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ARTICLE

Sustainability and genetic algorithms: An approach to asset portfolio optimization

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Abstract

Purpose – This study aims to investigate the integration of climate change risk factors into asset portfolio optimization. Specifically, it seeks to evaluate the impact of maximizing sustainability on portfolio performance, and whether a balanced approach between profitability and sustainability can be achieved.

Theoretical framework – The research is based on the Markowitz portfolio selection model combined with the principles of sustainable finance. A genetic algorithm is used to optimize asset allocation while incorporating sustainability metrics.

Design/methodology/approach – A quantitative research method using a genetic optimization algorithm is employed to assess the effects of integrating a sustainability index into portfolio selection. The study compares traditional financial performance metrics with results incorporating climate change risk factors.

Findings – The findings reveal that while maximizing sustainability may lead to short-term reductions in profitability, a balanced approach that integrates sustainability considerations can enhance long-term profitability. This balance enables investors to meet both financial goals and environmental responsibilities.

Practical & social implications of research – The research contributes to the sustainable finance literature by offering insights into optimizing portfolios with ESG integration. Practically, it provides investors with strategies for aligning profitability and sustainability to promote economic growth while supporting environmental and social well-being. Future research could explore sector-specific implications and the different impacts of sustainability criteria.

Originality/value – This study presents an innovative approach to asset portfolio optimization, advancing both the theoretical understanding of sustainable finance and providing practical tools for investors seeking to integrate climate change factors without compromising financial performance.

Keywords: Sustainable investing, asset portfolio optimization, climate metrics, ESG.

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1 Introduction

In recent decades, the rapid increase in human activities has contributed to a significant accumulation of greenhouse gas (GHG) emissions, leading to notable climate changes. These changes have impacted terrestrial and aquatic biodiversity, threatened food security, and increased the frequency of extreme weather events (Intergovernmental Panel on Climate Change, 2021). As these risks become more pressing, institutions, companies, and individuals are taking proactive measures to mitigate the effects of climate change and adapt to its inevitable consequences.

In response to the global environmental crisis, the concept of sustainability gained prominence with the publication of the Brundtland Report (Brundtland, 1987), which first defined sustainable development as the ability to meet current needs without compromising the ability of future generations to meet their own. This report, presented to the World Commission on Environment and Development (WCED), marked the beginning of a broader understanding of sustainability that soon expanded beyond environmental issues to include social and governance dimensions. The Environmental, Social, and Governance (ESG) framework now guides investment decisions worldwide. Established in 2006, the UN Principles for Responsible Investment (PRI) have become a standard for responsible investing, encouraging institutional investors to integrate ESG factors to improve long-term performance while addressing societal challenges (Eccles, 2010). ESG principles have become central to sustainable finance, which aims to achieve both competitive financial returns and positive societal outcomes (Nicholls, 2021).

The growing awareness of sustainability issues has also been reflected in financial markets, where investors increasingly seek opportunities that align with ESG criteria. Sustainable investing is no longer a niche strategy; it has entered the mainstream of global finance. According to Brühl (2022), the demand for ESG-compliant financial products continues to grow, demonstrating that sustainability has been integrated into investor preferences. The financial sector, therefore, plays a critical role in promoting sustainability by facilitating the flow of capital into projects and businesses that address environmental and social challenges while generating economic value.

In this context, a critical sustainability issue is climate change. The financial risks associated with climate change are now widely recognized, and integrating these risks into investment strategies has become essential. These risks are generally classified into two categories: physical risks, such as the increased frequency and severity of extreme weather events, and transition risks, which include regulatory changes, shifts in market preferences, and technological advances aimed at reducing carbon emissions (Task Force on Climate-related Financial Disclosures, 2017). Climate metrics are increasingly being used in asset portfolio management to provide investors with a more comprehensive approach to assessing these challenges.

This study focuses on the integration of climate risk factors into the algorithmic construction of asset portfolios. Specifically, it aims to assess the impact of including climate change metrics on portfolio optimization, addressing both financial performance and sustainability. Two key climate metrics are considered in this research: GHG intensity and carbon intensity (Hoffmann & Busch, 2008; De Spiegeleer et al., 2023). These measures are used to quantify climate change risks within the context of sustainable investing, offering insights into how incorporating such factors can influence asset allocation and overall portfolio performance.

Most studies in the literature find a positive correlation between ESG performance and company financial performance (Friede et al., 2015; Wang et al., 2016). This growing body of evidence suggests that firms that prioritize ESG factors tend to perform better financially over the long term, likely due to better risk management and alignment with evolving regulatory and market environments. However, while substantial research has focused on individual company performance, less attention has been paid to how these factors affect portfolio allocation strategies. This study aims to fill this gap by approaching the problem from a portfolio optimization perspective.

First, we consider the impact of GHG intensity as a metric for evaluating the impact of the European Green Deal on equity portfolios. The European Green Deal emphasizes the reduction of GHG emissions across sectors, and companies that adapt to these requirements may see changes in their stock performance as regulatory and market forces evolve (Siddi, 2020). Second, the inclusion of carbon intensity as a sustainability metric reflects the environmental footprint of companies relative to their economic output. This measure is critical for investors looking to balance carbon efficiency with profitability. Together, these two metrics provide a robust framework for assessing the environmental performance of asset portfolios.

Since investors typically seek to optimize their portfolios by maximizing returns while minimizing volatility, this study adapts Harry Markowitz's Modern Portfolio Theory (MPT) (Markowitz, 1976)) to incorporate a sustainability index composed primarily of climate metrics. MPT revolutionized portfolio management by introducing the concept of the efficient frontier, which enables the construction of portfolios that maximize expected returns for a given level of risk or minimize volatility for a given return. By integrating sustainability metrics into this framework, the study aims to develop an optimization model that balances financial performance with environmental responsibility.

To achieve this, the study employs a genetic algorithm that incorporates both financial and sustainability criteria into the portfolio optimization process. This innovative approach aims to maximize the sustainability index without compromising profitability. In doing so, the study seeks to quantify the trade-offs involved in increasing the sustainability of an asset portfolio, providing investors with a clearer understanding of the potential return sacrifice required to align their investments with climate goals.

Ultimately, this research contributes to the academic and practical discourse on sustainable finance by offering new insights into the integration of climate risk factors into asset portfolio management. The findings show that while maximizing sustainability may lead to short-term reductions in profitability, a balanced approach can enhance long-term returns while fulfilling environmental and social responsibilities. This underscores the importance for investors of carefully weighing their sustainability goals against their financial objectives, as both profitability and volatility can be influenced by the extent to which ESG criteria are integrated into their portfolios

The remainder of the paper is organized as follows: Section 2 covers the theoretical foundations, Section 3 outlines the methodology, Section 4 presents the results, and Section 5 discusses the conclusions and implications.

2 Literature review on sustainable investing and climate change risk integration

Sustainable finance is broadly defined as financial services that integrate Environmental, Social, and Governance (ESG) criteria into their core business practices or investment decisions, aiming to generate positive outcomes for customers, society, and the environment (Uzsoki, 2020). This approach goes beyond merely avoiding harm or mitigating risks; it actively seeks to create lasting, positive impacts across social and environmental dimensions. Within this framework, portfolio optimization has evolved to include sustainability considerations, balancing financial returns with ESG criteria (Friede et al., 2015; Wang et al., 2016).

Within the broader umbrella of sustainable finance, two important categories stand out: green finance and climate finance. Green finance specifically focuses on channeling capital into projects and technologies that promote environmental sustainability (Berrou et al., 2019). On the other hand, climate finance is more narrowly tailored to address climate change directly. It involves financing projects that aim to mitigate the adverse effects of climate change, such as investing in climate-resilient infrastructure, developing low-carbon technologies, and supporting the transition to a green, low-carbon economy (Giglio et al., 2021).

In the context of climate risk, physical risks (e.g., increased frequency of extreme weather events) and transition risks (e.g., regulatory changes and shifts towards low-carbon technologies) have become key considerations for investors (Task Force on Climate-related Financial Disclosures, 2017). Recent studies have highlighted the importance of integrating these risks into financial models. For instance, De Spiegeleer et al. (2023) show how ESG considerations, including climate-related metrics, can be systematically incorporated into portfolio allocation decisions. These studies find that integrating such metrics can enhance long-term portfolio stability by mitigating exposure to sustainability-related risks.

The field of climate finance has evolved as investors seek to balance financial returns with climate mitigation and adaptation objectives. Fang et al. (2019) examined the financial performance of portfolios under different sustainability scenarios and concluded that maximizing sustainability could lead to reduced profitability in the short term, but offers long-term resilience. This finding aligns with Schoenmaker and Schramade's (2018) argument that sustainable finance is not just about risk avoidance, but also about leveraging opportunities in the transition to a low-carbon economy. Both studies support the integration of climate change risks into financial decision making and show that ESG-enhanced portfolios tend to outperform conventional portfolios over time, particularly when the economic impacts of climate change are taken into account.

2.1 Theoretical foundations and evolution of sustainable portfolio optimization

Portfolio optimization models have evolved significantly to accommodate non-financial factors, including climate risks. Building on Markowitz's Modern Portfolio Theory (MPT), this research incorporates climate change risk metrics into the traditional risk-return framework. A recent study by Le Guenedal and Roncalli (2022) proposes specific climate metrics, such as carbon intensity and greenhouse gas (GHG) emissions, that are integrated into portfolio selection processes to balance financial returns with sustainability goals.

