and MF indicate the size effect (small-minus-big), value effect (high-minus-low), momentum factor (winners-minus-losers), and market factor. Let F_j denote these factors, with dispersion matrix Ω. Also, let $\boldsymbol{\beta}$ be the matrix of loadings and Δ be the diagonal matrix of specific risk variances. Then, the dispersion of the excess returns is $\boldsymbol{\beta}\Omega\boldsymbol{\beta}^T + \Delta$. Consequently, the volatility of any portfolio with returns $\boldsymbol{r}$ and weights $\boldsymbol{w}$ is $\sqrt{\boldsymbol{w}^T(\boldsymbol{\beta}\Omega\boldsymbol{\beta}^T + \Delta)\boldsymbol{w}}$. This, in (2), implies

$$\boldsymbol{w}^{\boldsymbol{d}} = \underset{\boldsymbol{w}=(w_i)_{1\le i\le N}}{\arg\min} \sqrt{(\boldsymbol{w} - \boldsymbol{w}^{\boldsymbol{b}})^T \left(\boldsymbol{\beta}\Omega\boldsymbol{\beta}^T + \Delta\right)(\boldsymbol{w} - \boldsymbol{w}^{\boldsymbol{b}})}. \tag{4}$$

To strike a balance between reducing carbon footprints and preserving diversity in the composition, we employ two distinct methodologies to construct decarbonized indices (DCI). Each methodology has its own advantages and disadvantages, as we explicate below.

In the first approach, we exclude k worst performers in carbon intensity, and the remaining stocks are re-weighted to minimize TE. Here, the DCI is constructed using weights w_i^d, obtained by solving (4) subject to the constraints

$$\begin{aligned} &\sum_{i=1}^{N} w_i^d = 1, \text{ with} \\ &w_i^d = 0, \text{ for } i = 1, 2, \ldots, k, \text{ and } 0 \le w_i^d \le 1, \text{ for } i = k+1, \ldots, N. \end{aligned} \tag{5}$$

We solve this minimization problem using the Trust-Region Constrained Algorithm (TRCA), which is useful to deal with the following problem:

$$\text{minimize } f(x), \text{ subject to } c^{lb} \le c(x) \le c^{ub}, \ x^{lb} \le x \le x^{ub}. \tag{6}$$

It can take multiple linear and non-linear constraints as inputs (Conn *et al.*, 2000). The objective function is approximated by a quadratic model restricted to the trust-region centered at the initial guess or the current point. The algorithm works by iteratively improving the initial guess (Kimiaei, 2022). We omit technicalities of the algorithm, and refer to Byrd *et al.* (1987) for further details.

Our second methodology includes all stocks without specifically targeting those with high carbon footprints. In this case, the minimization problem (4) is solved by setting a threshold C for the total footprint of the index. This approach ensures a largely unchanged composition, maintaining its diversity, yet reducing the footprint. Mathematically, we find the weights in (4) considering

$$\begin{aligned} &\sum_{i=1}^{N} w_i^d = 1, \text{ with} \\ &\sum_{i=1}^{N} q_i w_i^d \le C \text{ and } 0 \le w_i^d \le 1, \text{ for } i = 1, \ldots, N. \end{aligned} \tag{7}$$

For implementation, we again rely on TCRA discussed before. Hereafter, this index is denoted as DCI_2 while the first index is coded as DCI_1.

A brief comparison of the ideology behind the construction of the indices is critical here. A potential drawback of the first approach is that it may lead to a less diverse index composition. Lower diversity leads to higher volatility and risk. On the positive side, possibility of inclusion in the index can serve as an incentive for the high-emission companies to proactively reduce their emissions. Contrastingly, the overall carbon footprint reduction with the second approach is significant but limited when compared to the first approach.

3. Application

We consider NIFTY-50 data for 5 years, 2017-18 until 2022-23. To quantify the carbon footprint of the stocks, we consider greenhouse-gas intensity per sale and total carbon-dioxide emissions (abbreviated as GHG and CO2 hereafter) as proxies. Then, four decarbonized indices are created from each benchmark, using the two methods and the two proxies. We rely on Bloomberg and Yahoo!Finance for obtaining these data. The factors data for (3) are obtained from IIM-A Data Library (Agarwalla *et al.*, 2013). Comprehensive information about stocks used for our calculations are detailed in Table 1.

Table 1: Number of stocks included (St.Incl), omitted (St.Omit) and corresponding omission percentage of market capitalization (MktCap.Omit) in the construction of DCI.

