Sustainability-Driven Portfolio Construction

Evaluating investor preference for ESG investment approaches.

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Contents

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Executive Summary

In recent years, sustainable investing has become increasingly relevant because of the climate crisis and growing criticism of corporate short-termism. Considering the significant investment and societal risks that such issues pose, sustainable investments can be expected to play a significant role in supporting the transition to a net-zero economy. Money managers are frequently posed with the challenge to find a balance between generating returns and considering environmental, social, and governance factors. In supporting the construction of such balanced portfolios, optimization tools can play an important role in helping investors strike the desired balance between their ESG and other investment goals, thereby enabling them to decarbonize the global economy and fight climate change, among other ESG objectives.

In this paper, we will provide an overview of the Morningstar Portfolio Construction Engine, an advanced portfolio construction tool that allows users with a variety of portfolio optimization capabilities. Our primary focus will be to build strategies over a representative broad fund universe that simultaneously tests popular ESG investment approaches while empowering investors to find a balance between multiple competing objectives like minimizing risk, maximizing return, and maximizing the portfolio's sustainability while incorporating relative preferences for the three. Since the United States and Europe are among the largest markets where ESG awareness in investment has picked up, we will create a representative universe of funds in these two regions and test out our strategy. Accordingly, asset managers can compare the two, and it could provide a differentiated product-development road map for them to follow in the two domiciles.

Key Takeaways

- The Morningstar Portfolio Construction Engine allows for the evaluation of popular ESG investment approaches on diverse universes. The engine has the capability to be extended across other use cases.
- Investor ESG preferences—Agnostic, Unaware, Intentional, Aware Integration, Intentional and Low Climate Impact, and Motivated—have varied strategy outcomes when measured through the lenses of performance, sustainability, and fund attributes in the representative U.S. and Europe universes.
- Investor preference for ESG is indicative of balanced performance outcomes while also maintaining healthy sustainability attributes when evaluated over representative universes.
- Investor preference for ESG is indicative of a tilt toward large-cap asset allocation.
- An intentional ESG approach, reflective of screening, fares better in terms of performance attributes than a deep integration approach.

- Among ESG investment approaches, a Motivated ESG strategy— one that screens for ESG factors and then optimizes on top of it—performs best on sustainability attributes.
- Attributing performance to popular style factors indicates that ESG strategies may be driving returns through higher exposure to the quality and value style factors with sector tilts also toward technology.
- ESG Unaware and ESG Agnostic strategies tilt toward higher Morningstar Medalist ratings.
- Investors can generally expect to pay a premium (expense ratio) for sustainability integrated portfolios.
- Introducing a preference for low climate impact alongside sustainability lowers the expected volatility while also increasing the expense ratio.

Introduction

Portfolio optimization is a crucial aspect of the investment process to help portfolio managers and investors achieve their goals while incorporating preferences to multiple competing objectives. Rather than simply selecting the best investments based on certain criteria, this process involves a holistic approach of selecting the best portfolio, wherein we analyze how the allocation to different investments influences investor outcomes.

Traditionally, the main objectives of optimization problems in the investment industry have been managing risk and maximizing the return on a set of investments. However, investors are now becoming increasingly inclined toward newer objectives pertaining to ESG and Thematic investing. With the adoption of the Paris Agreement and the UN Sustainable Development Goals, several regions, particularly the EU, are proposing new regulations and strategies that can help direct financial flows on a path toward a low-carbon economy. As financial markets begin to redirect capital toward more sustainable investments, investors are now focusing heavily on incorporating ESG factors into their investment decisions while constructing portfolios.

In this paper, we extend Markowitz's mean-variance portfolio optimization approach to sustainability-based factors in creating investment portfolios. To achieve this, we use a technique of multi-objective optimization, or MOO, which considers three criteria: minimizing risk, maximizing return, and minimizing ESG risk. Regarding the first two objectives, we leverage the Morningstar Global Risk Model for required capital market assumptions (expected returns, residuals, and covariance matrix). As for ESG risk, we leverage the Morningstar Sustainability Rating for funds, which measures the peer-group-relative portfolio-level risk from ESG factors. As per the latest Morningstar Sustainable Fund Flows report, the U.S. and Europe are the two largest markets in terms of flows, product launches, and assets under management. So, we perform this process of optimization on the broad fund universes of US and EU open-end funds and exchange-traded funds. In addition, we specify a series of filters and constraints that would ensure diversification of the portfolio and avoid overweighting certain funds relative to others. Further, we carry out back-testing to understand how the optimized portfolios have performed during our period of study. During the process, we incorporate newer ESG data points like carbon intensity and sustainability scores.

Integrating Sustainability in Investment Portfolios

Approaches to ESG-Driven Portfolio Optimization

There are multiple approaches to ESG strategy creation. The terminology of such approaches may vary considerably owing to the unavailability of a global framework. Generally, the investment strategy creation can be categorized into five approaches:

- **ESG Integration:** This approach involves looking at material ESG issues of a company and analyzing whether they will have a positive or negative impact on the company's finances. This approach is essentially followed by investors whose motivation is to reduce ESG risk while finding a balance between returns and risk. Investors can use the Morningstar Sustainability Ratings to identify funds with lower ESG risks.

  Negative Screening: Negative screening has been the most popular approach of ESG investing. It involves the exclusion of funds by implementing certain mandates and restrictions. There are also exclusions around product involvement and controversies, which investors may try to apply and can be referred to in the Morningstar Portfolio Product Involvement Methodology.

- **Best-in-Class/Positive Screening:** The best-in-class approach focuses on investors creating a positive impact on society with a focus on gender diversity, renewable energy, community development, and so on. Investors can plan usage of a range of Sustainable Attributes to identify funds with positive characteristics.

- **Thematic Investing:** This approach involves identifying certain topics and trends specific to ESG factors, such as climate change and water scarcity, with a focus on generating superior returns. Investors motivated to have a positive impact while generating better returns may follow this approach. Investors can use the sustainable attributes available with Morningstar products to identify such funds.

In addition to the above approaches, investors may also exercise voting rights and actively engage with companies to influence their activities and behavior regarding ESG matters. Moreover, some investors may also consider the path of philanthropy, in which they may not consider financial returns.

Given investor goals and preferences, there are varied motivations for incorporating ESG. The case studies in this paper are focused on portfolio optimization with these varied preferences in mind. We define a spectrum of ESG tilts, and each of these cases identifies a unique investor with a different approach and willingness to incorporate ESG into her portfolio. These include:

- **ESG Agnostic:** The perspective for this approach will be that of an investor who screens the universe to keep only those funds that are not sustainable (as measured by the tag "Sustainable Investment Overall"). This case is indicative of investor trying to have least impact on the society.

- **ESG Unaware:** In this approach, we focus on the traditional mean-variance portfolio optimization with no ESG-based screening on the universe. The focus of the optimization will be on maximization of returns and minimization of risk with no consideration for ESG. This approach will act as a baseline use case as it is reflective of traditional investing for an investor who does not have any preferences for ESG.

- **ESG Aware Integration:** In this approach, we aim exclusively for ESG integration by specifying relative preference on competing objectives of risk, return, and ESG. Here, we do not have any ESG filtering or screening on the universe of funds. This variant is indicative of investor preference for ESG integration versus ESG screening.

- **ESG Intentional:** We aim for ESG-based universe screening without any integration into the optimization. We consider the perspective of an investor who wants to invest exclusively in sustainable funds as measured by the tag "Sustainable Investment Overall." The case is indicative of an investor trying to create positive impact on society by limiting the universe to funds having positive sustainability attributes.

- **ESG Intentional and Low Climate Impact:** Much like the last approach, we aim for ESG-based universe screening without any integration into the optimization. The perspective this time will be of an investor who wants to invest exclusively in a universe of funds that are not only sustainable but also have positive climate impact. We use the tags Sustainable Investment Overall and Low Carbon Designation to identify such investments.

- **ESG Motivated:** This approach takes the perspective of an investor who is strongly driven by ESG factors. We first filter the universe of funds on multiple screens to keep only sustainable funds with a positive climate impact (which are again measured by the tags "Sustainable Investment Overall" and "Low Carbon Designation"). Furthermore, we also integrate ESG in the objective function of the optimization through relative preference on competing objectives. ESG consideration at both the steps (screening and integration) would ensure that we have the most impactful ESG characteristics in our portfolio.

A relative evaluation of the ESG Motivated and ESG Intentional approaches against the ESG Unaware and ESG Agnostic approaches will reveal the differences in performance and fund attributes.

Overview of the Morningstar Portfolio Optimization Engine

The Morningstar Portfolio Optimizer is an advanced portfolio construction tool that offers users the power to evaluate a wide variety of investment approaches effectively. In current use case the tool leverages the Morningstar Global Risk Model to decompose a portfolio's risk and help develop strategies that are aligned with the investment process. The optimizer is flexible and can incorporate capital market assumptions from both holdings-based style analysis and returns-based style analysis. Built on top of strong foundation, the engine not only allows for finding a balance between traditional investor utilities like return and risk but also supports multiple emerging investor objectives like ESG, thematic, and strategic beta (factor-tilted portfolios), to name a few. In addition, the engine provides users with the flexibility to apply constraints on proprietary Morningstar data supported by in-depth fund, equity, and sustainability research, along with standard data points. The numerical optimization routine is supported by proven open-source packages like CVXPY, IPOPT (interior point), and the latest generation of NSGA (nondominated sorting genetic algorithm) to support multi-objective use case. The robustness of this engine allows for evaluation of various ESG investment approaches and varying degrees of ESG incorporation on diverse universes while building portfolios.

