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FUZZY CLUSTERING APPROACH TO PORTFOLIO MANAGEMENT CONSIDERING ESG CRITERIA: EMPIRICAL EVIDENCE FROM THE INVESTMENT STRATEGIES OF THE EURO STOXX INDEX

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Environmental, social and governance (ESG) criteria are becoming increasingly important in the construction of investment portfolios. Analysis of the investment markets confirms that these criteria are being actively integrated into investment strategies. This paper presents our approach to incorporating ESG criteria into the portfolio construction process based on an index investment strategy. This strategy is enhanced by the inclusion of ESG criteria in the form of ESG scoring. Investment portfolio construction focuses on the application of three criteria: maximizing ESG score, minimizing risk and maximizing expected return. Our approach applies a fuzzy clustering toolkit to the set of index components. In the resulting fuzzy clusters, their core part (companies that do not belong to other clusters) and the fuzzy part are separated. The proposed investment strategy involves the construction of portfolios with a variation of the components of the fuzzy part. A VAWI (Value Added Weekly Index) curve is designed for each portfolio. The optimal strategy is implemented by constructing and reconstructing portfolios according to the upper line of the VAWI set. This investment strategy is demonstrated using the example of the EURO STOXX 50 index, which includes large companies from 11 Eurozone countries.

Keywords: *stock market, stock index, ESG criteria, ESG score, portfolio optimization, fuzzy clustering, portfolio performance evaluation*

JEL Classification: C45, G11, Q01

Introduction

ESG investment has proliferated in recent years. Forecasts [1] suggest that in 2025 such investments will account for around $50 trillion. This represents approximately one-third of global assets under management. According to a survey [2], 50% of global professional investors plan to increase their ESG investments by 2023. The importance and impact of ESG investing is now undeniable. Many institutional investors are changing how they construct their portfolios by integrating these ESG criteria into the investment process. However, such integration should include consistency between ESG criteria and traditional risk-minimization and return-maximization criteria. Providing this consistency is a rather complex task. It involves the definition of investment strategy objectives, the development of portfolio construction and optimization tools, the organizational resources required for such portfolio management, the logic for performance measurement and much more.

There are several approaches used by institutional investors to integrate ESG factors into their investment strategies [3]. The first set of approaches referred as "negative screening" involves the elimination of certain companies (or whole industries) from the investment portfolio construction process. It implies the exclusion of companies with low ESG scores (e.g. tobacco and alcohol companies). After such exclusion, "classical" approaches to building an investment strategy are applied. The second set of approaches is called "positive screening". The essence is symmetrical: investors identify companies with a high level of implementation of ESG criteria and the "classical" investment management approaches are then applied. From a mathematical point of view, the negative and positive screening approaches reduce the three-criteria problem to a two-criteria correspondence between risk and return. Classical mean-variance based optimization is then applied.

There is also an approach based on MPT (Modern Portfolio Theory) logic. Such an approach leads to a generalization of the classical two-criterion problem of MPT by including the criterion of maximizing the ESG score of the portfolios. ESG scoring is used for the numerical formalization of ESG criteria. The challenge is to solve a modified optimization problem with three criteria. The problem that arises is that classical Markowitz diversification mixes ESG levels in the portfolio. Portfolio with minimum risk may include companies with completely different ESG levels. The ESG-focused portfolio strategy is to some extent the opposite of the diversification effect [4, 5].

In this paper, we present a cluster approach to portfolio optimization with the ESG criteria involving. The rationale for this approach is to formalize the investor's priority on the risk-return ratio and the ESG level. The logic of such an approach encompasses the set of clusters of assets. The starting point of our approach is the institutional investor's index strategy. The index components are segmented using fuzzy clustering. Considering the property of this method, which allows to vary the set of components in the portfolio to improve performance, an investment strategy has been developed. It corresponds to the top line of the Value-Added Weekly Index set for portfolios generated by the fuzzy parts of clusters.

The paper is structured as follows. The first part provides a comprehensive review of the existing literature, highlighting the issues studied and related aspects. This is followed by a discussion of the research methodology, including the approach and tools used for the study. The next part summarizes the research findings and provides an in-depth discussion of the key points and their implications. The final part concludes with a summary of the findings and suggestions for future research directions in this area.