	GHG			CO2		
Period	St.Incl	St.Omit	MktCap.Omit	St.Incl	St.Omit	MktCap.Omit
2017-18	30	20	35.3%	32	18	33.7%
2018-19	33	17	28.5%	35	15	26.9%
2019-20	34	16	25.3%	36	14	23.7%
2020-21	35	15	23.6%	38	12	21.1%
2021-22	35	15	23.6%	38	12	21.0%

Our analysis broadly consists of three parts – determining optimal values of k and C for calculating the two DCI, generating optimal portfolio weights using a window of one year for five years (in-sample calculations), calculating the monthly performance of DCI and comparing their performances with the benchmark (out-of-sample calculations). It is useful to present a brief summary of our main findings first. As expected, DCI_2 maintains the composition yet provides a lower carbon footprint than benchmark index, whereas DCI_1 renders an even lower carbon footprint because of excluding several stocks. In-sample calculations illustrate that the second index offers a very low active risk as compared to the benchmark. On the other hand, out-of-sample results demonstrate that both indices outperform the benchmark during major climate events throughout the five years.

Delving deeper into our analysis, recall that the optimal values of k and C in our methods (refer to (5) and (7)) are determined through an assessment of TE using 5 years of data. Here, a series of optimizations are executed for a range of k (5%-50% of N) and C (50%-95%). In GHG, optimum k is 6 and C is 80%, whereas the numbers are 5 and 70% for CO2. These values are employed in the subsequent steps.

Next, in Figure 1, we compare the carbon footprints of the decarbonized indices with the considered benchmark in each case. A substantial reduction in the carbon footprint of the index is evident, achieving more than 50% reduction in method-1. This methodology can be expanded to consider sector compositions and optimize while maintaining fixed sector representations. With method-2, reductions of around 20-30% were achieved in different cases, which should be perceived as a significant accomplishment without alterations to sector representations.

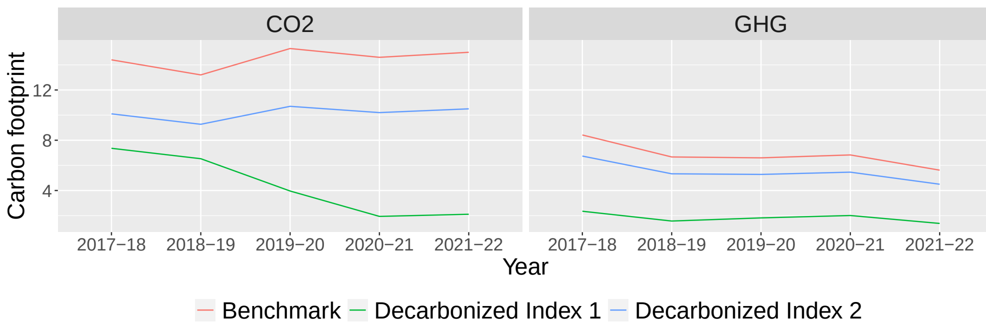

Figure 1: Comparison of carbon footprints of the considered benchmark index and the decarbonized indices

Turn attention to in-sample estimation of TE for the four DCIs constructed using a moving window of one-year and optimal values of k and C. We provide a summary in Table 2. Please refer to the supplement for additional figures and discussions on this. The risk on the benchmark portfolio is measured by $\mathrm{sd}(R^b)$, whereas the TE of DCI relative to the benchmark can be calculated by $\mathrm{sd}(R^d - R^b)/\mathrm{sd}(R^b)$. These in-sample estimations reveal significant carbon footprint reductions in both methods, with low TE in most cases. Interestingly, DCI_1 for CO2 exhibits high TE due to the exclusion of valuable stocks. DCI_2, meanwhile, demonstrate low TE everywhere because it avoids dropping valuable stocks.

Table 2: Risk on the Benchmark portfolio (BM) and tracking error of the decarbonized indices relative to the benchmark index in each Method.

Period	GHG			CO2		
	BM	TE(DCI_1)	TE(DCI_2) (in 10^{-3})	BM	TE(DCI_1)	TE(DCI_2) (in 10^{-3})
2017-18	27.25	2.72	1.13	26.14	2.54	3.07
2018-19	53.62	1.40	6.31	51.55	1.28	1.37
2019-20	159.7	0.52	1.49	153.8	4.09	0.74
2020-21	159.8	0.79	2.96	150.4	9.0	0.45
2021-22	176.9	1.07	9.22	166.3	6.36	0.52

Our last point of discussion is the out-of-sample performance, where monthly returns are computed for 2018-19 to 2022-23 using weights generated from in-sample calculations conducted in the previous year. A comparison is made between the monthly performance of the decarbonized indices, the actual benchmark, and the considered benchmark. We observe that the constructed indices track the considered benchmark very closely and on the average outperform the benchmark index. We then explore whether during climate events, the decarbonized indices exhibit superior performance compared to their parent benchmark indices. To investigate this effect, we identify and highlight significant climate events from the past few years in the out-of-sample results of our indices. Figure 2 illustrate these findings. We observe that both indices outperform the benchmark in terms of out-of-sample returns in at least seven of the twelve such events. Particularly, DCI_1 of GHG outperforms the benchmark in 75% of the events.