Below is a high-level overview of various components of the Portfolio Optimization Engine:

- **Universe Definition:** The first step to building a portfolio is to define the universe of assets, from which the investor can determine an optimal allocation. These assets can be funds, equities, fixed-income securities, or alternative assets. We examine use cases that include open-end funds and ETFs in the U.S. and EU regions with assets under management greater than USD 10 million and EUR 10 million, respectively. To enable ESG-driven portfolio creation, the optimizer enables several screens to identify the ESG objectives of the investor and take exposures accordingly.
- **Asset-Class Support:** The engine can support multiple asset classes like equities, fixed income, allocation, commodities, and so on. While the current use case is mostly fund-based, the optimizer also supports index creation on direct equities.
- **Decision Variables:** These are essentially the asset allocations the optimizer is trying to determine leveraging a numerical solver.
- **Investor Objectives:** The investor defines a set of objectives or investor utilities that are either maximized or minimized. The current optimizer supports many investor objectives, such as maximizing return/alpha, minimizing risk (variance, VaR/cVaR, higher moments), maximizing factor exposure, minimizing tracking error, and so on. While these objectives have been built on the premise of traditional investor utilities, the expanding sophistication of global markets has also required for investors to simultaneously balance for emerging utilities like ESG, thematic, and factors. Hence, the Portfolio Optimization Engine now supports building portfolios with a focus on multiple competing objectives. To effectively support multi-objective optimization, investors need to specify their relative preferences among various utilities like ESG, risk, and return.
- **Investor Constraints:** The Optimizer supports a range of constraints like diversification (limiting max exposure to sector, factor, expense ratio, medalists, Morningstar Style Box), turnover (limit the max changes in asset allocations at each rebalancing date), target date allocations for retirement planning, and so on. In terms of ESG strategy construction, we can limit exposure to product involvement, or the individual E, S, and G elements.
- **Capital Market Assumptions:** The essential numerical inputs for an optimizer are alpha expectations, residual risk, and the covariance matrix. While the current optimizer works on top of capital market assumptions, or CMAs, defined by the risk model, it also supports other models such as return-based style analysis and statistical factor models. In the use cases for this paper, we leverage the Morningstar Global Risk Model inputs for CMAs.
- **Portfolio Performance and Attribution Analysis:** To analyze the output of the optimizer, it is important to back-test rebalanced portfolios and evaluate performance over time. This involves examining performance measures like CAGR, portfolio risk, Sharpe ratio, information ratio, and tracking error. We

also perform a holdings-based analyses to uncover the characteristics of our optimized portfolio over a period. Additionally, we can evaluate the strategy outcomes in terms of proven fund attributes like expense ratio, Morningstar Analyst Ratings, assets under management, and so on to aid investors in making more informed decisions. We will be rebalancing our portfolios quarterly.

For a more detailed discussion of the above elements, please refer to the Appendix section.

Comparison of the European and U.S. Sustainable Fund Universes

We now move on to universe evaluation. We leverage the Morningstar Risk Model universe for this study. As the risk model supports global equity asset class, so we restrict our universe to equities. It is worth pointing out here that the optimization is flexible to other asset classes by using inputs from a different model like returns-based style analysis. Solving the problem for only equities is just indicative of demonstrating the optimization engine's capabilities. As remarked earlier, since the US and Europe are among the largest markets where ESG awareness in investment has picked up, we test our strategy on a broad representative universe of funds in these two regions.

To identify the broad US equity fund universe, we apply the following filters:
Investment Type: Open-end Funds and ETFs, AUM > 10 million USD; Domicile: U.S.; Base Currency: USD; Oldest Share Class: Yes; Morningstar Category should be one of the following: Large Growth, Large Blend, Large Value, Mid-Cap Growth, Mid-Cap Blend, Mid-Cap Value, Small Growth, Small Blend, and Small Value. All analysis is at a share-class level.

To identify the broad European fund universe, we apply the following filters:

Investment Type: Open-End Funds and ETFs, AUM > 10 million EUR; Base Currency: EUR; Oldest Share Class: Yes; Morningstar Category should be one of the following: Europe Large-Cap Blend, Eurozone Large-Cap, Europe Flex-Cap, Europe Large-Cap Growth, Eurozone Flex-Cap, Europe Small-Cap, Eurozone Small-Cap, Europe Large-Cap Value, Europe ex-UK, and Europe ex-UK Small/Mid-Cap. All analysis is at a share-class level. Note that we will only be focusing on funds that have euros as their base currency. This will lead to a drop in funds that have other currencies (like pound sterling, franc, krone, and so on).

Sustainability Rating Distribution Across Europe and the U.S.

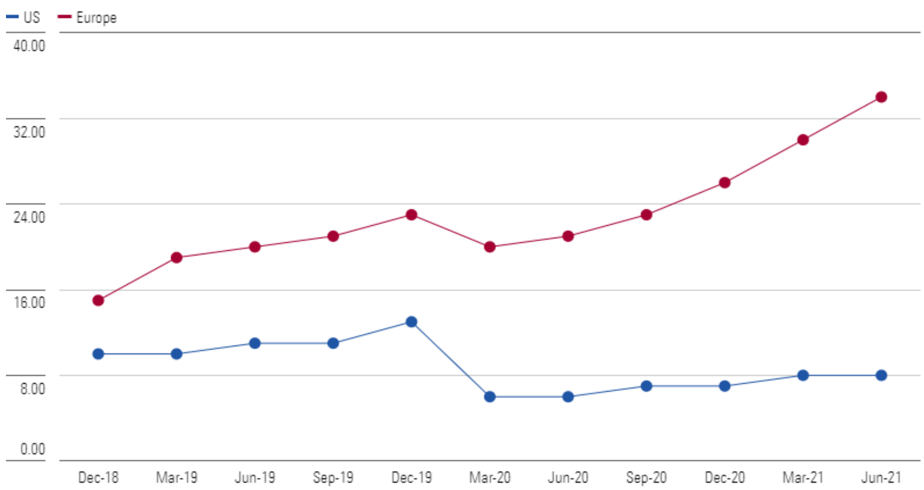
Exhibit 1 Sustainability Ratings, U.S. vs. Europe

Sustainability Rating	US	Europe
High	9.2	13.6
Above Average	21.7	25.7
Average	36.9	35.7
Below Average	22.9	15.2
Low	7.8	4.9

Source: Morningstar.

After filtering the two universes, we had about 3,500 unique fund share classes combined as of June 30, 2021. Exhibit 1 shows the funds under each Morningstar Sustainability Rating as a percentage of the total funds in the respective universes. Europe has a higher proportion (73% compared with 67% for the US) of funds with Sustainability Ratings of Average, Above Average, or High.

Exhibit 2 Percentage of Funds With the Sustainable Investment Overall Tag, U.S. vs. Europe

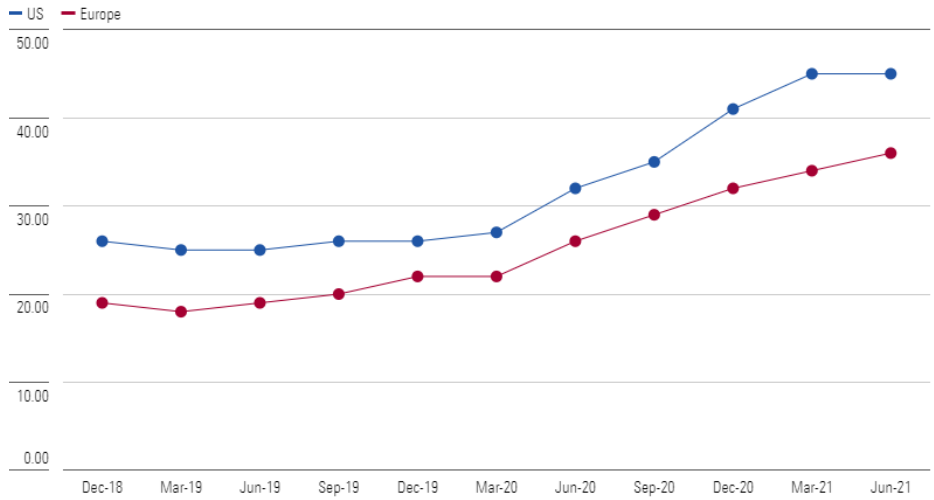


Source: Morningstar.

Similarly, we can see from Exhibit 2 that within this universe, Europe not only has a significantly higher proportion of funds with exposure to sustainable products, the growth in the percentage of funds marked sustainable is also higher compared with U.S.

Exhibit 3, on the other hand, indicates that the European representative universe has a lower percentage of carbon-efficient funds compared with the U.S. universe. The growth in the percentage of carbon-efficient funds has been good for both universes.

Exhibit 3 Percentage of Funds With a Low Carbon Designation, U.S. vs. Europe



Source: Morningstar.

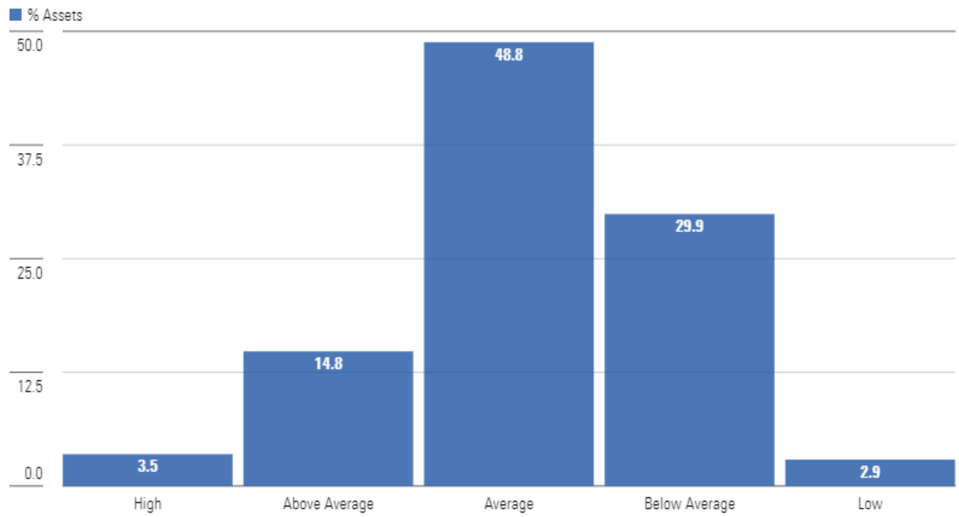
Comparison of Fund Attributes Across the European and U.S. Fund Universes

While analyzing the funds based on ESG factors, it is important to understand how they relate to various fund attributes. In this section, we look at some of the fund factors and their relationship with the Morningstar Sustainability Ratings for the U.S. and European global fund universes. Inferences from this section will help us adapt appropriate constraints while setting up our optimization problem. It is worth mentioning again that all the analysis presented here is on the universe filtered on the parameters presented in the previous section, and not on all the funds in the U.S. and Europe.

