REPORT

CFA Institute
Research & Policy Center

SUSTAINABILITY

Examining the Resilience of Green Portfolios

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Executive Summary

This paper investigates whether equity portfolios constructed using green investment criteria—specifically environmental, social, and governance (ESG), Environmental (Env), and Emissions (Emi) scores—demonstrate different exposures to tail risk when measured through historical value at risk (VaR). I consider that the relationship between ESG factors and financial risk, particularly tail risk, remains unclear, as shown in the varied research literature. In this regard, this study explores the historical VaR of portfolios constructed for equities under varying green criteria compared to a market-capitalisation-weighted benchmark.

This research uses LSEG data from 2019 to 2023. Portfolios are constructed from equities in major developed market indexes (S&P 500 Index, FTSE 100, EURO STOXX 50, and the Swiss Market Index, or SMI), where I implemented constraints on portfolio size and average market capitalisation to ensure comparability among different green scores. Green portfolios are optimised based on ESG, Env, or Emi scores, respectively, and benchmarked against a market capitalisation-weighted portfolio based on all securities in the aforementioned indexes, to compare trends in historical VaR under green criteria.

As in the literature, the results reveal no consistent pattern in which green portfolios' VaR differs from the market-cap benchmark. In some periods, such as 2020–2022, the Env portfolio exhibited higher VaR than the benchmark portfolio, suggesting greater vulnerability of portfolios based on environmental scores during certain periods.

I then explore an additional sensitivity analysis in which I impose changes on sector and index constraints for security selection, particularly limiting the overrepresentation of the United States and the technology sector. I show that the historical VaR for constrained green portfolios is relatively lower than

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that of the market-capitalisation (MCap) benchmark portfolio, where there is an increase in the range of historical VaR between green portfolios. Moreover, all portfolios constructed with securities with low green scores, denoted as "brown portfolios," had a higher historical VaR than the benchmark MCap portfolio, with some brown portfolios having a higher historical VaR than their green counterparts. This result was observed for the brown portfolio based on the Emi score, for instance, where the historical VaR peaked at 4.82% in 2021, indicating a 5% probability of a minimum potential loss of $4.82 million in a $100 million notional portfolio. While the average pairwise correlation of securities offers some insight into portfolio behaviour, the study finds it is not a definitive predictor of tail risk. For example, despite higher correlations for Env in green portfolios, its historical VaR trends diverged from the trend in average correlations. This finding reinforces the need to consider all components of historical VaR—for example, volatility and dynamic portfolio weights—when evaluating risk. Further, this study highlights the limitation of using historical VaR alone, noting that it reflects past losses and may not capture future climate-related risks. Complementary methods, such as reverse stress testing and scenario analysis, could provide a more forward-looking view of climate risk.

Ultimately, this research underscores that integrating green criteria into portfolio construction does not automatically reduce tail risk. The effect depends heavily on how green scores are applied, the constraints used in security selection, and the evolving macroeconomic context. For investors, the findings suggest that a more nuanced approach to sustainable investing is necessary—one that balances green scores with robust risk management. While green portfolios can offer environmental alignment, they can introduce new vulnerabilities if not carefully designed. Hence, aligning financial resilience with sustainability goals requires thoughtful construction and a data-driven approach to evaluate how green criteria interact with market dynamics.

Introduction

The potential for enhanced risk-adjusted performance through ESG investing offers sustainability-focused investors the possibility to "do well by doing good" (Buller 2020). Whelan, Atz, Van Holt, and Clark (2021, p. 10) reviewed 1,000 research papers between 2015 and 2020 that considered the impact of ESG ratings on investment and found 58% of studies showed a positive relationship between ESG factors and financial performance, with only 8% finding a negative relationship.

While assets with higher ESG scores are less exposed to climate physical risks and transition risks (Cepni, Demirer, Pham, and Rognone 2023), the association with financial tail risk is unclear. Suppose a portfolio is constructed from securities with the highest market capitalisation, where ESG factors are also considered in the security selection process. In that case, it may not hold that securities with high market capitalisation will also have a high ESG score, resulting in a trade-off in security selection. As a result, choosing securities by favoring ESG criteria over market capitalisation criteria can lead to a decrease in the average market capitalisation of the portfolio of included securities. Research by Fahling, Ghiani, and Simmert (2020) shows that the volatility and returns of smaller-market-cap securities are higher than those of larger-market-cap securities, which can lead to an increase in tail risks for ESG-based portfolios if examined using volatility-based risk measures. However, other evidence shows that securities with high ESG scores experience lower market risk. Research by Morningstar found that from 2015 to 2020, 91% of the firm's ESG-based indexes experienced lower losses than their non-ESG counterparts (Lefkovitz 2021). The contrasting conclusions between ESG scores and tail risk are important if ESG considerations are incorporated into portfolio construction.

To evaluate portfolio tail risk, I use value at risk. VaR is a statistical measure for the minimum portfolio losses assuming a given period of asset returns and a given probability of the event occurring (Holton 2003). I use VaR because it accounts for portfolio diversification between securities (accounting for the covariance of returns and portfolio weights) that can increase tail risk.

In this study, I use historical time-series data to evaluate VaR between 2019 and 2023 for equity portfolios constructed using one of three "green" scores (I use the term *green* because the ESG score is a separate score used to construct portfolios): ESG score, encompassing the firm's overall environmental, social, and governance performance; Environmental score (Env), which represents only the firm's environmental impact through resource use, emissions, and innovation; and Emissions score (Emi), which represents the firm's commitment to reducing emissions in production and operations (Refinitiv 2022). I consider different green scores to account for the shades of "greenness" investors use to construct portfolios. Additionally, I introduce a portfolio for which securities are chosen only based on their market capitalisation. I consider an MCap portfolio as a benchmark to compare trends in historical VaR that may arise from incorporating any level of green criteria into security selection. Horn and Oehler (2024) found that green scores and investment objectives can considerably alter the securities included in a portfolio, which I investigate from the perspective of historical VaR.

The data section provides full details on the construction of the green portfolios. I constructed portfolios by choosing equities from a pool of global indexes. I chose equities because there is extensive information on equities with which to evaluate historical VaR over historical periods. Since equities are often the predominant asset class in investors' portfolios, they account for a material proportion of portfolio risk. Although I focus on equities, this work can be extended to other asset classes, although data availability for other asset classes, such as alternative assets, can be limited (Sridharan 2023).

The literature shows that research in this field is active. Branch, Goldberg, and Hand (2019) considered how portfolio weights for different green portfolios affect market risk, and Xidonas and Essner (2024) constructed portfolios using mean–variance optimisation with various green constraints. In the current study, I constructed portfolios by maximising the relevant score associated with the green criteria of securities, accounting for the market capitalisation and the number of securities in portfolio selection. I consider green portfolios with additional constraints to compare portfolios of similar size based on the average market capitalisation of securities and the number of securities in each portfolio.