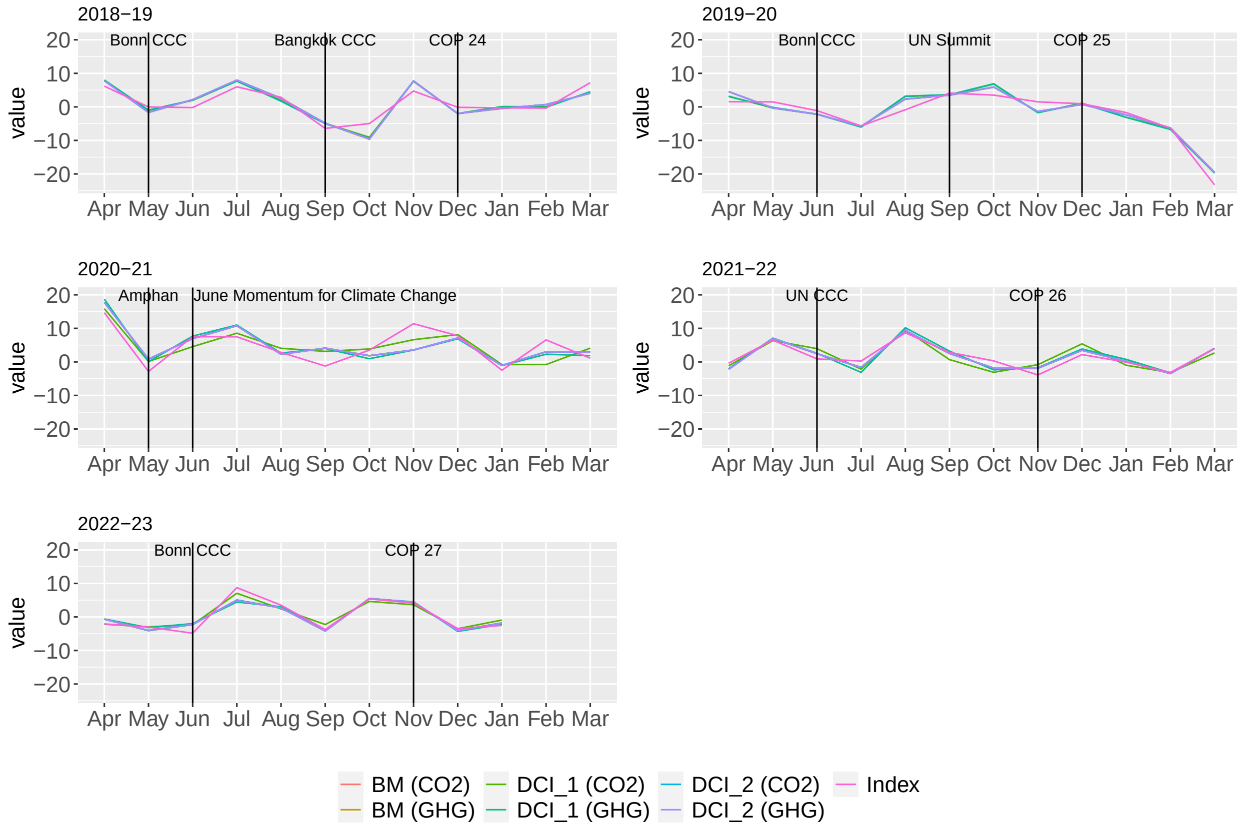

Figure 2: Out-of-sample performance of difference indices during important climate events across five years. BM stands for considered benchmark, DCI is proposed decarbonized index following the two methods. CCC stands for climate change conference.

4. Conclusion

With the World Resources Institute (Friedrich *et al.*, 2020) identifying China, USA and India as top GHG emitters, there arises a compelling need for decarbonized indices in India. We devised two novel optimization methods for creating practical decarbonized indices which complement existing green indices and foster investment awareness. These indices offer real-world utility, granting investors time to acclimate to economic shifts and financial uncertainties. Leveraging real-time data, they mitigate risks tied to climate policy execution. For long-term passive investors, these indices hold promise over clean energy options. They exhibit comparable returns to benchmark indices, gaining an edge once carbon pricing and stringent emissions policies take effect, potentially outperforming benchmarks.

Measurement of company-wise GHG emissions is crucial for constructing the indices.

We faced the challenge of missing data due to poor reporting. This in turn impacted benchmark composition, potentially excluding stocks sensitive to climate change and policies. Regression results showed limited explanatory power of common factors for stock returns. In future, we plan to extend the current method to deal with missingness. We also believe that consideration of sector compositions with suitable data can enhance future results. Moreover, we have laid the theoretical framework for integrating ideas like Value-at-Risk in optimization. These quantities might capture the extreme movements in prices during climate events in a better fashion.

Conflict of interest

The authors do not have any financial or non-financial conflict of interest to declare for the research work included in this article.

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