Sustainability Ratings and Assets Under Management

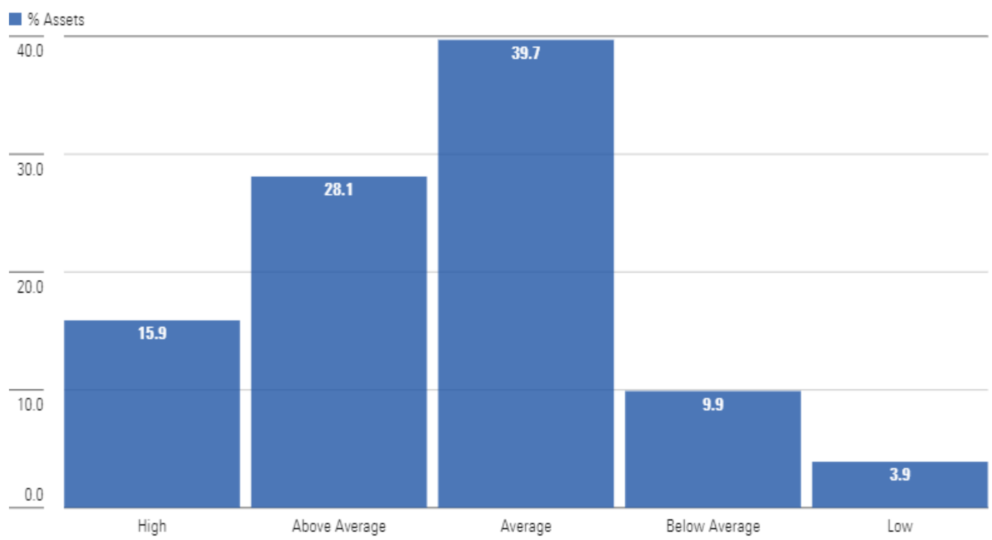
We analyzed funds domiciled in the representative European and U.S. universes while considering the AUM breakup across the five Sustainability Rating groups as of June 30, 2021.

Exhibit 4 Percentage AUM vs. Sustainability Rating, U.S.



Source: Morningstar.

Exhibit 5 Percentage AUM vs. Sustainability Rating, Europe



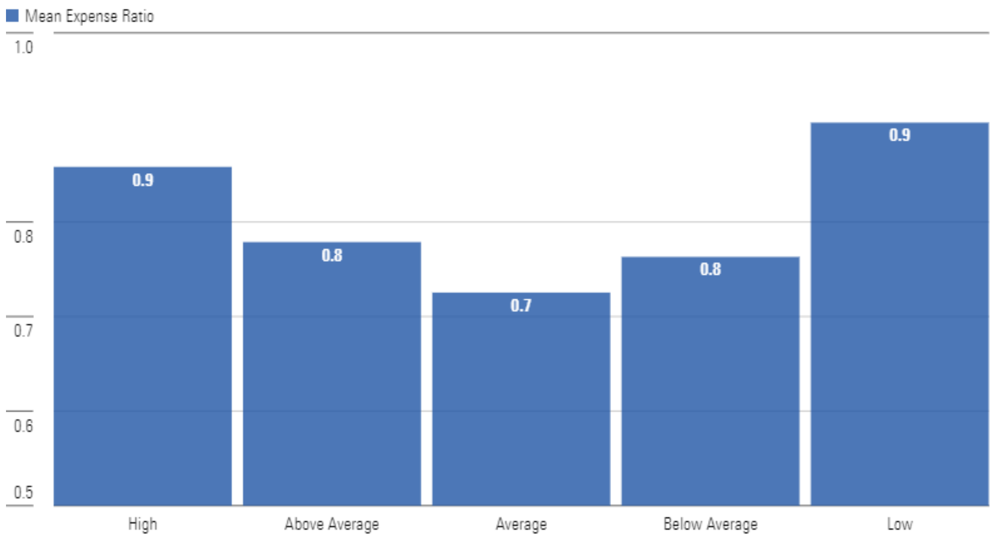
Source: Morningstar.

As evident by Exhibits 4 and 5, Europe being a leader in Sustainable investing has higher percentage of assets in top three ratings categories. In contrast, U.S. has higher proportion of funds rated Average and Below Average.

Sustainability Ratings and Expense Ratios

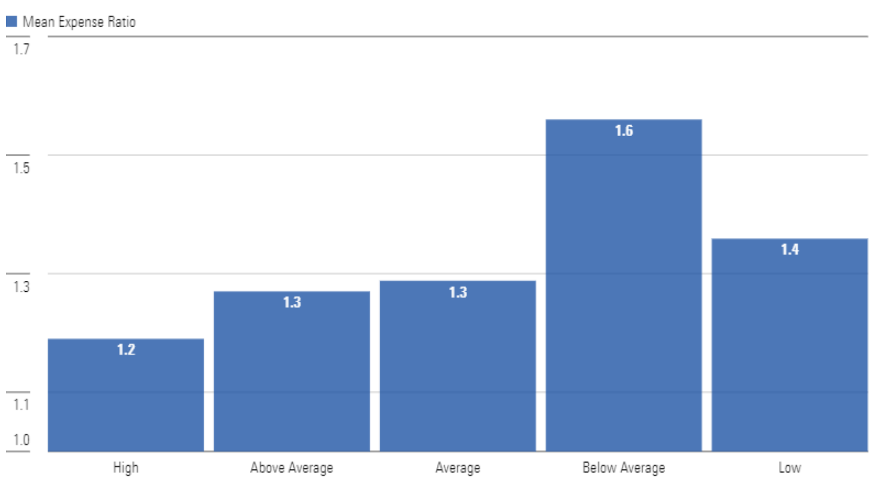
To understand the relationship with expense ratio, we looked at the median expense ratio of funds domiciled in the representative Europe and U.S. universes at the end of June 2021.

Exhibit 6 Mean Expense Ratio, U.S.



Source: Morningstar.

Exhibit 7 Mean Expense Ratio, Europe



Source: Morningstar.

We can infer from Exhibits 6 and 7 that expense ratios in the European universe are generally higher than in the US universe. There is also no major difference between expense ratios across the Sustainability Ratings groups for both the European and U.S. universes. This goes against the general notion that it may be necessary to pay additional costs for funds with higher ESG ratings.

Relationship With Morningstar Analyst Ratings

We believe that high Sustainability Ratings are not enough for a fund to outperform its peers. We should also look at a fund's Morningstar Medalist Rating because this metric indicates the likelihood that a fund will outperform its peer group and category benchmark over a full market cycle. Therefore, we need to consider the relationship between the Morningstar Sustainability Rating and the Morningstar Medalist Rating.

To perform this analysis, we identify the medalist rating of each fund's primary share class We use both Morningstar Analyst Ratings and Morningstar Quantitative Ratings to expand the coverage universe[1]. Next, we look at the distribution of funds across Sustainability and Medalist Ratings in our defined universe. Exhibits 8 and 9 display the proportion of funds in each cohort as of June 2021. We note that most funds with High or Above Average Sustainability Ratings have a Neutral Medalist Rating. If we look at all the rated funds (Gold, Silver, and Bronze) that have either High or Above Average Sustainability Ratings, they still represent around 13% to 15% of the entire universe. This count is sufficient for our optimizer to find the efficient frontier and allocate weights, while we include additional constraints related to fund characteristics, such as AUM and expense ratio.

Exhibit 8 US Fund Universe: Medalist Ratings vis-à-vis Sustainability Rating (% of Universe)

	Negative	Neutral	Bronze	Silver	Gold
High	1.3%	3.0%	1.8%	1.3%	0.7%
Above Average	3.3%	7.3%	4.9%	4.0%	2.0%
Average	6.2%	12.8%	7.7%	8.0%	3.0%
Below Average	4.1%	9.2%	5.2%	3.2%	1.8%
Low	1.8%	2.6%	1.7%	1.1%	0.7%

Exhibit 9 European Fund Universe: Medalist Ratings vis-à-vis Sustainability Rating (% of Universe)

	Negative	Neutral	Bronze	Silver	Gold
High	2.1%	5.1%	1.6%	1.7%	0.9%
Above Average	4.8%	10.6%	5.0%	2.4%	1.4%
Average	8.0%	15.3%	6.3%	4.5%	2.9%
Below Average	4.0%	8.4%	1.9%	1.7%	0.5%
Low	1.5%	2.3%	0.8%	0.4%	0.2%

1 Learn more about Morningstar Analyst Ratings here. Additionally, more information on the Morningstar Quantitative Ratings for Funds can be found here.

The comparison shown in Exhibits 8 and 9 across the U.S. and European representative universes aligns well with general trends. There is a slightly higher percentage of funds rated positively for sustainability with either Gold or Silver Analyst Rating in the European universe against the U.S. universe.

The analysis here reiterates the fact that there is in general higher level of awareness of ESG investing in Europe compared with the US. The region has seen several regulations of ESG investing to meet the EU goal of a net-zero economy by 2050. For instance, the Sustainable Finance Disclosure Regulation, or SFDR, mandates that asset-management firms provide more information about the ESG risks in their portfolios and classify their products into categories that will dictate additional disclosure requirements. Fund data points related to SFDR, especially whether a fund promotes ESG factors and is classified as Article 8 or 9, can also be found in Morningstar products, enabling investors to apply more constraints while setting up the optimization.

The universe analysis indicates that the universe selected is diverse enough for the optimization to run effectively and generate insights that would help identify the relative importance of ESG as a factor incorporated in portfolio construction.

ESG Fund Case Studies

In this section, we illustrate how our optimization framework can be used for various ESG investing approaches. We will define variants that capture the different levels of ESG awareness (or willingness to incorporate ESG in portfolio construction) of these approaches. We will cover the entire spectrum ranging from an ESG Agnostic investor to an ESG Motivated investor. We have two broad objectives for all these cases: maximizing the expected return of the portfolio of funds and minimizing the risk of significant investment losses. For different variants of ESG awareness/willingness, we shall introduce different levels of ESG screening and integration. As a measure of integration, we'll be focusing on ESG as a risk. In cases where we integrate the ESG into the optimization, we essentially break down the overall risk of the portfolio into two parts: 1) conventional risk, which is measured using the Morningstar Global Risk Model, and 2) portfolio-level risk from ESG factors, as measured by the Morningstar Sustainability Rating. By decomposing risk into two parts, we are essentially driving ESG integration. As such, we are looking at investors who have a motivation to improve their investment outcomes while simultaneously reducing ESG risk in their portfolios. Given that lower-ESG-risk portfolios have higher Sustainability Ratings, we aim to maximize the portfolio's overall Sustainability Rating.

As a result, our optimization objectives are threefold. These shall be solved simultaneously using a multi-objective framework as described in the appendix.

- **Objective 1**: Maximize expected return of the portfolio
- **Objective 2**: Minimize ex-ante risk of the portfolio
- **Objective 3**: Maximize the weighted-average Sustainability Rating of the portfolio

For the first two objectives, we leverage the Morningstar Risk Model and use the following equations for risk and return:

- $Risk \ = WCovW^T + WDW^T$
- $Return\ E(R_w) \ = WE\mu E^T W^T$

Where:

- W is an $1 \times n$ weight matrix of n investments
- Cov is the covariance matrix of the returns of n investment assets calculated using the covariance of the factors of our risk model
- X is an $n \times k$ matrix of n investments' exposure to k risk factors
- F is a $k \times k$ factor covariance matrix of k risk factors
- D is an $n \times n$ idiosyncratic risk matrix of n investments
- E is a $n \times k$ risk factor exposure matrix of n investments to k risk factors
- μ is a $k \times 1$ factor premia matrix of k risk factors

More information on how the risk model can be found in the Morningstar Global Risk Model section in the Appendix.

