REVISTA DE ADMINISTRAÇÃO DA UFSM
Brazilian Journal of Management
ReA UFSM
UFSM
ISSN 1983-4659
OPEN ACCESS

Rev. Adm. UFSM, Santa Maria, v. 17, n. 3, e2, 2024 https://doi.org/10.5902/1983465985183
Submitted: 09/24/2023 • Approved: 07/04/2024 • Published: 07/25/2024

Original Article

ESG integration strategy with a multivariate normal distribution

Estratégia de integração ESG com uma distribuição normal multivariada

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ABSTRACT

Purpose: The paper aims to present a new framework for ESG integration strategies in portfolio optimization problems. The optimization in the new structure focuses on the portfolio level, and the procedure is not focused on utility functions or on preliminary weights applied to the asset level. It applies the resampling technique, and all the portfolios are optimal portfolios in the mean-variance space. It uses a filtering process where only optimal portfolios with lower ESG risks are considered. Therefore, this technique works only with optimized portfolios, avoids concentration bias, and considers estimation errors in the expected returns and in the covariance matrix.

Design/methodology/approach: The sample mean returns and covariance matrices generated by a multivariate normal distribution are applied in mean-variance optimization to generate several portfolios in the efficient frontiers. An ESG filtering process is used to select portfolios with lower ESG risks from a sample of 42 companies listed on the Brazilian stock exchange with returns from the period of 2018/01/01 to 2024/04/22.

Findings: Integration strategy costs may be lower than the best-in-class strategy costs and may be similar to the costs of a negative screening strategy.

Social implications: The paper presents a framework that considers social, environmental, and governance factors in the portfolio optimization process.

Originality: The main contribution of this paper is to present a new framework that combines resampling of returns' mean and covariance based on a multivariate normal distribution with an ESG portfolio filtering process.

Keywords: ESG integration; ESG portfolio optimization[I]

I The authors would like to thank PIBIC/UFBA, and Professors W. Brent Lindquist and Zari Rachev for valuable comments on the paper presented at a seminar sponsored by the Department of Mathematical Finance at Texas Tech University.

RESUMO

Finalidade: Este artigo apresenta uma abordagem para a estratégia de integração ESG no problema da otimização usando a técnica de reamostragem. A abordagem não utiliza funções de utilidade ou pesos preliminares no nível do ativo, focando nas carteiras. As carteiras são ótimas no espaço de média-variância, para cada amostra de retornos esperados e matriz de covariância. No processo de filtragem, são selecionadas as carteiras com menor risco ESG. Essa técnica trabalha somente com carteiras otimizadas, evita o viés de concentração (poucos ativos na carteira) e considera erros de estimativa nos retornos esperados e na matriz de covariância.

Desenho/metodologia/abordagem: As amostras de retornos médios e matrizes de covariância geradas por uma distribuição normal multivariada são aplicadas na otimização média-variância para gerar várias carteiras nas fronteiras eficientes. É utilizado um processo de filtragem ESG para selecionar carteiras com menores riscos ESG de uma amostra com 42 empresas listadas na B3 com retornos no período de 2018/01/01 a 2023/12/31.

Constatações: Os custos da estratégia de integração podem ser inferiores aos custos da estratégia "best-in-class" e podem ser semelhantes aos custos de uma estratégia de "negative screening", dependendo dos parâmetros de ambas as estratégias.

Implicações sociais: O artigo apresenta uma abordagem que considera fatores sociais, ambientais e de governança no processo de otimização de carteiras.

Originalidade: A principal contribuição deste artigo é a apresentação de uma nova abordagem que combina a reamostragem da média e covariância dos retornos com base numa distribuição normal multivariada com um processo de filtragem de carteiras ESG.

Palavras chaves: Integração ESG; otimização ESG de carteiras

1 INTRODUCTION

Climate change and the commitments that nations are making to reduce carbon emissions—mitigating global warming and environmental impacts—have driven efforts to create investment portfolios with assets that are aligned with environmental responsibility. Investors are increasingly seeking companies with strong non-financial factors such as environmental, social, and corporate governance (ESG) scores (Bollen, 2007; Gutsche and Ziegler, 2019; Fan and Michalski, 2020), also known as ESG factors. The Principles for Responsible Investments (PRI) considers that institutional investors have a duty to act in the best long-term interests of their beneficiaries and that ESG issues can affect the performance of investment portfolios (PRI, 2023).

The modern portfolio theory is an additional tool that helps investors in the complex activity of selecting portfolios for a specific risk aversion and time horizon. It has evolved since the work of portfolio optimization published by Markowitz (1952) and the work of asset pricing from Sharpe (1964). Both works deal with the investment problem based on the financial risk and return relationship. In Markowitz's work, the solution of portfolio optimization problem leads to the well-known efficient frontier, as the result of finding portfolios that maximize returns for a range of financial risk levels. Finding the optimal portfolios, i.e., the efficient frontier, is a traditional quadratic programming task.

The inclusion of ESG objectives in the portfolio selection makes the strategic asset allocation (SAA) decision making more complex, since the investor needs to pursue an additional objective; thus, changing the task from a risk-return optimization to a multi-criteria decision-making problem. The complexity will depend on the ESG strategy and it will also depend on the technique that is chosen to find the optimal portfolios.

Among ESG investments strategies are the negative screening (removing companies from the portfolio), positive screening (best-in-class selection), ESG integration (adding ESG factors to the investment objectives), active ownership (corporate engagement), and impact investing (specific sectors and projects investments).

The Corporate Sustainability Index from the Brazilian Stock Exchange B3 (ISE B3) was the fourth sustainability index created in the world—in 2005—to support investors in their decision-making and to induce companies to adopt the best sustainability practices, since ESG practices contribute to business continuity. Companies holding the 200 most liquid shares of B3 are invited to participate in an objective criterion as eligible candidates. Created in 2010, the B3 Carbon Efficient Index (ICO2 B3) has the purpose of being an instrument to induce discussions about climate change in Brazil, since a companies' adherence to the ICO2 demonstrates their commitment to the transparency of their emissions and shows how they are preparing for a low-carbon economy. Both indices are used to guide investors in best-in-class strategy.

The negative screening needs a criterion to exclude from the investment universe those companies that do not meet a specific objective. For example, companies in the oil sector could be excluded from the investment universe.

There are many strategies to consider ESG in the strategic asset allocation. The integration strategy has different frameworks for the optimization process. Many procedures modify the utility function including an ESG dimension or they include weights in the asset level to consider ESG factors. These procedures are not intuitive because they need a mapping function of ESG to returns, weights and/or risks. Therefore, these procedures deal with suboptimal portfolios for a given mean-variance input. They do not consider errors in expected returns and variance and they do not deal with the concentration problem of the Markowitz approach. It means that an optimization for a given level of ESG risk will lead to portfolios that may concentrate investments in few assets, a feature of the Markowitz optimization.

The research problem is: how to include ESG factors in the integration strategy for portfolio optimization using a resampling technique? The assumption behind this research is that it is possible to calibrate the procedure to have ex-ante portfolios that are better or equal to other ESG strategies like negative screening and best-in-class selection.