The aim and tasks of the research

This paper aims to develop an investment strategy that incorporates ESG criteria alongside classical risk-minimizing and return-maximizing criteria. To do this, we use a fuzzy clustering approach. Its advantage is that it allows investors to identify the relationship between ESG levels, risk, and return. At the same time, the fuzzy clustering toolkit allows us to optimize the risk-return ratio based on the variation of the fuzzy components of all clusters. We study a set of portfolios with minimal risks in terms of variation in the fuzzy part of the clusters.

Literature review

Previous studies [6, 7] have shown that investors could have significantly improved the ESG quality of their portfolios over the past decade without compromising financial performance by using ESG criteria for investment screening.

Challenges to promoting ESG investing include the limitations of ESG data, the perception that ESG indicators aren't seen as risk factors, skepticism about meaningful environmental improvements, and the lack of robust ESG-related funds that track non-financial performance [8].

The empirical researches explore the evolving landscape of sustainable finance and portfolio management, ranging from the impact of ESG factors on market volatility and risk-adjusted returns to the interplay of ESG across regions and sectors. The study [9] analyses global ESG investment strategies from 2011 to 2021 and finds significant variation in the governance (G) factor across regions, while environmental (E) and social (S) factors show strong correlations and similar risk-return profiles. It has been shown that developed economies prioritize environmental and social issues, while in the US market and emerging markets, governance delivers better risk-adjusted returns.

Cerqueti et al. [10] found that during periods of lower market volatility, high ESG-ranked funds tended to demonstrate smaller relative market value losses than low ESG-ranked funds. This wasn't always a consistent advantage for one class over the other during periods of higher volatility. The empirical study finds that ESG-screened indexes created through negative screening have beta coefficients below 1, suggesting lower volatility and risk relative to the overall market, making them suitable for value-oriented investors. But those seeking higher risk-adjusted returns from passive ESG investing may need to explore indexes with greater ESG exposure deviation [11].

The study [12] presents the results of broad empirical studies of the relationship between sustainability, stocks' risks and returns. In general, no clear identifiable relationship has been established between these characteristics. In particular, looking at various portfolios based on data from 2006 to 2020, the authors found that only in the S&P 500 and Dow Jones databases do the most sustainable portfolio strategies show the better financial results than portfolios with low sustainable structure. This study shows that there was no identified clear link between Socially Responsible Investing (SRI) regulatory developments and ESG impacts on portfolio profitability. However, another interesting fact has been established. Analyzing two partial periods: the first – from 2006 to 2013 and second – 2014 to 2020, the authors revealed differences in interdependency between profitability and sustainability. Thus, before 2014 the least sustainable portfolios provided better results in profitability. After 2014 situation became reverse situation. Impact ESG on portfolio profitability became significant and the financial results of portfolios with higher ESG were better than those with lower ESG. In 2013, the second commitment period of the Kyoto Protocol started and the Paris COP21 agreement was signed in 2015. Thus, in a sense, regulatory changes have been a factor in sustainable development.

The study [13] finds a momentum premium among European stocks, including both ESG-ranked high and ESG-ranked low stocks. At the same time research indicated lower absolute returns for subset of high ESG-ranked stocks in the case of pursuing momentum strategies. The momentum portfolios based on low ESG-ranked stocks experience significantly lower returns during momentum crashes. An examination of the interplay of return patterns between green bonds, carbon prices and renewable energy stocks from 2015 to 2020 finds that clean energy has a dominant role in the transmission of shocks across the network, with green bonds and wind energy stocks being the main recipients of these shocks [14]. The authors also show that constructing portfolios based on the information about the return transmission processes can improve portfolio performance.

Various aspects of this topic are explored to contribute to a deeper understanding of ESG investing in the context of modern portfolio management. A number of researches provide valuable insights into its dynamics, challenges and potential benefits for portfolios creation. Cagli et al. [15] analyzed the connectedness between high ESG rating corporations and commodities subsets. The results demonstrated that connectedness can be estimated at a mediocre level. The estimations are based on the volatility spillover analysis. Namely, the results indicate that all ESG indices are net volatility transmitters, and all commodity indices (except crude oil and copper) are net volatility receivers. The results show a moderate correlation level, driven by short-term uncertainties.

