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Research Article

Sustainable Equity Discrimination in Asset Liability Management for Practitioners: A Practical Approach

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Context: As the financial sector increasingly emphasizes responsible investment, insurance companies are actively seeking user-friendly approaches to incorporate sustainability criteria for equities into their Asset and Liability Management processes.
Objectives: This paper aims to introduce a novel practitioner-centric methodology focused on seamlessly integrating publicly available Environmental, Social, and Governance (ESG) criteria. The objective is also to ensure ease of implementation for companies, emphasizing independence from ESG scoring provided by private data providers.
Methods: The proposed approach involves leveraging accessible sustainability data to construct both a sustainable equity index and a complementary index for non-included shares, utilizing clustering techniques. Subsequently, an efficient frontier is generated through the application of the Markowitz methodology. The effectiveness of the method is demonstrated through its application to a real portfolio, showcasing stability with a notable emphasis on sustainable assets, guided by the efficient reallocations suggested by the Markowitz model.
Results: Both constructed indices exhibit similar trends, with the ESG index outperforming, albeit with slightly higher volatility. This performance discrepancy is mirrored in the strategic asset allocation, where a preference is given to the ESG class over the non-ESG class.
Implications and limitations: The findings suggest the feasibility of a financial institution successfully developing its own cohesive sustainability index using solely publicly available data. While our constructed ESG index demonstrated superior performance in this study, further research involving alternative data sources is essential to generalize this result.

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1. Introduction

"We believe that sustainable investing provides the strongest foundation for client portfolios moving forward," stated Larry Fink, CEO of BlackRock, in an open letter. This statement illustrates how investors are increasingly recognizing the significance of sustainable investments. The demand for responsible assets grows. Regulations that promote low carbon emission investments become more robust, and the financial sector strives to align its strategies accordingly. Among these changes, insurance companies are also required to adapt [1]. As a result, they need to overhaul their Assets Liability Management (ALM) processes to accommodate these shifts while adhering to European regulations like Solvency 2 [2].

Recently, the new requirements from the professional sector have spurred numerous academic research endeavors related to incorporating sustainability criteria into investment strategies (e.g. [3][4][5][6]). The most conventional approach involves modifying the Markowitz allocation model to incorporate an Environmental, Social, and Governance (ESG) dimension.

Most of the studies tend to indicate that this type of strategy demonstrates some qualities. For instance, Fried *et al.* affirmed that "The results show that the business case for ESG investing is empirically very well founded" [7]. However, due to the relative novelty of this kind of research, the results remain somewhat inconclusive, as pointed out by Chakrabarty and Nag in their literature review [8]: "We find that there is a lack of consensus about the existence of a carbon premium or an equity greenium in stock prices".

One of the primary limitations in much of the existing work on this subject is the reliance on ESG scoring. ESG scoring is a metric designed to rank companies based on three dimensions: environmental, social, and governance practices. These metrics are calculated by private rating agencies such as Morningstar Sustainalytics or The Shift Project. Nevertheless, the process of assigning these ratings is often opaque, leading to difficulties in auditing the scores, and purchasing the scores can be costly, discouraging companies from using multiple sources. Furthermore, Gibson et al. compared the ESG scores provided by seven different companies and demonstrated that these scores lack correlation with one another [9]. The discrepancies between the ESG ratings from various rating agencies can be explained by several factors. Firstly, the number of evaluated ESG variables differs significantly, and rating agencies may measure the same variable using different indicators, which, according to Berg *et al.*, constitutes the main source of divergence. Secondly, data quality can play a significant role in these discrepancies. Additionally, rating agencies may interpret ESG parameters differently, resulting in the assignment of different ratings. Finally, the weight assigned to indicators during the calculation of the overall rating can also be a source of divergence [10]. Consequently, choosing one ESG score over another introduces significant model risk. To ensure full compliance with regulations, insurance companies should thus opt for objective and open-source data instead of relying solely on ESG scores. Yet, a notable gap in the literature is the scarcity of articles that explore approaches independent of ESG scoring. The majority of existing research remains heavily reliant on these metrics, emphasizing the increasing need for diverse methodologies in evaluating companies' ESG practices.

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The objective of this paper is, therefore, to perform an ALM process that incorporates sustainable indicators distinct from ESG scores. Additionally, the process must be readily applicable for use by insurance companies. The methodology should yield consistent results, be straightforward enough to facilitate audit procedures, and utilize readily available open data. Moreover, the proposed method should be validated using actual insurance portfolio data.