The literature on the association of green scores and VaR is mixed. Capelli, Ielasi, and Russo (2023) incorporated green ratings into the covariances of price returns to compute a green VaR, finding that in periods of stress, portfolios whose securities were chosen using green considerations increase VaR. Demartis and Rogo (2024) studied the association of green scores with VaR for equity portfolios using a vine copula GARCH approach, finding that assets in portfolios with high green scores reduce portfolio losses except during periods of stress, when VaR is higher. Aldieri, Amendola, and Candila (2023) considered portfolios from securities selected using green ratings and found no clear association between changes in green scores and portfolio VaR. In line with the literature, I also find mixed results on the association between green scores and VaR.

Specifically, I found that historical VaR for green portfolios is lower than that of the MCap benchmark portfolio over the entire sample period, but it can be higher in some periods. This was observed during 2020–2021, when the minimum loss for an Env portfolio under historical VaR was $3.60 million, compared with $3.47 million for MCap, where I assumed a 5% probability of losses occurring under historical VaR and a portfolio with a notional value of $100 million (this value was chosen for illustrative purposes).

I also performed a sensitivity analysis to explore how additional constraints on security selection regarding the index and sector designation of securities affect historical VaR. For portfolios with index and sector constraints, the results show an increase in the range of historical VaR represented by the difference in the lowest and highest historical VaR among green portfolios. I found a maximum range in historical VaR between constrained green portfolios at any given period of $810,000, compared with a range of $640,000 for the baseline green portfolios, where losses are illustrated for a portfolio with a notional value of $100 million.

I also considered the change in historical VaR for portfolios when securities are chosen on the basis of the lowest green scores. For portfolios constructed from securities with the lowest green scores (denoted as “brown” portfolios), in periods of market stress, the brown emission portfolio has a higher VaR than the MCap portfolio, as well as other types of brown portfolios.

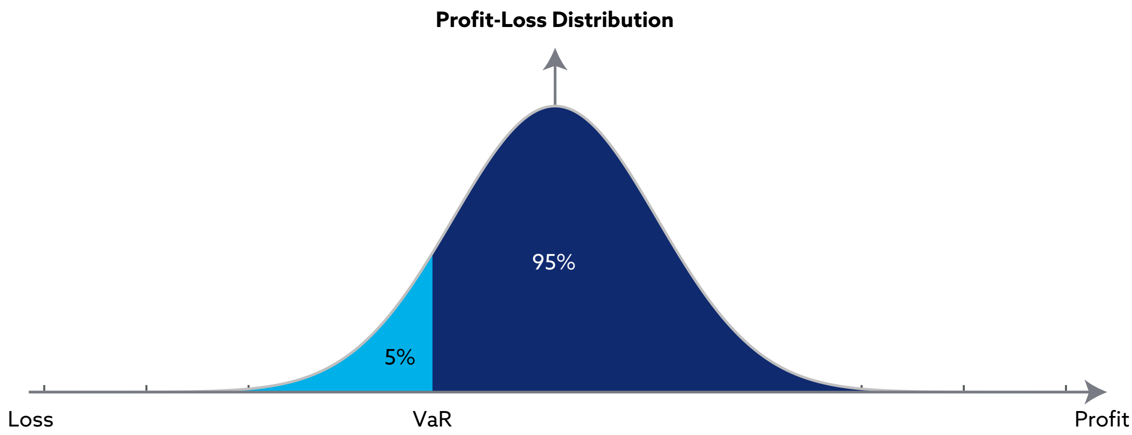
Overall, the sensitivity analysis shows mixed trends for historical VaR with respect to changes in portfolio selection under green criteria. As such, tail risks should be individually assessed for each portfolio.

Methodology and Data

I evaluated portfolio tail risk using VaR, which measures the minimum portfolio losses assuming a given period of asset returns and a probability for the event to occur. To calculate portfolio VaR, the probability is denoted as p over a time horizon t with portfolio weights w. The lower the p, the more unlikely the event and the higher the resulting VaR. **Exhibit 1** illustrates the concept of VaR, assuming that security price returns are normally distributed and assuming a 5% quantile (light blue threshold) representing the probability for losses to occur.

Example: Assume the portfolio volatility equals 0.1, where volatility is calculated over one year, and p = 5%. Then, under a normal distribution, the historical VaR would equal the portfolio volatility of 0.1 multiplied by the Z-score under the normal distribution (1.64) with p = 5%, giving a historical VaR of 16.4% over one year. For a portfolio with a notional value of $100 million, the historical VaR under the assumed values would correspond to a minimum loss of $16.4 million.

Exhibit 1. Value at Risk under a Normal Distribution



VaR can be calculated using asset return covariances, which is denoted as the historical VaR.[1] Specifically, historical VaR is determined using the covariance of securities' price returns from historical data, accounting for the weights of each security holding in the portfolio. The measure is therefore reflective of the level of diversification in the portfolio, where the contribution of covariance values can either increase or decrease the portfolio's historical VaR. An example calculation in the appendix provides further details on computing historical VaR.

I retrieved data on the historical closing prices, green scores, and market capitalisation of securities from LSEG. For selection, I constructed a basket of securities from core developed market indexes, including securities in the S&P 500 (United States), FTSE 100 (United Kingdom), EURO STOXX 50 (eurozone), and SMI (Switzerland). I chose these indexes as the basis for portfolio construction because they represent a global pool of high-market-capitalisation securities for which green scores are readily available.[2] I chose securities for each green portfolio under an optimisation problem such that the average green score of the portfolio is maximised, subject to constraints on market capitalisation and the number of securities (discussed next). I used green scores as of 2024, as provided by LSEG, and denote the resulting portfolios as "green" portfolios.

The constraints include a minimum average market capitalisation of securities included in the portfolio, set to $100 billion. The number of securities in the portfolio is fixed at $N = 30$. These constraints were implemented to compare similar-sized portfolios.[3] For the MCap portfolio, I included all securities from all indexes; this portfolio is used as a benchmark to compare changes in portfolios based on tilts to different green scores, where portfolio weights are set based on the market capitalisation of securities. The appendix provides further details of the portfolio optimisation problem.

Securities chosen using the 2024 green scores are fixed (i.e., they remain in the portfolio across all periods), where only portfolio weights w vary over time. In total, we have three green portfolios and one MCap benchmark portfolio to compare historical VaR. Details on the specific securities of green portfolios are provided in the appendix.

