ESG integration in portfolio optimization: A Brazilian market study

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Abstract This paper investigates the performance of investment portfolios in the Brazilian financial market from 2016 to 2024, constructed using a factor-based approach. The study examines the impact of incorporating ESG (Environmental, Social, and Governance) factors into investment strategies. By evaluating the excess returns of portfolios adjusted for risk, and using the Sharpe index for comparisons, the research concludes that the inclusion of ESG factors generally improves the risk-adjusted performance of simple factor-based portfolios.

Keywords: Risk measures; ESG investing; Portfolio theory; Factor models; Asset pricing.

JEL codes: G11, G12, G17, C13.

1. Introduction

This article investigates the performance of portfolios in the Brazilian financial market, constructed using a factor-based approach, including ESG factors, over the period from 2016 to 2024.

Since the seminal work of Markowitz (1952), portfolio theory has revolved around investment optimization, balancing expected returns with risk, measured through variance. Building upon this foundation, the CAPM model by Sharpe (1964) and the work of Lintner (1965) introduced the concept of systematic risk factors to explain asset returns and diversification strategies.

These early models established a framework for risk-based pricing, later enhanced by Fama and French (1992), Carhart (1997), and Fama and French (2015) with three, four, and five-factor models, respectively.

Over the decades, these factor-based approaches have become central to academic financial research. In Brazil, the research group of NEFIN[1] calculates

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Brazil-specific daily risk factors, enabling localized applications of factor-based models.

Recently, the global financial community has witnessed a growing interest in ESG-related investments, which represent a broader domain of the concept of Socially Responsible Investments (SRI). ESG emphasizes sustainability and ethical considerations alongside financial returns. In 2015, more than 60 trillion in assets were being managed under ESG-aligned strategies (Friede et al., 2015). Studies such as those by Naffa and Fain (2022) and Shanaev and Ghimire (2022) suggest that ESG factors can influence portfolio performance, although there is still debate regarding their risk-adjusted efficacy.

Despite the growing importance of ESG factors globally, their application to the Brazilian market through a factor-based approach remains an under-explored area, forming the research problem of this study. In this context, the article aims to analyze the behavior of portfolios that include ESG factors compared to those that do not, evaluating risk-adjusted returns and their implications for different rebalancing horizons.

By evaluating the excess return of portfolios adjusted by their risk measure, we conclude that for the universe of the most liquid assets between 2001 and 2014, and for all levels of investor risk aversion, the performance of factor-based investments that include the ESG factor is positive when compared to the same investment without considering the ESG factor for portfolios calculated through the simpler return prediction models. The opposite occurs in portfolios calculated by including the factors of Fama and French (1992) and Fama and French (2015) provided by NEFIN (2024).

2. Methodology

The portfolios were grouped and evaluated according to various parameters,[2] allowing a detailed analysis of the impacts of different approaches.

This study compares mean-variance portfolios with other market portfolios using the Sharpe ratio. Each mean-variance portfolio is the solution to a minimization problem of the following type:

$$\min_{w} \quad -w^T \cdot E + \phi_p \cdot w^T \Sigma w \quad \text{subject to} \quad |w_i| \leqslant 1, \forall w_i \in w, \tag{1}$$

where w is the weight vector, E is the expected returns vector, ϕ_p is a function of the investor's risk parameter p, and Σ is the covariance matrix of the assets.

[2] Risk aversion parameters, market portfolio factors, and time parameters for regressions and optimization problems involved in portfolio calculations were considered.

For the selection of the asset universe composition, a methodology based on the liquidity of assets traded on the Brazilian stock exchange between 2001 and 2014 was used. For the calculation of expected values, twelve out-of-sample methodologies inspired by the CAPM[3] (Sharpe, 1964) and the multifactor models of Fama and French, conditioned by lag, rebalancing period, and the liquidity of each asset, were employed. For the calculation of the covariance matrix, the sample covariance approach and the shrinkage method by Ledoit and Wolf were used.

2.1 Asset universe and investment period

The data used spans the period from May 2, 2014, to August 31, 2024. The choice of this window is justified by the daily availability of the ESG index from the S&P-Dow Jones indices (S&P Global, 2025) for the Brazilian market, which was only released starting May 2, 2014, and is a necessary input for the study. For the beginning of the investment period, May 2, 2016, was adopted to ensure the availability of at least two years of historical data necessary for model calibration.