Our aim is to present a framework for ESG integration strategy with the objective of helping investors to include ESG integration in portfolio optimization problem. This study discusses the consequences of the ESG integration in the construction of portfolios using Brazilian stocks and the Sustainalytics' ESG Risk Ratings. Furthermore, this work presents a comparison between ESG integration, best-in-class and negative screening strategies for Brazilian stocks and it is an important contribution for managers that deal in local markets from emerging economies where the number of assets available for portfolio selection is lower compared to the number of assets available for global portfolio managers and therefore the strategic asset allocation has lower degrees of freedom.

In the resampling technique combined with the mean-variance optimization here, all the portfolios are optimal portfolios in the mean-variance space, for each sample of expected returns and covariance matrix. The framework uses a filtering process and only optimal portfolios for samples with lower ESG risks are considered. This technique works only with optimized portfolios, avoids concentration bias (a small number of stocks) and it considers estimation errors in the expected returns and in the covariance matrix.

This paper is organized as follows: firstly, we will review the literature and discuss the effects of ESG integration in the optimization problem; then, we will present the methodology that incorporates Sustainalytics' ESG Risk Ratings in the portfolio selection based on a resampling approach, which will be followed by a discussion of the results; and finally, we will conclude by highlighting the main issues of our investigation.

2 LITERATURE REVIEW

This section discusses three issues in the literature that are related to strategic asset allocation considering ESG factors. First, there is the issue of excluding some assets from the investment universe, concentrating investments in specific assets that have better ESG evaluation or building strategies that target specific ESG criteria. Second, there is the issue of the risk-return relationship of ESG strategies. Finally, investors have to choose between optimization strategies.

2.1 Strategies of considering ESG factors in the SAA

There are many different strategies when considering the ESG criteria for strategic asset allocation. When portfolio managers started to incorporate ESG factors in their investments, the most common strategy was the negative screening. In this strategy a portfolio manager can choose not to invest in companies that are considered not aligned to ESG factors, like businesses considered morally or ethically wrong or companies known for their pollution.

Negative screening adds non-financial constraints in the portfolio optimization process. Henriques and Sadorsky (2018) worked with a negative screening strategy by divesting from fossil fuels. They concluded by saying that it is possible to divest from fossil fuels and utilities and achieve a higher risk-adjusted return by including clean energy. Indeed, divesting from fossil fuels is a natural decision to align to the Paris Accord.

Another ESG strategy is the best-in-class selection, focusing on including rather than excluding companies. A best-in-class process might consider ESG factors in identifying best ESG companies for investment, creating what might be called a positive screening (Gary, 2019). Lauria et al. (2022) presented a discussion where investors prefer to reward firms who display overall positive social policies rather than exclude the less responsible through negative screening.

There is also the impact investing strategy, in which the investor intentionally seeks both a financial return and a specific environmental or social result. An impact investor may want to address a local problem or encourage innovation to help solve an identified social or environmental issue. Another strategy is active ownership, in which the investor's intentions is to engage in the company's ESG decisions.

Finally, there is the ESG integration strategy that can be described as an investment strategy that combines material ESG factors with traditional financial metrics to analyze companies. In this paper we will present the ESG integration strategy and compare it with the best-in-class and negative screening strategies.

2.2 Ex-ante or Ex-post evaluation of ESG strategies

Socially responsible investing (SRI) has long been perceived as an ex-ante costly investment style, since it constrains the investment universe. Indeed, this practice was essentially based on the exclusion of industries that do not satisfy some social or environmental norms, which may sometimes perform better than others over time (Alessandrini and Jondeau, 2020). There is no consensus about whether this constrained strategy results in worse ex-post risk-adjusted returns (actual returns and covariance matrix). In fact, many studies indicate the opposite, that considering ESG into portfolio building can lead to equal or better risk-adjusted returns.

Alessandrini and Jondeau (2020) found that in the 2007–2018 period, applying an ESG screening to an otherwise passive portfolio improved the portfolio ESG scores and resulted in unchanged or improved Sharpe ratios. They also propose an investment strategy that maximizes the ESG quality of the portfolio while maintaining regional, sectoral, and risk factor exposures within stated limits. They provided evidence that such a portfolio would have produced a risk-adjusted performance at least as high as the standard MSCI benchmark for a wide range of ESG criteria and regions over the 2007–2018 investment period.

On the other hand, Schmidt (2020) worked with an expanded mean variance portfolio theory to accommodate investors' preferences for the portfolio ESG value (PESGV). He found that higher PESGVs yield more concentrated portfolios and lower Sharpe ratios.

Souza et al. (2018) found that companies that joined the ICO2 (index from Brazilian stock exchange) did not show higher stock returns compared to the group of companies that did not join the ICO2, but showed lower sensitivity to market risk than the group of companies that did not join the index. In addition, an analysis focused only on the companies that participated in the index did not show a change in behavior in the returns and sensitivity to market risk of the shares of this group of companies after they joined the index compared to the period before they joined the initiative. The results therefore suggest that companies that are less sensitive to market risk are more likely to join the ICO2 and that does not necessarily imply higher financial returns.

Utz et al. (2013) compared the performance of conventional (or unscreened) mutual funds to ESG mutual funds, or screened portfolios in general. They found that conventional mutual funds tend to have a higher portfolio return volatility. Furthermore, they also found that ESG investors do not have to accept significantly higher risk, despite their screening process leading to fewer opportunities for diversification and a smaller feasible region in decision space.

Gary (2019) indicates that studies comparing ESG funds and non-ESG funds have found mostly positive or neutral results for the ESG funds. According to her work, the few studies that show negative results for ESG funds focus on negative screening; although two meta studies concluded that funds using negative screening are more likely to show neutral rather than negative or positive performance when compared to non-ESG benchmarks. Furthermore, in some cases, ESG funds have outperformed or underperformed based on market conditions.

Jin (2022) argues that ESG integration to portfolio optimization can enhance the portfolio's ESG quality and improve the portfolio's risk-adjusted return during the out-of-sample period. He uses a double-index model for portfolio optimization and shows that this strategy can help investors analyze how the systematic ESG risk is relevant to future risks or returns.

Cao and Wirjanto (2023) discuss approaches to incorporate ESG factors into a portfolio optimization. The authors find that thematic investing (investment approach that focuses in trends in the long run) appears to be the best performer, which raises issues related to the comparison with best-in-class, integration strategy and negative screening. In addition, the authors also found that there is no evidence that ESG portfolios underperform the market.

Looking at the evaluation of the risk-return relationship in the above literature, the papers of Alessandrini and Jondeau (2020) and Gary (2019), Jin (2022) and Cao and Wirjanto (2023) have conclusions that are neutral or more ESG favorable compared to the traditional approach for investments. The work of Souza et al. (2018) is more neutral regarding the risk and return relationship of the ESG investments, compared to the traditional approach. The papers of Schmidt (2020) and Utz et al. (2013) are neutral but they recognize the constraints of ESG strategies in the mean-variance approach.