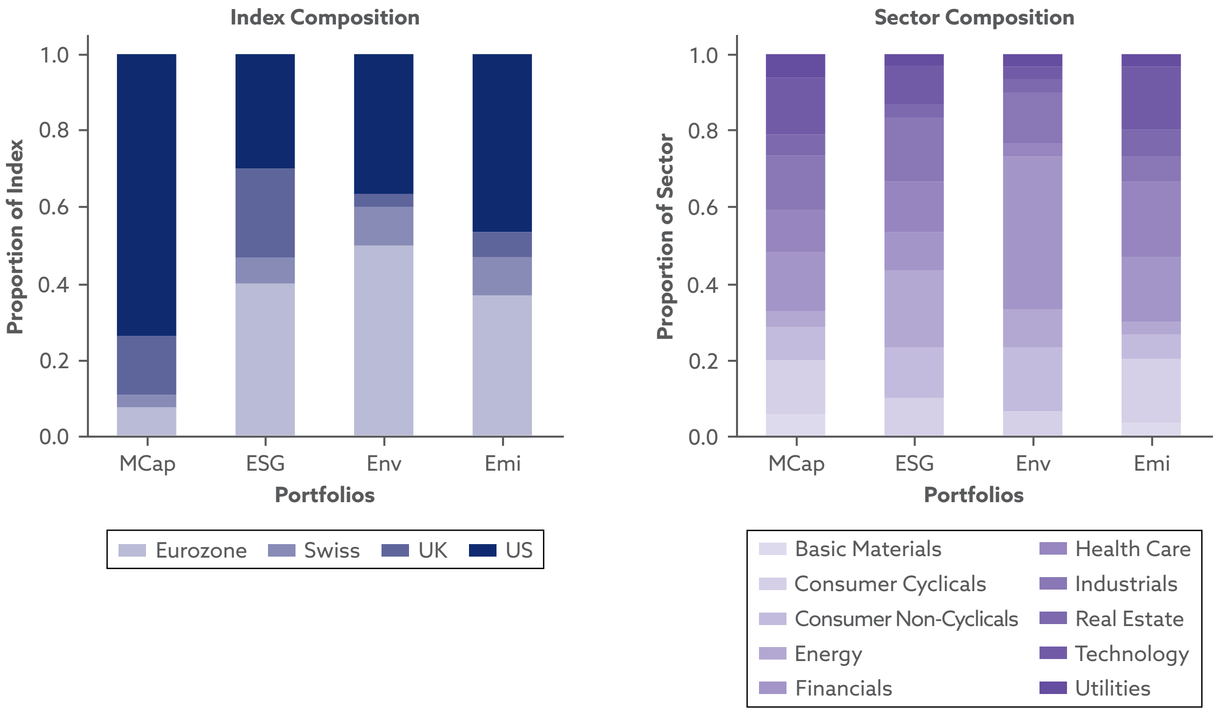
Exhibit 2 represents the allocation of securities for different portfolios based on their index (left panel) and sector (right panel) association. The exhibit shows that securities for MCap are mainly chosen from the S&P 500, representing more than 90% of the total securities selected. This outcome reflects the high market capitalisation of US-based firms, such that US companies dominate the portfolio construction when optimising based on market capitalisation. This situation contrasts with the green portfolios, where securities are mainly

[1]Other approaches to compute historical VaR, such as using empirical or Monte Carlo simulations, can also be considered.

[2]In total, around 600 securities were available to construct portfolios. This number is lower than the total number in all indexes because I excluded securities with more than 5% of total missing data or two weeks of continuous missing data at any given period between 2012 and mid-2023.

[3]This is a combinatorial optimisation resembling that of a packing problem—that is, the knapsack problem.

Exhibit 2. Distribution of Securities According to Index and Sector across All Green Portfolios



chosen from the eurozone (EURO STOXX 50) when optimising according to green scores because eurozone firms perform relatively highly on green scores compared to US firms, leading to a change in security selection. Even though the eurozone has greater inclusion, US firms still represent a sizable proportion of the portfolio for all green portfolios.

The sectoral composition shown in Exhibit 2 is well diversified across all portfolios, with the highest concentrations in any one sector at around 40%. The choice of securities shows that almost all sectors can contribute to historical VaR based on green scores, with only the communications sector not included in any portfolio. The largest sectoral concentration of securities is for the technology sector for the MCap portfolio, including such securities as Apple, Nvidia, and Google. The other largest sectoral concentration of securities is for financials for the Env portfolio, including such securities as Lloyds, Barclays, and UBS. The technology sector is prevalent in all portfolios because these companies often have high market capitalisations (one could attribute the rising valuations in technology firms to developments in AI; see Singla, Sukharevsky, Yee, Chui, and Hall 2025),[4] as well as relatively high green scores.

Exhibit 3 provides more statistics on portfolios, representing the commonality of securities between portfolios (left side) and an average portfolio score

[4]See https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai.

Exhibit 3. Portfolio Commonality and Average Portfolio Scores for Green Portfolios

	Portfolio Commonality				Average Portfolio Scores			
	MCap	ESG	Env	Emi	Market Capitalisation ($ billions)	ESG Score	Environmental Score	Emissions Score
MCap	100%	100%	100%	100%	95	69	68	74
ESG	—	100%	30%	16.67%	190	90	90	91
Env	—	—	100%	26.67%	104	84	95	95
Emi	—	—	—	100%	102	82	86	99

(right side) of securities, where the average portfolio score includes the average market capitalisation and green score of securities, based on 2024 data. The portfolio commonality is the percentage of securities that two portfolios share, where 100% indicates that two portfolios are identical based on included securities and 0% represents two portfolios that contain unique sets of securities.[5] For the MCap benchmark portfolio, the commonality with all other green portfolios is 100% because the portfolio includes all securities across all indexes.

The portfolio commonality in Exhibit 3 shows a wide difference between securities in portfolios, with the largest commonality between the ESG and Env portfolios, at 30%. Portfolios with the highest commonality are green portfolios, reflecting that securities chosen under one green score have a high performance across all other green scores. The fact that the average portfolio score for green scores is high across all portfolios, even when the portfolio commonality between green portfolios is small, shows that there is a wide selection of securities that can result in a high green score for the portfolio. Overall, securities chosen for each portfolio are mostly unique, showing that portfolios are diverse under different green scores, which can lead to varied trends in historical VaR.

For the average portfolio scores, values are mostly similar across all green portfolios. The largest difference is in the average market capitalisation of ESG, which is almost 2× higher than those of the Env and Emi green portfolios and the MCap benchmark portfolio. Because a lower bound is assumed on the minimum average market capitalisation when choosing securities, incorporating green scores into the security selection process for a fixed number of securities in the portfolio does not lead to a lower average market capitalisation compared with the benchmark MCap portfolio. The average market capitalisation of securities, along with differences in the index and sector designation among portfolio constituents, can impact historical VaR.

[5]Because portfolios have different securities, the commonality does not account for the change in securities' portfolio weights.