An important advance in sustainable finance is the integration of multi-objective models that consider not only profitability but also sustainability. For instance, García et al. (2020) introduced a multi-objective credibilistic portfolio selection model and demonstrated its application in the Latin American integrated market. This approach aligns with the growing focus on sustainable investing, where portfolios are optimized not only for financial performance but also for environmental impact. Similarly, Yadav et al. (2023) proposed a multi-objective sustainable financial portfolio selection approach under an intuitionistic fuzzy framework, further enriching the methodological landscape of sustainable finance.

2.2 Intregating climate risk metrics in portfolio optimization

The complexity of incorporating sustainability into financial models is underscored by recent developments in fuzzy logic and decision theory. Wang et al. (2023) explored multi-criteria fuzzy portfolio selection based on three-way decisions and cumulative prospect theory, providing a nuanced approach to handling uncertainty in sustainable investments. This aligns with the integration of climate risk metrics into portfolio optimization, as emphasized by Hoffmann and Busch (2008) and Le Guenedal and Roncalli (2022), where genetic algorithms are employed to balance profitability and sustainability objectives. These approaches are critical in addressing existing gaps in traditional portfolio optimization, which often fails to account for the uncertainty inherent in climate-related financial risks.

One of the most promising approaches for integrating climate risk into portfolio optimization is the use of genetic algorithms, as demonstrated by Hoffmann and Busch (2008). Genetic algorithms allow for multi-objective optimization, balancing profitability and sustainability objectives, and are well suited to handling the complexity of climate-related data. By incorporating climate metrics such as GHG emissions and carbon intensity into the optimization process, these algorithms can generate portfolios that minimize climate risks while maintaining competitive financial performance.

The integration of sustainability metrics, particularly those related to climate change, into asset portfolio selection has gained traction in both academic and practical applications. Recent work by Fang et al. (2019) shows that models incorporating climate risk factors outperform traditional models in the long run, despite potential short-term trade-offs in profitability. These findings reinforce the argument that investors can achieve a balanced approach that meets both financial and environmental goals, providing a more comprehensive risk assessment framework compared to conventional models.

2.3 Addressing gaps in prior research

Despite the growing body of literature on sustainable portfolio optimization, gaps remain in fully integrating sustainability indices into traditional risk-return frameworks. Valencia (1997) demonstrated how genetic algorithms could be applied to optimize portfolios that integrate sustainability indices, offering a dynamic approach to balancing financial returns and climate responsibility. These advances enable investors to develop portfolios that align with evolving environmental regulations and market trends, such as the European Green Deal (Siddi, 2020), while maintaining acceptable levels of risk and return.

Additionally, García et al. (2019) developed a credibilistic mean-semivariance per portfolio selection model tailored to the Latin American context. While this model incorporates sustainability considerations, further refinement is necessary to ensure broader applicability across different financial markets. Similarly, De Spiegeleer et al. (2023) highlighted the growing role of ESG-driven portfolio allocation, but their work does not fully consider algorithmic optimization techniques, which can provide greater precision in balancing financial and sustainability objectives. This study builds upon this prior work by integrating genetic algorithm-based optimization with sustainability indices to address the shortcomings in conventional portfolio selection methods. By refining and extending the theoretical foundations of sustainable investing, this research contributes to the ongoing discourse on ESG integration, offering a novel approach that aligns investor preferences with sustainability and profitability goals.

3 Methodology and data

3.1 Climate change risk factors and company selection

According to the GHG Protocol (see https://ghgprotocol.org/standards-guidance), the sources of a company's emissions are divided into three groups: Scope 1, Scope 2, and Scope 3 emissions. Scope 1 emissions are direct emissions from sources that are owned or controlled by the emitting company. Scope 2 emissions are indirect emissions associated with the purchase of electricity, heat or steam. These can be calculated from the energy mix of the country in which the company is located or from the energy mix of the utility providing the electricity. Scope 3 emissions include indirect emissions such as the production of purchased materials, transportation in non-owned vehicles and electrical activities outside of Scope 2.

Integrating climate change risk factors into asset portfolio optimization requires a nuanced understanding of the sources and impacts of GHG emissions, as they are a direct measure of a company's environmental footprint. GHG emissions are divided into three distinct scopes as defined by the Greenhouse Gas Protocol (World Resources Institute, 2004): Scope 1: Direct emissions from owned or controlled sources (e.g., emissions from fuel combustion in company-owned vehicles or facilities); Scope 2: Indirect emissions from the generation of purchased electricity, steam, heating, and cooling consumed by the reporting company; Scope 3: All other indirect emissions that occur in a company's value chain (e.g., emissions from suppliers or waste disposal).

Each scope contributes to the total emissions of a company, typically expressed in tons of CO_2 equivalent (tCO_2e) (Le Guenedal & Roncalli, 2022). For more accurate comparisons across companies and sectors, GHG emissions are often normalized to carbon intensity, which measures emissions relative to a company's output or revenue.

We define total GHG emissions as the sum of emissions across the three scopes for each company in the portfolio (Equation 1), using the following formula:

$$C\mathcal{E}_{i_T otal} = \sum_{\substack{i=1 \\ j=1}}^{\substack{N \\ 3}} C\mathcal{E}_{i_j} \tag{1}$$

where CEij represents Scope j type of emissions in company i. For the purposes of this research, the carbon intensity (CI) of a company is calculated by dividing total GHG emissions by the company's total revenue or another appropriate economic indicator (Equation 2):

$$CI_{i_j} = \frac{C\mathcal{E}_{i_T otal}}{Y_i} \tag{2}$$

where, CEiTotal represents the total GHG emissions of company i, and Yi represents the total performance of the company, as measured by the company's total revenue. The decision to use revenue as the denominator is maintained to facilitate cross-sector comparisons, as the analysis spans various industries, including banking, technology, and real estate (Task Force on Climate-related Financial Disclosures, 2017). This formulation allows us to compare the environmental efficiency of companies within the portfolio, taking into account their carbon footprint relative to their economic productivity (Le Guenedal & Roncalli, 2022).

As shown in Table 1, energy companies have significantly higher carbon intensities due to their primary activities, which include direct emissions from fuel combustion and other industrial processes (Scope 1). This is particularly evident in companies such as Repsol and Endesa, where Scope 1 emissions are the dominant factor in their total GHG emissions.

The selection of the 10 companies from the IBEX 35 stock market index was driven by a strategic consideration of both sector representation and sustainability practices. In addition to choosing companies listed in the index, the selection aimed to capture a diverse range of industries to ensure a well-rounded portfolio. Each company was evaluated based on its sustainability performance, including factors such as carbon emissions, energy usage, and overall environmental impact. This assessment was complemented by a review of financial performance metrics, such as revenue growth, return on investment, and risk-adjusted returns, to ensure that the

Table 1
Emissions and carbon intensity in IBEX35 companies

Company	Emissions (tCO_2e)			Revenue	Carbon Intensity (tCO_2e/mill. €) |			
	Scope1 (CE1)	**Scope2 (CE2)**	**Scope3 (CE3)**	**Revenue (mill €)**	**Scope1 (CO1)**	**Scope2 (CI2)**	**Scope3 (CI3)**	**Total (CI)**
Indra	1681	7211	378127	3,874.66	0.43	1.86	97.59	99.88
Acciona	159652	139733	2764890	11,195.00	14.26	12.48	246.98	273.72
Colonial	2853	7126	107557	370.92	7.69	19.21	289.98	316.88
Iberdrola	10681100	1879380	42679200	53,949.00	197.99	34.84	791.10	1,023.92
Repsol	19400000	400000	157	69,291.00	281.22	5.72	1,133.11	1,420.05
Telefonica	131809	1002190	1930050	39,993.00	3.30	25.06	48.26	76.61
Sacyr	120101	253441	1953610	4,976.97	24.13	50.92	392.53	467.58
Bankinter	1763,82	0	14102,5	2,202.70	0.80	-	6.40	7.20
Endesa	13698200	397332	21725100	32,896.00	416.41	11.33	660.42	1,088.16
Naturgy	14741500	363489	10080000	33,965.00	434.02	10.70	3,240.98	3,685.71

chosen companies represented a balanced mix of strong financial stability and progressive sustainability efforts. Additionally, companies from high-impact sectors, such as energy (Repsol, Iberdrola) and utilities (Endesa, Naturgy), were included to highlight those making progress towards decarbonization, while firms in sectors such as technology (Indra, Acciona) were chosen to reflect their lower carbon footprint and significant role in driving innovation. This multi-faceted approach ensured that the portfolio not only met sustainability goals, but also provided a comprehensive cross-sector representation of the Spanish market.

The emission data for each company are sourced from Refinitiv, which provides comprehensive ESG data, including emissions figures reported by the companies themselves (Supplementary Data 6 – Climate Metrics). Refinitiv aggregates data from a wide variety of sources, including company annual reports, regulatory filings, and public disclosures, ensuring a broad and authoritative basis for the analysis. However, inconsistencies in emissions reporting, such as those observed for Bankinter and Repsol, may arise due to differences in reporting standards, data availability, or company-specific disclosure practices. These inconsistencies highlight the importance of scrutinizing the transparency of each company's emissions data and their potential impact on the overall analysis.