It is possible to conclude that there is no consensus on ESG impact in the ex-post risk-adjusted returns and investors choose ex-ante ESG strategies in SAA decision-making because they believe they will have better risk-adjusted returns in the future and/or they want to adhere to initiatives towards ESG investing to align to others objectives. Indeed, investors may believe that incorporating ESG in ex-ante analysis may anticipate a better portfolio risk adjusted return in the future, despite an ex-ante cost in the portfolio optimization when an additional constraint is incorporated.

2.3 Considering ESG factors in the optimization

Adding a new objective to the traditional mean-variance approach is one of the many ESG approaches to SAA. Gasser et al. (2017) proposed a modification on Markowitz' Portfolio Selection Theory, allowing to incorporate not only asset-specific return and risk but also a social responsibility measure into the investment decision-making process. They applied the model to a set of over 6,231 international stocks and found that investors opting to maximize the social impact of their investments face a statistically significant decrease in expected returns. However, their social responsibility/risk-optimal portfolio yields a statistically significant higher social responsibility rating than the return/risk-optimal portfolio.

The literature presents some approaches to the ESG integration strategy. The mean-variance method combined with some multi-criteria decision-making approach is indeed a possible course of action. The mean variance approach analyzes the risk-return relationship; and for a specific level of risk, the portfolio manager seeks assets that maximizes return. If investors introduce an additional objective to the portfolio, i.e., an ESG objective, it will affect the investment financial performance, since the new objective will modify the investors' utility function. The work of Lundstrom and Svensson (2014), for instance, discusses portfolio selection as a trade-off between return, risk, and ESG factors. Zuber (2017) uses a Black Litterman based method and considers a structure that imposes on the covariance matrix some quantitative ESG criteria, working as input to a common mean-variance optimizer.

Fan and Michalski (2020) used a different approach for portfolio construction in which the allocations consider the ESG concerns and factors such as quality, low volatility, momentum, size, and value. The integration approach keeps long positions in assets with higher quality (return on equity – ROE), low volatility, better past performance (momentum), low capitalization, and prices considered undervalued, relative to their fundamental value. The authors argue that they can integrate ESG with the investment strategy and aggregate value to investors in the long run.

Calvo, Ivorra, and Liern (2015) used a fuzzy optimization model that provides a chance of finding satisfactory portfolios. The procedure is simple enough to be mathematically tractable by exact or heuristic rules. The authors discuss the strategy of fixing portfolio ESG requirements as constraints for the optimization problem. They assume that investors are not only concerned with the financial goals, but are also willing to favor socially responsible investments, if the financial cost of this strategy stays within a boundary. The first step of the Calvo, Ivorra, and Liern (2015) procedure is to define the universe of possible assets, the minimum and maximum buy-in threshold for convention and non-convention assets, the required expected return (based on the efficient frontier), the corresponding accepted risk, the degree of wiliness to favor ESG assets, and the level of tolerance for non-efficient portfolios. This first step allows for the implementation of an approach based on fuzzy logic. The approach also needs a utility function that depends on the social responsibility (SR) degree defined by the investor.

Fan and Michalski (2020) used three different methods for incorporating ESG factors on their work. In the first one, they performed a non-ESG screening, in which non-ESG rated firms within their sample were excluded. In the second one, they first arranged each factor using their sample. Subsequently, within the long and short quartiles of each factor, they eliminate non-ESG rated stocks. On the third method, they first perform a non-ESG screen by excluding non-ESG rated firms from their sample. Subsequently, they generate a new sorting variable for each stock in the remaining sample, by combining the ESG score and one factor signal. The combined signal is formed by assigning a 50/50 weight between the factor signal and the ESG score. This last procedure is designed to capture both the factor signal and the ESG rating simultaneously. This allows them to consider any possible interaction effects, which are otherwise omitted.

Nagy, Cogan, and Sinnreich (2013) use three strategies that implement an ESG tilt of the MSCI World Index, based on the IVA scores of underlying portfolio holdings. The first strategy is called an "ESG worst-in-class exclusion" approach. It is based on excluding the companies with the current lowest ratings, which results in a narrower investment universe. The second strategy is called a "simple ESG tilt" approach. In this one, they did not exclude any stocks based on their ESG ratings. Rather, they overweight stocks with high current ESG ratings and underweight those with low current ratings, while maintaining other exposures of the portfolio very close to the benchmark's exposures. The third strategy is called an "ESG momentum" approach, in which they did not exclude any stocks based on their ESG ratings. Instead, they overweight stocks that have improved their ESG ratings during the preceding 12 months over the time series, and underweight stocks that have decreased their ESG ratings over the same period.

Alessandrini and Jondeau (2020) used an approach to evaluate their portfolios simultaneously regarding financial performance and ESG profile. They computed a so-called efficiency measure, which combines financial performance through the excess return per unit of risk (Sharpe ratio) with ESG quality, through the ESG score per unit of risk (ESG ratio).

Chen et al. (2021) present a data envelopment analysis (DEA) approach with quadratic and cubic terms to evaluate the social responsibility performance, which emphasized aspects from environmental, social, and corporate governance attributes. They combine ESG scores with selected financial indicators and proposed a cross-efficiency approach as the fundamental analysis of assets. Then, they build a portfolio optimization model by incorporating risk, return, and social responsibility performance to obtain an SRI portfolio as an investment strategy.

Abate, Basile and Ferrari (2023) estimate and compare the ESG efficient frontiers of an investor who does not apply ESG information and one who does.

The authors calculate the efficient frontier for each ESG rating (an ESG performance of the portfolio) and they have the ESG efficient frontier (one frontier for each ESG portfolio performance), plotted in the Sharpe ratio-ESG rating plane. Cao and Wirjanto (2023) apply a similar approach, since they include in the optimization constraints an ESG performance target that is reduced to only require the ESG performance of the portfolio to be greater or equal to the 75th quantile of the overall ESG performance in the investment pool. The difference between these two approaches is the equality or inequality choice in the optimization procedure. The inequality choice of Cao and Wirjanto (2023) requires searching for a global minimum in the optimization process.

Bolton, Kacperczyk and Samama (2022) discuss a net-zero carbon portfolio alignment approach based on a carbon budget, keeping a low tracking error and small sector-weighted deviations. The approach is based on low-carbon indexes. Cheng, Jondeau and Mojon (2022) focus on portfolios of sovereign bonds and show how investors can build greener portfolios and report the impact of decarbonization changing the weights of the investments in the countries.

The works of Lundstrom and Svensson (2014), Zulber (2017), and Calvo, Ivorra, and Liern (2015) follow the same pattern of using utility functions combined with portfolio optimization. On the other hand, the work of Fan and Michalski (2020), Nagy, Cogan, and Sinnreich (2013), Alessandrini and Jondeau (2020), Bolton, Kacperczyk and Samama (2022), Cheng, Jondeau and Mojon (2022) and Abate, Basile and Ferrari (2023) followed SAA approaches that avoid manipulation of the utility function.

No matter the approach, including ESG issues in the SAA problem raises some challenges in the process. Generally, decision-making in multi-criteria problems require deliberation over the objectives or other forms of prioritization of objective functions. Therefore, investors must subjectively choose the weights for the many objectives before optimizing their portfolios. Also, the investors face the problem of which metrics they will choose to maximize ESG objectives. Furthermore, Bose and Springsteel (2017) report the problems of ambiguous and contingent results, as well as data sufficiency and quality challenges, as obstacles to integrate ESG issues in asset allocation.

