ESG integration versus best-in-class strategies for portfolios – a comparison based on a resampling optimization methodology

1 INTRODUCTION

Investors are increasingly seeking companies with strong non-financial factors such as environmental (E), social (S) and governance (G) scores (Bollen, 2007; Gutsche and Ziegler, 2019; Fan and Michalski, 2020), also known as ESG factors.

The inclusion of ESG objectives in the portfolio selection makes the strategic asset allocation task more complex, since the investor needs to pursue an additional objective, which changes the task from a risk and return optimization to a multi-criteria decision-making problem. For the last two decades, institutional investors have debated whether considering Environmental, Social and Governance factors can lead to better financial returns. Skeptics state that so-called "Socially Responsible Investing" (SRI) does not support fundamental analysis and put constraints in the investable universe. On the other hand, proponents argue that markets do not efficiently price ESG factors because these factors address long-term risks that have not been absorbed by the economy, and that alpha generation is possible as markets begin to recognize these undervalued influences (Nagy, Cogan and Sinnreich, 2013).

Among ESG investments strategies are 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).

This work presents a comparison between ESG integration and best-in-class strategies for Brazilian stocks and it has the objective of helping investors to include ESG concerns in the portfolio optimization problem. The paper considers ESG integration by using the Sustainalytics' ESG Risk Ratings and ESG best-in-class strategy using the Brazilian stocks and the ISE and ICO2 indices from B3.

The paper is organized as follows: Section 1 was this introduction; section 2 presents a literature review and discusses the effects of ESG integration and best-in-class strategies in the optimization problem, section 3 presents the methodology that incorporates Sustainalytics' ESG Risk Ratings in the portfolio selection based on a resampling approach, section 4 discusses the results and finally the conclusion highlights the main issues of the work.

2 LITERATURE REVIEW

Socially responsible investing (SRI) has long been perceived as a costly investment style. Indeed, this practice was essentially based on the exclusion of some industries that do not satisfy some social or environmental norms, that may sometimes perform better than others over time (Alessandrini and Jondeau, 2020). However, there isn't a consensus about whether considering ESG factors results in different financial returns, in a positive or negative way, or even if it is neutral.

There are many different strategies when trying to take into account ESG criteria in portfolio construction. The most common strategy used by investors was negative screening. In this strategy an investor can choose not to invest in companies that did something the investor considers morally or ethically wrong, perhaps to make a political statement, or perhaps because the investor did not want to support a ESG type of business. Negative screening adds non-financial criteria in the investment process and therefore constraints to the portfolio optimization. Another ESG approach is the best-in-class selection, focusing on including rather than excluding companies. A best-in-class process might consider ESG factors in identifying a sector for investment, creating what might be called a positive screen. A best-in-class process might consider ESG factors in ide ntifying a sector for investment, creating what might be called a positive screen. In other words, a best-in-class process looks for the "best" companies in an industry or sector, from the standpoint of environmental or social factors. Rather than excluding a sector, a best-in-class selection process could include a sector that did not have the highest sustainability ratings, and select the companies within that sector that were doing the best in terms of improving their environmental impact or providing good labor conditions for employees. For example, an investor might use “clean energy” as a positive screen and then look for best-in-class companies within the group of companies that meet the standards of the screen. (Gary, 2019)

There is also the so-called Impact Investing where 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 and the investor idea is engaging in corporate ESG decisions. There is also the ESG integration strategy that can be described as an investment strategy that combines material ESG factors with traditional financial metrics to analyze companies. Doing this allows us to analyze how taking ESG factor into account on portfolio optimization affects the blended value of the portfolio, defined by Gary (2019) as a combination of economic value and environmental or social value of an investment.

Including ESG issues in the SAA (strategic asset allocation) problem raises some challenges in the process. In general, multicriteria decision making problems require applying weights on the objectives or other ways of prioritizing the objective functions. Therefore, investors have to make the subjective choice of weights before optimizing their portfolios. There is also the problem of which metrics they will choose for ESG objectives maximization. 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.

The literature presents some approaches to the strategy of integration. The mean-variance method combined with some multi-criteria decision-making approach is a possible course of action. The mean variance approach analyses the risk-return relationship and for a specific level of risk, the portfolio manager seeks the set of 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 he takes into account a structure that imposes on the covariance matrix some quantitative ESG criteria, which serves as input to a common mean-variance optimizer.