For the selection of assets in the investment universe, trading data from the Brazilian market between January 1, 2000, and January 1, 2014, was used. This period resulted in the definition of two groups of assets, distinguished based on their trading frequency, as described below:

(i) **RIL:** Composed of 28 assets that were traded daily, without interruptions, throughout the considered period. Table 1 provides descriptive statistics of asset returns for the period from January 1, 2001, to May 1, 2014.
(ii) **RTR:** Composed of 41 assets that did not exhibit trading gaps exceeding 9 consecutive days during the mentioned period. Table 2 presents the descriptive statistics of the data obtained for the period. After processing the historical data, a summary of their statistics is provided below:

The choice of these two groups was motivated by secondary results obtained in (Voltolini, 2023), which highlighted that the trading frequency of assets plays a crucial role in the success of investment strategies using a methodology similar to the one that will be employed in this study. Thus, two asset universes were defined for analysis, aiming to investigate how the inclusion of the ESG factor affects the returns of portfolios generated through the methodology.

[3]Capital Asset Pricing Model

Table 1
Descriptive statistics with detailed categories of the Stocks in RIL

	count	mean	std	Skew	Kurtosis	min	max
BBDC3	3156	0.0010	0.0219	0.3638	3.3611	–0.0961	0.1672
BBDC4	3156	0.0009	0.0224	0.5119	5.0946	–0.1150	0.2213
BRAP4	3156	0.0008	0.0267	0.0442	3.2525	–0.1901	0.1509
BRKM5	3156	0.0006	0.0280	0.3955	2.9922	–0.1429	0.2124
CMIG3	3156	0.0012	0.0245	–0.0762	3.2299	–0.1951	0.1313
CMIG4	3156	0.0010	0.0238	–0.0709	3.2605	–0.1971	0.1156
CPLE6	3156	0.0006	0.0250	0.2016	2.9353	–0.1666	0.1683
ELET3	3156	0.0003	0.0294	0.2944	2.2344	–0.1506	0.1679
ELET6	3156	0.0006	0.0279	0.4363	3.5829	–0.1543	0.2356
EMBR3	3156	0.0006	0.0245	0.0142	3.8436	–0.1667	0.1538
EGIE3	3156	0.0013	0.0271	1.4281	14.6727	–0.1200	0.3581
GGBR4	3156	0.0010	0.0265	0.1621	2.7139	–0.1490	0.1840
GOAU4	3156	0.0011	0.0253	0.2179	3.1697	–0.1475	0.1933
ITSA4	3156	0.0012	0.0228	0.7027	7.2384	–0.1155	0.2515
ITUB4	3156	0.0010	0.0234	0.6422	6.1973	–0.1214	0.2337
KLBN4	3156	0.0011	0.0269	0.3907	2.7451	–0.1230	0.1821
LIGT3	3156	0.0003	0.0298	0.5866	6.0415	–0.1937	0.2436
OIBR4	3156	0.0001	0.0289	0.4894	5.0622	–0.1648	0.2331
PETR3	3156	0.0007	0.0240	0.2369	3.9077	–0.1385	0.1516
PETR4	3156	0.0008	0.0227	0.0696	3.6123	–0.1376	0.1416
SBSP3	3156	0.0008	0.0253	0.1959	3.1602	–0.1492	0.1685
CSNA3	3156	0.0012	0.0286	0.3716	3.8235	–0.1711	0.2169
VIVT3	3156	0.0008	0.0191	0.1855	2.4211	–0.0815	0.1124
TIMS3	3156	0.0009	0.0322	0.2731	6.4417	–0.2270	0.2994
TRPL4	3156	0.0012	0.0257	–0.1348	5.4009	–0.2406	0.1707
UNIP6	3154	0.0004	0.0236	0.3247	3.9037	–0.1481	0.1519
USIM5	3156	0.0010	0.0308	0.3299	2.5814	–0.1476	0.1809
VALE3	3152	0.0011	0.0232	0.0972	4.3506	–0.1858	0.1452

2.2 Portfolios

In this section, we describe the alternative models employed in the portfolio optimization procedures. The methods include the traditional Markowitz approach based on the mean-variance optimization model, a variation focused on minimum variance, and a naive strategy used as a benchmark. Additionally, we discuss the use of risk factors and out-of-sample forecasting models to evaluate the performance of the strategies.