Catalano et al. (2024) discuss how ESG ratings should be best included into the Markowitz framework and they conclude this is an open question. Including the ESG score into the returns vector is intrinsically ambiguous. This introduces a conversion law between returns and ESG scores, which is not simple. However, it would be preferable to have a unique framework for incorporating ESG scores into the Markowitz utility function. They define a best ESG portfolio and calculate for each portfolio an ESG distance and they use this distance in the optimization framework.

Based on this literature review, this paper applies a framework for an ESG integration strategy and compares integration with negative screening and best-in-class, an issue presented in section 2.1. The evaluation considers ESG strategies have an ex-ante cost, discussed in section 2.2. The framework in this paper is focused on generating random portfolios based on a resampling technique, and portfolios are filtered based on an ESG criteria. The framework is aligned to the approaches that work on the portfolio level, as the one in Basile and Ferrari (2023), instead of using approaches that choose weights to assets (based on their ESG score or performance) or choose weights to objective functions that include ESG factors, as in Chen et al. (2021) and the approaches based on utility functions that apply weights to assets.

The approach discussed in Abate, Basile and Ferrari (2023), Cao and Wirjanto (2023) and Catalano (2024) focus on ESG in the portfolio level like the approach in this paper discussed in the next section. Looking at the portfolio level is a more intuitive approach than choosing weights to utility functions, as in Svensson (2014), Zulber (2017), and Calvo, Ivorra, and Liern (2015), or tilting weights in assets level, as in Nagy, Cogan, and Sinnreich (2013).

The framework discussed in the next section applies a resampling technique to generate efficient frontiers. The resampling technique works with estimation errors in the expected returns and in the covariance matrix. After applying the resampling technique optimized portfolios are filtered based on their ESG score. The application of the resampling technique allows a different approach in selecting portfolios based on an ESG target.

After generating many efficient frontiers based on a Monte Carlo simulation, the filtering process could be compared to an ESG budget (in fact, an ESG boundary) as in Bolton, Kacperczyk and Samama (2022) when they apply a carbon budget to the portfolio, or it may be compared to Abate, Basile and Ferrari (2023), Cao and Wirjanto (2023) when they apply an ESG target.

The works of Abate, Basile and Ferrari (2023) and Cao and Wirjanto (2023) optimize portfolios applying an ESG target constraint in the optimization process. Therefore, each portfolio is a suboptimal portfolio in the mean-variance optimization. In the resampling technique applied here all the portfolios are optimal in the mean-variance space, for each sample of expected returns and covariance matrix. In the filtering process, only optimal portfolios for some samples are considered (those with lower ESG risks). This technique works only with optimized portfolios, avoids concentration bias (a small number of stocks) and it considers estimation errors in the expected returns and in the covariance matrix.

It is more intuitive to set a maximum level of an ESG score to the portfolio than to work in the level of objective function or in the level of portfolio assets. The combination of resampling technique with portfolio filtering presented here is an integration approach that does not exclude assets from the optimization problem (negative screening and best in class strategies exclude assets from the SAA). The resampling technique with portfolio filtering allows to choose the maximum level of ESG risks in the portfolio level and the investor may evaluate the ex-ante costs of the strategy.

3 METHODOLOGY

The research problem of this work is how to include ESG factors in the integration strategy for portfolio optimization using a resampling technique? The assumption behind this research is that it is possible to calibrate the procedure to have ex-ante portfolios that are better or equal to other ESG strategies like negative screening and best-in-class selection. The resampling technique uses a Multivariate Normal Distribution.

The inputs of the traditional Markowitz portfolio optimization problem are the covariance matrix and the expected returns on investments. In this paper, an additional input was used: the ESG risk rating score provided by the Sustainalytics. The higher the score, the riskier the asset regarding ESG. Sustainalytics is a company that rates the ESG risk (will be referred as ESG score) of listed companies based on their environmental, social, and corporate governance performance.

Solving the return maximization objective for a given level of risk allows building the efficient frontier—a set of optimal portfolios which offers the highest expected returns for the risk levels. A well-known problem from the Markowitz approach is the high probability of presenting portfolios that concentrate all investments in one single stock (or a small number of stocks).

To surpass this problem, Michaud and Michaud's (2007) approach was used, in which data is resampled from the original source of information several times. For each sample, the optimization problem was solved. Then, for a specific risk aversion, the portfolios weights were averaged for all simulations. This procedure avoids Markowitz problem of lack of diversification in optimal portfolios.

To produce random samples, a Monte Carlo simulation was used with a Multivariate Normal Density and Random Deviates routine from the R software. Based on the original expected returns and covariance matrix, this method yields unbiased estimates of new expected returns and covariance matrix, as it generates unbiased samples of returns that follow a Multivariate Normal Distribution. Then, the optimal portfolios were calculated on the efficient frontier for each sample of data and for each risk aversion level. Finally, the compositions were averaged for each risk aversion level.

In the Monte Carlo process, each simulated portfolio has an ESG degree calculated by summing the products of asset weights and asset ESG scores. This procedure allows for the development of a strategy of picking only portfolios with an ESG score (in our case a ESG risk) lower than a boundary defined by investors. To help the portfolio filtering process, the ESG score were normalized.

For the Brazilian stocks' prices, Yahoo Finance was consulted from 2018/01/01 to 2024/04/22. The period was chosen based on the following criteria: recent data, long horizon (more than five years) and maximizing number of assets with available information. Data from the ESG risk rating score were provided by the Sustainalytics website (https://www.sustainalytics.com/esg-rating). Considering data availability of prices and considering that some companies are not listed on Yahoo Finance and some do not have Sustainalytics score, we worked with 42 eligible companies and the criteria for selecting companies to the research was the availability of data for the whole period.

The information regarding companies considered in the ISE and ICO2 were collected in the beginning of the data period. Companies used in this study are presented in the annex of this work and they are from different sectors like financial, insurance, agrobusiness, real state, infrastructure, beverage, mining, oil and gas, logistics, food, chemical, industrial, energy, technology, education, and retail.

4 FRAMEWORK AND RESULTS

The framework for a multi-objective decision making in strategic asset allocation is based on a multivariate normal distribution and on portfolio filtering. We present the framework in the following steps:

- Step 1: Define the set of assets and get historical data.
- Step 2: Get ESG scores for each asset.
- Step 3: Calculate covariance matrix and expected returns.
- Step 4: Generate new time series for the assets with the original covariance matrix and expected returns, using a multivariate distribution (resampling).
- Step 5: Use the new time series from step 4 to portfolio optimization and generate optimal portfolios.

● Step 6: The weights of investments (output from Step 5) are used to calculate portfolios' ESG scores in the efficient frontier.

● Step 7: Repeat Steps 4 to 6 (N times)

● Step 8: Filter portfolios according to an ESG criteria (filtering).