The methodology developed in this article consists of two main steps. Firstly, equities are grouped into clusters based on sustainability criteria. The clustering process results in the creation of two distinct clusters, which can be designated as the Sustainable Index (SI) and the Other Shares Index (OSI). These two clusters yield two separate indices that are subsequently employed in the ALM process during the second step. The ALM procedure is executed using real asset allocations from a prominent French mutual company. The initial asset allocation is then projected using a Generator of Economic Scenarios (GES). Subsequently, employing the principles of Markowitz theory, an efficient frontier is delineated. The methodology has been tested on a sample of 106 companies that are part of either the Euronext 100 or the Euro Stoxx 50.

A decision has been made to formulate our own indices rather than relying on those already existing in the financial markets, such as the CAC 40 ESG. This choice stems from observations in the literature indicating that the currently available sustainable indices are unsatisfactory and lack significant differentiation from conventional ones [11][12][13].

The utilization of clustering methods to formulate share indices is a well-established practice in the literature (e.g. [14][15]). As highlighted by Nanda et al. [16], this approach simplifies the eventual application of Markowitz asset allocation by significantly reducing computational time. This is a critical consideration, particularly as, in contrast to much of the existing literature on the topic, our ALM process must account for a broader range of assets beyond equities, including real estate and bonds, to ensure practical applicability for insurance companies (see, for example, [17][18]). Consequently, a conventional Markowitz model that treats each equity independently is excessively time-consuming to be practically viable.

The paper is organized as follows: Section 2 outlines the methodology, detailing the data and methods employed in constructing the equity indices, as well as the data and methods utilized in the ALM process. Section 3 presents the results, while Section 4 discusses the results and limitations of the study, and Section 5 gives some concluding remarks.

2. Methodology

This section will outline both the data and the methodology employed in this article. The key steps of the methodology are illustrated in Figure 1.

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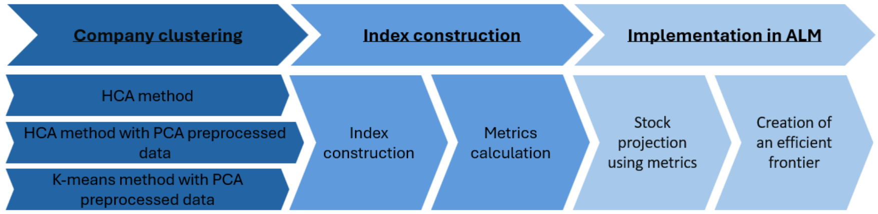

Fig. 1. Summary of the methodology used

2.1. Construction of equity indices

2.1.1. Data

The study focuses on two major European equity indices: the Euro Stoxx 50 and the Euronext 100. For each company present in either of these two indices on 31 December 2022, the historical equity prices were collected from the website boursorama.com, spanning from September 2019 to February 2023. Market data was cross-referenced with data from investing.com to ensure coherence. Following this verification, Randstad and Flutter Entertainment were excluded from the study due to significant discrepancies. Additionally, Universal Music Group was removed from consideration due to its recent inclusion in the Euronext 100.

Boursorama.com also provides several sustainability indicators: a controversy risk rating (ranging from 1 to 5), carbon intensity (tons of CO_2 emitted per million euros of turnover), 3-year carbon emissions (Scope 1 and 2), involvement in activities with a positive impact (ranging from 0 to 12), and involvement in activities with a negative impact (ranging from 0 to 23). Additionally, it offers an ESG score, which was not utilized in this study due to reasons previously discussed. The selected indicators are either objective or transparent in their construction. They are also publicly available. Despite their primary focus on environmental aspects, they also consider social and governance components through positive and negative impacts. Sustainability indicators were unavailable for 21 companies and thus were excluded from the study. After consolidating the companies listed in both the Euro Stoxx 50 and Euronext 100 (with some firms present in both), and accounting for the removed companies, a total of 106 companies were considered in the study.

There are two limitations associated with the data used in this study. Firstly, the observed period for the equities encompasses two major crises: the Covid-19 pandemic and the Ukrainian crisis. While this allows us to assess the method's performance under crisis conditions, it may potentially limit the generalizability of the results. Additionally, the sustainability indicators provided by the Boursorama.com website are ultimately sourced from the Morningstar company. Despite being more comprehensible than the ESG score and currently publicly available, this arrangement still entails a reliance on a private entity. Furthermore, while the computation process for these indicators is clearly explained, it remains subject to contestation. For instance, the positive impact score, theoretically ranging from 0 to 12, practically ranged only from 0 to 4. This is due to the requirement that, in order to earn a point, a company must demonstrate a minimum level of turnover in one of the 12 positive impact sectors selected by Morningstar. Even for large companies, investing in 12 different sectors, regardless of their virtuous intentions, may be impractical.

2.1.2. Clustering

Clustering is useful for aggregating points with similar characteristics into homogeneous classes without any prior assumptions. It has been particularly valuable in the context of Asset and Liability Management (ALM), where it is employed to group assets exhibiting similar behavior. In this paper, assets are exclusively clustered based on sustainable indicators. In this article, two methods are considered.