To ensure clarity and transparency, it is important to identify the source of emissions data for each company. For example, Refinitiv compiles and standardizes emissions information from multiple public disclosures and regulatory reports to ensure that data discrepancies are minimized. When comparing data across companies, we must also consider the reporting standards that each company adheres to, as this may influence the reported figures. It is also important to note that emissions data might be derived from different time periods, which can further affect consistency and comparability. Where applicable, the methodology used by Refinitiv to aggregate and report the emissions data should be mentioned to enhance transparency and confidence in the analysis.

However, the table also reveals inconsistencies in carbon intensities and CO_2e emissions for certain companies, such as Bankinter and Repsol, where the reported values are either lower than expected or absent. This discrepancy is due to the current reliance on corporate transparency for environmental data reporting. In cases like Bankinter, which operates in the financial sector, the reported emissions are disproportionately low compared to its industry peers, possibly due to a lack of Scope 1 emissions or insufficient reporting of indirect emissions (Scope 2 and 3). There are two main reasons for such discrepancies: either the data have not been published, or the emissions for a particular scope are actually minimal or non-existent.

3.2 Integrating climate metrics into the Markowitz model and the process of adapting the optimization model

In the pursuit of sustainable finance, decarbonizing asset portfolios has become a key strategy for aligning investment decisions with environmental goals. Andersson et al.

(2016) suggest two primary methods for achieving this. The first involves divesting from assets with an excessively high carbon footprint, thus reducing the overall carbon intensity of the portfolio. The second method involves rebalancing asset allocations to minimize tracking error relative to a benchmark index, while still lowering emissions.

This paper introduces a third approach that focuses on maximizing a sustainability index, *Sp* (see Equation 3), which incorporates the climate risk metrics previously described. *Sp,* the sustainability index, was chosen for its balanced approach to evaluating companies based on both profitability and carbon footprint reduction. This index goes beyond traditional financial metrics by incorporating sustainability-related factors such as carbon emissions and resource management alongside financial performance indicators such as revenue growth, profitability, and return on investment. By combining these elements, *Sp* allows investors to assess a company's long-term financial health while simultaneously ensuring that the company is committed to reducing its environmental impact.

Building on MPT, this methodology embeds sustainability into the optimization process by incorporating the sustainability index into the Markowitz model. The result is a more comprehensive approach to portfolio management that addresses both profitability and climate-related risks, ensuring that investments align with long-term sustainability goals while maintaining robust financial performance.

The practical implementation of this approach begins by defining a chromosomal representation of potential solutions, where each chromosome represents a portfolio of assets encoded as a vector of investment weights. For a portfolio consisting of *N* different assets, a chromosome is represented by a vector **W** = (w1, w2, ..., wn), where **W** is the chromosome and wi is the weight assigned to the asset i in the portfolio, indicating the fraction of total capital invested in that asset. The weights within the chromosome must sum to 1, as per Equation 4, which is one of the fundamental constraints of Markowitz's portfolio theory, also ensuring the portfolio satisfies the investor's minimum return requirement (Equation 5).

These chromosomes, also referred to as individuals, form the initial population. For this population, 10 companies are selected from the IBEX 35 stock market index. The selected companies are Indra, Acciona, Inmobiliaria Colonial, Iberdrola, Repsol, Telefónica, Sacyr, Bankinter, Endesa and Naturgy, identified by their ticker symbols: IDR.MC, ANA.MC, COL.MC, IBE.MC, REP.MC, TEF.MC, SCYR.MC, BKT.MC, ELE.MC, and NTGY.MC.[1] Each chromosome is scored based on a fitness function that integrates climate risk metrics and the expected return of the portfolio. This function penalizes portfolios that fail to meet the investor's predetermined minimum profitability requirements, ensuring that only viable solutions that balance profitability and sustainability are selected for further optimization.

$$MaximizeSp = f\left(w_1, w_2, \dots, w_n\right) \tag{3}$$

Subject to:

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

$$\sum_{i=1}^{N} w_i r_i = R_{min} \tag{5}$$

To define the metrics, LeGuenedal and Roncalli (2022) propose introducing a new measure to evaluate the risk of climate change in asset portfolios. For this purpose, Ci is considered as a climate metric for asset i. These climate metrics are treated as linear measures (Equation 6):

$$C = \sum_{i=1}^{N} w_i C_i \tag{6}$$

With the selected metrics of CO_2e emissions and carbon intensity established, the constraints can be adjusted as follows (Equations 7 and 8):

$$\sum_{i=1}^{N} w_i C\mathcal{E}_i \leqslant C\mathcal{E}_{max} \tag{7}$$

$$\sum_{i=1}^{N} w_i CI_i \leqslant CI_{max} \tag{8}$$

This concludes with the formulation of the sustainability index, which we aim to maximize (Equation 9).

$$MaxS_p = \sum_{i=1}^{N} w_i \left(\frac{\alpha}{C\mathcal{E}_i} + \frac{\beta}{CI_i} \right) \tag{9}$$

where n is the number of assets in the portfolio, wi is the weight of asset i in the portfolio, CEi represents the GHG

[1] The data required for this study, including daily closing prices, are sourced from Refinitiv Workspace. This platform provides a robust financial and sustainability database, including detailed reports on GHG emissions and other ESG indicators.

emissions of asset i, and CIi denotes the carbon intensity of asset i. The coefficients α and β are used to adjust for the relative importance of emissions versus carbon intensity. Finally, the inverse of the metrics is calculated to maximize *Sp*, thereby encouraging the inclusion of assets with the lowest CO_2 emissions and intensity.

3.3 Integrating the modified optimization model into the genetic algorithm

Integrating the optimization problem of an investment portfolio that maximizes sustainability under climate constraints while ensuring a minimum expected return into a genetic algorithm (GA) requires adapting the problem to the structure and operations of GAs. GAs, inspired by the processes of natural and genetic selection, offer a robust and flexible approach to exploring complex solution spaces (Valencia, 1997).

Applying GAs to this modified portfolio optimization model addresses the complexity of balancing multiple objectives, specifically return, risk, and sustainability. In this framework, sustainability is evaluated using the index defined in the previous section, which is weighted according to the allocation of assets in the portfolio. The algorithm ensures that the portfolio meets the investor's minimum expected return by applying penalties if the return falls below the threshold, thereby reducing the fitness of suboptimal solutions.

In this context, each individual (or chromosome) in the GA represents a vector of weights *W* corresponding to the asset distribution in the investment portfolio. The fitness function *f(W)*, which is used to evaluate the effectiveness of each portfolio, can be formulated as follows (Equation 10):

$$f(W)=\lambda\left(\sum_{i=1}^{N} w_i\left(\frac{\alpha}{c\varepsilon_i}+\frac{\beta}{CI_i}\right)\right)-\rho * \max\left(0, R_{\min}-\sum_{i=1}^{N} w_i r_i\right) \qquad (10)$$

By substituting Equation 9, the latter equation can be simplified to Equation 11:

$$f\left(W\right)=\lambda S_p-\rho^{*}\max\left(0, R_{min}-\sum_{i=1}^{N} w_i r_i\right) \qquad (11)$$

where λ is a scale factor that adjusts the relative importance of sustainability in the fitness function, and ρ is the penalty factor applied if the portfolio's return falls below the minimum threshold. The values of α and β determine whether the optimization prioritizes total emissions reduction, carbon efficiency per unit of revenue, or a balanced approach between the two. In this study, we choose to set them to the unit (α=1 and β=1) to give equal importance to both metrics, ensuring a balanced assessment of sustainability performance. This choice aligns with prior research on ESG-driven portfolio selection, which suggests that giving equal weight to different sustainability criteria leads to more diversified and stable portfolio allocations (Le Guenedal & Roncalli, 2022; Fang et al., 2019). From a financial perspective, treating both measures equally prevents overconcentration in firms with low absolute emissions, while also taking into account their relative environmental efficiency.

To assess the impact of different weightings, we conducted a sensitivity analysis by systematically varying α and β. We tested three alternative scenarios:

1 Emissions-focused scenario (α=2, β=1). Greater emphasis on total GHG emissions reduction.

2. Intensity-focused scenario (α=1, β=2). More emphasis on carbon efficiency per unit of revenue.

3. Balanced scenario (α=1.5, β=1.5). Slightly favors companies with high ESG transparency.

The results indicate that when α>β, the portfolio favors companies with low absolute emissions, often leading to a higher concentration in financial and tech companies. Conversely, when β>α, the model shifts towards companies with low emissions relative to their economic output, favoring firms in the utilities and energy sectors that have adopted carbon reduction strategies. The balanced scenario (α=1.5, β=1.5) produced a more diversified portfolio that reduced both volatility and carbon exposure while maintaining competitive returns.

These findings highlight the importance of properly selecting α and β based on investor priorities. If the goal is to maximize absolute carbon reduction, a higher α is preferable. However, for investors seeking financial performance with improved carbon efficiency, increasing β will provide better results. By default, the equal weighting (α=1, β=1) is retained as a neutral, balanced configuration that provides a fair trade-off between financial and environmental performance.