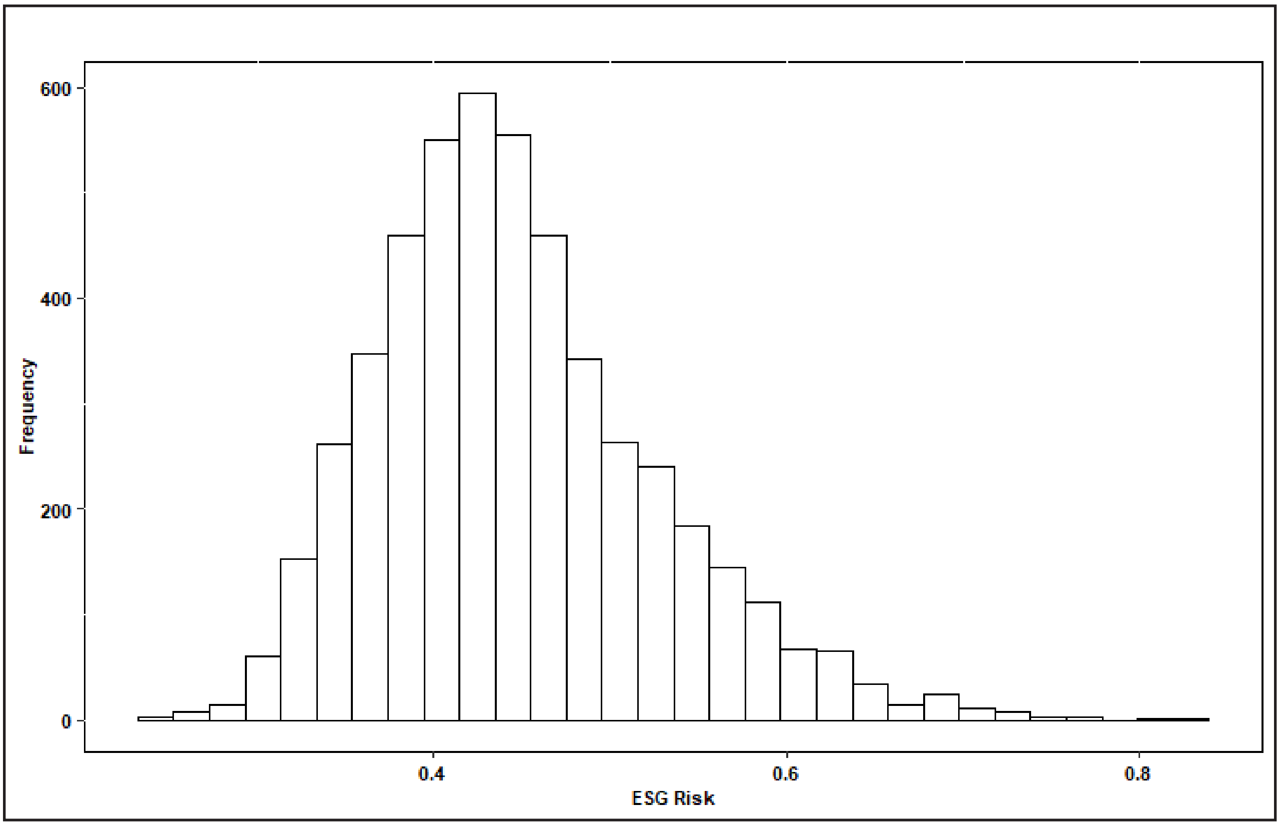
● Step 9: Average weights for each risk aversion parameter and compute the final portfolio in the efficient frontier.

It is important to reinforce the difference of this framework and the works of Abate, Basile and Ferrari (2023) and Cao and Wirjanto (2023) that use a similar approach to calculate portfolios' ESG risks. These two works consider an ESG target constraint in the optimization process. Applying the resampling technique to these two approaches implies that for some samples suboptimal portfolios will be selected and they will be considered in the "Step 9: Average weights for each risk aversion parameter and compute the final portfolio in the efficient frontier". In the approach presented here these samples are not considered in the Step 9, because these portfolios will not appear in the filtering process since the optimization here has no ESG constraint. In the framework here the filtering process is applied after optimizations for all samples.

First, we built the efficient frontier using a multivariate normal distribution in strategic asset allocation traditional approach and without considering any ESG strategy (Steps 1, 3 4, 5, 7 and 9 of the framework). We do not allow short selling and an additional diversification constraint was included so that no asset should have an allocation higher than 15% (MaxAlloc = 15%). Note that Steps 2, 6 and 8 are the relevant steps for incorporating ESG strategy in the decision making.

Several optimized portfolios were generated by applying the resampling approach with the Monte Carlo simulation and a multivariate normal distribution according the suggested framework (Steps 2 to 5 of the framework). As aforementioned, each portfolio has an ESG score calculated by summing the products of asset weights and asset ESG scores. Figure 1 shows the histogram of the ESG score for all generated portfolios and risk averse coefficients. Portfolios with higher ESG scores have higher ESG risks (Steps 5 to 7 of the framework).

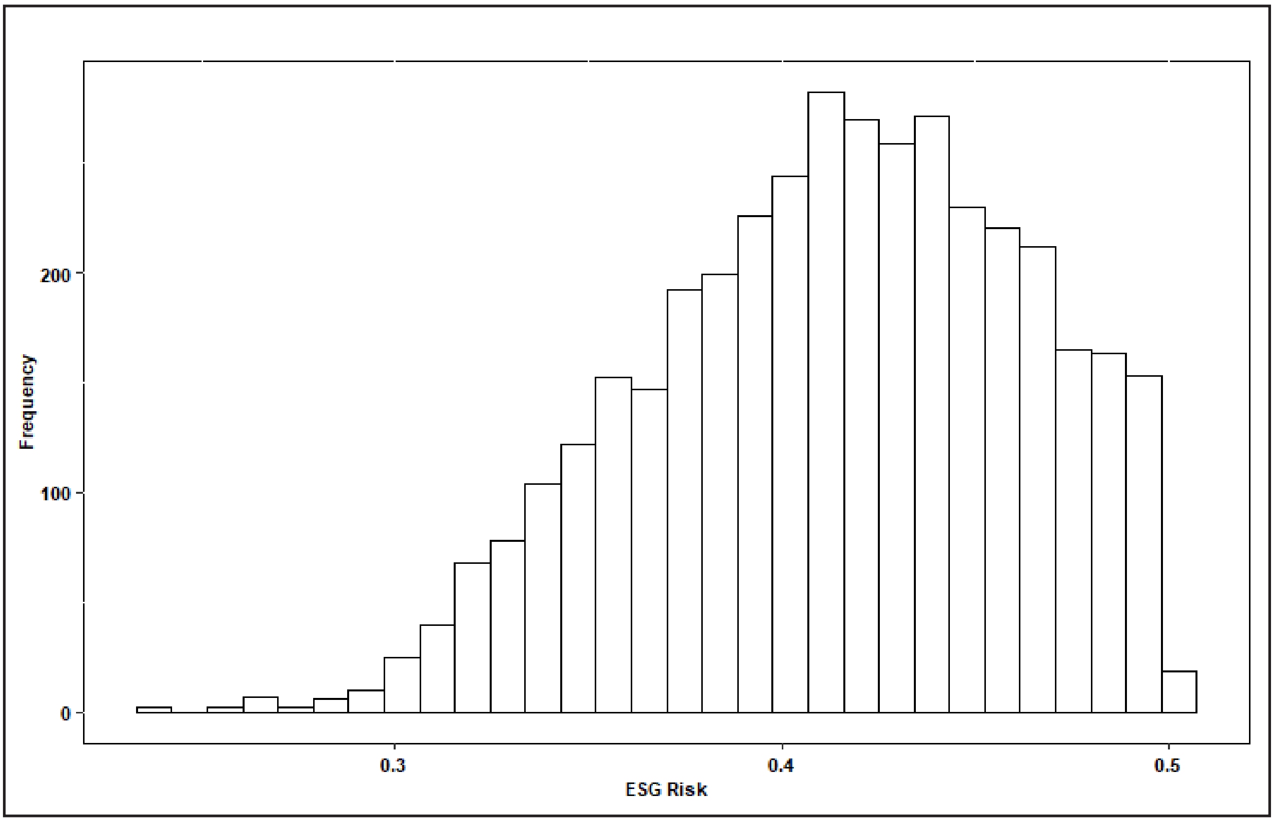
Figure 1 – Histogram of portfolios' ESG scores