The consideration of involving ESG criteria into portfolio structure is really multilateral question. Thus, paper [16] analyzed one important drawback of process of screening stocks by ESG quality. The authors proposed some special investment strategy that maximizes the ESG quality of the portfolio while maintaining regional, sectoral, and risk factor exposures within stated limits. By this multilateral portfolio management frameworks, it is necessary to refer to paper [17]. Authors coupled portfolio selection and optimization with ESG considerations based on "smart beta strategy". The main authors' finding lies in the fact that increasing in the level of sustainability does not deteriorate the risk-adjusted performances of most smart beta strategies.

Abhayawansa & Tyagi [18] suggest that rather than comparing ratings and rankings from different agencies, investors should identify the specific ESG factors that are relevant to their own investment strategies and choose an ESG rating or ranking system that is closely aligned with those factors. The study [19] examines the use of financial network indicators as inputs to machine learning strategies in global portfolio management and finds that these indicators are valuable for predicting global stock market and regional directions, especially during market crises.

Innovative approaches (such as soft computing techniques) continue to emerge in portfolio management, with the promise of improving risk-return correspondence [20]. In this context, Chourmouziadis & Chatzoglou [21] present a fuzzy short-term trading system that combines modified commonly used technical indicators and rarely used ones to enhance portfolio management, delivering superior returns compared to a buy-and-hold strategy while maintaining a conservative approach with smaller losses in bear markets and smaller gains in bull markets.

Fuzzy conception became an important part of modern portfolio management toolkit. Thus, a new portfolio risk measure called the fuzzy Sharpe ratio was proposed by Nguyen et al. [22]. The reward-to-uncertainty ratio to evaluate portfolio performance was analyzed by fuzzy modelling. Authors constructed two portfolio optimization models to minimize the uncertainty of portfolio fuzzy returns and maximize the fuzzy Sharpe ratio. It shows superior results compared to conventional mean-variance optimization models in terms of portfolio return uncertainty and performance evaluation.

The study [23] focuses on multi-period portfolio selection with fuzzy random variables which representing securities returns. The basic idea of this research emphasis to dynamic adjustment of risk tolerance and expected return levels. These are influenced by past investment results and risk attitude of decision makers. The estimation of future returns uses fuzzy variables to coupling together historical data and expert knowledge. Two portfolio selection models for different risk attitudes are developed. Authors’ modelling approach includes also a simulation-based particle swarm optimization algorithm for finding near-optimal solutions.

The effectiveness of Fuzzy Time Series (FTS) methods, in particular the First-Order FTS and Weighted First-Order FTS models, in forecasting the bitcoin market provided in [24]. Matviychuk [25] proposed an approach and the model of identifying and forecasting financial indices using the methods of the fuzzy logic theory. His approach takes into account a number of specific rules of the development of the price curve from the Elliott wave theory.

The model of the relationship between at-the-money local volatility, obtained through Dupire calibration using a genetic algorithm, and the realized volatility of Microsoft shares was provided in [26]. Non-iterative artificial intelligence tools for regression tasks were proposed in [27]. One of the main results encompass enhanced predictive accuracy for tasks with large volumes of data. The comparison of Binary Autoregressive Tree, Neural Network (Multilayer Perceptron) and Random Forest models was considered in [28] for cryptocurrency time series forecasting using machine learning.

The clustering approaches for portfolio optimization are considered in modern literature rather well. Thus, the study [29] shows that the cluster method can be used to form the optimal portfolio. Also, it is necessary to note recency of the article [30]. This study presents special of two phases clustering approach.

The study which presenting in [31] encompasses Kohonen maps clustering cryptocurrencies as alternative investment. Application of a cluster approach to portfolio management through the incorporation of sustainability components, specifically using the ESG score, is proposed by Kaminskyi et al. [32]. Authors used ESG score provided by the S&P Global Corporate Sustainability Assessment. The study examines both conventional and fuzzy clustering techniques. The results demonstrate the identification of clusters that can modify index strategies based on investors' sustainability preferences,

Taken together, these studies highlight the evolving landscape of portfolio management and confirm the relevance of the research areas of fuzzy and neural network modelling, novel risk measures and dynamic multi-period optimization.

Methodology

The logic of our methodology aims to incorporate ESG criteria into the investment portfolio construction process. Portfolios are constructed by applying fuzzy clustering to a set of criteria that combine ESG criteria with risk and return criteria. A key element of the methodology is to dynamically optimize portfolio structure based on the value-added approach for investors.