Results

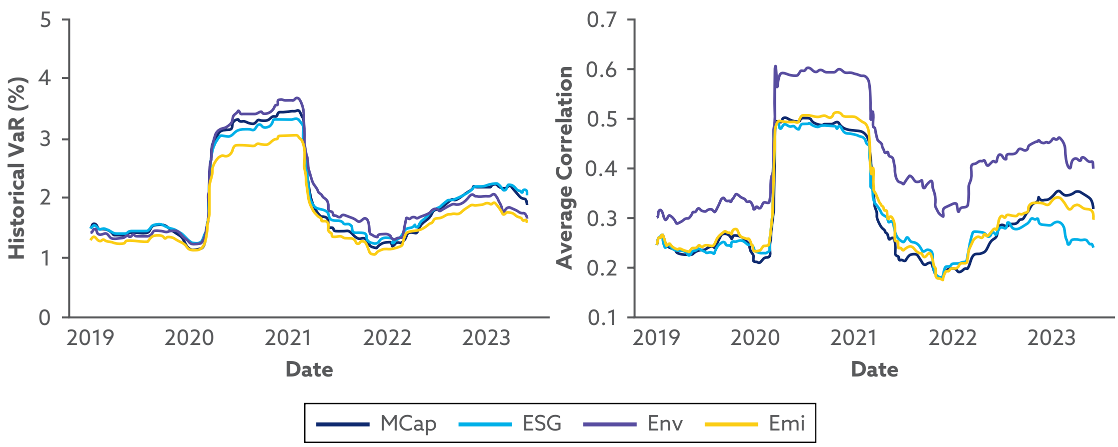
I considered the historical VaR for the one benchmark MCap portfolio and three green portfolios between 2019 and 2023. The portfolio weights used to compute historical VaR are based on the market capitalisation of portfolio securities, which are rebalanced monthly.[6] Probability was set at $p = 5\%$, and historical VaR was calculated over one year. I computed historical VaR trends across all portfolios under a daily rolling window approach.

Historical VaR

Exhibit 4 shows the trend in historical VaR (left panel) and the average pairwise correlation values (right panel) between portfolio securities. The results in Exhibit 4 show that the average correlation is highest between securities for the Env portfolio. There is a high correlation between securities in Env because of the high commonality of securities based on sector designation in each portfolio. Specifically, there is a high inclusion of financial securities in Env, as observed in Exhibit 3. The concentration of securities within a given sector leads to a higher average correlation of securities because securities in the same sector are impacted by a higher number of common financial and economic factors, which, in turn, is reflected in the historical VaR.

The correlation values are highest for all portfolios between 2020 and 2021, at approximately 0.5–0.6, representing a period when the COVID-19 pandemic was prevalent, having a widespread impact on all securities. From 2021 to 2022, there is a decrease in average correlations reflected in all portfolios, whereas from 2022 onward, average correlation values are similar to values observed between 2019 and 2020. While the trend in average correlation values

Exhibit 4. Historical VaR in Green Portfolios and Average Pairwise Correlation Values between Securities in Each Green Portfolio



[6]Other portfolio weight (e.g., 1/*N* naive equal allocation or mean–variance allocation) can be considered.

indicates the trend in historical VaR (Exhibit 4, left panel), crucially, changes in historical VaR can be fully determined only by accounting for all historical VaR components, including the volatility of securities' price returns and portfolio weights. Differences in the trend of historical VaR and the trend in average correlation for the Env portfolio are evident. Specifically, the historical VaR of Env is smaller than MCap in 2023, while the average correlation of Env is higher than MCap and all other green portfolios. In this regard, while the average correlation is an important indicator to assess historical VaR, it is only one of several indicators that can be used to assess the trend in historical VaR.

For historical VaR, our results in Exhibit 4 show that the MCap portfolio's historical VaR was exceeded by the Env portfolio during 2020–2022. Over the period, there is a mixed trend for MCap historical VaR and other green portfolios; notably, however, the MCap historical VaR is higher than the Emi historical VaR across the period. Overall, this suggests that under normal market circumstances, green portfolios typically have lower tail risk but can be susceptible to higher losses in periods of market-wide stress.

The greatest difference between historical VaR values for MCap and Env occurred during 2020, when the historical VaR for Env was 3.66%, compared to 3.47% for MCap. Under a p = 5% probability of the event occurring, there would be a minimum loss of $3.66 million for Env and $3.47 million for MCap under historical VaR, assuming a portfolio with a notional value of $100 million.

Sensitivity Analysis

Next, I constructed two additional types of portfolios to determine the sensitivity of the results to alternative portfolio optimisation approaches.

First, as with the original green portfolios, I constructed portfolios such that the average green score is maximised, subject to the same constraints regarding the market capitalisation (>$100 billion average market capitalisation across all securities) and the number of securities in the portfolio (N = 30). However, I introduced additional constraints on index and sector diversification to examine how a decrease in the concentration of securities, particularly for the United States in the index composition and technology in the sector composition, will affect historical VaR. Specifically, the constraints include limiting the number of securities that belong to a given index to 30% of the total portfolio and limiting the number of securities that belong to a given sector to 20% of the portfolio.

Second, I constructed portfolios in the opposite fashion, where securities were chosen by optimising on the lowest green scores, assuming the same constraints as with the original green portfolios regarding size and number of securities. I denote portfolios whose securities are chosen from the lowest green scores as "brown" portfolios. Additional constraints on index and sector diversification were not used for these brown portfolios. The purpose of constructing brown portfolios is to examine how the potential negative implications of green scores for selecting securities could affect historical VaR.

For index- and sector-constrained green portfolios, I denote the corresponding designations as C-ESG, C-Env, and C-Emi. Brown portfolios are denoted as B-ESG, B-Env, and B-Emi.

Index- and Sector-Constrained Green Portfolios

Exhibit 5, representing the index and sector distribution of securities, shows a lower concentration in US companies (left panel) and technology firms (right panel), with a corresponding increase in portfolio composition in the other indexes and sectors. Although securities in other sectors increase in the portfolio, there is still a relatively lower allocation of securities in some sectors, such as utilities and the energy sector, because firms in these sectors typically have lower green scores. Under the index constraint, the two largest markets represented in the portfolios are the United States (S&P 500 companies) and the eurozone (EURO STOXX 50 companies), both with approximately 30% allocations (the maximum) in all green portfolios, reflecting a relative underweighting of US companies and overweighting of eurozone companies compared to the equivalent portfolios without constraints on index composition.

Exhibit 6 shows that the respective portfolio market capitalisations and green scores of index- and sector-constrained green portfolios are still high and are comparable to the average portfolio scores observed for the original green portfolios (Exhibit 4). Specifically, the average ESG score for the C-ESG portfolio

Exhibit 5. Index and Sector Distribution of Securities across All Index- and Sector-Constrained Green Portfolios