Calvo, Ivorra and Liern (2015) use a fuzzy optimization model that provides a chance of finding satisfactory portfolios. The procedure is formally 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 concerned with the financial goals of course but investors also are willing to favor socially responsible investments as long as the financial cost of this strategy stays in a boundary. The first step of the Calvo, Ivorra and Liern (2015) procedure is to define the universe of possible assets, the amount of investments, minimum and maximum buy-in threshold for convention and non-convention assets, required expected return (based on the efficient frontier), corresponding accepted risk, the degree of wiliness to favor ESG assets, and the level of tolerance for non-efficient portfolios. This first step allows the implementation of an approach based on fuzzy logics, or fuzzy theory. The approach also needs a utility function that depends on the social responsibility (SR) degree defined by the investor. If a portfolio “x” dominates a portfolio “y” (for the three goals), then U(x) > U(y).

$$U(x) = \mu_{acc}(x)\left(w_{SR}\mu_{SR}(x) + (1 - w_{SR})\mu_{eff}(x)\right)$$

Calvo, Ivorra and Liern (2015) define $\mu_{acc}(x)$ as a degree of acceptance, taking the value 0 on those portfolios not attaining the minimum expected return or exceeding the maximum risk acceptable for the investor and taking the value 1 on those portfolios whose risk and return are within the limits he or she is well disposed to accept. Portfolios with intermediate values of risk and return have a degree of acceptance between 0 and 1, based on the minimum and maximum threshold discussed above (the four parameters fixed by the investor to specify his or her financial preferences).

The authors set $\mu_{SR}(x)$ as the degree of social responsibility of the portfolio "x" divided by the maximum attainable value in order to normalize it between 0 and 1 and make it comparable with the other indexes. Furthermore, $\mu_{eff}(x)$ is the degree of efficiency of the portfolio "x", which takes the value 1 if "x" is on the financially efficient frontier and gradually decreases to 0 as the pair risk–return approaches the opposite boundary of the acceptable region of risks and returns. w_{SR} is a weight between 0 and 1 to be fixed by the investor and it measures the preferred trade-off between social responsibility and efficiency. A high value means that the investor is well disposed to go far from the financially efficient frontier (within the region of acceptable pairs risk–return) in order to obtain higher social responsibility, whereas a low value means that the investor prefers to remain near the financially efficient frontier.

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.

Fan and Michalski (2020) use 3 different integration methods on their work. In the first one (M1) they first perform a non-ESG screen, where non-ESG rated firms within their sample are excluded. Subsequently, the remaining stocks are sorted based on factor signals such as quality, low volatility, momentum, size and value. Finally, they form ESG integrated factor portfolios by taking long and short positions in the highest and lowest stock quartiles. On the second one (M2) they first perform the sort for each factor using their sample. Subsequently, within the long and short quartiles of each factor, they eliminate non-ESG rated stocks. Unlike the first one, this procedure can lead to "unbalanced" long and short portfolios, i.e. the integrated factor portfolio could be net long or short. For example, if quartile sorted portfolios are formed on the quality signal, stocks in the long or short portfolio might not report an ESG score. This would lead to an "unbalanced" portfolio. On the third method (M3) 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 the respective factor signal. The combined signal is formed by assigning a 50/50 weight between the factor signal and the ESG score. Unlike methods one and two, M3 is designed to capture both the factor signal and ESG rating simultaneously. This allows them to take into account any possible interaction effects, which are otherwise omitted. Since they are using Bloomberg ESG scores that range from 0 to 100, they normalize each factor signal to a range of 0–100. Thus, the combined signal for each stock *i* at time *t* is computed as: [0.5 x ESG_score*it* + 0.5 x Signal_score*it*]. For example, for the momentum strategy under M3, non-ESG firms are initially screened out, a sorting signal is formed by allocating 50% weight to the momentum signal on the stock and another 50% weight to the ESG score of the same stock. Portfolios are then formed on the combined signal, which results in a balanced number of stocks in long and short portfolios.

Nagy, Cogan and Sinnreich (2013) also 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 lowest current ratings, which results in a narrower investment universe. They first analyze the performance of this restricted market cap weighted portfolio. As a second step, they further enhance this pure exclusion strategy by overweighting stocks with high current ESG ratings and underweighting those with low current ratings inside the smaller universe, while maintaining other exposures of the portfolio very close to the benchmark"s exposures. The second strategy is called a "simple ESG tilt" approach. In this one they do 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 this one they do not exclude any stocks based on their ESG ratings. Instead, we 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. It's expected that the resulting portfolio will reflect companies whose ESG trajectory is positive, even though it will be less tilted towards companies with high current ESG ratings than the simple ESG tilt portfolio referenced above.