The first method utilized is the Hierarchical Cluster Analysis (HCA), where assets are grouped based on the Ward criterion [19]. A dendrogram has been employed to determine the optimal number of clusters.

The second clustering method involves two steps. Initially, Principal Component Analysis (PCA) is applied as a preprocessing step to the data. This initial step effectively decorrelates the input variables, aiming to enhance the method's stability. Subsequently, the k-means method is utilized to cluster assets based on the new variables obtained in the PCA steps. Directly applying the k-means method to the data was deemed too unstable due to sensitivity to the initialization setup, thereby compromising its practical relevance.

In contrast to Hierarchical Cluster Analysis (HCA), this second clustering method is nondeterministic due to the initialization of the k-means algorithm and lacks an inherent way to determine the optimal number of clusters. Consequently, to determine the optimal number of clusters, 1000 clusterings were performed for each potential number of classes ranging from 2 to 10. Subsequently, the average quality of the clustering was compared using the average Silhouette index [20], the Dunn index [21], and the Davies-Bouldin index [22].

Despite HCA not showing stability issues, for a fair comparison, it was also tested with PCA-preprocessed data. Consequently, three clustering process outcomes were compared as inputs to the ALM steps: HCA alone (HCA), HCA with PCA-preprocessed data (PCA-HCA), and k-means with PCA-preprocessed data (PCA-kmeans).

The clustering step determines which equities will constitute the indices, but it is also necessary to assign weights to each equity to finalize this construction. As all the companies included in this study are present in the Stoxx Europe 600, the weights of this index have been adopted. These weights have been proportionally adjusted within both the Other Shares Index (OSI) and the Sustainable Index (SI) to ensure a total weight of 1 in each respective index (see also Appendix 6.1 for more details).

2.2. Asset liability management

2.2.1. Current Asset Allocation

In practice, an ALM process always begins with an initial allocation known as the Current Asset Allocation (CAA). For the sake of realism, the CAA employed in this study mirrors that of a prominent French mutual insurance company. To ensure consistency, both the Generator of Economic Scenarios (GES) model and the initial calibration align with those utilized by the same mutual insurance company. The data supplied by this company is as of 31/12/2022 and

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encompasses assets, liabilities, yield curve, and all other essential parameters for GES calibration.

2.2.2. Methods

In addition to the equities from the indices created in the preceding step, the Current Asset Allocation (CAA) encompassed 7 asset classes: Real Estate, unlisted shares, monetary funds, Collective Investment Funds (OPCVM in French), Fixed-rate bonds, variable-rate bonds, and inflation-adjusted bonds.

The GES employed in this study is sourced from the Software Solveo developed by the company Fractales. This GES has been verified by the French regulatory body ACPR and was chosen due to its alignment with the company providing the CAA, thus allowing for calibration coherence. It encompasses projections for both liabilities and assets. In contrast to the conventional approach, two stock indexes have been set up in the GSE to project part of the stocks according to the SI and part according to the OSI.

For each of the three clustering processes, 1,000 scenarios were projected over a 5-year period, after which a Markowitz model was applied to formulate an efficient frontier. Within each scenario, 144 reallocations were tested, conducted over a 3-year span. The 5-year periods correspond to the business plan timeframe usually considered by the insurer that provided the data. The portfolio was considered in a run-off state. Each scenario was performed in a real-world environment.

The 144 reallocations tested were consistent across all scenarios and clustering processes. The potential reallocations were selected in accordance with the established practices of the insurance company providing the portfolio data. The company had conducted a study to determine the maximum and minimum allocations they would consider for each asset class. The 144 selected allocations were well-founded choices that adhered to the company's practical constraints.

The CAA provided by the insurance companies solely encompassed two categories of equities: unlisted and market equities. The initial allocation between the SI and OSI was computed to mirror the equity financial performance captured by the CAA. This calculation was based on the financial performance of SI and OSI, as derived using the PCA-kmeans method.

The Markowitz analysis was performed using the financial performance of the reallocation. This analysis calculates the sum of all financial products over the 5-year projection period, along with the sum of Unrealized Gains or Losses on Non-Amortizable Assets. The risk was computed by using the 5% quantile of this measure. The financial performance is defined as the average of this measure across all scenarios.

3. Results

3.1. Clustering

For the HCA method, the analysis of the dendrogram indicated optimal solutions of either 2 or 5 clusters. With the PCA-HCA method, the analysis of the dendrogram consistently suggested two clusters as the best option. When applying the PCA-kmeans method, the analysis of all three metrics consistently indicated 2 clusters as optimal. However, the kmeans method did not yield a clear optimal number of clusters due to unstable results, leading to its rejection. As a result, a choice of two clusters was adopted for the study.