For the third objective, we calculate the weighted average portfolio Sustainability Rating. For instance, if the portfolio consists of two funds, one with a Sustainability Rating of 4 globes and a weight of 60% and another with a rating of 3 globes and 40% weight in the portfolio, this will result in the weighted average rating of 3.6 globes.

As this is a multi-objective problem, we need to specify a relative preference between the three use cases. Accordingly, we plan to run multiple variants across the US and European fund universes with a diverse focus on ESG inclusion in portfolio optimization.

We performed optimization on the first business day of every quarter beginning Jan. 1, 2019, on two fund universes—the U.S. and Europe. As such, our analysis period extends from Jan. 1, 2019, to June 30, 2021. As there was a change in methodology around Sustainability Ratings in early 2019, we have performed our analysis after that time. The following section now looks at implementation in more detail for the U.S. and European regions.

Case Study 1: A Strategy for US Open-End Funds and ETFs

Universe Criteria

- Only U.S.-domiciled open-end funds and ETFs are eligible.
- For each fund, only the primary class is eligible. This is determined based on the oldest share class that is active at the time of rebalance.
- The share class should have managed assets of at least $10 million.
- The base currency of the fund should be in U.S. dollars.
- The Morningstar Category should be one among large growth, large blend, large value, mid-cap growth, mid-cap blend, mid-cap value, small growth, small blend, and small value.

Investment Constraints

- The weighted average Morningstar Medalist rating for the portfolio should be greater than 3.5.
- The overall expense ratio of the portfolio should be less than 75 basis points.
- The total weight for each style—value, blend, and growth—should not exceed 50%.
- The total weight of large-cap funds should be between 60% and 85%.
- The total weight of mid-cap funds should not exceed 30%.
- The total weight of small-cap funds should not exceed 30%.
- The maximum allocation to a single fund should not exceed 20%.

Benchmark

The benchmark Index for the U.S. use case is the S&P 500.

Rebalancing

Quarterly rebalancing with first portfolio on Jan. 1, 2019, and last rebalance on June 30, 2021.

After the above filters are applied, we create six major portfolio variants with various Investor Preferences for risk, return, and ESG as defined in the "Approaches to ESG-Driven Portfolio Optimization" section of the paper. As mentioned, we take a multi-objective optimization approach that lets us define relative preferences among the various objectives. These preferences are used to identify a unique portfolio that best suits investor preferences. Accordingly, the objective function definitions of the various approaches are as follows:

Portfolio Variant 1: ESG Agnostic

The relative preferences for Objectives 1 (return) and 2 (risk) are 50% each, with 0% for Objective 3 (Sustainability Rating).

Portfolio Variant 2: ESG Unaware

The relative preferences for Objectives 1 (return) and 2 (risk) are 50% each, with 0% for Objective 3 (Sustainability Rating).

Portfolio Variant 3: ESG Aware Integration

The relative preferences for Objectives 1 (return) and 2 (risk) are 20% each, with a 60% weight for Objective 3 (Sustainability Rating).

Portfolio Variant 4: ESG Intentional

The relative preference to Sustainability Rating in the objective function of the optimization is kept at 0 to isolate the effect of universe screening. This case is reflective of focus on the risk/return characteristics in the optimization of a sustainable universe.

The relative preferences for Objectives 1 (return) and 2 (risk) are 50% each, with 0% for Objective 3 (Sustainability Rating).

Portfolio Variant 5: ESG Intentional and Low Climate Impact

The relative preferences for Objectives 1 (return) and 2 (risk) are 50% each, with 0% for Objective 3 (Sustainability Rating).

Portfolio Variant 6: ESG Motivated

The relative preferences for Objectives 1 (return) and 2 (risk) are 20% each, with a 60% weight for Objective 3 (Sustainability Rating).

Now, we will try to determine the outcomes of these preferences on holdings, portfolio attributes, and performance back-testing.

This was the Morningstar Category exposure of the portfolios as of the last rebalance in June 2021.

Holdings Analysis

Exhibit 10 Portfolio Distribution Across Categories, U.S.

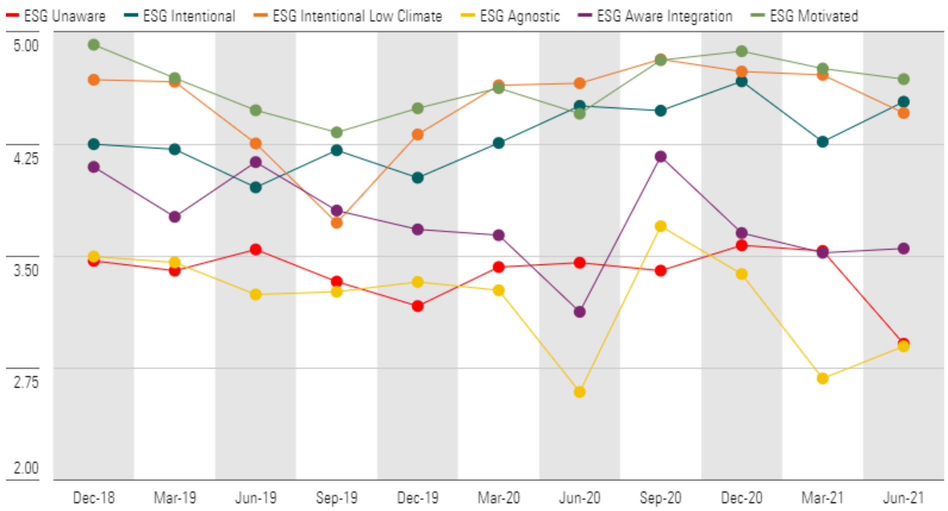
Category Weights	ESG Unaware	ESG Intentional	ESG Intentional Low Climate	ESG Agnostic	ESG Aware Integration	ESG Motivated
Large Blend	25.4%	41.8%	43.7%	29.9%	18.7%	31.2%
Large Growth	17.2%	23.8%	26.7%	26.3%	22.3%	32.2%
Large Value	32.2%	14.6%	18.1%	12.7%	33.8%	14.4%
Mid-Cap Blend	17.1%	1.2%	1.8%	5.0%	8.8%	18.5%
Mid-Cap Growth	3.1%	11.7%	9.5%	0.6%	9.7%	3.6%
Mid-Cap Value	1.0%	0.3%	0.2%	0.8%	1.3%	0.1%
Small Blend	1.1%	5.9%	0.0%	4.3%	1.0%	0.0%
Small Growth	2.5%	0.4%	0.0%	17.3%	4.1%	0.0%
Small Value	0.5%	0.3%	0.0%	3.0%	0.4%	0.0%

Source: Morningstar.

Large-cap categories seem to be getting the maximum exposure in all the cases, while small-cap categories get the lowest. This is because only a very few mid- and small-cap funds in our selected universe pass the ESG screens. Since there are no such filters in ESG Unaware and ESG Agnostic cases, we do get some exposure to small-cap categories. Within the ESG-tilted strategies, we see substantially higher allocations to large-cap categories potentially driving the return and risk. As a general trend within our selected universe, we see that including an ESG metric shifts the portfolio away from small caps.

Portfolio Attributes

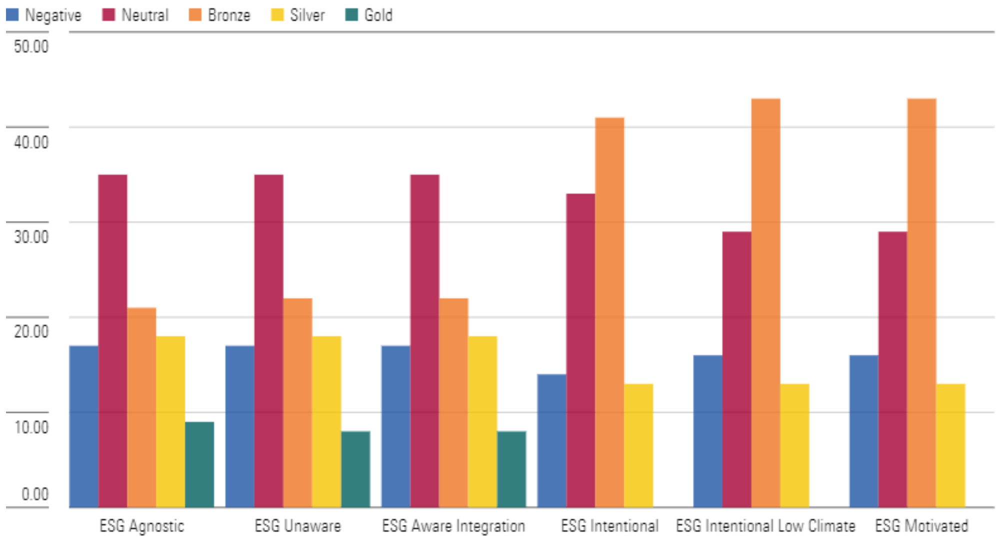
Exhibit 11 Sustainability Ratings for Variants Across Time, U.S.



Source: Morningstar.

As shown in Exhibit 11, the ESG Motivated strategy has the highest sustainability scores, followed by ESG Intentional and Low Climate Impact for most periods. The ESG Agnostic and ESG Unaware strategies have the lowest sustainability scores indicative of possible detrimental impact on environment, climate change, and other ESG factors. These findings are in line with expectations as we would expect the globe ratings exposure of ESG-tilted strategies to be higher than those tilted against it. Not just that, given upcoming regulations around ESG we might see negative investor outcomes, as is discussed in the next sections.