Once the variables of the sustainability index have been defined, we classify investors into three different types based on their level of commitment to sustainable portfolios: sustainable, balanced, and profitable investors (see Table 2). Each type of investor reflects a different balance between maximizing sustainability and prioritizing financial performance. In addition, a fourth type of investor is included that is characterized by not considering the sustainability index in their decision making. This type of investor focuses solely on financial profitability, ignoring sustainability criteria.

As shown in the table, each type of investor is associated with different values of λ and ρ, which represent their respective weights for sustainability and return constraints. Sustainable investors prioritize sustainability ($\lambda = 10$), while profitable investors place greater emphasis on financial returns ($\rho=10$). Balanced investors try to find a middle ground between the two.

Over successive generations, chromosomes are selected for reproduction based on their fitness, with more fit chromosomes having a higher chance of being chosen. In this study, we employ roulette selection (also known as Monte Carlo selection), a method commonly used in genetic algorithms to select individuals for the next generation or crossover (Velasco, 2022). In roulette selection, each chromosome is assigned a portion of the "roulette wheel" based on its fitness level, with fitter chromosomes occupying larger portions. A random number between 0 and 1 is generated, and the corresponding chromosome is selected by accumulating the fitness segments until the sum exceeds the randomly generated value. Chromosomes with higher fitness are therefore more likely to be selected for reproduction.

Although simple and effective, roulette selection can be computationally inefficient for large populations. However, given the population size in this study, it is a suitable choice. This method integrates well with the weighting of assets in the portfolio and is straightforward to implement in Python, as described in the following section (Blickle & Thiele, 1996).

Once selected, parent chromosomes undergo crossover and mutation to produce offspring for the next generation. Crossover combines genetic material from two parent chromosomes to produce offspring that ideally inherit beneficial traits from both parents. In this study, we use the 1-point crossover technique, which involves selecting a random crossover point within the chromosome and swapping the tail segments between two parents to generate new offspring. This method encourages solution diversity while maintaining genetic consistency. The probability of crossover is set to 0.6, a balance that allows sufficient recombination without excessive disruption. The crossover probability needs to find a balance between exploration (diversity of solutions) and exploitation (refinement of good solutions). Prior research suggests that values in the range of 0.6 to 0.8 are effective in financial applications because they allow sufficient recombination without excessive disruption of high-performing solutions (Sosa et al., 2014; Blickle & Thiele, 1996). Lower values could slow convergence, while excessively high probabilities might lead to premature convergence and loss of diversity (Holland, 1992).

After crossover, mutation is applied to introduce random changes to one or more genes in the chromosome, ensuring that the genetic algorithm explores a wider solution space and avoids premature convergence to local optima. Mutation helps to maintain diversity within the population. In this study, the mutation probability (Pm) is set to 0.01, a commonly used value that introduces variability without overwhelming the existing structure of the solutions. In financial portfolio optimization, mutation rates between 0.01 and 0.05 are commonly employed to maintain diversity without excessively disrupting the evolving solutions (Deb, 2001; Valencia, 1997). A higher mutation rate might lead to excessive randomness, reducing the efficiency of convergence, while lower values could result in stagnation around local optima. The choice of Pm=0.01 aligns with studies in evolutionary algorithms applied to financial modeling, which show that such a value effectively balances exploration and convergence (Sosa et al., 2014; Velasco, 2022).

This iterative process of selection, crossover, and mutation enables the population to evolve towards increasingly optimal solutions. Retention of the best individuals from each generation ensures that solutions gradually converge towards the global optimum, while maintaining enough diversity to prevent stagnation in suboptimal areas of the solution space.

The first step in the analysis is to calculate the daily continuous returns for each asset. This is done by

Table 2
Classification of investors depending on their level of commitment to a sustainable portfolio

Sustainable	Balanced	Profitable	No-Sp
$\lambda = 10$	$\lambda = 5$	$\lambda = 5$	$\lambda = 0$
$\rho = 0$	$\rho = 5$	$\rho = 10$	$\rho = 10$

taking the natural logarithm of the ratio of the closing prices of consecutive days, which allows the calculation of the average daily return for the IBEX 35 index. This average daily return serves as a key reference point for constraining the fitness function of the genetic algorithm used in subsequent analyses. This return, defined as the minimum return (Rmin), is calculated to be 0.0621% per day, which annualizes to 15.65%.

$$DailyContinousReturn_i = R_i = ln\left(\frac{Price_t}{Price_{t-1}}\right) \tag{12}$$

Once the daily returns are calculated, the expected return, standard deviation, and variance for each asset are determined and then annualized. These data are then employed to construct the covariance matrix using Excel's data analysis tools.

The study employs two different methods to determine optimal portfolios. The first method, referred to as the **traditional method**, constructs a control portfolio using the classical mean-variance optimization process, which does not incorporate sustainability indices. In this approach, portfolio weights are randomly generated using Excel's RANDARRAY function. The Excel Forecast module's Data Table tool is employed to simulate 1,500 iterations, allowing for the construction of the efficient frontier and the capital allocation line (CAL). The performance of the portfolios is evaluated by identifying the optimal portfolio that maximizes the modified Sharpe ratio, which in this context excludes the risk-free return.

The second method employs a **genetic algorithm** designed to optimize the portfolio by balancing the objectives of profitability and sustainability. The genetic algorithm is implemented using the DEAP library in Python, leveraging the computational power of libraries such as NUMPY, DEAP, and PANDAS for mathematical calculations and algorithmic processing. The fitness function of the genetic algorithm integrates parameters such as return, volatility, and sustainability metrics, with additional parameters such as lambda and rho to represent different investor preferences. The algorithm is run for 1,500 iterations, generating optimal portfolios for five different types of investors, including those with sustainable and profitability-oriented objectives. The results of this approach include portfolios that maximize both the Sharpe ratio and the sustainability index, providing a comprehensive assessment of performance. The efficient frontier of the portfolios is visualized using three-dimensional scatterplots in MATLAB that illustrate the complex relationships among return, volatility, and sustainability metrics.

The development of the genetic algorithm addressed limitations in the original algorithm design, particularly in the normalization of portfolio weights to satisfy the constraints of the Markowitz model.

In addition to genetic algorithms, the inclusion of other optimization techniques such as Particle Swarm Optimization (PSO) and Simulated Annealing (SA) can provide a more comprehensive comparison of algorithmic performance and enhance the robustness of the solution-finding process. PSO is an optimization technique inspired by the social behavior of birds and fish. It involves particles (potential solutions) moving through the search space, influenced by both their own best position and that of their neighbors. PSO is effective for continuous optimization problems and typically converges quickly to optimal or near-optimal solutions. Compared to genetic algorithms, PSO is often faster for problems with fewer parameters and continuous spaces, while genetic algorithms are better suited for complex, combinatorial problems. SA is inspired by the annealing process in metallurgy, where a material is heated and then slowly cooled to minimize energy. In optimization, SA explores the solution space by accepting both better and worse solutions with a decreasing probability over time. This helps the algorithm escape local optima and find global solutions. SA is especially useful for complex, non-linear, or multi-modal problems where identifying the global optimum is challenging (Sexton et al., 1999).

By comparing the efficiency and effectiveness of these algorithms, it is possible to gain a broader perspective on their strengths and weaknesses, ultimately leading to a more informed decision about the best optimization method for a given problem. Testing a combination of algorithms, or hybrid approaches, could also be explored to capitalize on the strengths of each method (Supplementary Data 7 – Appendix A and Supplementary Data 8 – Appendix B).

4 Results

The findings of this study, based on both traditional mean-variance optimization and genetic algorithm techniques, provide important insights into how the inclusion of sustainability considerations affects asset portfolio management. This section further explores

Table 3
Optimal asset portfolio composition

	IDR.MC	ANA.MC	COL.MC	IBE.MC	REP.MC	TEF.MC	SCYR.MC	BKT.MC	ELE.MC	NTGY.MC
Traditional Method	17.33%	1.03%	0.10%	14.01%	2.71%	11.19%	17.05%	4.27%	15.41%	16.89%

Table 4
Optimal asset portfolio composition - for each investor type and method

	IDR.MC	ANA.MC	COL.MC	IBE.MC	REP.MC	TEF.MC	SCYR.MC	BKT.MC	ELE.MC	NTGY.MC
SUST-SR	9.37%	0.00%	5.98%	10.20%	0.26%	13.49%	20.68%	27.36%	4.26%	8.42%
SUST-SI	0.61%	3.98%	0.16%	2.70%	4.69%	10.86%	1.02%	67.72%	0.07%	8.19%

the dominance at the asset level and explains why certain companies receive higher allocations in optimized portfolios.

Table 3 shows the optimal portfolio composition obtained through the traditional mean-variance optimization after 1,500 iterations. The allocations reveal a preference for certain assets, notably Indra (17.33%), Sacyr (17.05%), Endesa (15.41%), and Naturgy (16.89%), indicating that these companies were identified as offering a favorable balance between risk and return. In contrast, Acciona (1.03%) and Inmobiliaria Colonial (0.10%) received significantly lower allocations, indicating that their risk-return profiles were less attractive in this model. This distribution implies that the optimization process, when focused solely on traditional financial performance metrics, results in a portfolio concentrated in a few key assets with perceived strong financial characteristics.