2.2.1 Risk-free portfolio by Nefin

This strategy involves allocating 100% of the capital to the risk-free asset (r_f) calculated by Nefin. The r_f portfolio is calculated based on the 30-day DI Swap contract (NEFIN, 2024) and is used as a conservative benchmark, providing a performance reference without exposure to market risks.

Considering the period from May 1, 2014, to August 31, 2024, the r_f portfolio exhibited the statistics presented in Table 3.

Table 2
Descriptive statistics with detailed categories of the Stocks in RTR

	count	mean	std	Skew	Kurtosis	min	max
ABEV3	3053	0.0012	0.0186	0.2097	9.7381	–0.1765	0.1597
BBDC3	3156	0.0010	0.0219	0.3638	3.3611	–0.0961	0.1672
BBDC4	3156	0.0009	0.0224	0.5119	5.0946	–0.1150	0.2213
BRAP3	3017	0.0008	0.0270	–0.0196	3.2243	–0.1496	0.1718
BRAP4	3156	0.0008	0.0267	0.0442	3.2525	–0.1901	0.1509
BBAS3	3151	0.0014	0.0269	0.4647	3.2934	–0.1537	0.2071
BRKM5	3156	0.0006	0.0280	0.3955	2.9922	–0.1429	0.2124
CLSC4	3144	0.0005	0.0234	0.6315	4.1030	–0.1279	0.2000
CMIG3	3156	0.0012	0.0245	–0.0762	3.2299	–0.1951	0.1313
CMIG4	3156	0.0010	0.0238	–0.0709	3.2605	–0.1971	0.1156
CGAS5	3153	0.0008	0.0216	–0.0259	4.9808	–0.1621	0.1466
CPLE3	2991	0.0007	0.0254	–0.0301	7.2982	–0.1892	0.2063
CPLE6	3156	0.0006	0.0250	0.2016	2.9353	–0.1666	0.1683
ELET3	3156	0.0003	0.0294	0.2944	2.2344	–0.1506	0.1679
ELET6	3156	0.0006	0.0279	0.4363	3.5829	–0.1543	0.2356
EMBR3	3156	0.0006	0.0245	0.0142	3.8436	–0.1667	0.1538
EGIE3	3156	0.0013	0.0271	1.4281	14.6727	–0.1200	0.3581
ETER3	3083	0.0010	0.0198	–1.4644	35.3579	–0.3467	0.1317
FESA4	2961	0.0013	0.0236	0.6294	5.2468	–0.1122	0.1559
GGBR4	3156	0.0010	0.0265	0.1621	2.7139	–0.1490	0.1840
GOAU4	3156	0.0011	0.0253	0.2179	3.1697	–0.1475	0.1933
INEP4	3150	0.0002	0.0393	1.2680	12.3523	–0.2412	0.4464
ITSA4	3156	0.0012	0.0228	0.7027	7.2384	–0.1155	0.2515
ITUB4	3156	0.0010	0.0234	0.6422	6.1973	–0.1214	0.2337
KLBN4	3156	0.0011	0.0269	0.3907	2.7451	–0.1230	0.1821
LIGT3	3156	0.0003	0.0298	0.5866	6.0415	–0.1937	0.2436
POMO4	3091	0.0013	0.0234	0.3676	4.0174	–0.1337	0.1980
OIBR4	3156	0.0001	0.0289	0.4894	5.0622	–0.1648	0.2331
PETR3	3156	0.0007	0.0240	0.2369	3.9077	–0.1385	0.1516
PETR4	3156	0.0008	0.0227	0.0696	3.6123	–0.1376	0.1416
RAPT4	3019	0.0014	0.0248	0.4189	4.7162	–0.1230	0.1905
SBSP3	3156	0.0008	0.0253	0.1959	3.1602	–0.1492	0.1685
CSNA3	3156	0.0012	0.0286	0.3716	3.8235	–0.1711	0.2169
TASA4	3131	0.0012	0.0261	0.6297	5.6696	–0.1730	0.1967
TELB4	3154	0.0137	0.1817	2.9267	18.0324	–0.5000	2.0000
VIVT3	3156	0.0008	0.0191	0.1855	2.4211	–0.0815	0.1124
TIMS3	3156	0.0009	0.0322	0.2731	6.4417	–0.2270	0.2994
TRPL4	3156	0.0012	0.0257	–0.1348	5.4009	–0.2406	0.1707
UNIP6	3154	0.0004	0.0236	0.3247	3.9037	–0.1481	0.1519
USIM5	3156	0.0010	0.0308	0.3299	2.5814	–0.1476	0.1809
VALE3	3152	0.0011	0.0232	0.0972	4.3506	–0.1858	0.1452