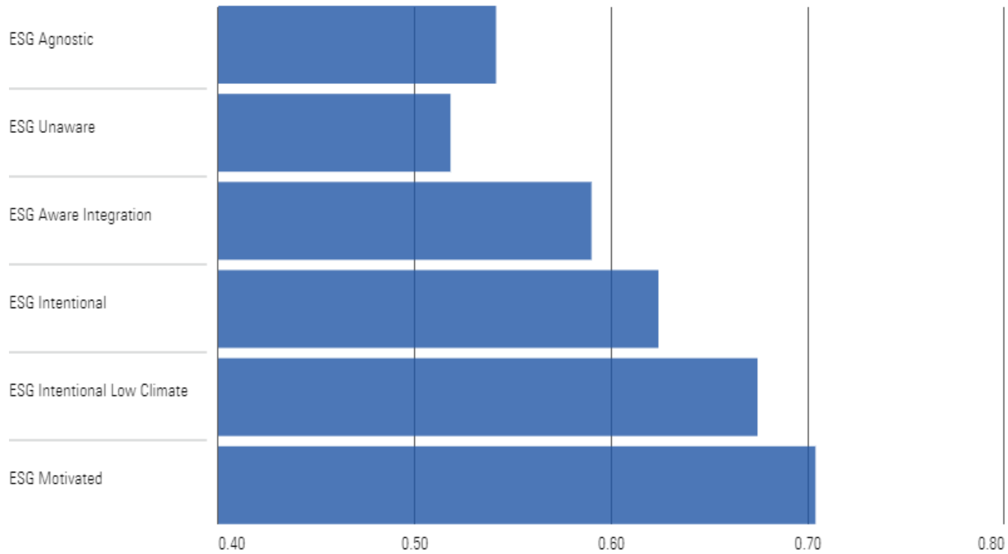
Exhibit 12 Funds' Medalist Ratings Across Variants, U.S.



Source: Morningstar.

Exhibit 12 illustrates that the strategies where we do not screen for ESG (ESG Unaware and ESG Agnostic) seem to have a somewhat higher percentage of funds with Gold and Silver ratings and the lowest expense ratios. ESG Motivated has the lowest percentage of Gold rated funds in the universe and the highest expense ratio among all the strategies. The higher medalist rating is most likely explained by the fact that there are few funds that have both a high medalist rating, and a high Sustainability Rating, as shown in Exhibits 8 and 9. When we apply further ESG filters on the universe, we can therefore expect to have a lower overall medalist rating. The percentage of funds rated Bronze or lower increases as we incline our portfolio toward ESG incorporation.

Exhibit 13 Weighted Average Expense Ratio Across Variants, U.S.



Source: Morningstar.

Performance Analysis

To understand how the different variants performed over our analysis period, we looked at the standard measures of risk and return.

Exhibit 14 Performance Summary, U.S.

Strategy	ESG Agnostic	ESG Aware Integration	ESG Intentional	ESG Intentional Low Climate	ESG Motivated	ESG Unaware	Benchmark
Start	31-12-2018	31-12-2018	31-12-2018	31-12-2018	31-12-2018	31-12-2018	31-12-2018
End	30-06-2021	30-06-2021	30-06-2021	30-06-2021	30-06-2021	30-06-2021	30-06-2021
CAGR	22.45	22.01	26.02	25.4	25.85	23.37	24.98
Monthly Volatility	18.85	18.42	18.23	17.05	16.94	18.69	17.61
Return/Risk	1.19	1.2	1.43	1.49	1.53	1.25	1.42
Max Drawdown	-36.35	-35.36	-34.89	-33.28	-33.25	-35.69	-33.93
Active Return (%)	-2.53	-2.97	1.04	0.42	0.87	-1.61	0

Source: Morningstar.

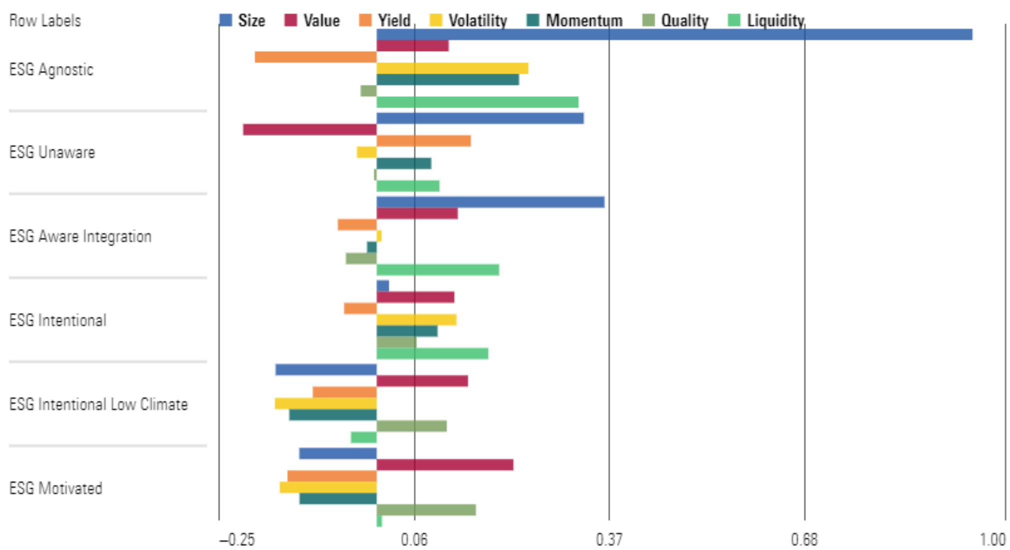
As can be seen in back-testing outcome, the non-ESG strategies lag most other variants and the benchmark in terms of compound annual growth rate and return/risk ratio. Not only that, but they also have the highest drawdown among all the variants considered. The best-performing strategies are ESG Motivated and ESG Intentional, where we observe a higher return/risk ratio, a lower risk (volatility), and good returns.

However, it is evident any kind of ESG screening on the initial universe leads to better investor outcomes in terms of the metrics mentioned compared with integrating in the objective (ESG Aware Integration).

Factor Attribution

Style Analysis

Exhibit 15 Factor Attribution, U.S.



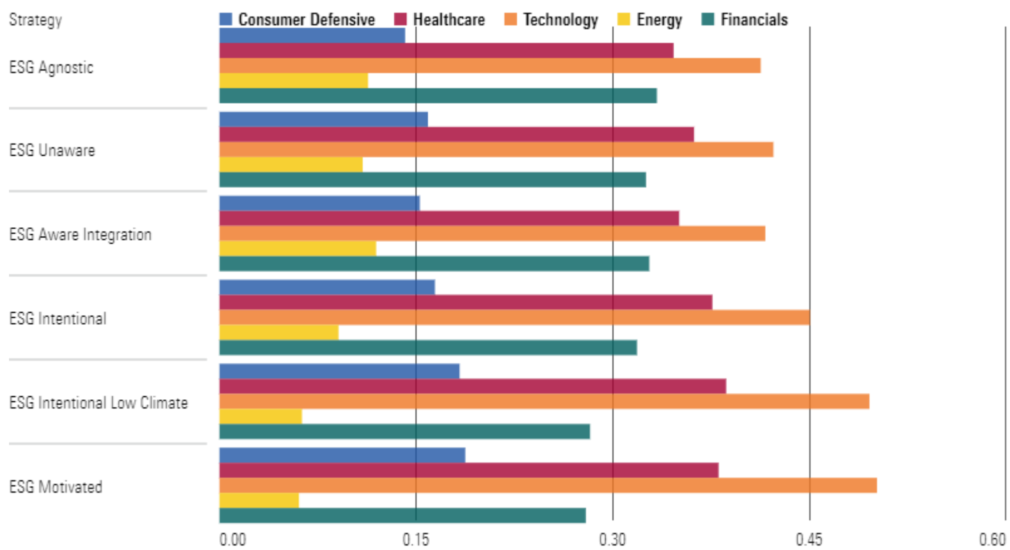
Source: Morningstar.

The exhibit shows that ESG strategies in the U.S. universe are strongly tilted toward value and quality, with a net negative exposure to size (which implies that ESG portfolios were made up mostly of large-cap funds). The exposure to factors like volatility and momentum is also lower (or negative) for ESG Motivated and ESG Intentional strategies when compared with ESG Agnostic and ESG Unaware.

Sector Analysis

ESG-tilted strategies have a relatively higher exposure to the technology sector. The exposure of such strategies to energy and financial sectors is low when compared to ESG Unaware or ESG Agnostic strategies. The rest of the sectors fail to show any clear trends across strategies and are therefore not shown here.

Exhibit 16 Sector Attribution, U.S.



Source: Morningstar.

Case Study 2: A Strategy for European Open-End Funds and ETFs

The case study setup for the European universe is defined below:

- Only open-end funds and exchange-traded funds are eligible.
- For each fund, only the primary class is eligible. This eligibility is determined based on the oldest share class that is active at the time of rebalance.
- The share class should have managed assets of at least EUR 10 million.
- The base currency of the fund should be euro.

The Morningstar Category should be one of Europe large-cap blend, eurozone large-cap, Europe flex-cap, Europe large-cap growth, eurozone flex-cap, Europe small-cap, eurozone small-cap, Europe large-cap value, Europe ex-UK, Europe ex-UK small/mid-cap.

Investment Constraints

- The weighted average Morningstar Medalist Rating for funds should be greater than 3.
- The overall expense ratio of the portfolio should be less than 80 basis points.
- The total weight for each style—value, blend, and growth—should not exceed 40%.
- The maximum weight of a fund will be 20%

Benchmark

The benchmark Index for this case study is the Morningstar Europe Index.

Rebalancing
Quarterly rebalancing with first portfolio on Jan. 1, 2019, and last rebalance on June 30, 2021.

After the above filters are applied, we create six major portfolio variants with various Investor Preferences for risk, return, and ESG as defined in the "Approaches to ESG-Driven Portfolio Optimization" section of the paper. As mentioned, we take a multi-objective optimization approach that lets us define relative preferences among the various objectives. These preferences are used to identify a unique portfolio that best suits investor preferences. Accordingly, the objective function definitions of the various approaches are as follows:

Portfolio Variant 1: ESG Agnostic
The relative preferences for Objectives 1 (return) and 2 (risk) are 50% each, with 0% for Objective 3 (Sustainability Rating).

Portfolio Variant 2: ESG Unaware
The relative preferences for Objectives 1 (return) and 2 (risk) are 50% each, with 0% for Objective 3 (Sustainability Rating).

Portfolio Variant 3: ESG Aware Integration
The relative preferences for Objectives 1 (return) and 2 (risk) are 20% each, with a 60% weight for Objective 3 (Sustainability Rating).

Portfolio Variant 4: ESG Intentional
The relative preference to Sustainability Ratings in the objective function of the optimization is kept at 0 to isolate the effect of universe screening. This case is reflective of focus on the risk-return characteristics in optimization of a sustainable universe.

The relative preferences for Objectives 1 (return) and 2 (risk) are 50% each, with 0% for Objective 3 (Sustainability Rating).

Portfolio Variant 5: ESG Intentional and Low Climate Impact
The relative preferences for Objectives 1 (return) and 2 (risk) are 50% each, with 0% for Objective 3 (Sustainability Rating).

Portfolio Variant 6: ESG Motivated
The relative preferences for Objectives 1 (return) and 2 (risk) are 20% each, with a 60% weight for Objective 3 (Sustainability Rating).

