Qeios

A method for discriminating equities based on sustainability criteria in an ALM process designed for practitioners

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Abstract As the financial sector increasingly prioritizes responsible investment, insurance companies seek user-friendly methods to incorporate sustainability criteria for equities into their assets and liability management processes. This paper presents a practical two-step approach tailored for practitioners. The initial step involves leveraging publicly available sustainability data differing from the ESG score to construct both a sustainable equity index and a complementary index for shares not included in the former, achieved through clustering techniques. The subsequent step entails generating an efficient frontier using the Markowitz methodology. The proposed method has been applied to an authentic portfolio, demonstrating stability with a strong emphasis on sustainable assets when using the efficient reallocations given by the Markowitz model.

Keywords: sustainability, ALM, clustering, insurance, green finance.

1 Introduction

"We believe that sustainable investing provides the strongest foundation for client portfolios moving forward" was stated by 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 have become more robust, and the financial sector strives to align its strategies accordingly. Among these changes, insurance companies are also required to adapt [11]. As a result, they need to overhaul their Assets Liability Management (ALM) processes to accommodate these shifts while adhering to European regulations such as Solvency 2.

Recently, new requirements from the professional sector have spurred numerous academic research endeavors related to incorporating sustainability criteria into

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investment strategies (e.g., [4], [10], [14]). The most conventional approach involves modifying the Markowitz allocation model to incorporate an 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" [6]. However, due to the relative novelty of this kind of research, the results remain somewhat inconclusive, as noted by Chakrabarty and Nag in their literature review [2]: "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 [8]. 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.

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.

This methodology consists of two main steps. First, equities are grouped into clusters based on sustainability criteria. The clustering process results in the creation of two distinct clusters, which can be designated 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 the Markowitz theory, an efficient frontier was delineated.

A decision has been made to formulate our own indices rather than relying on indices that already exist in 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 indices [13], [15], [17].

The utilization of clustering methods to formulate share indices is a well-established practice in the literature (e.g., [16]). As highlighted by Nanda et al. [9], 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 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, [7], [1]). Consequently, developing a conventional Markowitz model that treats each equity independently is excessively time-consuming to ensure practical viability.

Furthermore, insurance companies are required to employ intricate generators of economic scenarios (GESs) to project their balance sheets.

The paper is structured as follows: In the initial section, the complete process and the utilized data are thoroughly outlined. The results will be analyzed in the subsequent section. Finally, a brief discussion concludes the paper.

2 General process

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 as of 31 December 2022, historical equity prices were collected from the website boursorama.com, spanning from September 2019 to February 2023. The market data were cross-referenced with the data from investing.com to ensure coherence. Following this verification, Randstad and Flutter Entertainment were excluded from the study due to significant discrepancies. Additionally, the 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 CO2 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 for reasons previously discussed. Sustainability indicators were unavailable for 21 companies; thus, they were excluded from the study. After consolidating the companies listed in both the Euro Stoxx 50 and the Euronext 100 (with some firms present in both) and accounting for the removed companies, a total of 106 companies were considered in the study.

This study has two limitations associated with the data used. First, 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 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 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 because, 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 Methods

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 assets and liability management (ALM), where it is employed for group assets exhibiting similar behavior. In this paper, assets are exclusively clustered based on sustainability indicators.

The initial method utilized is HCA, where assets are grouped based on the Ward criterion. A dendrogram was generated to determine the optimal number of clusters.

The second method employed is the k-means method. In contrast to HCA, this method is not deterministic due to its initialization and does not inherently offer a clear way to determine the optimal number of clusters. As a result, to ascertain the optimal number of clusters, 1000 clusters 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 [12], the Dunn index [5], and the Davies–Bouldin index [3].

The direct application of the k-means method to the data was found to be too unstable due to the sensitivity of the initialization setup, which impeded its practical relevance. To enhance the stability of the method, principal component analysis (PCA) was applied as a preprocessing step on the data. This preprocessing step effectively decorrelated the input variables and significantly improved the method's stability. Even though HCA did not exhibit stability issues, for the sake of fair comparison, it was also tested with PCA-preprocessed data. As a result, a total of 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 constitute the indices; however, it is also necessary to assign weights to each equity to finalize this construction. Given that all the companies included in this study are in Stoxx Europe 600, the weights of this index have been adopted. These weights were proportionally adjusted within both the Other Shares Index (OSI) and the Sustainable Index (SI) to ensure a total weight of 1 for each respective index.

2.2 Asset liability management

2.2.1 data

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 are as of 31/12/2022 and encompass assets, liabilities, yield curves, 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.

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, which provides the data. The portfolio was considered to be in a run-off state. Each scenario was performed in a real-world environment.

The 144 reallocations tested were consistent across all the 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 encompassed only two categories of equities: unlisted and market equities. The initial allocation between the sustainable index (SI) and other shares index (OSI) was computed to mirror the equity financial performance captured by the CAA. This calculation was based on the financial performance of the SI and OSI, as derived using the PCA-k-means 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. 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 that 2 clusters were optimal. However, the k-means 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.

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 such as 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 88, 91, or 95 companies, alongside another cluster containing 18, 15, or 11 companies, depending on initialization. Three companies differ between 15-element and 18-element clusters—Saint Gobain, Sanofi, and Philips. Four companies differ between 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 was not 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 the other shares index (OSI). The compositions of all the indices are provided in the Appendix.