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The HCA method resulted in one cluster containing 74 companies and another with 32 companies. Notably, these 32 companies included all aeronautics and energy sector firms. Additionally, companies involved in major scandals like Volkswagen, Danone, and Bayer were observed within this cluster.

Using the PCA-HCA method, the output displayed one cluster comprising 85 companies and another with 21 companies. The latter group primarily consisted of companies from the aeronautics and energy sectors, and all the firms in this smaller cluster were also part of the smaller HCA method cluster.

Applying the PCA-kmeans method produced one cluster containing either 88, 91, or 95 companies, alongside another cluster containing 18, 15, or 11 companies, depending on initialization. Three companies differ between the 15-element and 18-element clusters — Saint Gobain, Sanofi, and Philips. Four companies differ between the 11-element and 15-element clusters — Bayer, Iberdrola, EDF, and Basf. Apart from Saint Gobain, all companies in the smaller cluster were part of both small clusters identified by the HCA and PCA-HCA methods. To enhance subsequent index robustness, and given that all three configurations yielded similar Silhouette indicator scores, the 18-company cluster was chosen for further analysis.

Across all three methods, the smaller cluster demonstrated a strong correlation with sustainability indicators, exhibiting higher average carbon emissions, negative carbon intensity impact scores, and controversy risk ratings. However, it wasn't particularly correlated with positive impact ratings. Consequently, the index featuring companies from the larger cluster was termed the Sustainable Index (SI), while the other was labeled as the Other Shares Index (OSI). The compositions of all indexes are provided in Appendix 6.2.

To facilitate comparison, both indexes have been standardized to a base of 100. They followed similar trends, with a decline in March 2020 due to the Covid crisis, albeit with this drop slightly more pronounced for the SI. Furthermore, all sustainable indexes exhibited greater financial performance and higher volatility compared to their OSI counterparts. For instance, Figure 2 illustrates the evolution of OSI and SI derived using the PCA-kmeans method. Graphically, the SI demonstrates outperformance, accompanied by more significant fluctuations compared to the OSI. The only period when the OSI beat the SI is during the Covid crisis, from March 2020 to February 2021. These graphical observations are further supported by indicator calculations. The OSI's (SI's) annual volatility stood at 23.32% (24.9%), and its average mean performance was 3.34% (7.09%). The correlation between the two indices is 82%; thus, modeling stocks by segmenting them into two classes provides diversification.

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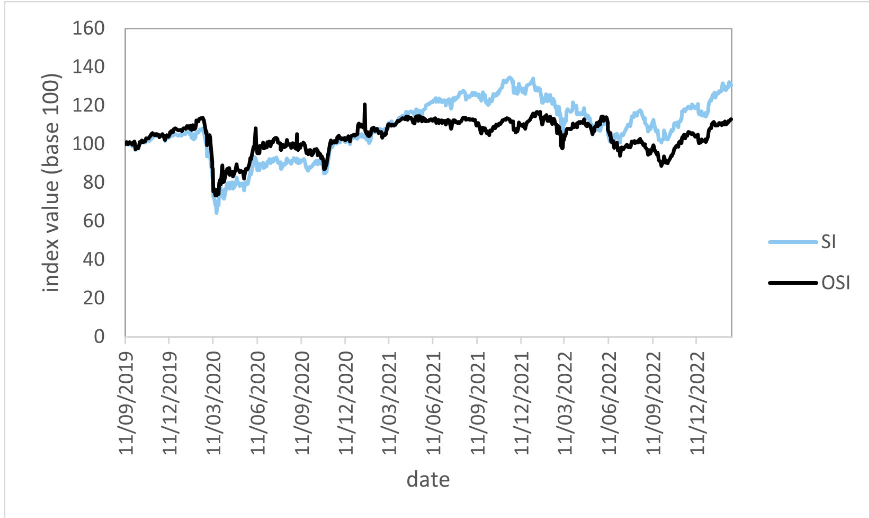

Fig. 2. The SI obtained with the PCA-kmeans outperforms the OSI.

3.2. Allocation

The Markowitz model applied to all three pairs of indexes produced an efficient frontier consisting of the same 6 asset allocations. Figure 3 illustrates the efficient frontier generated using the PCA-kmeans method, while Figure 4 details the composition of each allocation on the efficient frontier, along with the CAA.

The frontier in Figure 3 is inverted compared to a classical Markowitz frontier due to the utilization of a performance indicator quantile as a risk indicator, in contrast to the standard deviation of returns traditionally employed by Markowitz. Additionally, the numbers on the figure correspond to the names of the different efficient allocations. Allocation 102 optimizes returns while maintaining a risk level equivalent to the current allocation. Allocations 91, 92, and 93 are conservative, aiming to reduce risk. Conversely, allocations 105 and 108 prioritize maximizing returns.