Now we will try to determine the outcomes of these preferences on Holdings, Portfolio Attributes & Performance back testing.

Holdings Analysis

This was the category exposure of the portfolios as of the last rebalance in June 2021.

Exhibit 17 Portfolio Distribution Across Categories, Europe

Category Weights	ESG Unaware	ESG Intentional	ESG Intentional Low Climate	ESG Agnostic	ESG Aware Integration	ESG Motivated
Europe Large Blend	32.3%	39.3%	27.2%	28.8%	22.9%	31.0%
Eurozone Large-Cap	28.6%	31.9%	33.6%	34.9%	37.8%	36.9%
Eurozone Flex-Cap	14.0%	0.4%	0.9%	15.2%	14.3%	1.6%
Europe Large Growth	10.2%	20.4%	8.9%	5.2%	1.7%	16.7%
Eurozone Small-Cap	6.9%	0.0%	0.0%	0.3%	0.5%	0.0%
Europe Large Value	4.3%	0.7%	0.0%	2.6%	1.6%	0.0%
Europe ex-UK	2.2%	0.7%		3.1%	9.0%	
Europe Flex-Cap	0.9%	6.3%	28.7%	2.6%	2.2%	12.5%
Europe Small-Cap	0.4%	0.4%	0.4%	6.1%	1.5%	1.2%
Europe ex-UK Small/Mid	0.3%	0.0%	0.2%	1.1%	8.5%	0.0%

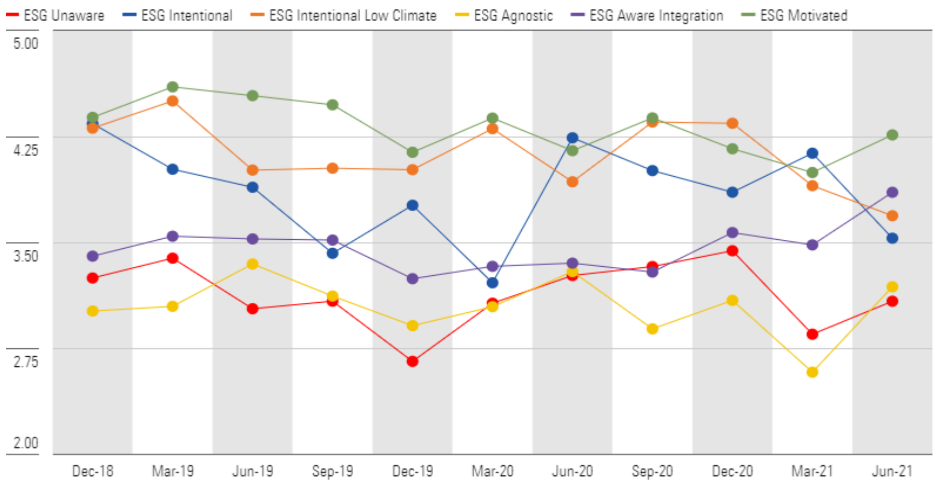
Source: Morningstar.

The large-cap and flex-cap categories seem to be getting the maximum exposure in all the cases, while mid/small-cap gets the lowest. Much like the U.S. universe, very few mid and small-cap funds pass the ESG screens (Sustainable Investment Overall and Low Carbon Designation). Since there are no such filters in ESG Unaware, ESG Aware Integration, and ESG Agnostic, we do get some exposure to mid and small-cap categories there. Having said that, large-cap funds appear to clearly dominate the final portfolios across the board.

Portfolio Attributes

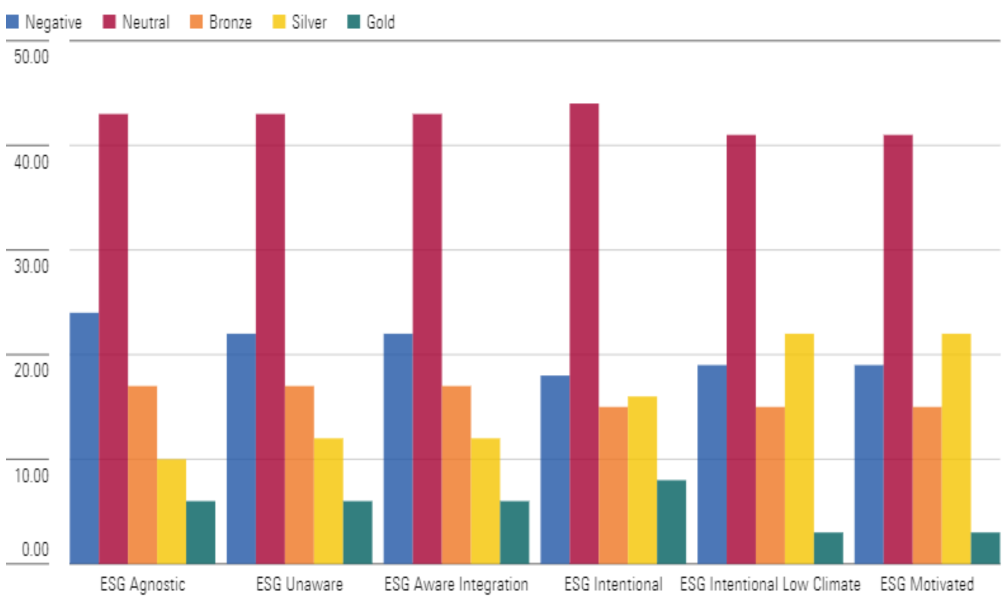
Like the US outcomes, Exhibit 18 shows that ESG Motivated has the highest sustainability scores, followed closely by ESG Intentional Low Climate Impact for most periods. ESG Unaware and ESG Agnostic have the lowest sustainability scores, indicative of possible detrimental impact on the environment, climate change, among other ESG factors. Not just that, given upcoming regulations around ESG, we might see negative investor outcomes.

Exhibit 18 Sustainability Ratings for Variants Across Time, Europe



Source: Morningstar.

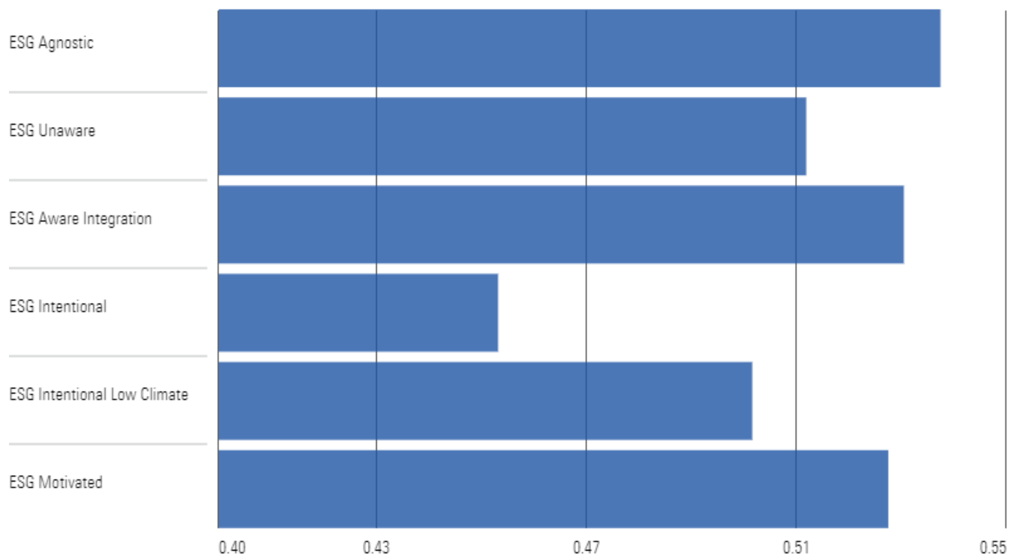
Exhibit 19 Percentage of Funds Against Medalist Ratings Across Variants, Europe



Source: Morningstar.

Comparing other portfolio attributes, we observe that unlike the U.S., European ESG Unaware and ESG Agnostic strategies have a lower percentage of funds with Silver ratings, although a slightly higher percentage of Gold-rated funds compared with ESG Motivated and ESG Intentional strategies. In terms of the expense ratio, we see that compared with the U.S. universe, there is a lack of a clear trend among variants.

Exhibit 20 Weighted Average Expense Ratio Across Variants, Europe



Source: Morningstar.

Performance Analysis

To understand how the different variants performed over our analysis period, we looked at the standard measures of risk and return.

Exhibit 21 Performance Summary, Europe

Case	ESG Agnostic	ESG Aware Integration	ESG Intentional	ESG Intentional Low Climate	ESG Motivated	ESG Unaware	Benchmark
Start	31-12-2018	31-12-2018	31-12-2018	31-12-2018	31-12-2018	31-12-2018	31-12-2018
End	30-06-2021	30-06-2021	30-06-2021	30-06-2021	30-06-2021	30-06-2021	30-06-2021
CAGR	17.01	17.95	21.75	21.53	21.18	17.24	21.42
Monthly Volatility	17.95	17.38	17.79	17.7	17.58	17.61	16.4
Return/Risk	0.95	1.03	1.22	1.22	1.2	0.98	1.31
Max Drawdown	-36.26	-35.47	-35.4	-34.88	-34.84	-35.7	-35.31
Active Return (%)	-4.41	-3.47	0.33	0.11	-0.24	-4.18	0

Source: Morningstar.

For the European universe, we see that all ESG-tilted portfolios generated better returns than others for the period under consideration. The difference, however, is starker here, with a wide difference in performance between the ESG Agnostic (or ESG Unaware) and ESG Motivated strategies. An ESG

Motivated strategy performs the best. Screening the universe again appears to be a considerably better approach than integration for the inclusion of ESG factors.

Factor Attribution

Style Analysis

The exhibit shows that ESG strategies in the European universe are positively tilted to value, quality, and liquidity, with a strong net negative exposure to Size (which again implies that ESG portfolios were made up mostly of large-cap funds). The exposure to volatility and momentum is again negative for ESG Motivated and ESG Intentional strategies when compared with ESG Agnostic or ESG Unaware strategies.