Figure 1 illustrates the performance of this portfolio on the efficient frontier, with a total return of 15.77%, volatility of 11.73%, and a Sharpe ratio of 134.51%. The figure effectively shows the risk-return trade-offs and demonstrates that the traditional optimization method emphasizes maximizing returns for a given level of risk without considering sustainability factors. Indra, for instance, benefits from stable government contracts that reduce its exposure to market fluctuations, making it a preferred asset for profit-driven portfolios. Similarly, Sacyr, which operates in the infrastructure sector, demonstrates resilience through long-term projects and steady revenue growth, increasing its attractiveness for risk-adjusted return optimization. Meanwhile, Naturgy and Endesa, both energy firms with stable revenues supported by government incentives for a sustainable energy transition, emerge as highly preferred choices in traditional portfolio optimization.

The concentration of the portfolio in a few key assets aligns with the intention to increase return relative to risk, which is a hallmark of mean-variance optimization.

Table 5
Sustainable investor asset portfolio indicators

Indicators	Most profitable portfolio (max. Sharpe)	Most sustainable portfolio (max. Sp)
Profitability (Rp)	12.12%	0.66%
Volatility (σp)	14.02%	20.48%
Sharpe Ratio	86.48%	3.24%
Sustainability Index (Sp)	41.50%	95.79%

Unlike the traditional approach, the genetic algorithm method allowed for the simulation of portfolios tailored to five different investor profiles described in Section 3.3. For each investor type, the algorithm produced two portfolio variants: one optimized for the Sharpe ratio (referred to as the most profitable portfolio) and another that maximized the sustainability index (referred to as the most sustainable portfolio).

Focusing on the sustainable investor, defined by the parameters λ=10 and ρ=0, the resulting most profitable portfolio (SUST-SR) is relatively balanced but shows a significant concentration in Bankinter (27.36%), as shown in Table 4. This allocation led to a return of 12.12%, volatility of 14.02%, a Sharpe ratio of 86.46%, and a sustainability index of 41.50% (see Table 5). The results suggest a moderate approach to balancing sustainability and profitability, as evidenced by the diversity of the asset allocation and the relatively high risk-adjusted return. This is driven by Bankinter's low carbon intensity and high ESG transparency. The financial sector generally has a lower carbon footprint compared to industrial sectors, and Bankinter's strong ESG disclosure practices align well with sustainability-focused optimization models.

However, the most sustainable portfolio for this investor profile (SUST-SI) has a significantly different asset distribution, heavily favoring Bankinter with an allocation of 67.72%. This shift towards Bankinter results in a significant increase in the sustainability index to 95.79%, reflecting the portfolio's strong sustainability orientation. However, this comes at the expense of financial performance, as the portfolio's return drops significantly to 0.66%, with a corresponding increase in volatility to 20.48% (see Figure 2). Figure 3 illustrates the trade-off between maximizing sustainability and achieving financial stability (Supplementary Data 3 – Sustainable Portfolio).

For the balanced investor, characterized by the parameters λ=5 and ρ=5, the genetic algorithm achieves a balance between profitability and sustainability, resulting in a portfolio with a diversified asset allocation.

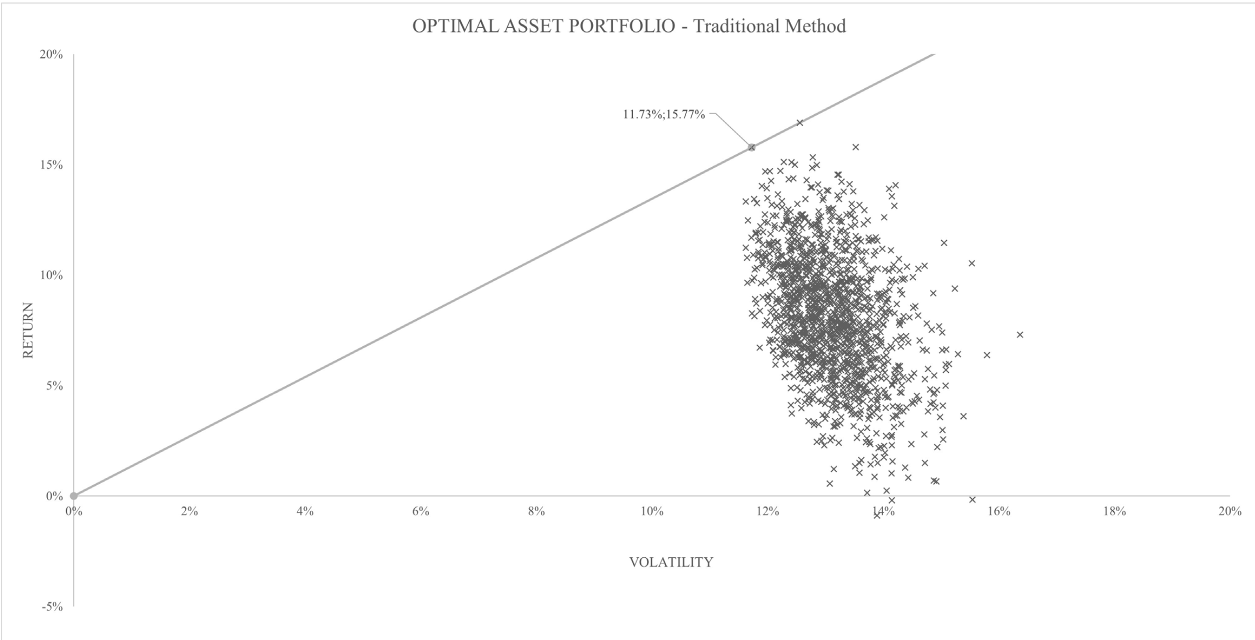

Figure 1. Traditional method

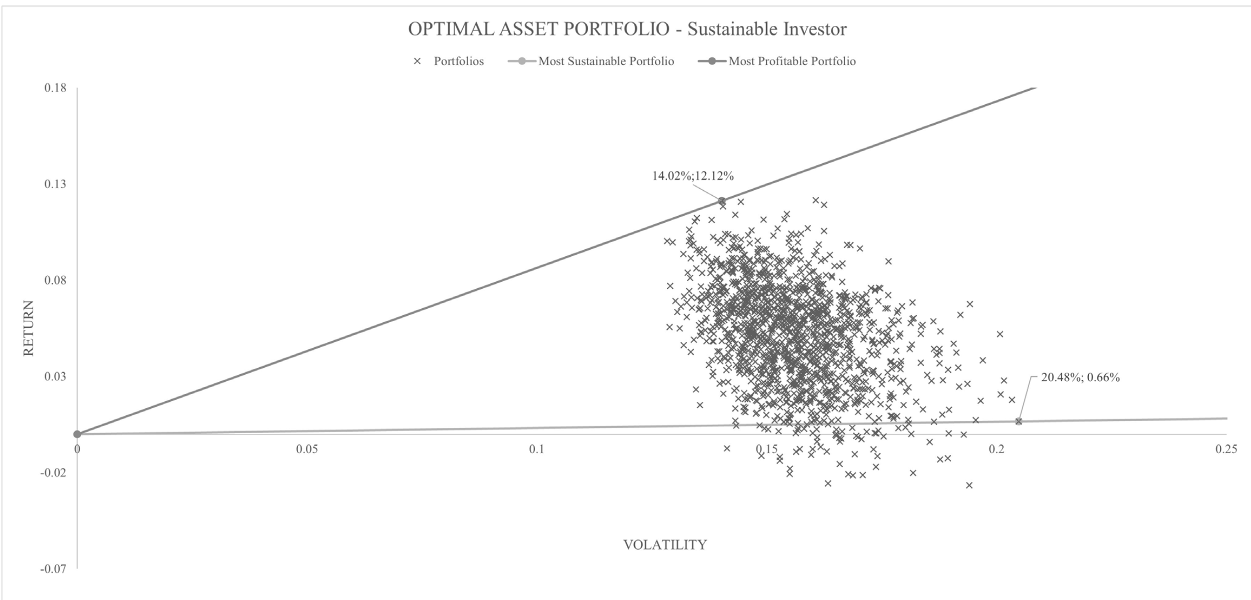

Figure 2. Sustainable investor

Table 6
Optimal asset portfolio composition - for each investor type and method

	IDR.MC	ANA.MC	COL.MC	IBE.MC	REP.MC	TEF.MC	SCYR.MC	BKT.MC	ELE.MC	NTGY.MC
EQU-SR	41.32%	0.42%	1.01%	0.00%	1.20%	0.64%	22.02%	4.67%	13.06%	15.66%
EQU- SI	30.99%	1.83%	4.09%	0.00%	0.00%	0.00%	24.22%	27.89%	7.40%	3.59%

The most profitable portfolio (EQY-SR), as shown in Table 6, has a notable emphasis on Indra (41.32%) and Sacyr (22.02%), suggesting that these assets represent an optimal trade-off between return and sustainability within this investor profile. This portfolio yields a return of 20.76%, with a relatively low volatility of 13.05%, giving a Sharpe ratio of 159.12% (see Table 7). The sustainability index for this portfolio is 5.70%, indicating that while sustainability is a consideration, it does not dominate the portfolio composition (Supplementary Data 1 – Balanced Portfolio).