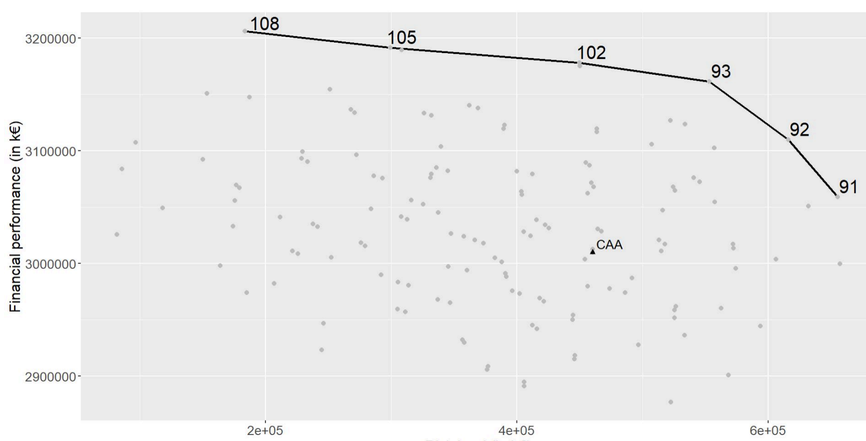

Fig. 3. Efficient frontier obtained with the PCA-kmeans method.

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Through Figure 4, it is apparent that all efficient allocations, except for 91 and 108, feature a higher proportion of sustainable stocks compared to OS. As observed in Figure 2, the sustainable index's superior financial performance outweighs its heightened volatility. The findings above indicate that the performance gain of sustainable stocks compensates for the increase in volatility.

Therefore, to achieve a lower-risk allocation, it is necessary to reduce the proportion of stocks, starting with OS. Concerning Allocation 91, to mitigate risk, all minimum thresholds for stock classes are met. Given that the minimum threshold for the sustainable class is lower than that of the other shares class, the proportion of sustainable stocks is lower compared to other shares. For Allocation 108, the effect is similar with the maximum bounds.

Notably, the allocations strongly favor the SI, with a substantial portion of the allocations approaching the maximum feasible allocation. The SI's superior financial performance outweighs its heightened volatility, resulting in a preference for the SI, even at allocation 92, which represents a relatively low-risk allocation. Additionally, it's interesting to observe that even if hypothetical CAA values were used instead of those provided by the insurance company, the SI would still have been favored.

Allocation	CAA	91	92	93	102	105	108
Equities	6,7	4,7	5,7	6,7	7,8	8,8	9,8
OSI	2,6	***1,6***	***1,6***	***1,6***	***1,6***	2,6	**3,6**
SI	2,1	***1,1***	2,1	**3,1**	**3,1**	**3,1**	**3,1**
Unlisted	***1,9***	***1,9***	***1,9***	***1,9***	**3,0**	**3,0**	**3,0**
Bonds	73,4	71,4	70,4	69,4	68,3	67,3	66,3
Fixed rate	63,6	61,7	60,7	59,7	58,6	57,6	56,6
Variable rates	5,5	5,5	5,5	5,5	5,5	5,5	5,5
Inflation adjusted	4,2	4,2	4,2	4,2	4,2	4,2	4,2
Real estate	***4,6***	**6,6**	**6,6**	**6,6**	**6,6**	**6,6**	**6,6**
Monetary funds	1,3	1,3	1,3	1,3	1,3	1,3	1,3
Collective investment founds	14,0	**16,0**	**16,0**	**16,0**	**16,0**	**16,0**	**16,0**
	100,0	100,0	100,0	100,0	100,0	100,0	100,0

Fig. 4. Efficient frontier assets allocation. Underlined bold figures are allocations that reached the maximum allocation, while italic bold figures are the ones that are at the minimum level permitted.

4. Results discussion

The results show the efficacy of categorizing market equities into two asset classes using the proposed indexes, facilitating the construction of an efficient frontier. Notably, the Sustainable Shares Index consistently outperforms the Other Shares Index, with an average mean performance exceeding 3 points higher. This observation takes place in a context where there is currently no clear consensus regarding the outperformance or underperformance of ESG funds compared to traditional funds. Nevertheless, a meta-analysis conducted by Clark et al. on over 200 of these studies has resulted in the following conclusion: "80% of the studies examined demonstrate that prudent sustainable development practices have a positive influence on investment performance" [23].

In our data, the method exhibits minimal sensitivity to changes in clustering techniques. Indeed, three different groupings were tested, with a number of non-ESG companies ranging from 18 to 32. Despite these variations, the efficient allocations remained the same. This implies a potentially low subsequent model

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risk. Additionally, although not required in our study, within our framework, Figures 3 and 4 illustrate that practitioners could readily tilt the balance towards the Sustainable Index over the Other Shares Index if they wish to distance themselves from more contentious activities.