Definition 1. Let p be an investment portfolio, and the **adjusted return** r_{adj} of p in period d is measured as the difference in returns between p and r_f in d given by:

$$r_{adj} = -1 + \frac{(1 + r_{p,d})}{(1 + r_{f,d})}. \tag{2}$$

2.2.2 Market portfolio

The market portfolio represents the aggregated performance of the main assets traded in the financial market. This portfolio is composed of a weighted combination of assets, and its universe of stocks may vary over time. Table 4 presents the descriptive statistics of this portfolio for the period from May 1, 2014, to August 31, 2024.

2.2.3 Naive portfolio

The naive portfolio is constructed by assigning equal weights to all assets in the considered universe, with each asset receiving an allocation weight of $1/n$, where n is the total number of assets. This strategy is widely adopted as a benchmark due to its ease of implementation and independence from assumptions about returns, offering a reference for evaluating more sophisticated methods.

The descriptive statistics of naive portfolios, categorized by rebalancing frequency, can be summarized by the statistics in Table 5.

2.2.4 Mean-variance composed portfolios

Using the Markowitz model, these portfolios are constructed with the objective of maximizing expected returns for a given level of risk.

2.3 Use of factors in the prediction model

For the mean-variance optimization problem, we work with out-of-sample predictions, estimating asset returns for the subsequent period. To carry out this process, we use historical data and risk factors as explanatory variables in regression models, following the flowchart in Figure 1.

2.3.1 Data

The dataset compiled for this analysis was obtained from various sources:

Table 3
Descriptive statistics with detailed categories of r_f

	Total return	Count	mean	std	min	25%	50%	75%	max	skew.	kurtosis
Value	1.38934	2453	0.00036	0.00015	0.00007	0.00025	0.00040	0.00050	0.00054	–0.46285	–1.12786

Table 4
Descriptive statistics with detailed categories of r_m

	Total return	Count	mean	std	min	25%	50%	75%	max	skew.	kurtosis
Value	1.38908	2453	0.00046	0.01436	–0.14703	–0.00684	0.00065	0.00815	0.13361	–0.78017	14.61943

Table 5
Descriptive statistics with detailed categories of the naive portfolios

	Total return	Count	mean	std	min	25%	50%	75%	max	skew.	kurtosis
RTr_Naive_D	3.98493	2453	0.00077	0.01506	–0.15106	–0.00681	0.00115	0.00852	0.12338	–0.78697	13.56789
RIl_Naive_D	3.26760	2453	0.00072	0.01623	–0.15628	–0.00754	0.00099	0.00894	0.14145	–0.52776	11.85534
RTr_Naive_W	3.65893	539	0.00335	0.03109	–0.22750	–0.01434	0.00384	0.02019	0.18605	–0.50425	8.81112
RIl_Naive_W	3.28024	539	0.00325	0.03297	–0.22812	–0.01512	0.00305	0.02210	0.21310	–0.30752	8.20490
RTr_Naive_2W	3.56684	270	0.00678	0.04683	–0.35273	–0.01877	0.00473	0.03215	0.24603	–0.97101	14.15597
RIl_Naive_2W	3.21993	270	0.00663	0.04976	–0.35225	–0.02128	0.00558	0.03431	0.27398	–0.68239	12.28024
RTr_Naive_ME	3.43039	124	0.01450	0.06980	–0.28825	–0.02707	0.00925	0.05796	0.21696	–0.12492	2.36511
RIl_Naive_ME	3.24038	124	0.01440	0.07345	–0.29295	–0.02834	0.00932	0.05736	0.24483	–0.07644	2.12729