Source: Authors

An ESG score boundary of 0.50 (normalized scale 0–1) was applied to select only portfolios with lower ESG risks (Step 8 of the framework). Then, we used Michaud and Michaud (2007) to calculate portfolios' weights by averaging, for each risk aversion coefficient, the final portfolio (Step 9 of the framework). This procedure allows us to have the new efficient frontier after the filtering process, which is the result of integrating ESG strategy to the investment decision making. Figure 2 shows the histogram after the filtering process.

Figure 2 – Histogram of filtered portfolios (MaxScore = 0,5)

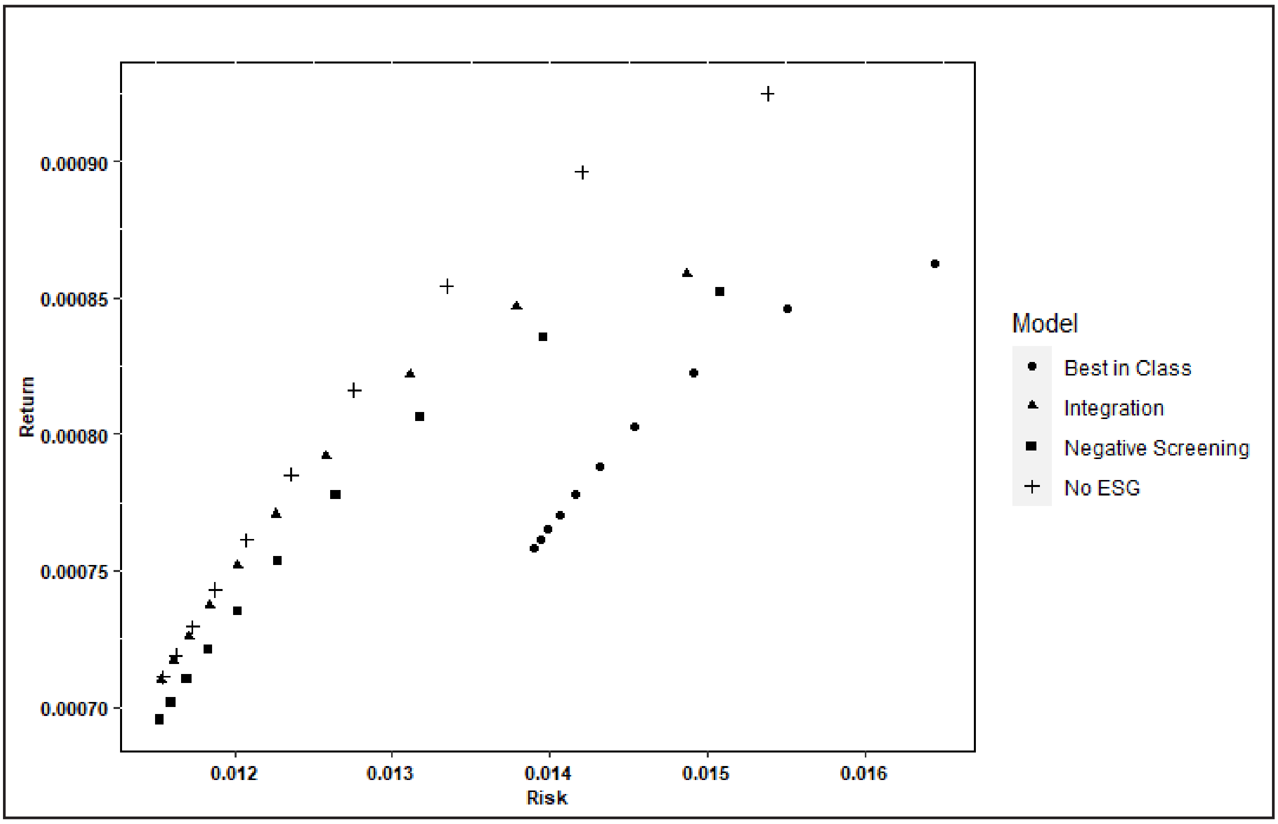


Source: Authors

In the negative screening strategy assets with normalized ESG score higher than 0.95 were not considered in the optimization process. In the best-in-class strategy only assets in the ISE or ICO2 indices were considered in the optimization process. Figure 3 shows the efficient frontier with no ESG strategy, with ESG integration strategy, and with negative screening and best-in-class strategies.

Figure 3 shows that all the three ESG strategies generate ex-ante costs, since they impose additional constraints to the portfolio optimization and, therefore, the efficient frontier is moved to below the frontier without ESG strategy. Therefore, the efficient frontier is moved below the efficient frontier without ESG filtering. The best-in-class approach generates efficient frontiers below the integration and negative screening approaches. It means that with the parameters we set in the simulations the best-in-class approach has an ex-ante higher cost in the optimization process compared to the integration and negative screening approaches.

Figure 3 – Efficient frontiers with and without ESG strategies



Source: Authors

The number of assets used in the no-ESG strategy and in the integration strategy is 42 (the integration strategy does not reduce the number of assets in the optimization process). The number of assets in the best-in-class strategy with ISE+ICO2 indices is 22. The number of assets in the negative-screening strategy is 38 (if we only take assets with ESG score lower than 0.95) or 34 (if we only take assets with ESG score lower than 0.70).

Table 1 shows the average of assets' ESG score in each strategy and the average of assets' ESG score in the no-ESG and integration strategies are the same (0.465), since both strategies have the same assets in the optimization process. Note that the average of assets' ESG score in best-in-class and negative screening strategies are lower, since riskier ESG assets were removed from the set of assets in the optimization process.

Table 1 also shows the average ESG score of portfolios generated by the optimization process in each strategy. The average score of the no-ESG strategy is the highest (0.447). Integration strategy with a filtering parameter equal to 0.5, best-in-class and negative screening with an asset selection parameter of 0.95 give portfolios with similar average of ESG score (0.417, 0.417 and 0.405, respectively). Best-in-class strategy generates an average ESG score of 0.417, but it considers only 22 assets in the optimization process. It is possible to generate less ESG riskier portfolios with integration and negative screening with lower filtering parameter (0.45) in the integration strategy and with lower asset selection parameter (0.70) in the negative screening strategy.