However, it is essential to underscore that the generalization of our results may be constrained by the limitations inherent in our study. The primary limitations stem from the data utilized. Firstly, it would be valuable to assess the robustness of the results against various alternative current asset allocations, thereby challenging both the simulated and company-provided current asset allocations. Additionally, the set of available ESG indicators in Boursorama was somewhat restricted, leading to the exclusion of certain assets due to a lack of available data. Diversifying data providers could help counter this limitation. Furthermore, it is crucial to acknowledge that the timeframe of the data used encompasses the Covid-19 crisis. While it is important to evaluate new methods under stress conditions, exploring the methodology under more conventional conditions could provide valuable insights. A final limitation is the reliance on European-only stock data.

Several minor practical challenges may arise when it comes to generalizing this methodology. Regarding data retrieval and formatting, although the data exist, they are not always readily accessible or immediately usable for insurers. The process may require additional efforts to adapt them to the proposed methodology. Similarly, methodological choices, such as the number of ESG data to consider, can pose dilemmas. Fine granularity may offer in-depth analyses, but it can make the data more complex to handle. Thus, it is crucial to strike a balance between analysis precision and data usability. An additional aspect to consider regarding practical challenges is that the addition of a new asset class entails the need to establish its correlations with all other existing asset classes. Consequently, this necessitates the implementation of an additional process of backtesting and validation.

5. Conclusion

The methodology presented in this article constitutes a valuable addition to the literature. While many papers acknowledge the limitations of relying on ESG scoring, few delve into strategies for overcoming such limitations. The method utilizes straightforward clustering techniques to construct a Sustainable Equity Index and an Other Equity Index, based solely on publicly available sustainability indicators. It demonstrates the feasibility of relying on transparent and readily available indicators to achieve meaningful results. Furthermore, the method has been applied to actual data from an insurance company, yielding realistic outcomes. This method doesn't necessitate a too long additional time-consuming calibration phase and doesn't excessively extend the overall ALM process duration. It remains easy to audit and provides comprehensible results, aligning with regulatory requirements. Notably, the method avoids relying on an ESG scoring system, thereby mitigating many biases (including opacity) often highlighted in the literature.

Despite the limitations mentioned in Section 4, which are predominantly related to data, the approach remains promising. The simple methods employed, applicable to various types of portfolios and already proven effective on a real portfolio, further strengthen the feasibility of this integration. The findings also contribute additional evidence supporting the notion that an ALM strategy favoring sustainable assets can yield superior outcomes compared to conventional strategies. This should incentivize financial institutions to explore and adopt such strategies, aiming to enhance their societal impact while preserving profitability.

For future endeavors, it might be worthwhile to test the incorporation of this method within an Own Risk and Solvency Assessment (ORSA) process. Furthermore, re-running the method with enriched sustainability indicators sourced from other data providers or enriched by including a greater number of variables, especially concerning Social and Governance aspects, could yield interesting insights.

6. Appendix

6.1. Indexes constructions

Some companies are present in both the Eurostoxx 50 and the Euronext 100, while others are only included in one of the two indices. In order to establish the weighting of each company, the weights of the Stoxx Europe 600 have been used because all the companies considered are present in this index. These weights are calculated based on free float market capitalization. This is the market capitalization used taking into account only shares that are likely to be traded. Indeed, some investors hold securities for reasons other than financial, such as, for example, to have control over them. These securities are therefore not taken into account when calculating market capitalization.

The weight of each company i within its group (SI or OSI) is given by

$$\text{New weight}_\text{i} = \frac{\text{weight}_i \times 100}{\sum_{i\in I} \text{weight}_i},$$

with $I = \{SI, OSI\}$. A key Cl_i for each company i was then defined by

$$Cl_i = \frac{\text{Stoxx 600 price}_t \times \text{company new weight i}_t}{\text{company price i}_t},$$

with t fixed to December 30, 2022, since the weights of each company in the Stoxx 600 index were retrieved as of December 30, 2022. This key is then used to calculate the value of the two indexes (SI or OSI) for any time t

$$\text{I price}_t = \sum_{i\in I} Cl\text{é}_i \times \text{Company price i}_t.$$

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6.2. Compositions of all indexes