Figure 1
Pipeline for the predicted Expected values of r_i

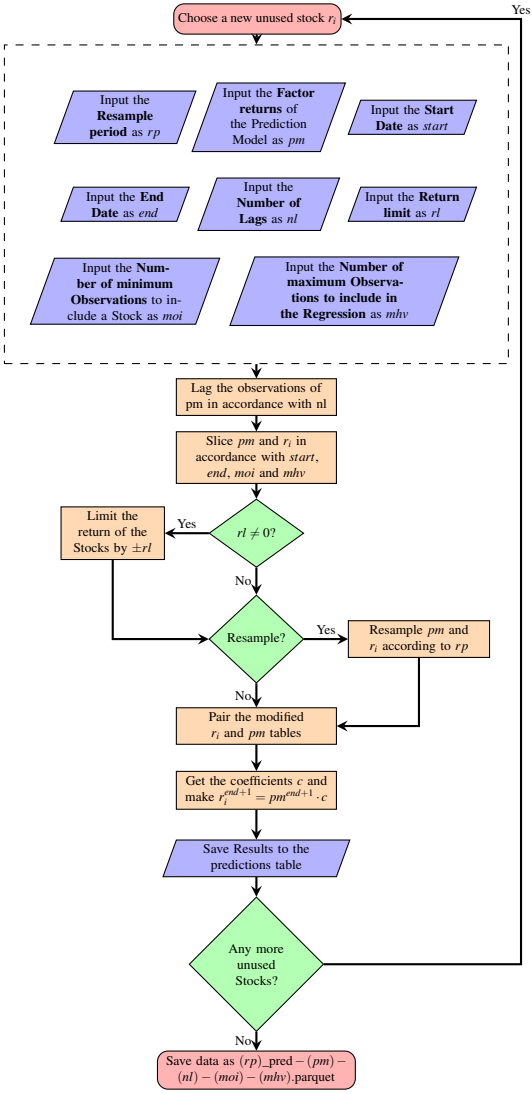
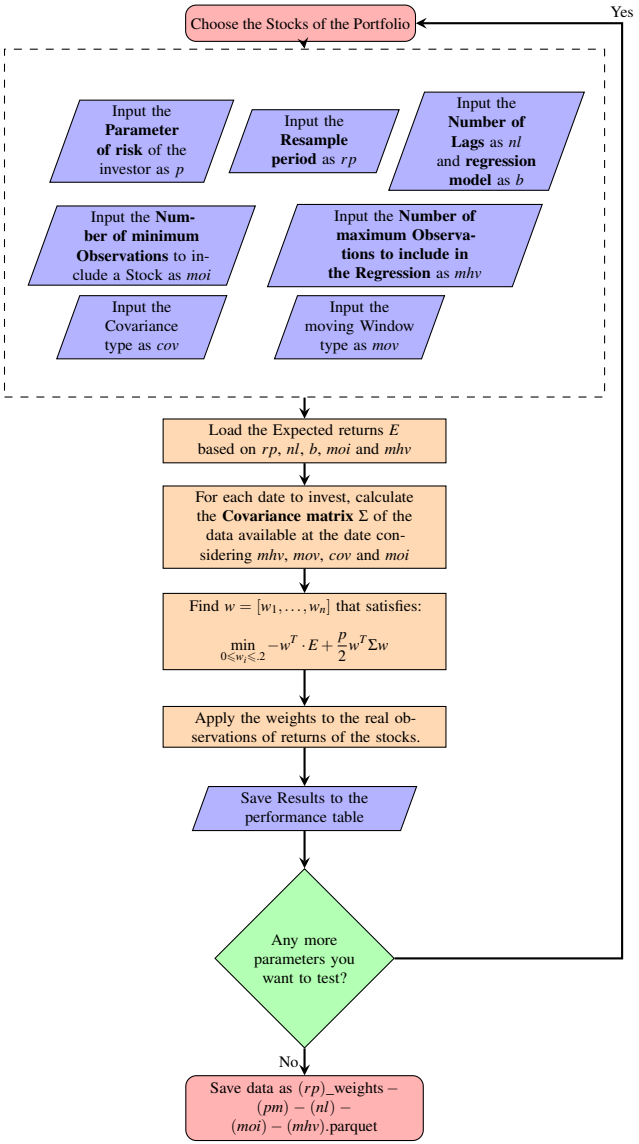