Alessandrini & Jondeau (2020) use an approach, to evaluate their portfolios simultaneously with respect to financial performance and the ESG profile. They compute a so-called efficiency measure. This indicator combines financial performance through the excess return per unit of risk (Sharpe ratio) and ESG quality through the ESG score per unit of risk (ESG ratio). Formally, they define this indicator for a portfolio p as follows:

$$Eff_p = (1-\gamma)\left(\frac{\bar{R}_p - \bar{R}_f}{\sigma_p}\right) + \gamma\left(\frac{Score_p}{\sigma_p}\right) = (1-\gamma)SR_p + \gamma ESGR_p$$

where R_p, σ_p, and $Score_p$ denote the average annualized return, the annualized volatility, and the average score of portfolio p, and R_f denotes the average risk-free rate. The measure is a weighted average of the Sharpe ratio and a second ratio, which relates the ESG profile of the portfolio to its volatility. Given that scores are roughly on the same scale as annual returns (expressed in percent), the two ratios are comparable in magnitude and can easily be combined to evaluate the overall profile of the portfolio. The weight attributed to the two components of the indicator is arbitrary and reflects the preferences of an investor. For example, if it were attributed an equal weight of 0.5 for each component it would reflect an investor who cares as much about financial returns as ESG quality.

3 METHODOLOGY

The traditional inputs of the portfolio optimization problem are the covariance matrix and the expected returns on investments. In this paper, we use an additional input i.e. an ESG score provided by the Sustainalytics, for the ESG integration strategy. 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. In order to determine which stocks are the best in their class we used ISE and ICO2 indexes from B3.

The Índice de Sustentabilidade Empresarial from B3 (ISE B3) was the 4th sustainability index created in the world, in 2005, with the objective of support investors in investment decision-making and induce companies to adopt the best sustainability practices, since ESG (Environmental, Social and Corporate Governance) practices contribute to business continuity. Companies holding the 200 most liquid shares of B3 are invited to participate, as eligible, in an objective criterion. The process presupposes the completion of a questionnaire composed of 7 dimensions: Economic-Financial, General, Environmental, Corporate Governance, Social, Climate Change and Nature of the Product, and up to 40 companies make up the index portfolio (effective annually).

The ISE is a tool for comparative analysis of the performance of companies listed on B3 under the aspect of corporate sustainability, based on economic efficiency, environmental balance, social justice and corporate governance. It also broadens the understanding of companies and groups committed to sustainability, differentiating them in terms of quality, level of commitment to sustainable development, equity, transparency and accountability, nature of the product, in addition to business performance in the economic and financial dimensions, social, environmental and climate change. This is why we chose this index to auxiliate in the process of positive screening.

Created in 2010, the B3 Índice Carbono Eficiente (ICO2 B3), from the beginning, had the purpose of being an instrument to induce discussions on climate change in Brazil since the companies' adherence to the ICO2 demonstrates their commitment to the transparency of their emissions and anticipates the vision of how they are preparing for a low-carbon economy. This is why we also chose this index to help the process of positive screening.

The maximization objective is the problem of building the efficient frontier, a set of optimal portfolios which offers the highest expected return for a defined level of risk. A well-known problem from the approach used by Harry Markowitz is the high probability to present portfolios that concentrate all weight in one single stock (or a small number of stocks).

We used Michaud and Michaud (2007) approach of resampling data from the original source of information several times, and running many optimizations problems in order to averaging portfolios compositions.

We used the idea of a random selection based on Monte Carlo simulation. This method yields unbiased estimates as it is based on the unbiased samples of all the possible results of the data studied. The routine that we ran on this research was developed in the R program and in order to generate the unbiased samples we used a function of R software called Mvnorm: Multivariate Normal Density and Random Deviates. This function generates random numbers to the Multivariate Normal Density. Then we calculate the portfolios on the efficient frontier by averaging compositions for each risk aversion factor, creating an efficient frontier.

In the Monte Carlo process, each simulated portfolio has an ESG degree calculated by summing the products of asset weights and asset ESG scores. Portfolios' ESG data allow the development of a strategy to get portfolios with an ESG score lower than a boundary defined by investors. To help the portfolio creation and filtering we used a statistics normalization to set the numeric values of the ESG rating in a common scale.