PCA-HCA		PCA-kmeans		HCA	
Company	Cluster	Company	Cluster	Company	Cluster
ABINBEV	SI	ABINBEV	SI	ABINBEV	OSI
ADIDAS	SI	ADIDAS	SI	ADIDAS	SI
ADP	SI	ADP	SI	ADP	SI
ADYEN	SI	ADYEN	SI	ADYEN	SI
AEGON	SI	AEGON	SI	AEGON	SI
AGEAS	SI	AGEAS	SI	AGEAS	SI
AIRBUS	OSI	AIRBUS	SI	AIRBUS	OSI
AIRLIQUIDE	OSI	AIRLIQUIDE	OSI	AIRLIQUIDE	OSI
AKZONOBEL	SI	AKZONOBEL	SI	AKZONOBEL	SI
ALLIANZ	SI	ALLIANZ	SI	ALLIANZ	SI
ALSTOM	SI	ALSTOM	SI	ALSTOM	SI
AMUNDI	SI	AMUNDI	SI	AMUNDI	SI
ARCELORMITTALSA	OSI	ARCELORMITTALSA	OSI	ARCELORMITTALSA	OSI
ARGENXSE	SI	ARGENXSE	SI	ARGENXSE	SI
ASMINTERNATIONAL	SI	ASMINTERNATIONAL	SI	ASMINTERNATIONAL	SI
ASMLHLDG	SI	ASMLHLDG	SI	ASMLHLDG	SI
AXA	SI	AXA	SI	AXA	SI
BANCOSANTANDER	SI	BANCOSANTANDER	SI	BANCOSANTANDER	SI
BASF	OSI	BASF	OSI	BASF	OSI
BAYER	OSI	BAYER	OSI	BAYER	OSI
BBVA	SI	BBVA	SI	BBVA	SI
BIOMERIEUX	SI	BIOMERIEUX	SI	BIOMERIEUX	SI
BMW	SI	BMW	SI	BMW	SI
BNPPARIBAS	SI	BNPPARIBAS	SI	BNPPARIBAS	SI
BOUYGUES	SI	BOUYGUES	SI	BOUYGUES	SI
BUREAUVERITAS	SI	BUREAUVERITAS	SI	BUREAUVERITAS	SI
CAPGEMINI	SI	CAPGEMINI	SI	CAPGEMINI	SI
CARREFOUR	SI	CARREFOUR	SI	CARREFOUR	SI
CREDITAGRICOLE	SI	CREDITAGRICOLE	SI	CREDITAGRICOLE	SI
CRHPLC	OSI	CRHPLC	OSI	CRHPLC	OSI
DANONE	SI	DANONE	SI	DANONE	OSI
DASSAULTSYSTEMES	SI	DASSAULTSYSTEMES	SI	DASSAULTSYSTEMES	SI
DEUTSCHEBOERSE	SI	DEUTSCHEBOERSE	SI	DEUTSCHEBOERSE	SI
DEUTSCHEPOST	SI	DEUTSCHEPOST	SI	DEUTSCHEPOST	SI
DEUTSCHETELEKOM	SI	DEUTSCHETELEKOM	SI	DEUTSCHETELEKOM	SI
D'IETERENGROUP	SI	D'IETERENGROUP	SI	D'IETERENGROUP	SI
DSMKON	SI	DSMKON	SI	DSMKON	OSI
EDENRED	SI	EDENRED	SI	EDENRED	SI
EDF	OSI	EDF	OSI	EDF	OSI
EDP	OSI	EDP	OSI	EDP	OSI
EIFFAGE	SI	EIFFAGE	SI	EIFFAGE	SI
ELIAGROUP	SI	ELIAGROUP	SI	ELIAGROUP	SI
ENEL	OSI	ENEL	OSI	ENEL	OSI
ENGIE	OSI	ENGIE	OSI	ENGIE	OSI
ENI	OSI	ENI	OSI	ENI	OSI
ESSILORLUXOTTICA	SI	ESSILORLUXOTTICA	SI	ESSILORLUXOTTICA	OSI
EUROFINSSCIENT,	SI	EUROFINSSCIENT,	SI	EUROFINSSCIENT,	OSI
EURONEXT	SI	EURONEXT	SI	EURONEXT	SI
GALPENERGIA-NOM	SI	GALPENERGIA-NOM	SI	GALPENERGIA-NOM	OSI
GBL	SI	GBL	SI	GBL	SI
GECINA	SI	GECINA	SI	GECINA	SI
GETLINKSE	SI	GETLINKSE	SI	GETLINKSE	SI
HEINEKEN	OSI	HEINEKEN	SI	HEINEKEN	OSI
HERMESINTL	SI	HERMESINTL	SI	HERMESINTL	SI
IBERDROLA	OSI	IBERDROLA	OSI	IBERDROLA	OSI
IMCD	SI	IMCD	SI	IMCD	SI
INDITEX	SI	INDITEX	SI	INDITEX	SI
INFINEONTECHNOLO	SI	INFINEONTECHNOLO	SI	INFINEONTECHNOLO	SI
INGGROUP	SI	INGGROUP	SI	INGGROUP	SI
INTESASANPAOLO	SI	INTESASANPAOLO	SI	INTESASANPAOLO	SI
IPSEN	SI	IPSEN	SI	IPSEN	SI
J,MARTINS,SGPS	SI	J,MARTINS,SGPS	SI	J,MARTINS,SGPS	SI
KBC	SI	KBC	SI	KBC	SI
KERING	SI	KERING	SI	KERING	SI
KONAHDEL	SI	KONAHDEL	SI	KONAHDEL	OSI
KPNKON	SI	KPNKON	SI	KPNKON	SI
LEGRAND	SI	LEGRAND	SI	LEGRAND	SI
LINDE	OSI	LINDE	OSI	LINDE	OSI
LOREAL	SI	LOREAL	SI	LOREAL	OSI
LVMH	SI	LVMH	SI	LVMH	OSI