Figure 2
Pipeline for obtaining the weights of each portfolio



(i) **The daily returns of all assets traded on the stock exchange** were sourced from the Economatica portal (Economatica, 2024), with observations spanning from January 1, 2000, to September 1, 2024.
(ii) **The daily returns of market risk factor portfolios** are the returns of various portfolios calculated and made available daily by NEFIN (2024). The Nefin portfolio set includes the risk-free portfolio r_f (calculated from a derivative of the CDI), the market portfolio r_m, *Small Minus Big* (*SMB*), *High Minus Low* (*HML*), *Winners Minus Losers* (*WML*), and *Illiquid Minus Liquid* (*IML*). Observations span from January 1, 2001, to September 1, 2024.
(iii) **The daily returns of the ESG portfolio** were sourced from the S&P-Dow Jones indices (S&P Global, 2025), with observations spanning from May 2, 2014, to September 1, 2024.
(iv) **The daily returns of the IBOVESPA portfolio** were sourced from *Yahoo Finance* using the yfinancePyPI library (Aroussi, 2024), with observations spanning from May 2, 2014, to September 1, 2024.

2.3.2 Prediction models

The prediction models used are detailed in Table 6 and are based on the approach used in Voltolini (2023). The models were calibrated under the following conditions:

(i) **Window:** Rolling data windows with intervals of one year, two years, and fixed windows starting from May 2, 2016.
(ii) **Number of observations:** If, on a specific date, asset i does not have the minimum required number of observations, the model will not predict the asset's value for that date.

2.4 Covariance matrix estimators

For the calculation of the covariance matrix, we employ two estimators: the sample matrix and the Ledoit-Wolf matrix, which applies the shrinkage method discussed in (Ledoit and Wolf, 2004b).

2.4.1 Sample covariance matrix

The sample covariance matrix was calculated using the historical returns of the assets over the considered period. This matrix is defined as

$$S = [s_{r_i,r_j}], \tag{3}$$

Table 6
Pricing model codes

Name	Code	Formula
CAPM	br1	$r_i - r_f = \beta_1 \cdot (r_m - r_f) + \varepsilon$
3-Factor Model	br2	$r_i - r_f = \beta_1 \cdot (r_m - r_f) + \beta_2 \cdot (SMB) + \beta_3 \cdot (HML) + \varepsilon$
5-Factor Model	br3	$r_i - r_f = \beta_1 \cdot (r_m - r_f) + \beta_2 \cdot (SMB) + \beta_3 \cdot (HML) + \beta_4 \cdot (MOM) + \beta_5 \cdot (ILLIQ) + \varepsilon$
ESG - CAPM	bn1	$r_i - r_f = \beta_1 \cdot (esg - r_f) + \varepsilon$
ESG - 3-Factor Model	bn2	$r_i - r_f = \beta_1 \cdot (esg - r_f) + \beta_2 \cdot (SMB) + \beta_3 \cdot (HML) + \varepsilon$
ESG - 5-Factor Model	bn3	$r_i - r_f = \beta_1 \cdot (esg - r_f) + \beta_2 \cdot (SMB) + \beta_3 \cdot (HML) + \beta_4 \cdot (MOM) + \beta_5 \cdot (ILLIQ) + \varepsilon$
CAPM + ESG	be1	$r_i - r_f = \beta_1 \cdot (r_m - r_f) + \beta_2 \cdot (esg - r_f) + \varepsilon$
3-Factor Model + ESG	be2	$r_i - r_f = \beta_1 \cdot (r_m - r_f) + \beta_2 \cdot (SMB) + \beta_3 \cdot (HML) + \beta_4 \cdot (esg - r_f) + \varepsilon$
5-Factor Model + ESG	be3	$r_i - r_f = \beta_1 \cdot (r_m - r_f) + \beta_2 \cdot (SMB) + \beta_3 \cdot (HML) + \beta_4 \cdot (MOM) + \beta_5 \cdot (ILLIQ) + \beta_6 \cdot (esg - r_f) + \varepsilon$
CAPM + ESG + IBOV	bi1	$r_i - r_f = \beta_1 \cdot (r_m - r_f) + \beta_2 \cdot (esg - r_f) + \beta_3 \cdot (ibov - r_f) + \varepsilon$
3-Factor Model + ESG + IBOV	bi2	$r_i - r_f = \beta_1 \cdot (r_m - r_f) + \beta_2 \cdot (SMB) + \beta_3 \cdot (HML) + \beta_4 \cdot (esg - r_f) + \beta_5 \cdot (ibov - r_f) + \varepsilon$
5-Factor Model + ESG + IBOV	bi3	$r_i - r_f = \beta_1 \cdot (r_m - r_f) + \beta_2 \cdot (SMB) + \beta_3 \cdot (HML) + \beta_4 \cdot (MOM) + \beta_5 \cdot (ILLIQ) + \beta_6 \cdot (esg - r_f) + \beta_7 \cdot (ibov - r_f) + \varepsilon$