Table 1 – Assets and portfolios ESG scores

	# Assets	Mean Assets	SD Assets	Mean portfolio
No ESG	42	0.465	0.268	0.447
Integration (0.50)	42	0.465	0.268	0.417
Integration (0.45)	42	0.465	0.268	0.395
Best in Class	22	0.403	0.279	0.417
Neg. Screening (0.95)	38	0.411	0.219	0.405
Neg. Screening (0.70)	34	0.370	0.192	0.366

#Assets: number of assets

Source: Authors

The Annex presents portfolios' weights for the three strategies, with a filtering parameter equal to 0.5 for the integration strategy and exclusion of assets that have ESG risk higher than 0.95 in the negative screening strategy. In the negative screening four assets were excluded and they are from the oil, food, and steel sectors. One important thing to highlight looking at the data from the Annex is that the best-in-class is based on assets from indices (ISE and ICO2) and these indices were not built based on the same assumptions used in the ESG score methodology (Sustainalytics).

Even with fewer assets the average ESG score of the 22 assets in the best-in-class strategy is 0.417 and it is higher than the average ESG score of the 34 assets in the negative screening strategy with screening parameter equal to 0.95 or 0.70. It means that there are assets in the best-in-class approach that are ESG riskier (in the Sustainalytics measure) than assets in the negative screening strategy because there are differences in the two methodologies (ISE plus CO2 indices compared to Sustainalytics).

We ran simulations with maximum asset allocation of 20% (MaxAlloc = 20%). We ran the ESG integration strategy using an ESG filter with maximum portfolio ESG score of 0.5 and 0.45 and negative screening strategy with 0.95 and 0.7 parameters. Note that, the boundaries may be set according to one's ESG risk appetite; and the lower the two ESG parameters of the integration and negative screening strategies, the less portfolio ESG risk.

Table 2 presents results of the simulations with two efficiency metrics: a cost efficiency metric and an ESG efficiency metric. These metrics aim only helping us on the discussion about the results and do not have the intention to be a standard for efficiency evaluation. The cost efficiency metric (eCost) represents the ratio between expected returns of the ESG strategy and expected returns of the no-ESG strategy for a given level of risk. The higher the cost efficiency metric, the closer the ESG constrained efficient frontier to the unconstrained ESG efficient frontier. The ESG efficiency metric (eESG) represents the result of one minus the ratio between the ESG scores of the portfolio generated by the ESG and the no-ESG strategies. The higher the ESG efficiency metric, the better ESG resilience of the portfolio.

Simulations 1 and 2 in Table 2 show that changing the maximum portfolio allocation from 0.15 to 0.2 improves cost efficiency, as expected, since the optimization constraint is less restrictive. This result is the same if we compare simulations 3 with 4, 5 with 6 and 7 with 8. The effect of changing the allocation is mixed on ESG efficiency, since the integration and best in class strategies improve ESG efficiency while negative screening has worse ESG resilience when the maximum allocation constraint is changed.

Figure 3 and Table 2 show that best-in-class strategy has lower cost efficiency due to a set of fewer assets in the optimization. It is important to highlight that these results come from an ex-ante analysis.

Depending upon the parameters on the integration and negative screening it is possible to achieve similar or higher ESG efficiency compared to the best-in-class strategy with lower costs. See for example that the comparison of simulations 1-7 shows that with reducing the integration filter from 0.5 to 0.45 generates better ESG efficiency to integration strategy compared to best-in-class strategy. The comparison between simulations 1 and 5 shows that reducing negative screening parameter from 0.95 to 0.7 generates higher ESG efficiency. So, simulations could show that best-in-class strategy may be a dominated strategy by the other two strategies. However, results will depend on the indices chosen by the best-in-class strategy and on the universe of assets (mean and covariance matrix) for the strategic asset allocation exercise.

Looking only to integration and negative screening strategies, simulations 1 and 7 show the tradeoff between ex-ante cost and ESG efficiencies. Simulation 7 has more ESG efficient portfolios. Cost efficiencies for integration strategies are 0.9851 and 0.9712, for simulations 1 and 7, respectively (lower cost efficiency to higher ESG efficiency). Cost efficiencies for negative screening are 0.9619 and 0.9517 respectively (also lower cost efficiency to higher ESG efficiency). The analysis also shows that comparison between integration strategy and negative screening strategy depends on the parameter choice. Therefore, it is not possible to say that one strategy is better than the other.

Table 2 – Simulations' results from ESG strategies

Sim	NS_Filter	INT_Filter	MaxAlloc	eCost_ Int	eCost_ BC	eCost_ NS	eESG_ Int	eESG_ BC	eESG_ NS
1	0.95	0.50	15%	0.9851	0.7903	0.9619	0.0682	0.0677	0.0941
2	0.95	0.50	20%	0.9857	0.8067	0.9687	0.0758	0.0874	0.0893
3	0.95	0.45	15%	0.9712	0.7903	0.9619	0.1160	0.0677	0.0941
4	0.95	0.45	20%	0.9735	0.8067	0.9687	0.1236	0.0874	0.0893
5	0.70	0.50	15%	0.9851	0.7903	0.9517	0.0682	0.0677	0.1811
6	0.70	0.50	20%	0.9857	0.8067	0.9594	0.0758	0.0874	0.1724
7	0.70	0.45	15%	0.9712	0.7903	0.9517	0.1160	0.0677	0.1811
8	0.70	0.45	20%	0.9735	0.8067	0.9594	0.1236	0.0874	0.1724

INT_Filter: maximum ESG filter score for portfolios in the integration strategy. NS_Filter: maximum ESG filter score for assets in the negative screening strategy. MaxAlloc: optimization constraints of maximum asset allocation. eCost: metric used to evaluate distance to the efficient frontier without filtering (value of 1 = no filter and no cost). The lower the eCost, the higher the cost). eESG: relative reduction of the average ESG score (risk) of portfolios in the efficient frontier.
Source: Authors

We compared the three ESG strategies based only on cost efficiency and ESG risk evaluation. The choice of the ESG strategy may consider other aspects like communication to stakeholders. Investors may want to communicate that they are not investing in companies from fossil fuel industry for example (negative screening), or investors may want to communicate that they invest only in assets that comply with a set of ESG requests from an index (best-in-class). The ESG integration strategy discussed here does not necessarily remove assets from the investment universe. It considers that all assets have a level of ESG risk and portfolios are selected based on an ESG risk tolerance defined based on an ESG rating.

Table 3 presents allocations by sectors and as it is expected the best-in-class strategy is less diversified. Negative screening has no allocation in the oil sector and it has lower allocations in the Beverage, Food and Technology sectors when compared to the integration strategy.