The starting point of our methodology is the selection of a stock market index. Such index strategies are attractive to investors, particularly retail investors. The advantage of an index investment strategy for the application of our methodology is that it removes the problem of liquidity when rebalancing the portfolio.

The second point of our methodology is the consideration of inclusion criteria E, S and G. We have used an approach based on

ESG scores. ESG scores are tools for quantifying a company's environmental (E), social (S) and governance (G) policies, practices and programs. ESG scores are provided by a number of agencies. The largest (in terms of coverage) ESG scoring providers are MSCI and Sustainalytics. Bloomberg and Refinitiv also provide ESG scores, as do rating agencies such as Moody's, S&P and Fitch. For a comprehensive review of the comparative assessment of ESG scores across providers, see [33]. Thus, ESG scores vary between providers due to differences in methodologies, indicators, data used and weightings. Following a comparative analysis, we have used data from S&P Global and Refinitiv in our research.

The methodology for incorporating ESG scores into investment decisions is thus based on a numerical representation of the criteria. This provides an opportunity to implement the key components of our methodology – the use of clustering techniques and the selection of criterion or criteria from the set of E, S and G. The fact is that the scoring system, being hierarchical, includes a wide range of criteria. The choice can be either an integral criterion or more focused criteria that show concrete characteristics. This is reflected in the hierarchical structure of ESG scoring in Fig. 1.

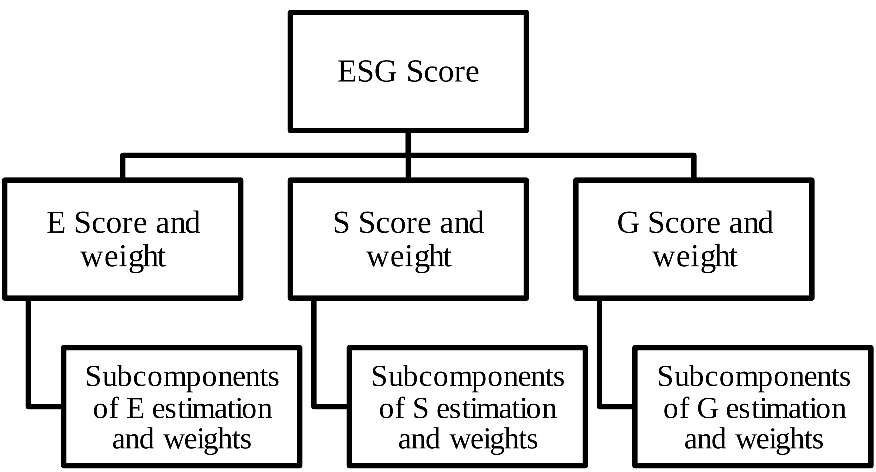

Fig. 1. Hierarchical structure of ESG score

The choice of criteria can be corresponded to certain level. The most general criterion is based on the integral ESG score. The next level is the criteria for the subcomponents E, S, and G. Continuing in this direction, we can choose a criterion (or criteria) from the level of subcomponents. Examples of subcomponents in the S&P Global and Refinitiv scoring systems are shown in Table 1.

Table 1

COMPARISON OF SUBCOMPONENTS IN S&P GLOBAL ESG SCORE AND REFINITIV ESG SCORE

Sample of subcomponents of S&P Global ESG Score	Sample of subcomponents of Refinitiv ESG Score
Emissions	Resource Usage
Climate Strategy	Emissions
Corporate Governance	Environmental Innovation
Human Capital Development	Workforce
Innovation Management	Human Rights
Occupational Health & Safety	Community
Product Stewardship	Product Responsibility
Supply Chain Management	CSR Strategy
Talent Attraction & Retention	Management
	Shareholders

As can be seen from the Table 1, the criteria in various scoring systems are differing. Therefore, the results will vary when concrete scoring will be used. Thus, it is methodologically correct to compare companies evaluated by one specific scoring system. We have chosen for our research S&P Global ESG scores. It is explained in the following way. S&P Global ESG Scores are researched and constructed via the S&P Global Corporate Sustainability Assessment (CSA). It is annual assessment of companies' sustainability performance. 10,000+ publicly listed companies are invited to participate in the CSA – a group representing 99% of global market capitalization (calculated using the S&P Global Broad Market Index). Moreover, openness of ESG scoring methodology allows a full understanding of its structure.