where $s_{r_i,r_j} = \frac{1}{n-1} \cdot \sum_{t=1}^{n} (r_{i,t} - \bar{r_i}) \cdot (r_{j,t} - \bar{r_j})$, such that $r_{i,t}$ is the return of asset i in period t, n is the total number of observations in the period up to the date, and $\bar{r_i}$ is the mean of the observations of $r_{i,t}$.

2.4.2 Ledoit-Wolf covariance matrix

The covariance matrix obtained by Ledoit-Wolf's "constant variance" method is derived from a convex combination of the sample covariance matrix and the shrinkage matrix $\sigma^2 \cdot I$, where I is the identity matrix and σ^2 is the average variance. We define

$$\sigma^2 \cdot I = [J_{i,j}], \tag{4}$$

where $J_{i,i} = \sigma^2$ and $J_{i,j} = 0$ for $i \neq j$. Thus, to find the Ledoit-Wolf covariance matrix Σ, we use

$$\Sigma = (1 - \gamma) \cdot \Sigma_s + \gamma \cdot \sigma^2 \cdot I, \tag{5}$$

where Σ is the covariance matrix we want to obtain, Σ_s is the sample covariance matrix, and $\gamma \in [0,1]$ is the weight of $\sigma^2 \cdot I$ in Σ.

3. Portfolio calculation

Once the expected returns of the assets are obtained through the regressions described in Table 6, and the covariance matrices are calculated using equations (3) and (5), we can calculate the portfolios using the pipeline described in Figure 2.

4. Results

The result of the calculations is the generation of 18,452 portfolios, obtained from the application of the prediction model and Markowitz optimization, considering the parameters below:

- Rebalancing: Rebalancing can be done daily, weekly, bi-weekly, or monthly;
- Asset Selection: The portfolio can be one of the Benchmark portfolios (market portfolio, risk-free portfolio, and naive portfolios), or it can be calculated from the asset universes rTR and rIL;
- Covariance Matrix: It can be calculated using either the sample covariance matrix or the Ledoit-Wolf covariance matrix;
- Risk Aversion: Parameters of 0.1, 0.5, 0.7, 1, 1.5, 3, 5, and 10;

- Weight Limit for a Single Asset: The optimization problems were calculated based on weight limits of 20%, 50%, and 100%;
- Beta: The methodology for predicting the expected values of the assets. It can be be1, be2, be3, bi1, bi2, bi3, bn1, bn2, bn3, br1, br2, br3;
- Moving Window: It can be 1 or 2 years;
- Minimum Observation Window: It can be 1 or 2 years.

Additionally, for each rebalancing period, 5 portfolios were added to the list, as follows:

- Naive Portfolio of RTr;
- Naive Portfolio of RIl;
- RM Portfolio from Nefin;
- r_f Portfolio from Nefin;
- *ibov* Portfolio;

For each portfolio, the risk-adjusted return, the standard deviation of returns, and the Sharpe ratio were calculated for the entire period. Finally, the portfolios were grouped into "Pooled Portfolios," and Table 7 presents the annualized Sharpe ratio averages for each portfolio group.