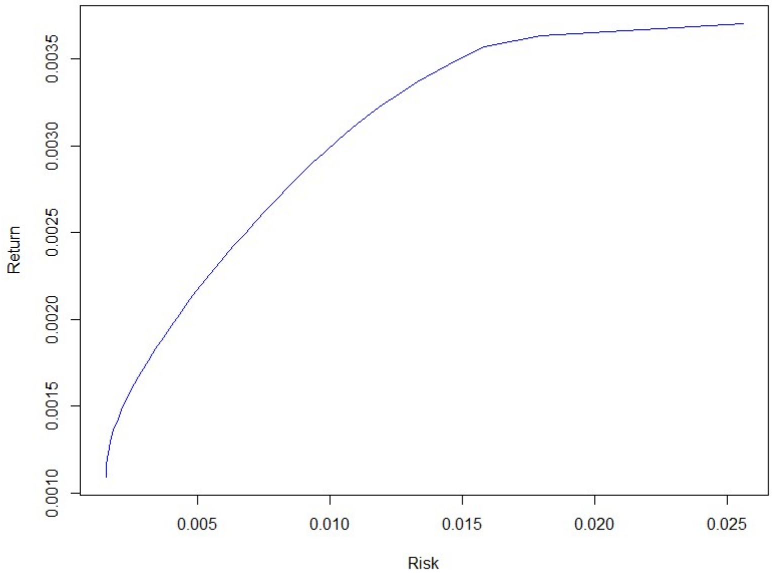
We used 2 sources of data in our research. First of all, the stocks prices were from Yahoo Finance. There we got the price of Brazilians stock market (B3) that we use as the universe of stocks. We used data from 01/01/2019 to 12/31/2020. Second, data from the ESG score were provided by the Sustainalytics website. There are some companies that are not on Yahoo Finance or don't have the Sustainalytics score, because of that, 17 out of 65 companies were not used on this research, leading us to 48 eligible companies to analyze.

The ESG score was normalized between 0 and 1 where 0 is the score of the minimum ESG Sustainalytics score and 1 is the maximum ESG Sustainalytics score of the companies in the sample. It means that an asset with a score near to zero has less ESG risks than an asset with a score near to one.

4 RESULTS

Figure 1 shows the efficient frontier of a traditional optimization process using Markowitz with only one constraint, which is not allowing short selling, and using Michaud and Michaud (2007) resampling approach. Applying the resampling approach with the Monte Carlo simulation with a multivariate normal distribution we generate several optimized portfolios, each one with an ESG score, as mentioned before, calculated by summing the products of asset weights and asset ESG scores. We applied an additional constraint that no asset should have an allocation of more than 10% (MaxAlloc = 10%).