Table 3 – Allocations by sectors

Sector	Integration	Best in Class	Neg Screening
Beverage	0.02059	0.00000	0.01685
Financial	0.11319	0.20502	0.12531
Food	0.03475	0.10899	0.00647
Chemical	0.01049	0.02437	0.01194
Logistics	0.01585	0.06434	0.02196
Technology	0.00492	0.01474	0.00384
Energy	0.18830	0.24071	0.19108
Industrial	0.25219	0.26807	0.26407
Retail	0.11735	0.00458	0.12588
Real State	0.00244	0.01310	0.00349
Insurance	0.09209	0.00000	0.09517
Oil&Gas	0.01922	0.05608	0.00000
Chemical	0.01049	0.02437	0.01194
Mining	0.02539	0.00000	0.03077

Source: Authors

The analysis of Table 3 and the annex reveals that the resampling technique indeed minimizes the problem of concentrating allocation. Only the best-in-class strategy has allocation near to the maximum value (15%) and many assets with zero allocation (see the annex). The integration strategy does not have zero allocation in any asset and it also does not have any allocation near to the maximum value.

The framework and the results presented in this section show how to include ESG factors in the integration strategy for portfolio optimization using a resampling technique. The results also shows that it is possible to calibrate the procedure to have ex-ante portfolios that are better or equal to other ESG strategies like negative screening and best-in-class selection.

5 CONCLUSIONS

This paper presents an ESG integration strategy for investments in stocks based on a resampling methodology. We compared three ESG portfolio optimization strategies. The integration strategy is built with an ESG filtering approach based on ESG scores. Portfolios are generated by an optimization process combined with a Monte Carlo simulation using a multivariate normal distribution of returns. The best-in-class approach is based on ISE and ICO2 indices from the Brazilian stock exchange. The negative screening is built on the ESG scores.

In the resampling technique applied here all the portfolios are optimal portfolios in the mean-variance space, for each sample of expected returns and covariance matrix. In the filtering process, only optimal portfolios for some samples are considered (those with lower ESG risks). This technique works only with optimized portfolios, avoids concentration bias (a small number of stocks) and it considers estimation errors in the expected returns and in the covariance matrix.

After applying an ESG filtering strategy to portfolios, we showed that the costs of this integration strategy may be similar or lower when compared to costs of best-in-class and negative screening strategies. Our methodology differs from many presented in the literature, since it is not necessary to optimize portfolios by modifying the utility function or by changing the optimization problem, being the main contribution of this paper.

We showed that the strategies costs depend on the investment process, since constraints choices may affect the efficient frontier.

The choice of the ESG strategy may consider other aspects than only returns and risks like communication to stakeholders. Investors may want to communicate that they are not investing in companies from fossil fuel industry for example (negative screening), or investors may want to communicate that they invest only in assets that comply with a set of ESG requests from an index (best-in-class). The ESG integration strategy discussed here does not necessarily remove assets from the investment universe.

Notably, the costs due to a new ESG constraint in the portfolio optimization is an ex-ante cost. The optimization is based on the inputs of ex-ante returns and covariance matrix. There is no guarantee that the costs will exist in the ex-post evaluation of the portfolios; however, this is a well-known limitation of the investment process, since we cannot say that history will repeat or that we may predict the future.

Another limitation of this research is that it relies on an ESG rating and this measure is sensitive to the rating provider's methodology.

For further studies, we recommend to explore criteria for the choice of boundaries in the ESG filtering process.

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Annex – Portfolio Weights and Assets' ESG scores

Assets	Integration	Best in Class	Neg Screening	ESG score	Sector
ABEV3	0.02059	0.00000	0.01685	0.3204	Beverage
B3SA3	0.00263	0.01740	0.00312	0.1748	Financial
BBAS3	0.00928	0.02649	0.01370	0.4126	Financial
BBDC3	0.00045	0.00167	0.00139	0.3859	Financial
BBSE3	0.08843	0.00000	0.09034	0.3155	Insurance
BPAC11	0.01779	0.00000	0.01780	0.4951	Financial
BRAP4	0.05308	0.00000	0.05750	0.3859	Financial
BRFS3	0.00460	0.01617	0.00647	0.7136	Food
BRKM5	0.00361	0.01089	0.00382	0.4393	Chemical
CCRO3	0.00126	0.00827	0.00262	0.0971	Logistics
CIEL3	0.00492	0.01474	0.00384	0.1626	Technology
CMIG4	0.02638	0.08484	0.03275	0.4563	Energy
COGN3	0.00004	0.00000	0.00030	0.0898	Education
CPFE3	0.07194	0.00000	0.07778	0.5825	Enegy
CRFB3	0.01731	0.00000	0.01893	0.4903	Retail
CSAN3	0.00350	0.00000	0.00318	0.6845	Agrobusiness
EGIE3	0.11423	0.14647	0.10196	0.1845	Energy
ELET3	0.00379	0.00940	0.00664	0.7500	Energy
EMBR3	0.01349	0.00000	0.01670	0.6893	Industrial
EQTL3	0.04390	0.00000	0.04973	0.8155	Energy
GGBR4	0.00544	0.00000	0.00000	0.9806	Siderurgy
GOAU4	0.00196	0.00000	0.00000	0.9806	Siderurgy
HYPE3	0.00896	0.00000	0.01158	0.6990	Retail
IRBR3	0.00366	0.00000	0.00483	0.5170	Insurance
ITSA4	0.01454	0.07402	0.01288	0.1359	Financial
ITUB4	0.00862	0.05661	0.01290	0.4976	Financial
JBSS3	0.03015	0.09282	0.00000	0.9515	Food
KLBN11	0.06923	0.14521	0.07159	0.1408	Industrial
LREN3	0.00070	0.00458	0.00126	0.0995	Retail
MGLU3	0.00268	0.00000	0.00287	0.2840	Retail
MULT3	0.00244	0.01310	0.00349	0.2985	Real State
PCAR3	0.02486	0.00000	0.02289	0.3568	Retail
PETR3	0.01922	0.05608	0.00000	1.0000	Oil&Gas
RADL3	0.06284	0.00000	0.06835	0.3932	Retail
RAIL3	0.00742	0.03765	0.01284	0.5218	Logistics
RENT3	0.00717	0.01842	0.00649	0.0000	Logistics
SANB11	0.00680	0.02883	0.00602	0.3034	Financial
SBSP3	0.02034	0.00000	0.02193	0.5631	Infrastructure
SUZB3	0.11310	0.00000	0.11330	0.2621	Industrial
UGPA3	0.00688	0.01347	0.00812	0.6578	Chemical
VALE3	0.02539	0.00000	0.03077	0.7791	Mining
WEGE3	0.05637	0.12286	0.06248	0.4757	Industrial

Weights for optimal portfolios with INT_Filter=0.5, NS_Filter = 0.95 and intermediary risk aversion

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Contribution	[Author 1]	[Author 2]	[Author 3]
1. Definition of research problem	√	√	√
2. Development of hypotheses or research questions (empirical studies)	√		
3. Development of theoretical propositions (theoretical work)			
4. Theoretical foundation / Literature review	√	√	√
5. Definition of methodological procedures	√		
6. Data collection	√	√	√
7. Statistical analysis	√	√	√
8. Analysis and interpretation of data	√	√	√
9. Critical revision of the manuscript	√		
10. Manuscript writing	√	√	√
11. Other (please specify)			

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