The results presented show a trend where simpler models, identified by the suffix "1," exhibit superior performance compared to more complex models. This pattern was consistently observed throughout the analyses, suggesting that simplifying the approaches may have contributed to better portfolio performance.

Additionally, the comparison between the different methods used revealed a significant distinction between the models that consider the ESG factor, represented by the categories be, bn, and bi, and the model that does not incorporate this factor, identified as br. This difference is particularly relevant and will be analyzed in greater depth in the conclusion chapter, as it highlights the importance of including social, environmental, and governance aspects in the financial decision-making process.

5. Conclusion

In this article, a detailed analysis was conducted on the performance of different financial models, with a focus on comparing simple and complex models, as well as distinguishing between ESG and non-ESG strategies.

To mitigate bias from any single approach, this study incorporated the strategy of using pooled portfolios. This methodology ensures that the final performance reflects a more accurate representation of the overall performance

Table 7
Annualized Sharpe ratios of pooled portfolios grouped by selection and resampling strategies

selection	Resamp Beta	D	W	2W	ME
RM	RM	1.9700	1.0223	0.7526	0.4874
Risk-Free	Risk-Free	0.0000	0.0000	0.0000	0.0000
ibov	ibov	1.8474	0.9673	0.7220	0.4561
rIL	Naive	7.4208	3.7764	2.4991	1.6479
	be1	10.2019	2.5115	1.7671	1.3953
	be2	9.3109	2.4368	1.6015	1.0937
	be3	9.1656	2.1511	0.8682	1.1246
	bi1	11.0130	2.2513	2.0044	1.2539
	bi2	10.1490	1.9523	1.9672	1.0169
	bi3	10.3809	1.8075	1.2251	1.0802
	bn1	9.5048	2.6352	2.4966	1.5165
	bn2	9.8584	1.8337	1.9011	1.1501
	bn3	9.3104	1.8468	0.9086	1.0548
	br1	8.9329	3.1197	2.4088	1.5056
	br2	8.8279	2.1300	1.9004	1.1833
	br3	9.0421	2.0634	1.0431	1.0821
rTR	Naive	9.3456	4.3796	2.8957	1.8991
	be1	6.4979	0.6912	2.3310	0.6526
	be2	5.1482	0.0048	1.8893	0.3028
	be3	5.2644	–0.0087	1.4886	0.2934
	bi1	8.1184	0.2256	2.6074	0.4132
	bi2	6.5773	–0.4946	1.9511	0.2961
	bi3	6.9812	–0.3490	1.8488	0.3221
	bn1	6.3853	1.2201	2.3249	0.8452
	bn2	4.6482	–0.1281	1.6997	0.3743
	bn3	4.9444	–0.1323	1.1512	0.3024
	br1	5.2356	1.3930	2.3289	0.8087
	br2	4.0956	–0.1892	1.6802	0.4336
	br3	4.6630	0.0551	1.2621	0.2916

of the groups of portfolios under consideration, rather than being influenced by any one strategy.

The results indicated that the performance discrepancy between prediction models is most pronounced when comparing simpler and more complex models. In general, simpler models (identified by the suffix “1”) outperformed more complex models (identified by suffixes “2” and “3”) in terms of adjusted return and Sharpe ratio. Furthermore, within the simpler models, ESG-integrated strategies (be, bn, bi) consistently demonstrated superior risk-adjusted returns compared to their non-ESG counterparts (br).

In conclusion, this study demonstrates that simpler models often deliver superior performance, with ESG strategies exhibiting a clear advantage when applied to these models. The methodology employed here was designed to minimize bias, enabling an objective evaluation of the various approaches

and highlighting the potential of ESG-oriented investment strategies within a broader financial context.

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Conflict of interest The authors declare no conflict of interest.

Artificial Intelligence This research utilized AI tools to assist in data analysis, manuscript drafting, and figure generation. All AI-generated content was critically reviewed and validated by the authors to ensure accuracy and alignment with the scientific integrity of the study. The use of AI adhered to ethical guidelines, ensuring transparency and compliance with academic standards. Any biases or limitations inherent to the AI tools were carefully considered in the interpretation of results. The authors affirm that the AI tools did not compromise the originality or integrity of the work.

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