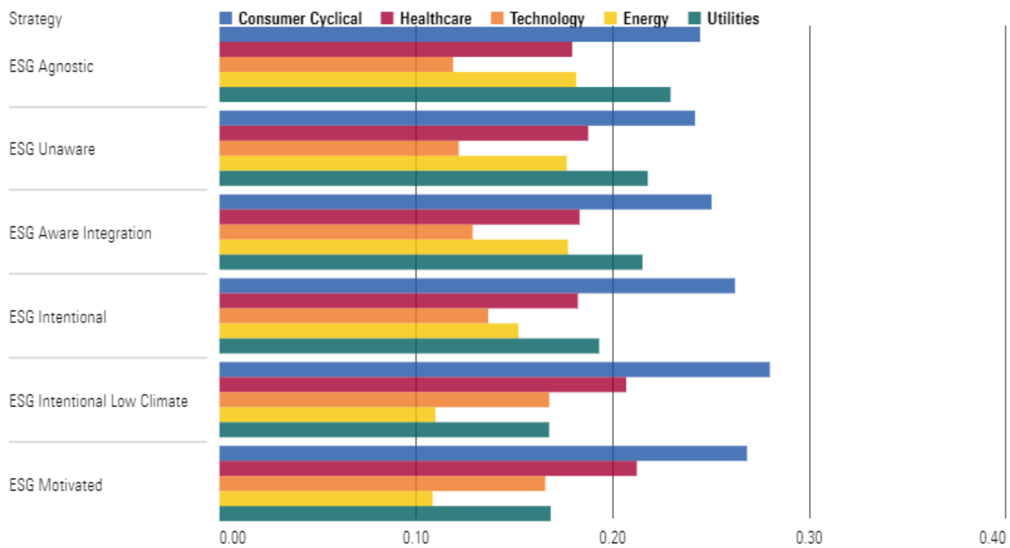
Exhibit 22 Factor Attribution, Europe

Source: Morningstar.

Sector Analysis

For ESG-tilted strategies, the portfolio has a relatively higher exposure to the healthcare, technology, and consumer defensive sectors, along with lower exposures to energy and financials. The rest of the sectors fail to show any clear trends across strategies and are therefore not shown here.

Exhibit 23 Sector Attribution, Europe



Source: Morningstar.

Comparison of U.S. and European Strategy Outcomes on the Representative Universe

The U.S. and European case studies may not be fully comparable because of differences in data availability across the two regions. Nonetheless, they are the broadest form of equity universe comparison on which ESG investment approaches have been evaluated.

ESG Unaware and ESG Agnostic strategies have similar performances in terms of all the metrics evaluated. They have lower returns and higher risk for the period and universe under consideration with a larger allocation to the size factor (small-cap fund categories) and the energy and utilities sectors. They also, generally, have the highest medalist ratings, lowest Sustainability Ratings, and the lowest expense ratios among the cohort of variants considered here.

ESG Motivated and ESG Intentional Low Climate strategies lie on the other end of the spectrum with higher returns, lower risk, a higher allocation to the technology sector, and higher exposures to value factor and large-cap funds. They generally have the lowest medalist ratings but the highest Sustainability Ratings along with somewhat higher expense ratios.

ESG Intentional and ESG Aware Integration lie somewhere in between with average performance metrics. Portfolio attributes like medalist ratings, expense ratios, Sustainability Ratings, and other allocations lie somewhere in between the two extremes discussed above.

Accordingly, the key insights that we can draw from comparing them are:

1. In both universes, screening for ESG attributes help get a better exposure to ESG factors than simply incorporating them in the optimization objective. Integrating after screening expectedly gives the best ESG exposure.
2. The ESG strategies (ESG Motivated, ESG Intentional, ESG Intentional Low Climate Impact, ESG Aware Integration) seem to have a higher exposure to the large-cap categories for the US region. In comparison, while large cap categories do get the maximum exposure there is also some exposure to flex-cap categories in European markets.
3. Different strategies on the spectrum of ESG preferences—each with a unique degree of tilt toward ESG incorporation—have unique characteristics.
4. On one hand, the characteristics of ESG Intentional Low Climate strategy are close to those of ESG Motivated. On the other hand, the performance and characteristics of ESG Aware Integration are closer to ESG Unaware than to ESG Motivated. This indicated that screening for ESG attributes does a better job at tilting the portfolio toward ESG than simply integrating it in the portfolio construction process.
5. Style factor attribution shows that ESG strategies generally have higher exposure to the quality and value factors, and a net negative exposure to the size and volatility factors. Sector attribution indicates an overall tilt toward technology and healthcare sectors and lower exposure to energy.
6. ESG Agnostic and ESG Unaware strategies are usually tilted strongly toward the size factor.
7. The ESG strategies have a higher sustainability score compared with non-ESG strategies. This is indicative of higher positive regulatory, social, and environmental outcomes for investors over the long run.
8. Expected volatility decreases and the Sharpe ratio increases when a low climate impact filter is introduced along with sustainability filter as in the ESG Intentional Low Climate case. On the other hand, it increases the net expense ratio of the optimized portfolio,
9. Investors in US and Europe can expect to pay a premium in form of expense ratios for ESG-tilted portfolios.
10. Lastly, a higher investor preference for ESG Integration leads to better sustainability scores without compromising on other portfolio metrics like risk and returns.

Conclusion and Next Steps

This paper touches on multiple aspects of portfolio optimization with a focus on incorporating investor preferences for ESG investment approaches. On one end, we saw how the Morningstar Portfolio Optimizer helps us incorporate various ESG investment approaches like screening and integration for portfolio construction. On the other end, we touched on the robust capabilities of the Morningstar Portfolio Optimizer, which include the Multi Objective Optimizer alongside diverse universe filtering and constraint applications. In addition, it allows for the inclusion of a variety of Morningstar proprietary data points with robust back-testing and attribution analysis. This would allow a lot of power in the hands of advisors and asset managers for improving investor outcomes with inclusion of all Morningstar research within one engine. While this paper focuses on return, risk, and ESG utilities, there is a whole set of emerging utilities around factor and thematic exposures that the optimizer can support. We will probably delve into these additional cases in the next series of papers.

We saw that ESG-focused strategies help improve sustainability outcomes when evaluated in a representative US and European fund universe while balancing performance attributes. The outperformance is stronger (higher active return and sustainability scores) in Europe than in US for our selected fund universe. We would next like to evaluate ESG investment approaches on emerging-markets universes. We also saw that ESG-focused strategies may command a higher premium in form of expense ratios from investors. The above case studies demonstrate that the Portfolio Optimization Engine puts a lot of power in the hands of decision-makers to test and evaluate multiple ESG investment approaches on diverse universes. While this paper focuses only on a couple of ESG data points, we could incorporate other ESG attributes around product involvement, controversy scores, and so on, when evaluating investor outcomes. ESG Commitment Level and SFDR are new areas of research and as coverage improves, we will incorporate them as well in the portfolio optimization process. The optimizer framework is flexible across various asset classes, and hence we can demonstrate ESG strategy performance on the fixed-income and allocation asset classes in the next series of papers.

Appendix

Morningstar Global Risk Model

To construct a portfolio that maximizes or minimizes investor utility, it is important to have a holistic view of risk that can assist in making investment decisions tailored to individual risk preferences. A robust risk model is therefore necessary to analyze and forecast the risk of the portfolio. The Morningstar Global Risk Model seeks to provide investment managers with the tools to create portfolios consistent with their risk preferences. The important features of the Morningstar Global Risk Model are:

- Decomposition of risk into proprietary fundamental-based factors that we consider to be superior drivers of returns.
- The model has the capacity to analyze risks across a range of horizons.
- Our model captures higher co-movements of returns such as skewness and kurtosis, enabling our optimizer to build portfolios with a range of diverse objectives such as the CARA (constant absolute risk aversion) utility.

Morningstar identifies 36 risk factors that are classified into four groups: style, sector, region, and currency. Factor exposures are transformed so that the distribution is approximately normal with a mean of 0 and a standard deviation of 1. Here are the important outputs of the Morningstar Global Risk Model required to solve the optimization problem:

- **Factor Covariance Matrix:** It is a short-term risk forecast that describes the trade-offs between each common factor in the model.
- **Risk Factor Exposure:** This is essentially the exposure of investments to different risk factors considered in the model.
- **Idiosyncratic Risk:** This refers to an investment's specific risk that is independent of an asset's exposure to risk factors.
- **Factor Premia**: This is the average return of one additional unit of exposure to a single risk factor once all other risk factors have been considered.

Once we have the above matrices, we can define our covariance matrix for n investment assets as:

$$Cov \ = XFX^T + D$$

Where:

- X is an $n \times k$ matrix of n investments' exposure to k risk factors
- F is a $k \times k$ factor covariance matrix of k risk factors
- D is an $n \times n$ idiosyncratic risk matrix of n investments

In addition, the risk and return of a portfolio can be determined as:

- $Risk \ = WCovW^T$
- $Return\ E(R_w) \ = WE\mu E^T W^T$

Where:

- W is an $1 \times n$ weight matrix of n investments
- E is a $n \times k$ risk factor exposure matrix of n investments to k risk factors
- μ is a $k \times 1$ factor premia matrix of k risk factors

Formulating the Optimization Problem

The goal of a typical optimization problem is to either maximize or minimize the utility function in accordance with the set of constraints imposed depending on the nature of the problem.

These problems can be represented mathematically as:

$$Minimize\ Z\ = [f_1(w), f_2(\mathrm{w}), \dots, f_m(\mathrm{w})]^T$$

The optimization solver searches for values of decision variables $w_1, w_2, \dots, w_n$ subject to:

$$g_i(w)\ \geq\ 0, i = 1, \dots, m$$
$$h_j(w)\ =\ 0, j = 1, \dots, p$$
$$w =\ w_1, w_2, \dots, w_n \in S$$

Where:

- Z is a set of m objective functions to be minimized over the feasible region S
- $g_i \geq 0$ are a set of inequality constraints
- $h_j = 0$ are a set of equality constraints
- w is a weights vector $w_1, w_2, \dots, w_n$ of n investments in the universe
- $w_1, w_2, \dots, w_n$ are decision variables
- S is the feasible region that satisfies all constraints

It is important to note that a maximization problem can be converted into a minimization problem by inverting the sign of the function f such that: $Maximize\ f(w) =\ -Minimize\ (-f(w))$.

Classification of Optimization Problems

Every optimization problem requires an optimization solver to find a feasible solution that provides the smallest (largest) possible value of optimization function for a minimization (maximization) problem. These solvers require us to first classify the problem in either of the following:

- **Linear Programming:** If the objective function and all constraints as either linear or piecewise linear functions, the problem is a linear programming (LP) problem.
- **Quadratic Programming:** If the objective function is quadratic, and all constraints are either linear or piecewise linear, the problem is referred to as a quadratic programming (QP) problem. Convex quadratic programming problems are a special form of a QP problem.
- **Quadratically Constrained Programming**: If the constraints are quadratic functions, we may classify a problem as a quadratically constrained programming (QCP) problem.
- **Nonlinear Programming**: A problem in which one or more than functions are nonlinear is referred to as a nonlinear programming (NLP) problem. Both QP and QCP are special forms of NLP problems.
- **Mixed Integer Programming:** Generally, most optimization problems have decision variables that are assumed to be continuous values. However, if any decision variable must assume only integer values, we consider such problems to be mixed integer programming (MIP) problems.