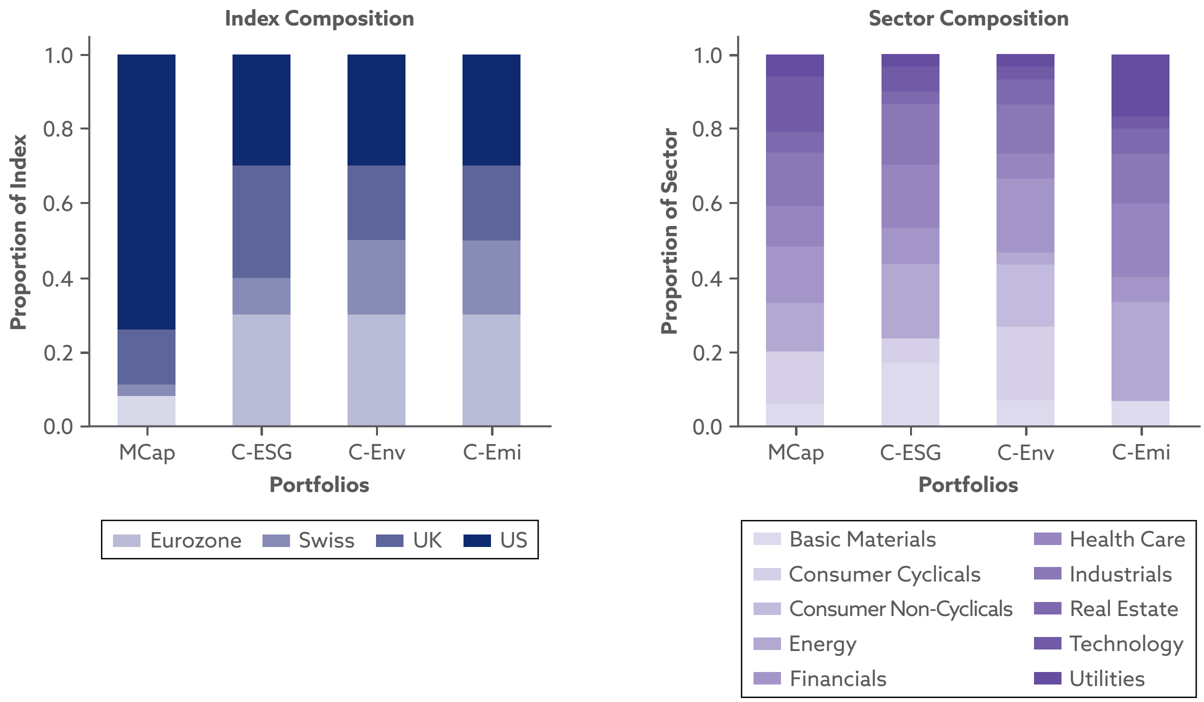


Exhibit 6. Portfolio Commonality and Average Portfolio Scores for Index- and Sector-Constrained Green Portfolios

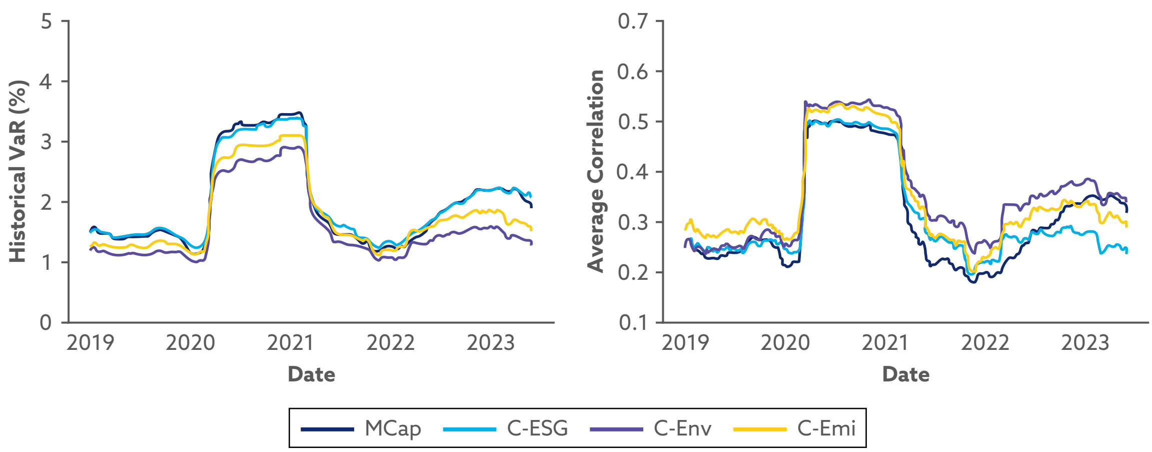
	Portfolio Commonality				Average Portfolio Scores			
	MCap	C-ESG	C-Env	C-Emi	Market Capitalisation ($ billions)	ESG Score	Environmental Score	Emissions Score
MCap	100%	100%	100%	100%	95	69	68	74
C-ESG	—	100%	30%	23.33%	184	90	90	92
C-Env	—	—	100%	36.67%	100	95	95	95
C-Emi	—	—	—	100%	100	81	86	98

is 90 (equal to the ESG portfolio), the average Environmental score for the C-Env portfolio is 95 (equal to the Env portfolio), and the average Emissions score for the C-Emi portfolio is 98 (only a 1 percentage point decrease from the Emi portfolio).

The results on portfolio commonality show a general increase in securities common to any two portfolios. The commonality is higher than for green portfolios. The minimum proportion of common securities between index- and sector-constrained green portfolios is 23.33%, compared with 16.67% for green portfolios.

In **Exhibit 7**, the trend in historical VaR for index- and sector-constrained green portfolios is similar to that of green portfolios and the MCap portfolio shown in Exhibit 4. In terms of magnitude, there are differences; the MCap historical VaR

Exhibit 7. Historical VaR in Index- and Sector-Constrained Green Portfolios and Average Pairwise Correlation Values between Securities in Index- and Sector-Constrained Green Portfolios



appears to be mostly higher relative to the historical VaR of constrained green portfolios over the period.

The difference between the lowest and highest historical VaR across constrained green portfolios is 0.81%, which is higher than that of green portfolios (0.64%). This represents an increase of around $170,000 in the range of historical VaR for green portfolios with index and sector constraints, assuming a portfolio with a notional value of $100 million. An increase in the range of historical VaR between constrained green portfolios is possible because of the changes in portfolio weights and volatility of security returns. This can lead to higher historical VaR even with the restriction on the available number of securities that satisfy all constraints under the optimisation approach.

Brown Portfolios

Exhibit 8 shows that portfolios constructed from securities with the lowest green scores have a higher concentration in specific indexes and sectors, compared with green portfolios, for which the average green score is maximised. The concentration in the index is mainly from the United States, reflecting the higher pool of large-capitalisation equities in the S&P 500. While there is still sector diversification across securities, there is a decrease in securities belonging to the technology and financial sectors (relative to green portfolios) and an increase in portfolio weighting to such sectors as industrials and health care. Because the technology and financial sectors are associated

Exhibit 8. Index and Sector Distribution of Securities across All Brown Portfolios