Our analytical procedure supposes to combine the estimates of E, S, G with the estimates of return dynamics of the companies' stocks. Considering the classical "risk-return" ratio, various measures of risk can be used. A possible set of risk measures is given, for example, in the paper [32]. At the same time, we decided to use as criteria the classic metrics of Markowitz portfolio theory: standard deviation and expected return.

Clustering is a key feature of our methodology. The portfolio forming process involves categorizing companies into clusters, giving investors the flexibility to select a cluster that meets their desired levels of return, risk or ESG score. Methodological point of clustering plays important role in identifying investors' preferences. Some investors in the priority may focus to return, others – to risk, third – to ESG criteria.

We have used fuzzy clustering [34]. This technique makes it possible to identify a core of cluster, which includes stocks whose metrics closely match the investor's preferences. Within the fuzzy part of the clusters, some companies may also have characteristics consistent with other clusters. Precisely, fuzzy clustering in our research allows to implement the strategy of maximization of added value while maintaining the priorities of investors.

The basic idea behind our portfolio construction methodology is to use the cluster that best meets the investor's criteria. The initial portfolio is based on the core (non-fuzzy part) of chosen cluster. Then we gradually add companies from the fuzzy part of the cluster, one at a time. We use the Markowitz approach to construct a portfolio with minimal risk for stocks from core and for each expanded core. Thus, the initial portfolio focuses on the cluster core and subsequent portfolios are developed by gradually adding companies from the fuzzy set, tailoring the portfolio to the investor's preferences and risk tolerance.

The next step in our methodology is to construct a Value-Added Weekly Index (VAWI) to implement the investment strategy. VAWI is a performance measure and a current analogue of the Value-Added Monthly Index (VAMI) [35]. VAWI at the period T for portfolio k is calculated as following:

$$VAWI(T) = 1000 \cdot \prod_{t=1}^{T} (1 + r_{kt}), \tag{1}$$

where r_{kt} are weekly returns of this portfolio from period 1 to T.

Economic sense of VAWI is representation of value-added process on the weekly base. The higher variability of r_{kt} values lead to higher variability of the index dynamics. The higher level of VAWI line (which consists of calculations (1) for various points in time *T*) corresponds to the higher rate of value-added.

The logic of our approach is explained as follows. The core of the cluster is unchanged and forms the "benchmarking" for this cluster. Next, the remaining stocks from "fuzzy part" are ordered by "worsening" of the selected indicator. Let us consider the integral ESG score (this indicator represents the scores E, S, G for which clustering was performed). We add stocks from the fuzzy part to the core of the cluster. Such a procedure includes step-by-step decreasing ESG score of adding stocks. After each addition, we will find a portfolio with minimum risk. Thus, we will have the number of portfolios equal to the number of stocks from the fuzzy part plus 1 (corresponding to the core part of the cluster). The VAWI is constructed for each portfolio received.

Such an approach has the advantage that the set of VAWIs reflects the investment opportunities from the cluster core to the "full cluster". The VAWI curves cross because the returns of the companies behave differently in dynamic. Returns change over time and consequently the VAWI curves for different portfolios intersect. The logic of our investment strategy is to follow the portfolio that corresponds to the maximum of VAWIs at each point in time. The upper circumferential line represents a portfolio solution in dynamics (see Fig. 3 and 4 as example). In this way, our approach allows us to construct a set of optimal portfolios that reflect a particular cluster. In each period, the portfolio with the maximum VAWI is selected. In other words, the portfolio is rebalanced by adding or removing stocks from the fuzzy part.

The benefit of our strategy comes from the combination of cluster selection and optimization procedures. I.e., the investor is in the framework of the chosen cluster (which corresponding to investor's priorities) and at the same time the portfolio management strategy is actively used to maximize the VAWI. The passive strategy of investing in clusters is effectively combined with the rebalancing strategy to maximize VAWI using fuzzy cluster components.

Results and discussion

We apply our methodology to the EURO STOXX 50 index, which comprises 50 stocks from 11 Eurozone countries. Investment strategy with this index is suitable for investors who prefer to invest in the shares of large, mostly well-known companies. The shares of these companies are highly liquid. This allows portfolios to be rebalanced without high transaction costs, which is one of the advantages.