In contrast, the most sustainable portfolio for the balanced investor (EQU-SI) has a more varied distribution, with Bankinter (27.89%), Indra (30.99%), and Sacyr (24.22%) having the largest weights. This configuration results in a sustainability index of 20.56%, significantly higher than that of the most profitable portfolio. However, this shift towards sustainability has an impact on financial performance: the portfolio achieves a lower return of 15.50%, with an increased volatility of 14.97%, resulting in a Sharpe ratio of 103.55%.

Figures 4 and 5 illustrate these different results. Figure 4, which shows the most profitable portfolio, highlights its strong financial performance and relatively modest sustainability orientation. Figure 5, showing the most sustainable portfolio, highlights a more balanced asset allocation that aims to maximize sustainability while maintaining reasonable levels of profitability and risk. The trade-off between maximizing returns and improving the sustainability index is evident, as the equilibrium approach maintains a notable balance between financial performance and environmental considerations.

These findings suggest that an equilibrium approach, which balances profitability and sustainability objectives, can produce a portfolio with favorable risk-adjusted returns while also enhancing its sustainability profile. Although there is a modest trade-off in financial return and increased volatility when sustainability is prioritized, the balanced investor achieves a more comprehensive outcome that aligns with both financial goals and sustainability principles.

Table 7
Balanced investor's asset portfolio indicators

Indicators	Most profitable portfolio (max. Sharpe)	Most sustainable portfolio (max. Sp)
Profitability (Rp)	20.76%	15.50%
Volatility (σp)	13.05%	14.97%
Sharpe Ratio	159.12%	103.55%
Sustainability Index (Sp)	5.70%	20.56%

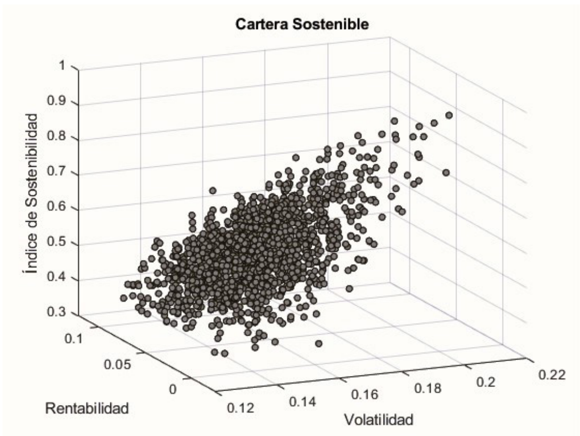

Figure 3. Sustainable portfolio

For the profitable investor, defined by the parameters λ=1 and ρ=10, the genetic algorithm focuses on maximizing financial returns, resulting in a concentrated asset distribution in the most profitable portfolio (PROF-I-SR). As shown in Table 8, this portfolio is heavily weighted in Indra (36.75%) and Naturgy (22.64%), reflecting the favorable financial performance and risk-return characteristics of these assets for this investor type. Consequently, the portfolio achieves a high return of 19.14% with a relatively low volatility of 12.29%, resulting in an impressive Sharpe ratio of 155.68% (see Table 9). The sustainability index of 3.21% indicates a minimal emphasis on sustainability in this portfolio, aligning with the investor's primary focus on profitability.

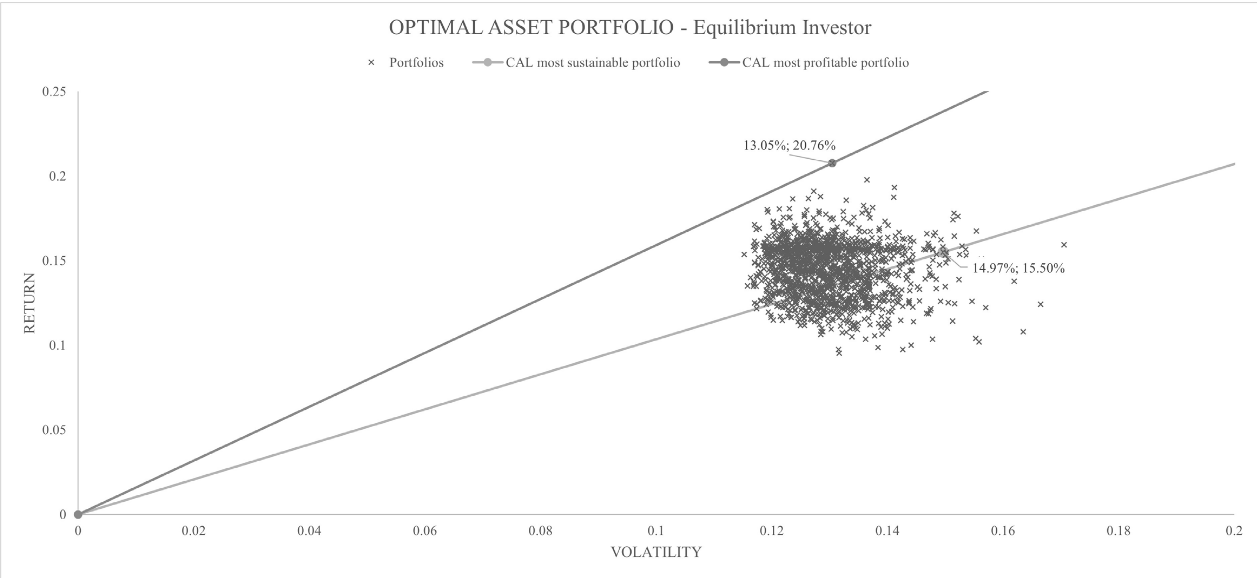

Figure 4. Balanced investor

Table 8
Optimal asset portfolio composition - for each of investor type and method

	IDR.MC	ANA.MC	COL.MC	IBE.MC	REP.MC	TEF.MC	SCYR.MC	BKT.MC	ELE.MC	NTGY.MC
PROF-I-SR	36.75%	1.31%	0.00%	9.52%	0.06%	15.51%	11.80%	0.17%	2.24%	22.64%
PROF-I-SI	33.58%	2.24%	1.01%	5.29%	0.00%	1.59%	26.32%	27.49%	2.47%	0.00%

In contrast, the most sustainable portfolio for the profitable investor (PROF-I-SI) has a more diversified asset allocation, with significant holdings in Sacyr (26.32%) and Bankinter (27.49%), as shown in Table 8. This shift raises the portfolio's sustainability index to 21.25%, a significant improvement compared to the profitability-maximizing portfolio. However, there is a trade-off in financial performance: the return decreases to 15.92%, and volatility rises to 14.98%, resulting in a Sharpe ratio of 106.29%. These outcomes reflect a clear compromise between maximizing returns and sustainability, with a more moderate approach to profitability (Supplementary Data 5 – Profitable Portfolio).

Figure 6, showing the most profitable portfolio, highlights the high return and relatively stable risk profile, consistent with the investor's profit-driven approach. Figure 7, which illustrates the most sustainable portfolio, shows the recalibration towards a more balanced but less financially optimized structure, reflecting the impact of sustainability integration on the risk-return profile.

The results confirm the inherent trade-offs between profitability and sustainability: prioritizing financial returns generally reduces the sustainability index, while integrating more sustainable assets requires a modest sacrifice in both return and risk-adjusted performance.

Table 9
Profitable investor's asset portfolio indicators

Indicators	Most profitable portfolio (max. Sharpe)	Most sustainable portfolio (max. Sp)
Profitability (Rp)	19.14%	15.92%
Volatility (σp)	12.29%	14.98%
Sharpe Ratio	155.68%	106.29%
Sustainability Index (Sp)	3.21%	21.25%

For the no-sustainability investor, characterized by the parameters $\lambda=0$ and $\rho=10$, the genetic algorithm focuses entirely on maximizing profitability without taking sustainability into account. As shown in Table 10, this approach results in a portfolio concentrated in assets such as Indra (34.40%) and Sacyr (20.79%), with significant allocations also to Naturgy (17.89%) and Endesa (10.43%). This emphasis on traditional financial performance results in a return of 19.54%, volatility of 12.35%, and a Sharpe ratio of 158.21% (Supplementary Data 4 – No Sp Portfolio).

The control configuration of the genetic algorithm, with both λ and ρ set to zero, serves as a baseline for comparing the effects of sustainability considerations. This setup yields a portfolio similar to that generated by the traditional mean-variance optimization, with a return of 15.16%, volatility of 11.97%, and a Sharpe ratio of 126.65%, as shown in Table 10. The control portfolio is more diversified compared to the no-sustainability investor's portfolio, with weights more evenly distributed across assets. This configuration confirms the efficiency of the genetic algorithm in replicating traditional optimization results, while serving as a benchmark for assessing the influence of sustainability on portfolio composition (Supplementary Data 2 – GA Control Portfolio).