Figure 1: Efficient Frontier



Source: Authors

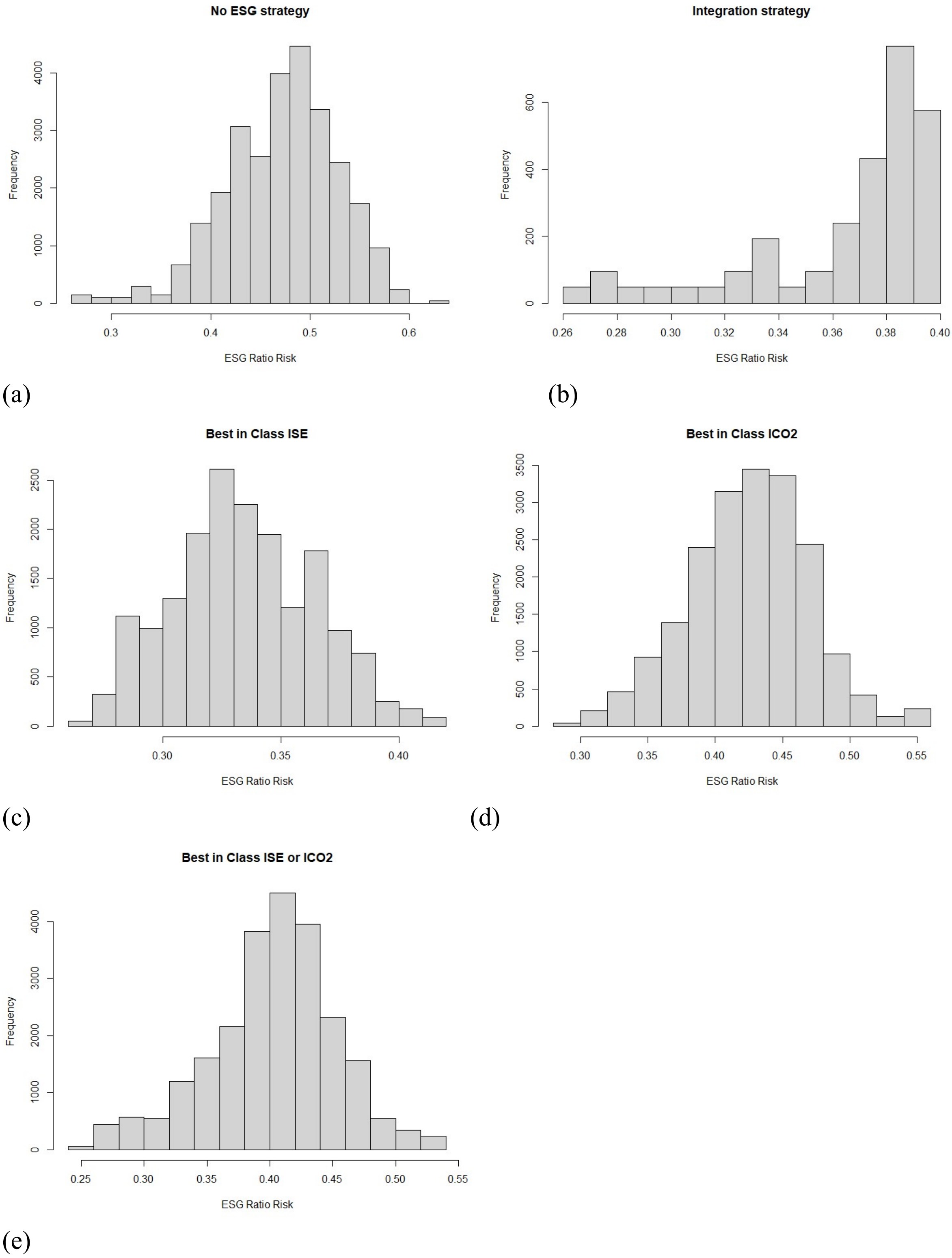
The assets in the ISE index have an average normalized ESG score of 0.331. The assets in the ICO2 index have an average normalized ESG score of 0.399. The assets in the sample have an have an average normalized ESG score of 0.441. Therefore, it should be expected that portfolios generated by assets that are in the ISE index should have better ESG results (less ESG normalized scores).

Figure 2a shows the histogram of the ESG score (normalized) for all generated portfolios and risk averse coefficients. Portfolios with higher ESG scores have more ESG risk. Therefore, the efficient frontier of Figure 1 is generated by using all the portfolios used to generate Figure 2a since they were generated without any ESG strategy.

The ESG integration strategy applies an ESG filter in portfolios used to generate Figure 2a. By using a filter to select only portfolios with ESG scores lower than 0.4 (a boundary) we generate the histogram presented in the Figure 2b, with portfolios with less ESG risks. We may choose the boundary according to our ESG risk appetite.

Figure 2c shows the histogram of a best-in-class strategy with portfolio optimizations that use only assets in the ISE index. The histogram in Figure 2d is a best-in-class strategy with portfolio optimizations that use only assets in the ICO2 index and Figure 2e shows the histogram of a best-in-class strategy with assets in the ISE or in the ICO2 indices.

Figure 2: Histogram of portfolios' ESG scores (MaxAlloc = 10%)