We have chosen two-time frames: 2016-2018 and 2019-2022. The first period was used to construct the clusters and the corresponding portfolios. The second period was used to analyze the performance of constructed portfolios in dynamics. The second period of the study is sufficiently long (1 year longer than the first). The timeliness of the long period is explained by the market crisis caused by the COVID-19 pandemic. Using a long period reduces the impact of sharp fluctuations in returns in 2020. We calculated returns on a weekly basis.

The data mining process generated data for 47 companies from the index basket (see Table 2). We have used the information resource [36] for returns. It was not possible to collect all the data required for the study for three companies (Adyen, Linde, Prosus). They were excluded from the research.

We used the fuzzy clustering procedure within the R software. The procedure is based on the FANNY algorithm [37], represented in R as “fanny.object”. This algorithm uses the exponential membership functions for fuzzy clustering. It attributes an exponentially decreasing value to each data point depending on its distance from the cluster center. The closer the data point is to the center, the higher its membership value, and the farther it is, the reverse situation: lower its membership value, until it reaches zero.

In our view, there is no universal algorithm for determining the number of clusters and boundary level membership. We assumed that each cluster had at least 5 shares, so that diversification could be applied meaningfully. Regarding membership value, we assumed that fuzzy part of cluster will not more than “core” of the cluster. These two rules lead us to choose 3 clusters and select membership function cutoff value of 0.3. Table 3 gives an overview of the average parameter values for the three clustering criteria: *ER* – expected return, *STD* – risk assessed through standard deviation, *ESG Score average* – the mean of ESG scores of cluster’s companies.

Table 2

DATASET OF 47 COMPANIES FROM THE EURO STOXX 50 INDEX

Company	Country	Ticker	Expected Return Weekly 2016-2018	Risk Weekly 2016-2018	ESG score 2018	Expected Return Weekly 2019-2022	Risk Weekly 2019-2022	ESG score 2022
ADIDAS	DE	ADSGn	0.54%	3.57%	84	-0.01%	5.19%	82
AHOLD DELHAIZE	NL	AD	0.13%	2.90%	72	0.14%	2.96%	83
AIR LIQUIDE	FR	AIRP	0.13%	2.54%	37	0.27%	2.94%	50
AIRBUS	FR	AIR	0.26%	3.45%	31	0.36%	6.53%	39
ALLIANZ	DE	ALVG	0.09%	2.87%	85	0.17%	4.15%	89
ANHEUSER-BUSCH INBEV	BE	ABI	-0.36%	2.91%	30	0.09%	4.81%	28
ASML HLDG	NL	ASML	0.39%	3.98%	77	0.80%	4.99%	80
AXA	FR	AXAF	-0.11%	3.67%	79	0.28%	4.64%	87
BASF	DE	BASFn	-0.03%	2.90%	55	0.02%	4.65%	49
BAYER	DE	BAYG	-0.29%	3.77%	64	-0.02%	4.40%	35
BCO BILBAO VIZCAYA ARGENTARIA	ES	BBVA	-0.11%	3.97%	81	0.30%	5.89%	89
BCO SANTANDER	ES	SAN	0.01%	4.14%	86	0.06%	6.05%	86
BMW	DE	BMWG	-0.14%	3.41%	74	0.21%	4.46%	74
BNP PARIBAS	FR	BNPP	-0.08%	3.93%	78	0.34%	5.65%	82
CRH	IE	CRH	-0.01%	3.26%	81	0.36%	4.71%	81
DANONE	FR	DANO	0.02%	2.39%	68	-0.06%	3.06%	57
DEUTSCHE BOERSE	DE	DB1Gn	0.21%	2.77%	63	0.25%	3.54%	73
DEUTSCHE POST	DE	DPWGn	0.00%	2.86%	73	-0.02%	4.40%	70
DEUTSCHE TELEKOM	DE	DTEGn	-0.03%	2.58%	83	0.18%	3.23%	91
ENEL	IT	ENEL	0.22%	2.92%	85	0.13%	4.08%	88
ENI	IT	ENI	0.07%	3.05%	50	0.10%	4.75%	46