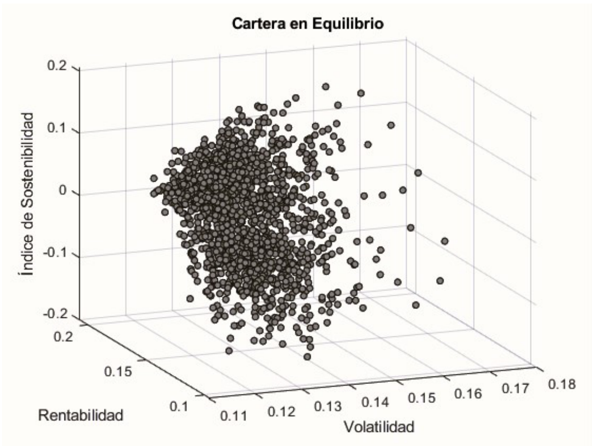

Figure 5. Balanced portfolio

Figure 8 shows strong financial returns and relatively low risk, achieved without any sustainability constraints. In contrast, the control portfolio (Figure 9) emphasizes a balanced risk-return profile that closely mirrors traditional optimization results.

A critical observation from the optimized portfolios is the significant concentration of assets in certain stocks, particularly in the portfolios with a strong sustainability focus. For example, the most sustainable portfolio (SUST-SI) allocates as much as 67.72% to

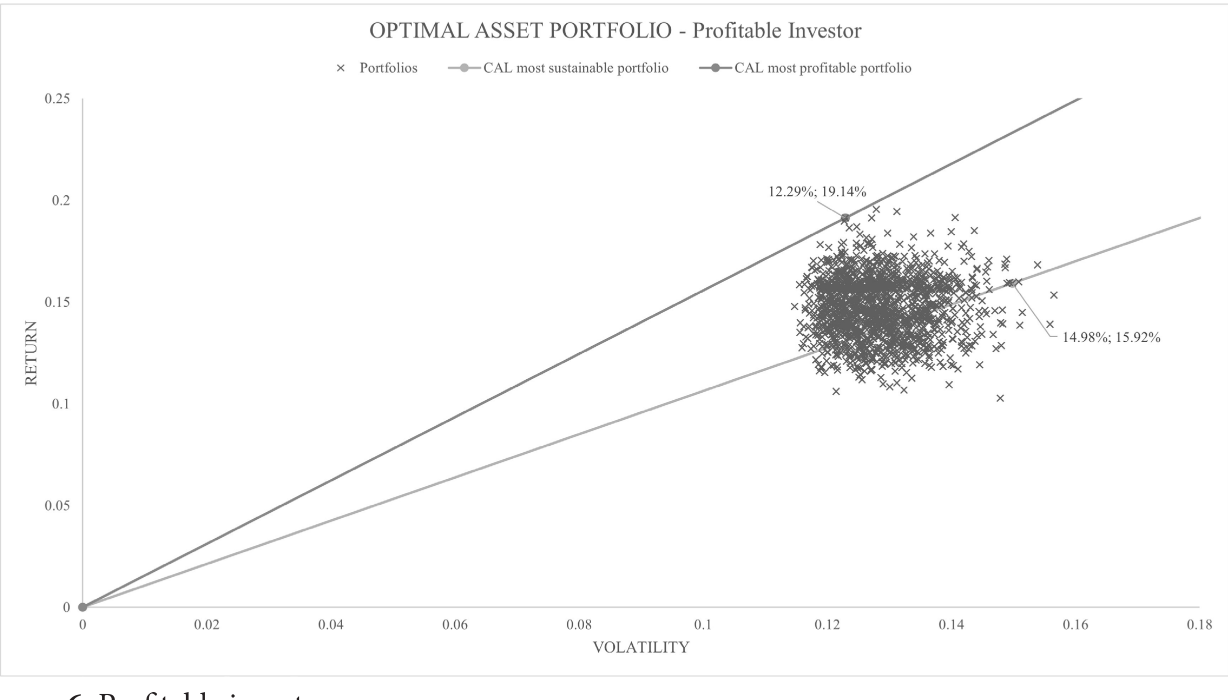

Figure 6. Profitable investor

Table 10
Optimal asset portfolio composition - for each investor type and method

	IDR.MC	ANA.MC	COL.MC	IBE.MC	REP.MC	TEF.MC	CYR.MC	BKT.MC	ELE.MC	NTGY.MC
No-SUS-I	34.40%	0.00%	1.06%	6.33%	3.37%	3.46%	20.79%	2.27%	10.43%	17.89%
Control	21.21%	0.08%	6.87%	1.91%	10.27%	13.33%	12.81%	0.63%	15.63%	17.25%

Bankinter, suggesting that stringent ESG constraints may lead to an over-reliance on a limited number of stocks. This concentration could pose a potential risk to portfolio diversification, as sustainability-focused strategies might inadvertently limit exposure to a broader range of sectors or asset classes.

On the other hand, the balanced investor (EQU-SI) and profitable investor (PROF-I-SI) portfolios have a more diversified allocation and strike a balance between financial performance and ESG integration. The control portfolio, generated through traditional mean-variance optimization, also reflects a broader distribution of assets, reinforcing the tendency of financial optimization models to favor concentration in high-performing companies. These observations underscore the delicate balance between concentration and diversification, with implications for investors seeking to align financial returns with sustainability goals.

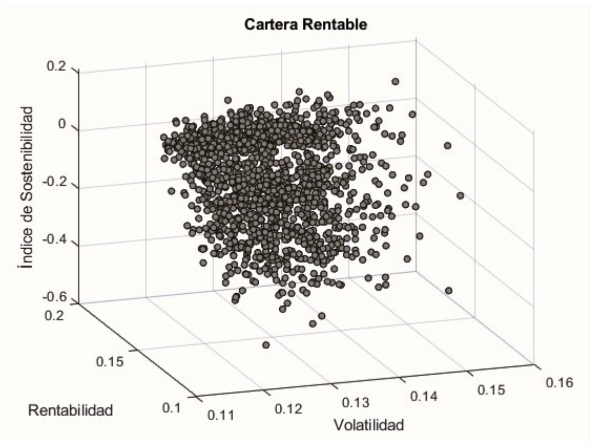

Figure 7. Profitable portfolio

To assess the robustness of the asset dominance, a sensitivity analysis was conducted by adjusting key parameters, such as ESG weightings, risk constraints, and sector-specific adjustments. Increasing the ESG weightings led to a concentration of assets in companies such as Bankinter, Endesa, and Iberdrola, which are characterized by a low carbon footprint and strong sustainability practices. Conversely, relaxing the risk constraints allowed for greater inclusion of high-return assets such as Indra and Sacyr, enhancing financial performance but reducing the sustainability index. These findings underscore the importance of carefully calibrating sustainability constraints to avoid overconcentration in specific stocks while ensuring that the portfolio remains financially viable.

Adjusting the sector-specific caps also led to a more balanced allocation, reducing the over-reliance on