Source: Authors

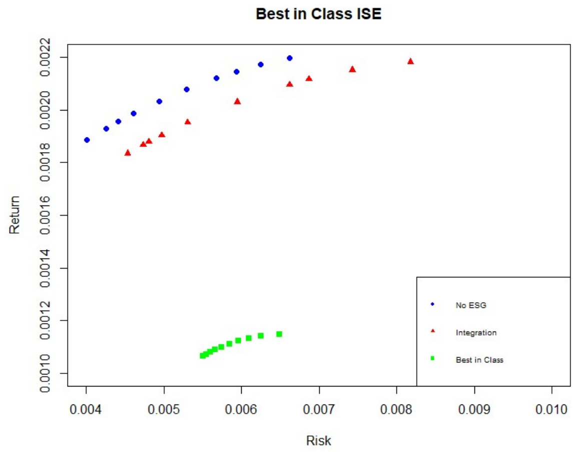
Table 1 shows means and standard deviations from the ESG score of the portfolios generated by the five approaches. The portfolios generated by the No ESG strategy have the higher ESG scores and therefore they have more ESG risks. The portfolios from the best-in-class approach with the ISE index have in average less ESG risk than the portfolios with the ICO2 index. The Integration strategy with a filtering process of 0.4 maximum ESG score generated a mean score higher than the best-in-class with ISE index. However, the Integration approach with the 0.4 boundary generated portfolios with a mean ESG score lower than best-in-class with ICO2 index or a combination of ISE and ICO2. Note that the ESG Integration strategy has a parameter that we may choose according to the ESG risk choice. The parameter is the boundary for the filtering process and a lower boundary of 0.35 generates portfolios with less ESG risks compared to the others investment strategies (mean ESG score of 0.31).

Table 1 – Mean and standard deviation of portfolios ESG scores

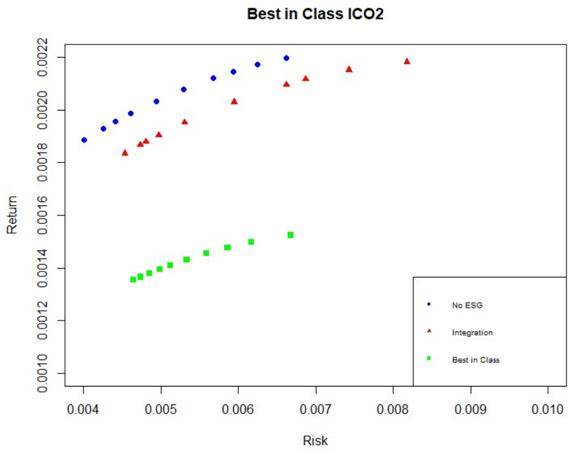
	Mean	SD
No ESG	0.4718	0.0561
Integration (0.40)	0.3649	0.0347
Integration (0.35)	0.3100	0.0253
ISE	0.3341	0.0300
ICO2	0.4250	0.0447
ISE/ICO2	0.4023	0.0509

Figure 3 shows the efficient frontier with and without ESG integration strategy by using a 0.4 boundary for filtered portfolios and with best-in-class strategies, where (a) presents ISE, (b) ICO2 and (c) ISE/ICO2. Figure 3 shows that ESG integration strategy generates an ex-ante cost, since it imposes an additional constraint to the portfolio optimization and therefore the efficient frontier is moved below the efficient frontier without ESG filtering. The best-in-class approach generates efficient frontiers below the integration approach. It means that best-in-class approach has an ex-ante cost in the optimization process with more constraints than the integration approach with a maximum ESG portfolio score of 0.4.

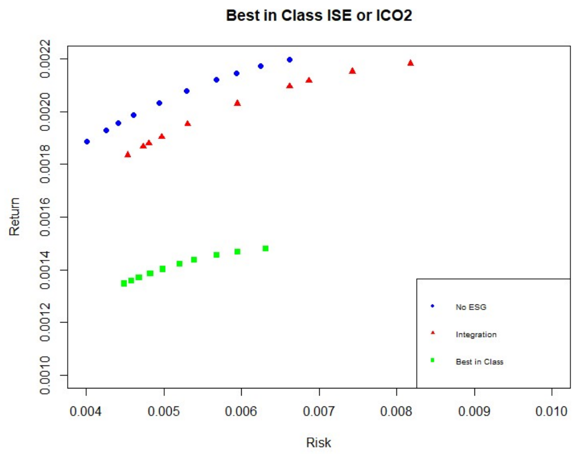
Figure 3: Efficient frontiers with and without ESG filtering and MaxAlloc = 10%



(a)



(b)



(c)

Source: Authors' code

Comparing figure 3b (Best in class with ICO2) and figure 3c (Best in class with ISE or ICO2) it can be seen that the difference between the efficient frontiers of these 2 strategies is almost imperceptible. This happens because, within our sample, there are only 2 companies that are in the ISE and are not in the ICO2.

Simulations in Table 2 present cost efficiency metrics and ESG efficiency metrics. The higher the cost efficiency metrics the closer the ESG constrained efficient frontier to the unconstrained ESG efficient frontier. The higher the ESG efficiency metrics the better ESG resilience of the portfolio.