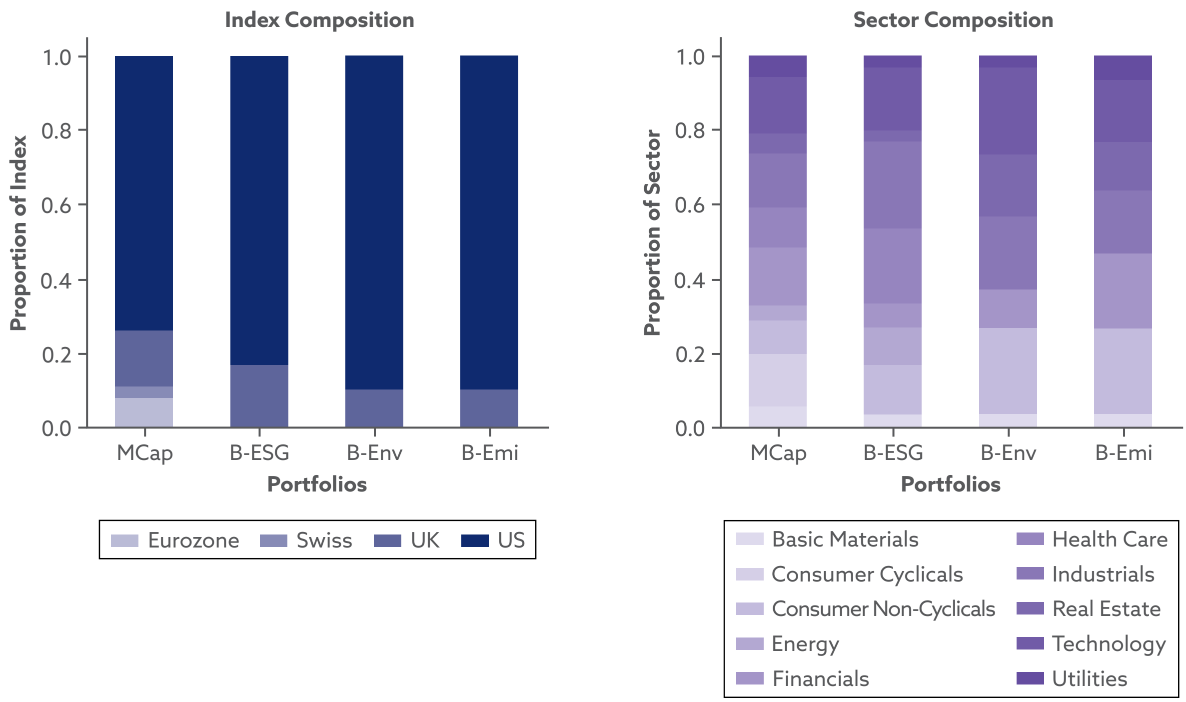


Exhibit 9. Portfolio Commonality and Average Portfolio Scores for Brown Portfolios

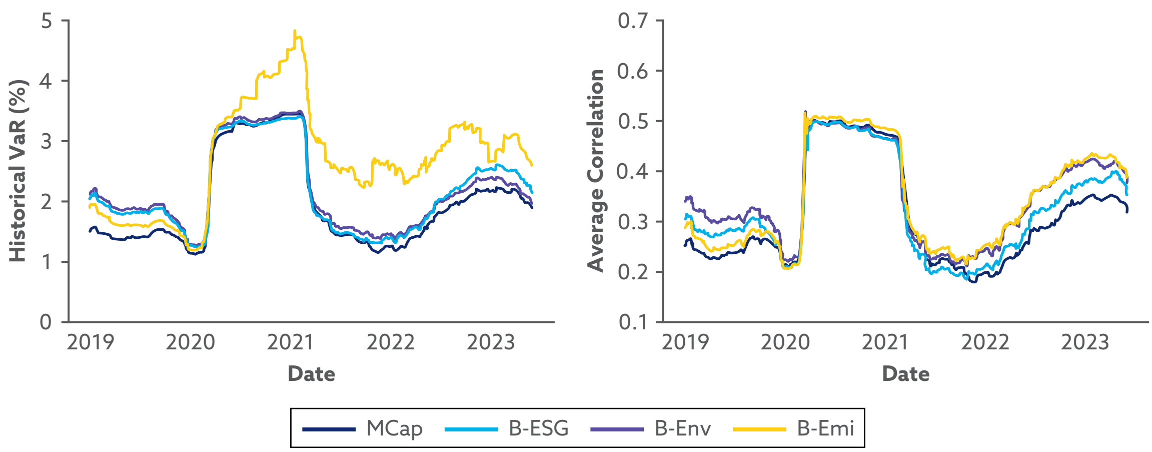
	Portfolio Commonality				Average Portfolio Scores			
	MCap	B-ESG	B-Env	B-Emi	Market Capitalisation ($ billions)	ESG Score	Environmental Score	Emissions Score
MCap	100%	100%	100%	100%	95	69	68	74
B-ESG	—	100%	53.33%	36.67%	100	36	36	42
B-Env	—	—	100%	53.33%	102	42	42	31
B-Emi	—	—	—	100%	101	45	45	23

with higher green scores, using lower green scores as the basis for portfolio construction shifts the concentration to sectors where green scores, on average, are lower.

Exhibit 9 shows a significant change for brown portfolios, as expected, with the average ESG score for the B-ESG portfolio equal to 36, the average Environmental score for the B-Env portfolio equal to 42, and the average Emission score for the B-Emi portfolio equal to 23. The results show that the variation of securities under the lowest green scores impacts the green performance of portfolios across all green scores. Exhibit 9 also shows a wider range in the commonality of securities between portfolios, where there is high commonality in securities for B-Env and the other two green portfolios, 53.33%, and a low commonality between all other portfolios, with the smallest being 36.67%.

Exhibit 10 shows an increase in historical VaR for the B-Emi portfolio, for which in 2021, there is a maximum of 4.82% historical VaR, representing a $4.82 million

Exhibit 10. Historical VaR in Brown Portfolios and Average Pairwise Correlation Values between Securities in Each Brown Portfolio



minimum loss per $100 million notional portfolio value. The higher historical VaR for B-Emi relative to the other two brown portfolios and the MCap benchmark portfolio from 2020 onward is notably different from the counterpart Emi and C-Emi portfolios, which have lower VaR than the corresponding MCap portfolio.

The increase in historical VaR for the B-Emi portfolio compared with the other brown portfolios arises from changes in volatility and portfolio weights. Most of the changes in historical VaR among brown portfolios can be attributed to changes in volatility and portfolio weights, not average correlations, because, as shown in Exhibit 10 (right panel), the average correlation for B-Emi remains similar to the average correlations of the other brown portfolios.

Discussion

The sensitivity results for historical VaR focused on optimising the green scores of securities with additional index and sector constraints or choosing securities with the lowest green scores. However, changes in other constraints can also be applied, which can affect security selection and historical VaR of portfolios—for example, the fixed number of securities in the portfolio, the minimum average market capitalisation of securities in the portfolio, and a linear assumption for how the average green score across securities is optimised. Changes in other aspects could be explored in future work to evaluate the sensitivity of portfolio selection using green scores to historical VaR.

I constructed portfolios using green scores for securities in 2024, and from these constructed portfolios, I calculated historical VaR. However, green scores are based on historical data and represent a backward-looking measure for evaluating climate risk. One can argue that backward-looking measures do not account for the potential size of climate risk that portfolios will be exposed to in the future. In this regard, one could consider scenario-based portfolios in which securities' portfolio weights are adjusted under an assumed future physical and transition risk scenario—for example, using scenarios developed by the Network for Greening the Financial System. Lazanas, Khambatta, Gan, Ma, and Smith (2025) considered such a scenario: They built portfolios for which portfolio weights change based on the trajectory of net-zero-aligned scenarios. These scenarios have high uncertainty, however, because of the complex modelling and the assumed behaviours used to generate the scenarios, which will be reflected in the portfolio selection.