Solving an Optimization Problem

Expected Return and Mean-Variance Optimization

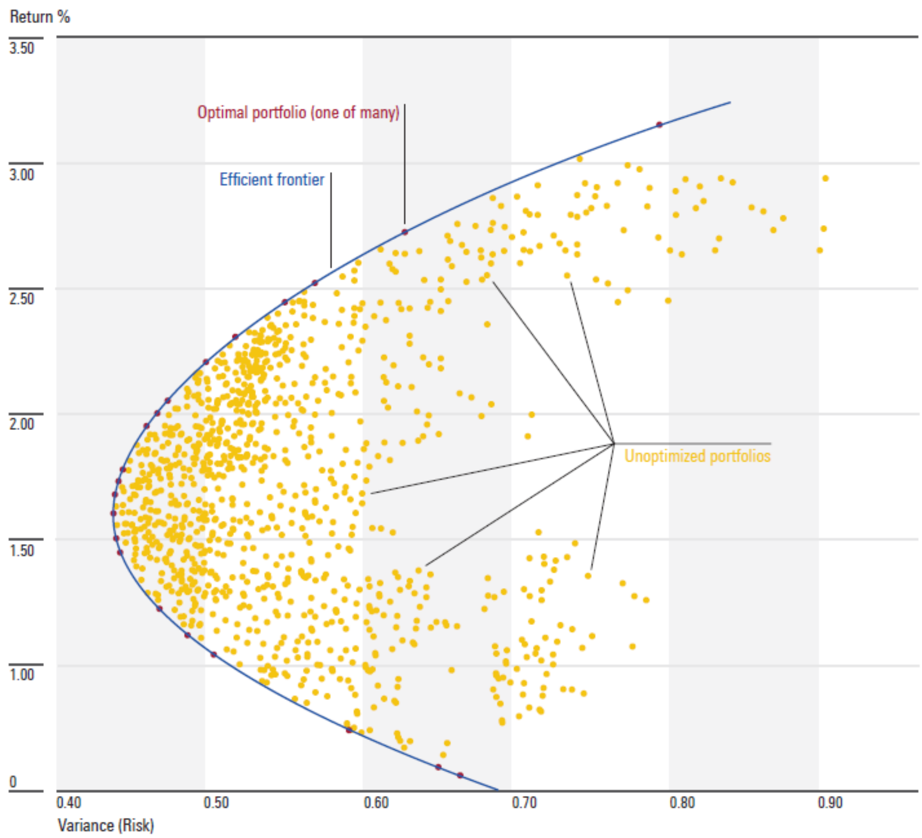
Modern Portfolio Theory establishes that it is possible to construct an efficient frontier of optimal portfolios that have the highest returns for a given level of risk. The following two statements are central to Modern Portfolio Theory:

- Investors are risk averse, that is, the goal of the investor is to maximize the returns for a given level of risk.
- Risk can be reduced by creating a diversified portfolio of unrelated assets.

In a typical mean-variance optimization problem, one would strive to minimize the variance term while maximizing the expected return based on the factor exposure and premia. The variance assumes the form of a convex quadratic function represented as a positive semidefinite covariance matrix, as shown in the section **Morningstar Global Risk Model**. Additionally, the investment constraints we include in the problem are generally linear or piecewise linear, making our problem a convex quadratic programming problem.

With these things in mind, one can create an efficient frontier, where every point on this curve is better than any point that lies below it. One can choose an optimal portfolio that is located on this frontier according to their risk and return preferences.

Exhibit 24 Efficient Frontier for a Mean-Variance Optimization Problem



Determining the Optimal Solution—A Multi-Objective Optimization Approach
This section describes the method we use to determine the optimal solution based according to the relative preferences defined by the user.

As we mentioned earlier, we intend to find solutions for three objectives, which makes our problem a multi-objective optimization problem. Since there is no single solution that optimizes every objective simultaneously, multiple objectives in a problem lead to multiple optimal solutions, also known as Pareto-optimal solutions. Here, a solution is Pareto optimal if none of the objective functions can be improved without degrading at least one of the other objective values. Traditionally, multi-objective optimization problems were converted to a single objective optimization problem, so that only one Pareto-optimal solution is found at a time when a simulation is run. If one were to use such a method for finding multiple solutions, one may have to run multiple simulations to create an efficient frontier.

In the past two decades, several multi-objective evolutionary algorithms have been proposed that can provide multiple Pareto-optimal solutions in a single simulation run. In our case, we leverage the Nondominated Sorting Genetic Algorithm (NSGA-II) to provide us our efficient frontier with three dimensions—risk, return, and ESG risk. Once we get all the non-dominated solutions, we select one of the portfolios based on how we want to balance our priorities. For a minimization problem, we find the solution by following the below steps:

- We normalize the values of each objective function by calculating their z-scores. This is done separately for each objective function
- We assign weights to each objective function such that the weights add up to one. These weights represent the relative preferences for each objective function
- $\sum w_j = 1$
    - Where: w_j determines the weight assigned to the objective function
- We find the resultant score for each Pareto-optimal solution using the below formula.

$$F_i = \sum_{i,j} w_j Norm(Obj_{i,j})$$

Where:

- F_i is the combined score of all objective functions
- w_j determines the weight assigned to the objective function
- Obj_j is the i[th] Pareto-optimal solution for the objective function j and $Norm$ denotes the normalization function

- We aim to find the minimum value of F. The values of decision variables (the weight vector) for this solution are considered the optimal solution

It is important to note that the above method is one way to choose a solution out of different methods. Users may wish to explore alternative methods that match their preferences.

Objective Functions

The below section describes some of the objective functions that can be used in the Morningstar Portfolio Optimizer. Each of these functions follows the terms given in section **Formulating the Optimization Problem**.

- **Mean-Variance Optimization**

  Mean-variance optimization involves allocating weights to assets based on the trade-offs between risk, expressed as variance, and return. Investors weigh how much risk they are willing to take on in exchange for different levels of reward. As such, these problems can be divided into two variants:

    - **Maximize Expected Return**

      In this case, the investor intends to maximize the expected return(R_w) for a given value of variance ${\sigma_0}^2$. We use the outputs of our Risk Model to determine expected risk and variance. Thus, we choose a portfolio with weights $\boldsymbol{w}$ by formulating the problem as shown below.

$$Maximize: \quad E(R_w) = \boldsymbol{w}'\boldsymbol{\alpha}$$
$$Subject\ to: \quad \boldsymbol{w}'\mathrm{Cov}\boldsymbol{w} \leq {\sigma_0}^2$$
$$\boldsymbol{w}'\boldsymbol{1_n} = \boldsymbol{1}$$

Here, the first constraint indicates that the portfolio variance should be less than, or equal to, the target variance, whereas the second constraint refers to a 'Fully Invested' portfolio. One may include additional constraints as shown in the section **Constraints Functions** in **Appendix**.

- **Minimize Risk**
  Here, the investor intends to minimize the expected risk (σ^2) for a given value of return (R_{w0}). Thus, we choose a portfolio with weights $\boldsymbol{w}$ by formulating the problem as shown below.

$$\begin{gathered} Minimize\text{:}\ \ \boldsymbol{w}'\mathrm{Cov}\boldsymbol{w} \\ Subject\ to\text{:}\quad \boldsymbol{w}'\ \boldsymbol{\alpha} \geq R_{w0} \\ \boldsymbol{w}'\mathbf{1}_{\boldsymbol{n}}\ =\ \mathbf{1} \end{gathered}$$

- **Tracking Error/Active Risk**
  Tracking error, or active risk, quantifies the risk of the portfolio in relation to its benchmark. It is a measure of divergence, measures by standard deviation, between the returns of a portfolio with those of the benchmark. If $\boldsymbol{w_b}$ denotes the weight vector of the benchmark portfolio, the Tracking Error objective function can be written as:

$$min\ Z = (w - w_b)Cov(w - w_b)^T$$

Constraint Functions

- **Fully Invested**
  This constraint ensures that the sum of all weights allocated to different assets must be equal to 1, or 100%. Mathematically, if $\mathbf{1}$ is a vector of ones, one can represent the condition as:

$$\boldsymbol{w}^{\boldsymbol{T}}\mathbf{1} = \mathbf{1}$$

- **Long-Only Portfolio**
  This constraint is added to ensure that no shorting is allowed in the portfolio. Mathematically, if $\mathbf{I}$ is a $N\ x\ N$ identity matrix, we will represent this constraint as:

$$\mathbf{Iw} \geq \mathbf{0}$$

- **Minimum Target Return**
  The portfolio return must be higher than a target level of return α_{min}. We use the Morningstar Risk Model to calculate the expected return. This constraint can be represented as:

$$\mathbf{w}^{\boldsymbol{T}}\boldsymbol{E}(\mathbf{R}) \geq \alpha_{\min}$$

- **Minimum/Maximum Total Risk**
  The portfolio volatility should be between some target level σ_{min} and σ_{max}:

$$\sigma_{min} \leq \mathbf{w}^{\mathbf{T}}\mathbf{Covw} \leq \sigma_{max}$$

- **Minimum/Maximum Active Risk**

  Active risk refers to the risk of a portfolio in relation to the benchmark. As such, we first determine the risk of the benchmark using the formula $\mathbf{w^T Cov w}$. Next, we define the maximum threshold of tracking error $\sigma_{a,max}$, beyond which the portfolio tracking error should not pass.

$$(w - w_b)Cov(w - w_b)^T \leq \sigma_{a,max}^2$$

- **Minimum/Maximum weights on certain stocks/group of stocks/sector**

  The maximum and minimum weights allocated to any sector or stock can be restricted by an upper and a lower bound. These lead to simple linear constraints.

- **Fixed 'K' Investments**

  Investor wants to choose a fixed number of investments (K). The optimizer engine identifies the fixed K investments for the investor by minimizing the objective function.

  We can pick the best 'K' investments by iteratively trimming the optimal portfolio using the following steps:

  11. Select the top $K + N$ stocks.
  12. Perform the optimization again with an extra constraint that limits the feasible solution to the selected $K + N$ stocks
  13. Iterate by shrinking N at each iteration until only K stocks are left in the portfolio

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Morningstar Quantitative Research is dedicated to developing innovative statistical models and data points, including the Morningstar Quantitative Rating, the Quantitative Equity Ratings, and the Global Risk Model.

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