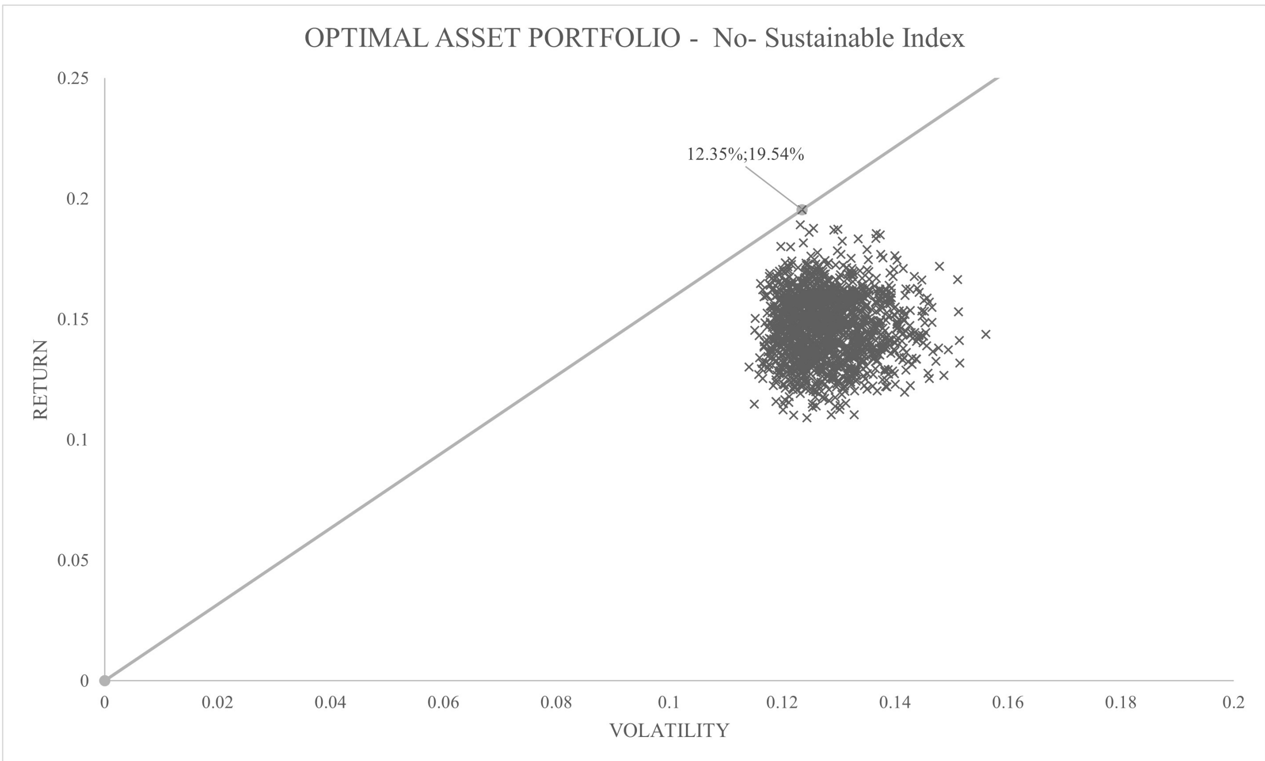

Figure 8. No-sustainability investor

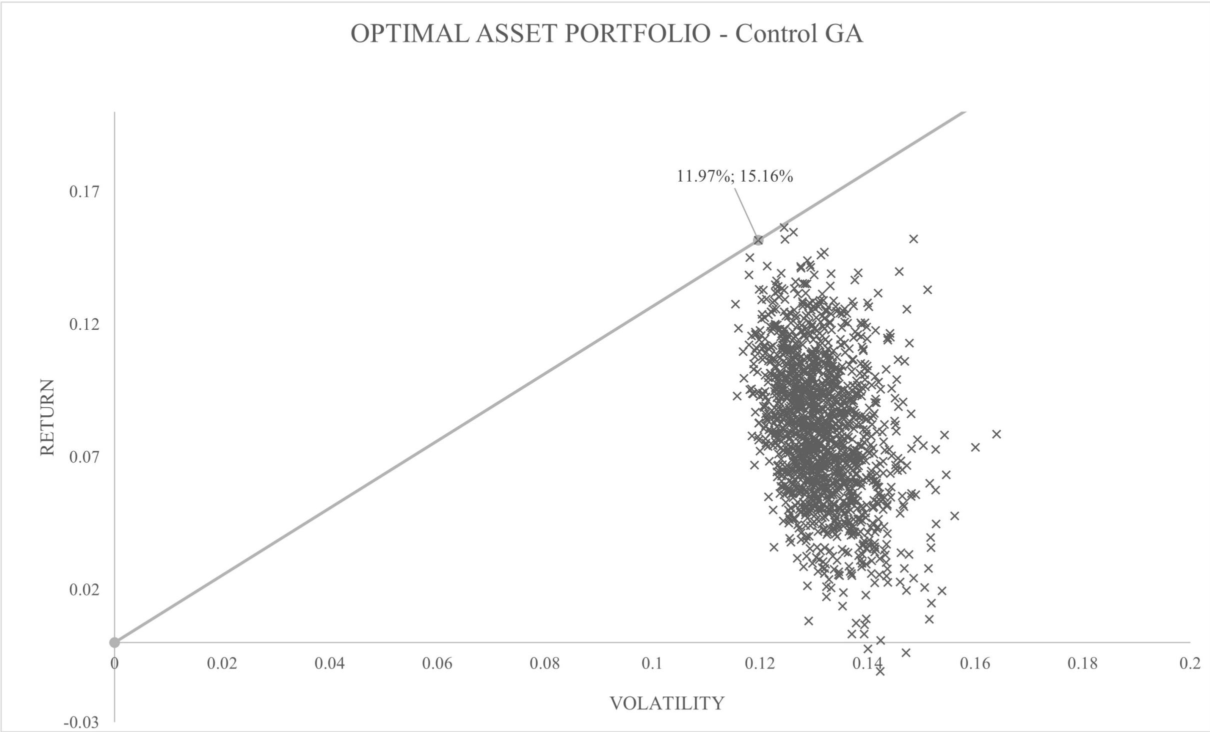

Figure 9. Control using GA

financial and energy stocks. This finding underscores the importance of considering sector diversification within optimization models, particularly for investors seeking to achieve a more holistic and sustainable portfolio.

This study highlights the trade-offs between financial returns and sustainability. The balanced investor's Sharpe-maximizing portfolio achieves the best risk-adjusted return (159.12%) with moderate sustainability. The no-sustainability investor performs similarly well in terms of profitability, but ignores sustainability. The sustainable investor's portfolios, particularly when maximizing sustainability, experience significant reductions in returns and increased volatility, underscoring the cost of prioritizing sustainability. The profitable investor balances profitability with some sustainability, but like the balanced investor, favors higher financial returns. The control and traditional portfolios serve as baselines for comparison, reflecting traditional financial optimization without sustainability integration.

These results suggest that while integrating sustainability into portfolio optimization may initially reduce returns, a strategically balanced approach can lead to favorable outcomes that effectively align financial performance with environmental and social responsibility objectives.

5 Discussion

Since sustainability includes the economic, social, and environmental elements necessary for long-term resilience, it is critical to business and finance. Businesses can ensure ongoing operations by adopting sustainable practices that help them better manage risks associated with resource scarcity and climate change. Additionally, businesses must adhere to stringent laws in order to avoid penalties due to the increasing global legislation aimed at minimizing environmental impacts (García Lupiola, 2022). This is particularly relevant as more concerned consumers favor goods and services that are ethically and sustainably produced, which can give businesses a competitive edge in places where corporate social responsibility is highly valued (Acedo Rey, 2019).

The study examines how environmental and social responsibility influences financial decision making, specifically in asset portfolio optimization. It compares two methods: the traditional approach and the genetic algorithm (GA), with the central question being whether maximizing sustainability reduces profitability. After verifying the functionality of the GA, it is confirmed that it produces similar results to the traditional method, but with greater variability, reflecting market randomness.

Furthermore, when the GA is optimized without considering the sustainability index, the return is 4% higher, with a slight increase in volatility. The GA proves to be more profitable than the traditional method, while keeping returns above the IBEX 35 benchmark.

When sustainability is the top priority, the most successful portfolio belongs to the return-seeking investor, with a return of 15.92% and volatility of 14.98%. On the other hand, the least effective portfolio is that of the sustainable investor, with a return of 0.66% and the highest volatility at 20.48%. The balanced investor's portfolio is quite similar to that of the profitable investor, but with slightly lower performance. The main difference between the portfolios is the sustainability index and its weighting: 95.29% for the sustainable investor, 20.56% for the balanced investor, and 21.25% for the profitable investor. This helps answer the central question of the study: by maximizing sustainability, the sustainable investor's portfolio sees a drastic reduction in returns, highlighting a sacrifice in profitability.

When examining the portfolios of investors who optimize the Sharpe ratio, the balanced investor's portfolio performs best, outperforming all others in the study. It delivers a return of 20.76% with volatility of 13.05%, making it the optimal choice for those who want to incorporate sustainability without compromising returns, with a sustainability index of 5.70%. The sustainable investor's portfolio shows a return of 12.12%, while the profitable investor achieves 19.14%. Additionally, as the weight given to sustainability in the GA fitness function decreases and the penalty increases, volatility tends to decrease.

The results indicate that an investor who chooses a portfolio that is balanced between sustainability and profitability achieves the best performance, outperforming the traditional Markowitz method. However, it is important to note that portfolios from the *Sp* method are always more volatile than the traditional or control portfolios. Therefore, investors must have different risk tolerance and return expectations, as the level of sustainability they wish to integrate may require them to accept lower initial returns or deal with higher volatility compared to traditional portfolios.

The study shows that incorporating sustainability criteria into asset portfolio management has a significant impact on both profitability and volatility. While maximizing sustainability can reduce short-term returns, as seen in the sustainable investor's portfolio, a balanced approach, like that of the balanced investor, can yield superior performance and meet environmental and social responsibility goals. These findings underscore the need for investors to carefully balance their sustainability objectives with profitability and risk tolerance.

6 Conclusion

Integrating sustainability into finance has become crucial, affecting economic, social, and environmental aspects that drive resilience and competitiveness. Companies with strong sustainable practices can effectively manage climate-related risks and benefit from compliance with emerging regulations and consumer demand for ethical products.

This study examines how prioritizing sustainability in asset portfolio management impacts profitability. By comparing traditional mean-variance optimization with genetic algorithm approaches, it explores whether sustainability integration comes at the expense of returns. The control portfolios validate the reliability of the genetic algorithm by closely aligning with traditional optimization results.

The analysis shows that portfolios emphasizing sustainability – particularly for sustainable investors – face lower returns and higher volatility, highlighting the costs of prioritizing environmental and social goals. However, the balanced investor, who balances both financial performance and sustainability, achieves superior risk-adjusted returns (Sharpe ratio of 159.12%) compared to other profiles. While profitable investors enjoy high returns with limited sustainability considerations, balanced portfolios can achieve favorable results, showing that sustainability and profitability are not mutually exclusive.

These findings suggest that investors can achieve a well-calibrated balance between profitability and sustainability that enhances long-term stability. However, integrating sustainability may require accepting lower short-term returns or increased volatility compared to traditional strategies. Investors should align their risk preferences with their sustainability goals, as a balanced approach can reconcile financial returns with social responsibility.

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SUPPLEMENTARY MATERIAL

Supplementary Data 1 – Balanced Portfolio
Supplementary Data 2 – GA Control Portfolio
Supplementary Data 3 – Sustainable Portfolio
Supplementary Data 4 – No Sp Portfolio
Supplementary Data 5 – Profitable Portfolio
Supplementary Data 6 – Climate Metrics
Supplementary Data 7 – Appendix A
Supplementary Data 8 – Appendix B
Supplementary material to this article can be found online at https://doi.org/10.7910/DVN/YFFEYS

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