A limitation of historical VaR is that tail risks represent only historical losses, which may not reflect the full spectrum of tail risks that the portfolio is exposed to. One could therefore use a reverse stress-testing approach to identify changes in correlations where VaR is maximised, where changes in VaR occur from a breakdown in correlations between different securities that are "plausible yet severe." Because the reverse stress test is maximised relative to historical data, the VaR under reverse stress testing is always higher than the historical VaR, where the difference between historical and reverse stress testing VaR represents the increased tail risk. As discussed by Packham and

Woebbeking (2019), reverse stress testing can be used to evaluate the scale of losses during the 2012 JPMorgan "London Whale" incident, where the unwinding of a derivatives portfolio with an expected loss of $400 million had a realised loss of $6 billion, showing the potential of such methods to enhance risk management practices.

Conclusion

In this study, I evaluated tail risk using the historical VaR of equity portfolios constructed according to different green scores. Constructing portfolios based on various green scores considers investors' differing views on aligning investment portfolios with climate risk. Using LSEG data between 2019 and 2023, I found a mixed trend in the historical VaR of MCap compared with green portfolios. I found the historical VaR of MCap is generally higher than that of green portfolios. However, in other periods, such as during 2020–2021, the historical VaR for the Env portfolio is higher than that of the MCap portfolio. I then conducted a sensitivity analysis to assess how changes in security selection with additional index and sector constraints affect historical VaR and how security selection based on the lowest green scores affects historical VaR. With index and sector constraints, the range of historical VaR among green portfolios decreases compared with green portfolios without constraints. For brown portfolios, the results show a mixed effect in historical VaR, as with green portfolios, but overall, historical VaR for the brown portfolios is higher than the benchmark MCap portfolio. This is most clearly observed in the case of the B-Emi portfolio which has the highest historical VaR among all portfolios.

Appendix

Portfolio Optimisation

Here, I show the portfolio optimisation for choosing securities under different green scores. For N total number of securities, where $i \in N$ represents a security in the set $N = \{1,\ldots,N\}$, I define the score, $P \in [0,100]^{N\times 1}$, and market capitalisation, $M \in [0,\infty)^{N\times 1}$, of each security, where P_i and M_i represent the associated green score and market capitalisation of security i.

$\mathbf{B}^I \in \{0,1\}^{N\times I}$ is defined as a binary matrix representing the index with which the security is associated, where $\mathbf{B}^I_{ij}$ represents that security i is associated with the index $j \in I$, where $I = \{1,\ldots,I\}$ represents the set of indexes associated with securities for I total number of indexes. Additionally, $\mathbf{B}^S \in \{0,1\}^{N\times S}$ is defined as the sector associated with the security, where $\mathbf{B}^S_{ij}$ represents security i under sector $j \in S$, where $S = \{1,\ldots,S\}$ represents the set of sectors associated for S total number of sectors. I assume securities are associated with only one index and sector in the index and sector matrices[7]—that is,

$$\sum_{j=1}^{I} \mathbf{B}^I_{ij} = \sum_{j=1}^{S} \mathbf{B}^S_{ij} = 1, \forall i \in N.$$

From the notation, the optimisation problem can be defined with bounds $C^k \geq 0$, where k represents the bound associated with the market capitalisation of the portfolio index constraint I or sector constraint S, $k \in \{M,I,S\}$, and $x \in \{0,1\}^{N\times 1}$ is a binary vector, where x_i represents whether the security is chosen for the portfolio. The portfolio optimisation is defined as follows:

$$\max_{x_i \in \{0,1\}} : \quad \sum_{i=1}^{N} P_i x_i, \tag{1}$$

$$\text{subject to}: \quad \frac{1}{N}\sum_{i=1}^{N} M_i x_i \geq C^M, \tag{2}$$

$$\frac{1}{N}\sum_{i=1}^{N} \mathbf{B}^I_{ji} x_i \leq C^I \;\; \forall j \in I, \; \frac{1}{N}\sum_{i=1}^{N} \mathbf{B}^S_{ji} x_i \leq C^S \;\; \forall j \in S, \tag{3}$$

$$\sum_{i=1}^{N} x_i = N. \tag{4}$$

The objective in (1) is represented through maximising chosen securities associated with the portfolio score (or minimising portfolios with green scores). The portfolio size under (2) represents the market capitalisation of securities bounded below. The diversification of securities under index and sector is constrained under (3), with the number of securities included in the portfolio fixed under (4). For the sensitivity analysis, constraints are included on the concentration of securities in any given index or sector under (3) for constructing portfolios.

[7]If securities are involved in multiple sectors, then we select the sector corresponding to their main operations.

Historical VaR Example

Here, I provide a demonstration of how portfolio VaR is calculated using the covariance approach, assuming that price returns of securities are normally distributed.

Consider two securities, X and Y, with returns $R_X = (-0.3,-0.2,0,0.2,0.3)$ and $R_Y = (0.15,0.1,0,-0.1,-0.15)$, respectively, over five days ($t = 5$). From these returns, we can calculate the covariance of price returns, cov(X,Y), from the price returns of securities:

$$\mathrm{cov}(X,Y) = \begin{pmatrix} 0.065 & -0.0325 \\ -0.0325 & 0.01625 \end{pmatrix},$$

where diagonal values represent the variance of securities (e.g., the variance of X is $\sigma_X^2 = 0.065$ and $\sigma_Y^2 = 0.01625$) and off-diagonal values represent the co-variation in price returns between securities $\sigma_{XY} = \sigma_{YX} = -0.0325$.

For portfolio weights, an equal allocation is assumed for both securities $\omega = (0.5,0.5)$, with a probability of $p = 5\%$ for losses to occur. I assume a normal distribution, where under the assumed probability, p, this translates into a Z-score $N^{-1}(p)$ of 1.64, corresponding to a magnitude of the standard deviation with the covariance of price returns and portfolio weights. Then, assuming the drift is equal to zero,

$$\begin{aligned}
\mathrm{VaR}_{t=5\,Days}(5\%) \quad &= N^{-1}(p)\sqrt{\omega^T \mathrm{cov}(X,Y)\omega} \\
&= 1.64 \times \sqrt{(0.5,0.5)\begin{pmatrix} 0.065 & -0.0325 \\ -0.0325 & 0.01625 \end{pmatrix}\begin{pmatrix} 0.5 \\ 0.5 \end{pmatrix}} \\
&= 1.64 \times \sqrt{0.0040625} \\
&\approx 0.105.
\end{aligned}$$

Based on the price returns and portfolio weights provided, $\mathrm{VaR}_{t=5\,Days}(5\%) \approx 10.5\%$ represents that over five days, the likelihood that the portfolio exceeds losses of 10.5% is equal to 5%. In this example, price returns between securities are negatively correlated, leading to a decrease in VaR. Also, from the price returns, the volatility of X is higher because of the deviation in price returns, leading to a higher contribution to VaR from X than Y.