The integration strategy is more cost efficient than the best-in-class approach as we can see comparing columns eCost_Int and eCost_BC. However, cost efficiency of the integration strategy decreases when we reduce the value of the filtering boundary (compare simulations 1,2, and 3 with 4,5 and 6). We can improve cost efficiency if we smooth constraint of maximum allocation, MaxAlloc (see simulations 7, 8 and 9). Cost efficiency depends also of the minimum allocation constraint, MinAlloc (see simulations 10, 11 and 12).

Both ISE and ICO2 have a similar composition. However we can see in table 2 that when we compare the best-in-class strategy using each index separately the ICO2 shows a considerably lower ESG efficiency than the ISE. This happens mainly because there are some companies in the ICO2 that despite having joined the ICO2 initiative, are part of industries that have a great negative impact on ESG. As an example, we can talk about Gerdau which is the largest Brazilian steel producer and one of the main suppliers of long steel in the Americas and special steel in the world. However, it has a bad (high) ESG score, mainly due to the type of industry that Gerdau is part of, since the steel industry typically causes visible impacts on the environment, its inhabitants, and surrounding communities.

Table 2 – Simulations' results

Sim	ESG_Score	Ind_BC	MinAlloc	MaxAlloc	eCost_Int	eCost_BC	eESG_Int	eESG_BC
1	0.40	ISE	0.0%	10%	0.9366	0.4869	0.2209	0.2918
2	0.40	ICO2	0.0%	10%	0.9366	0.6857	0.2209	0.1004
3	0.40	ISE/ICO2	0.0%	10%	0.9366	0.6871	0.2209	0.1494
4	0.35	ISE	0.0%	10%	0.8645	0.4869	0.3520	0.2918
5	0.35	ICO2	0.0%	10%	0.8645	0.6857	0.3520	0.1004
6	0.35	ISE/ICO2	0.0%	10%	0.8645	0.6871	0.3520	0.1494
7	0.40	ISE	0.0%	20%	0.9657	0.5627	0.2206	0.2339
8	0.40	ICO2	0.0%	20%	0.9657	0.7300	0.2206	0.0448
9	0.40	ISE/ICO2	0.0%	20%	0.9657	0.7314	0.2206	0.1006
10	0.40	ISE	1.5%	20%	0.9078	0.5489	0.1410	0.2078
11	0.40	ICO2	1.5%	20%	0.9078	0.8327	0.1410	0.0311
12	0.40	ISE/ICO2	1.5%	20%	0.9078	0.8289	0.1410	0.0813

MaxESG: maximum ESG filter score for portfolios. MinAlloc and MaxAlloc: optimization constraints of minimum and maximum asset allocation. EffCost: metric used to evaluate distance to the efficient frontier without filtering (value of 1 means no filter and no cost). The lower EffCost the higher the cost). EffESG: relative reduction of the average ESG score of portfolios in the efficient frontier.

Source: Authors

We cannot say that the ESG efficiency of the integration strategy is better or worse than the best-in-class strategy, regarding ESG. Indeed, the filtering boundary is a relevant parameter in this comparison. See that in simulations 4, 5 and 6 we achieve better ESG resilience with the integration strategy. Regarding maximum and minimum allocation constraints, the minimum allocation constraint reduces ESG resilience in the simulations and the effect of the maximum allocation constraint is not clear.

5 CONCLUSION

This paper presents ESG strategies for investments in stocks based on a resampling methodology. Portfolios are generated by an optimization process combined with a Monte Carlo simulation using a multivariate normal distribution of returns. The methodology presented in this paper differs from many presented in the literature, since it is not necessary to optimize portfolios by modifying the utility function.

We compare two ESG portfolio strategies. The integration strategy is built with an ESG filtering approach based on ESG scores. The best-in-class approach is based on ISE and ICO2 indices from Brazilian stock exchange. We show that the costs with the integration strategy are lower than the costs of the best-in-class strategy.

We show also that the ESG portfolios resilience of the integration strategy depends upon the ESG risk appetite. It is possible to generate portfolios with more ESG resilience in the integration strategy if we filter portfolios with low ESG risk score. We show that it is possible to manage the filtering process and to generate portfolios with low costs and higher ESG efficiency with the integration strategy compared to the best-in-class strategy. Finally, we show that minimum allocation constraints may reduce ESG efficiency.

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