MERCEDESBENZGR	SI	MERCEDESBENZGR	SI	MERCEDESBENZGR	SI
MICHELIN	SI	MICHELIN	SI	MICHELIN	SI
MUENCHENERRUECKV	SI	MUENCHENERRUECKV	SI	MUENCHENERRUECKV	SI
NNGROUP	SI	NNGROUP	SI	NNGROUP	SI
NOKIA	SI	NOKIA	SI	NOKIA	SI
ORANGE	SI	ORANGE	SI	ORANGE	SI
PERNODRICARD	SI	PERNODRICARD	SI	PERNODRICARD	OSI
PHILIPSKON	OSI	PHILIPSKON	OSI	PHILIPSKON	OSI
PROSUS	SI	PROSUS	SI	PROSUS	SI
PUBLICISGROUPESA	SI	PUBLICISGROUPESA	SI	PUBLICISGROUPESA	SI
REMYCOINTREAU	SI	REMYCOINTREAU	SI	REMYCOINTREAU	SI
RENAULT	SI	RENAULT	SI	RENAULT	SI
SAFRAN	OSI	SAFRAN	SI	SAFRAN	OSI
SAINTGOBAIN	SI	SAINTGOBAIN	OSI	SAINTGOBAIN	SI
SANOFI	OSI	SANOFI	OSI	SANOFI	OSI
SAPAGO.N.	SI	SAPAGO.N.	SI	SAPAGO.N.	SI
SCHNEIDERELECTRIC	SI	SCHNEIDERELECTRIC	SI	SCHNEIDERELECTRIC	SI
SIEMENSENERGY	SI	SIEMENSENERGY	SI	SIEMENSENERGY	SI
SOCIETEGENERALE	SI	SOCIETEGENERALE	SI	SOCIETEGENERALE	SI
SODEXO	SI	SODEXO	SI	SODEXO	SI
SOLVAY	OSI	SOLVAY	OSI	SOLVAY	OSI
STELLANTIS	SI	STELLANTIS	SI	STELLANTIS	SI
STMICROELECTRONICS	SI	STMICROELECTRONICS	SI	STMICROELECTRONICS	SI
TELEPERFORMANCE	SI	TELEPERFORMANCE	SI	TELEPERFORMANCE	SI
THALES	OSI	THALES	SI	THALES	OSI
TOTALENERGIES	OSI	TOTALENERGIES	OSI	TOTALENERGIES	OSI
UCB	SI	UCB	SI	UCB	SI
UMICORE	SI	UMICORE	SI	UMICORE	SI
UNIBAIL-RODAMCO-WE	SI	UNIBAIL-RODAMCO-WE	SI	UNIBAIL-RODAMCO-WE	SI
VEOLIAENVIRON,	OSI	VEOLIAENVIRON,	OSI	VEOLIAENVIRON,	OSI
VINCI	SI	VINCI	SI	VINCI	SI
VIVENDISE	SI	VIVENDISE	SI	VIVENDISE	SI
VOLKSWAGENVZ	SI	VOLKSWAGENVZ	SI	VOLKSWAGENVZ	OSI
VONOVIA	SI	VONOVIA	SI	VONOVIA	SI
WOLTERSKLUWER	SI	WOLTERSKLUWER	SI	WOLTERSKLUWER	SI
WORLDLINE	SI	WORLDLINE	SI	WORLDLINE	SI

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Fig. 5. Clusters obtained for each process

Statements and Declarations

Data Availability

Publicly available datasets were analyzed in this study. Equity price and sustainability indicator data can be found on boursorama.com and investing.com for the specified period. Data pertaining to the specific insurance company's Current Asset Allocation and Generator of Economic Scenarios parameters are proprietary and are not publicly available due to confidentiality agreements. Further inquiries regarding data access can be directed to the corresponding author.

Author Contributions

Conceptualization, S.Q., P-A.E., and R.G.; methodology, S.Q., P-A.E., and R.G.; software, S.Q. and P-A.E.; validation, S.Q., P-A.E., and R.G.; formal analysis, S.Q. and P-A.E.; investigation, S.Q. and P-A.E.; resources, R.G.; data curation, S.Q.; writing—original draft preparation, S.Q. and P-A.E.; writing—review and editing, R.G.; visualization, S.Q.; supervision, R.G.; project administration, R.G.

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