Securities' Portfolio Classification

Exhibit A1 shows the inclusion of securities in different green portfolios based on the following categories:

- Portfolios based on securities with the highest green scores: ESG portfolio (ESG), Environmental portfolio (Env), and Emissions portfolio (Emi)
- Portfolios based on securities with the highest green scores with additional index and sectoral constraints: ESG portfolio (C-ESG), Environmental portfolio (C-Env), and Emissions portfolio (C-Emi)

- Portfolios based on securities with the lowest green scores, denoted as brown portfolios: ESG portfolio (B-ESG), Environmental portfolio (B-Env) and Emissions portfolio (B-Emi)

Exhibit A1. List of Securities by Refinitiv Identification Code (RIC) in Different Portfolios

RIC	Portfolios	RIC	Portfolios
A.N	Emi	JNJ.N	Env, C-Env
ABBN.S	ESG, Env, C-ESG, C-Env	KDP.OQ	B-Emi
ABF.L	C-Env	KKR.N	B-ESG
ABT.N	Emi, C-Emi	L.N	B-ESG
ACN.N	Emi	LAND.L	C-Env
ADSGn.DE	ESG	LEN.N	B-ESG, B-Emi
AEE.N	B-Emi	LIN.OQ	ESG, Env, C-ESG, C-Env
AIR.PA	Env, C-Env	LKQ.OQ	B-Emi
ALVG.DE	Env	LLOY.L	Env, C-Env
AMT.N	Emi	LMPL.L	B-ESG
AOS.N	B-Emi	LOGN.S	C-Emi
ATO.N	B-ESG, B-Env	LVMH.PA	Emi, C-Emi
AXON.OQ	B-ESG, B-Env	LYV.N	B-Env
AZN.L	ESG, C-ESG	MBGn.DE	ESG, Env, Emi, C-ESG, C-Env, C-Emi
BAC.N	Env	MKC.N	Env, C-Env
BARC.L	C-Env	MLM.N	B-ESG, B-Env, B-Emi
BASFn.DE	ESG, C-ESG	MMM.N	ESG, C-ESG
BATS.L	ESG, C-ESG, C-Env	MNDI.L	C-ESG, C-Emi
BAYGn.DE	ESG, C-ESG	MNST.OQ	B-ESG, B-Env, B-Emi
BBVA.MC	ESG, Env, C-ESG, C-Env	MPWR.OQ	B-ESG, B-Emi
BKR.OQ	ESG, C-ESG	MSFT.OQ	ESG, C-ESG
BLK.N	Env	MUVGn.DE	Env
BMWG.DE	ESG, C-ESG	NEM.N	ESG, C-ESG
BNPP.PA	ESG, Env, C-ESG	NESN.S	C-Env
BP.L	ESG, C-ESG	NFLX.OQ	B-ESG, B-Env

(continued)

Exhibit A1. List of Securities by Refinitiv Identification Code (RIC) in Different Portfolios *(continued)*

RIC	Portfolios	RIC	Portfolios
BRKb.N	B-ESG, B-Env, B-Emi	NOKIA.HE	Emi, C-Emi
BRO.N	B-ESG, B-Env, B-Emi	NVR.N	B-ESG, B-Env, B-Emi
BX.N	B-ESG	ODFL.OQ	B-ESG
BXP.N	Emi, C-Emi	ORCL.N	B-ESG
CHTR.OQ	B-ESG	ORLY.OQ	B-ESG, B-Env
CL.N	ESG, C-ESG	PCG.N	Emi
CPRT.OQ	B-Env, B-Emi	PGR.N	B-Env
CTRA.N	B-ESG	PHM.N	B-Emi
CVS.N	ESG, Emi, C-ESG, C-Emi	PHNX.L	Emi, C-Emi
DANO.PA	ESG, Env, C-ESG	PM.N	Env, Emi, C-Env, C-Emi
DCC.L	B-Emi	POOL.OQ	B-Env
DG.N	B-Env, B-Emi	PRTP.PA	Env, Emi, C-Env, C-Emi
DGE.L	C-Emi	REL.L	Emi, C-Emi
DHI.N	B-Env, B-Emi	ROG.S	ESG, Emi, C-ESG, C-Env, C-Emi
DPLM.L	B-ESG, B-Env	ROL.N	B-ESG, B-Env, B-Emi
ENEI.MI	ESG, Env, C-ESG, C-Env	ROP.OQ	B-Emi
EQT.N	B-ESG	SAN.MC	Env
ERIE.OQ	B-Env, B-Emi	SAPG.DE	ESG
ETR.N	B-Emi	SASY.PA	Emi
EW.N	Emi, C-Emi	SCHN.PA	Emi, C-Emi
FCIT.L	B-ESG, B-Env, B-Emi	SCHW.N	B-Env, B-Emi
FFIV.OQ	B-Env	SCMN.S	Emi, C-Emi
FICO.N	B-ESG, B-Env	SGEF.PA	Env, C-Env
FMC.N	Env, Emi, C-Env, C-Emi	SGOB.PA	ESG, Env, C-Env
GEBN.S	C-Env	SHEL.L	ESG, C-ESG, C-Env, C-Emi
GLEN.L	C-ESG	SIEGn.DE	Emi, C-Emi
GNRC.N	B-ESG, B-Env	SLHN.S	Env, C-Env, C-Emi
GPC.N	B-Env	SMT.L	B-ESG, B-Env, B-Emi

Exhibit A1. List of Securities by Refinitiv Identification Code (RIC) in Different Portfolios *(continued)*

RIC	Portfolios	RIC	Portfolios
GPN.N	B-ESG	SNA.N	B-Emi
GS.N	Env, Emi, C-Env, C-Emi	STAN.L	ESG, C-ESG
GSK.L	ESG, C-ESG	STLAM.MI	Env, Emi, C-Env, C-Emi
HIG.N	Emi	STZ.N	B-ESG, B-Env, B-Emi
HII.N	B-ESG	TDG.N	B-Env
HRL.N	B-Emi	TSLA.OQ	B-Emi
HSBA.L	C-Emi	TTEF.PA	Emi, C-Emi
HST.OQ	Env, C-Env	TTWO.OQ	B-Env, B-Emi
IBM.N	Emi, C-Emi	TXN.OQ	Env, C-Env
IEX.N	B-Emi	UBSG.S	Env, C-ESG, C-Env, C-Emi
INTC.OQ	ESG, C-ESG	ULVR.L	ESG, C-ESG
ISP.MI	ESG, Env, Emi, C-ESG	V.N	B-Env
ITX.MC	Env, Emi, C-Env, C-Emi	VRSN.OQ	B-Env, B-Emi
JCI.N	Env, C-Env	WBA.OQ	ESG, Emi, C-ESG, C-Emi
JD.L	B-ESG	ZURN.S	Emi, C-Emi

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