All the SIs exhibited greater financial performance and greater volatility than did their OSI counterparts. For instance, Figure 1 illustrates the evolution of OSI and SI derived using the PCA-kmeans method. The OSI's (SI's) annual volatility stood at 23.32% (24.9%), and its average mean performance was 3.34% (7.09%). However, a diversification study of the indices was not conducted.

3.2 Allocation

The Markowitz model applied to all three pairs of indices produced an efficient frontier consisting of the same 6 asset allocations. Graph 2 illustrates the efficient frontier generated using the PCA-kmeans method, while Table 3 details the composition of each allocation on the efficient frontier, along with the CAA.

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.

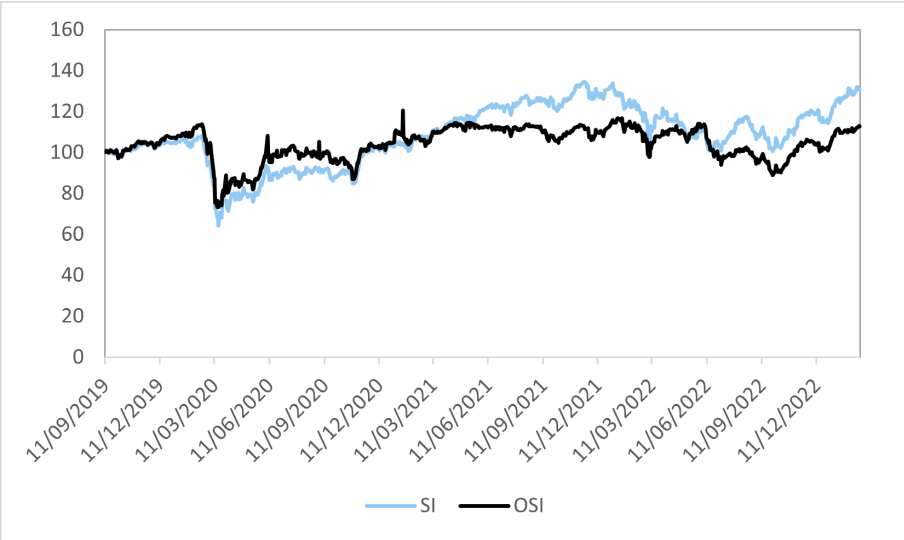

Fig. 1 The SI obtained with the PCA-kmeans outperforms the OSI

Interestingly, even if hypothetical CAA values were used instead of those provided by the insurance company, the SI would still have been favored.

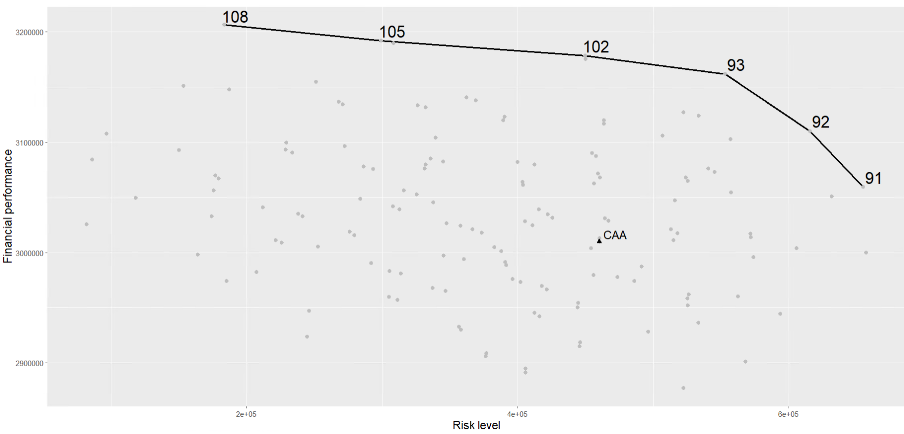

Fig. 2 Efficient frontier obtained with the PCA-kmeans method.

4 Conclusion

The method presented in this article utilizes straightforward clustering techniques to construct a sustainable shares index and an other shares index, which are based

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

solely on publicly available sustainability indicators. These two indices can be used to effectively categorize market equities into two asset classes, enabling the construction of an efficient frontier. Our data indicate that the Sustainable Shares Index consistently outperforms the Other Shares Index by a significant margin.

Although generalizing the outcomes of these last results may be limited by the constraints of our study (suppression of companies due to a lack of data and a somewhat constrained set of indicators), the method developed here has several merits.

First, the method has been applied to actual data from an insurance company, yielding realistic outcomes. This method does not necessitate an additional time-consuming calibration phase and does not excessively extend the overall duration of the ALM process. 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.

According to our data, the method exhibited minimal sensitivity to changes in clustering technique, implying potentially low subsequent model risk. Additionally, although not required in our study, within our framework, practitioners could readily tilt the balance toward the Sustainable Index over the Other Shares Index if they wish to distance themselves from more contentious activities.

For future endeavors, it might be worthwhile to test the incorporation of this method within an Own Risk and Solvency Assessment (ORSA) process. Furthermore, rerunning the method with enriched sustainability indicators that encompass the social and governance aspects could yield intriguing insights.

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5 Appendix

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

Fig. 4 Clusters obtained for each process