ESSILORLUXOTTICA	FR	ESLX	0.01%	2.63%	73	0.30%	3.93%	45
FLUTTER ENTERTAINMENT	IE	FLTRX	-0.21%	4.62%	11	0.46%	5.56%	21
HERMES INTERNATIONAL	FR	HRMS	0.30%	2.53%	23	0.65%	3.84%	28
IBERDROLA	ES	IBE	0.12%	2.75%	87	0.33%	3.41%	89
Industria de Diseno Textil SA	ES	ITX	-0.16%	2.99%	68	0.17%	4.32%	76
INFINEON TECHNOLOGIES	DE	IFXCn	0.23%	3.89%	78	0.45%	5.89%	83
ING GRP	NL	INGA	-0.09%	3.50%	76	0.30%	6.07%	50
INTESA SANPAOLO	IT	ISP	-0.17%	4.51%	83	0.18%	4.97%	80
Kering	FR	PRTP	0.70%	3.72%	80	0.25%	4.83%	84
KONE B	FI	KNEBV	0.09%	2.90%	41	0.14%	3.28%	43
L'OREAL	FR	OREP	0.19%	2.26%	40	0.34%	3.35%	62
LVMH MOET HENNESSY	FR	LVMH	0.40%	2.99%	32	0.60%	3.93%	71
MERCEDES-BENZ GROUP	DE	MBGn	-0.38%	3.13%	39	0.42%	5.78%	33
MUENCHENER RUECK	DE	MUVGn	0.05%	2.59%	76	0.35%	4.34%	86
PERNOD RICARD	FR	PERP	0.22%	2.53%	61	0.19%	3.24%	37
PHILIPS	NL	PHG	0.19%	3.09%	81	-0.21%	4.41%	81
SAFRAN	FR	SAF	0.37%	3.01%	28	0.26%	6.12%	35
SANOFI	FR	SASY	0.01%	2.86%	76	0.15%	3.27%	74
SAP	DE	SAP	0.14%	2.60%	70	0.17%	4.22%	79
SCHNEIDER ELECTRIC	FR	SCHN	0.13%	3.28%	81	0.50%	4.06%	86
SIEMENS	DE	SIEG	0.10%	2.90%	79	0.29%	4.26%	81
STELLANTIS	IT	STLA	0.38%	5.66%	82	0.35%	5.47%	56
TOTALENERGIES	FR	TTEF	0.13%	2.74%	76	0.22%	4.88%	70
VINCI	FR	SGEF	0.16%	2.56%	71	0.24%	4.23%	40
VOLKSWAGEN PREF	DE	VOWG_p	0.12%	4.34%	56	0.12%	5.62%	62
Vonovia SE	DE	VNAn	0.26%	2.79%	35	-0.13%	3.87%	68

Table 3

CLUSTERS PARAMETERS

Cluster 1	Cluster 2	Cluster 3
ER = 0.11% *STD* = 3.47% *ESG Score average* = 80.35	*ER* = 0.05% *STD* = 3.02% *ESG Score average* = 68.36	*ER* = 0.09% *STD* = 3.01% *ESG Score average* = 33.08

The parameters from Table 3 provide insight into the risk-return profile and ESG characteristics of each cluster, allowing for a more comprehensive understanding of the dataset and the underlying groups of companies.

Further insights into the cluster structures and the characteristics of their cores are detailed in Table 4.

Table 4

FUZZY CLUSTERING RESULTS

Core of Cluster 1	Intersection of Cluster 1 and Cluster 2	Core of Cluster 2	Intersection of Cluster 2 and Cluster 3	Core of Cluster 3	Intersection of Cluster 1 and Cluster 3
17	**6**	**12**	**1**	**11**	**0**
ADSGn, ALVG, AXAF, BBVA, SAN, BNPP, CRH, DTEGn, ENEL, IBE, IFXCn, ISP, PRTP, PHG, SCHN, SIEG, STLA	ASML, BMWG, INGA, MUVGn, SASY, TTEF	AD, BASFn, BAYG, DANO, DB1Gn, DPWGn, ESLX, ITX, PERP, SAP, SGEF, VOWGp	ENI	AIRP, AIR, ABI, FLTRX, HRMS, KNEBV, OREP, LVMH, MBGn, SAF, VNAn	-
ER = 0.13% *STD* = 3.57% *ESG Score average* = 81.94	*ER* = 0.06% *STD* = 3.18% *ESG Score average* = 75.83	*ER* = 0.05% *STD* = 2.94% *ESG Score average* = 66.17	*ER* = 0.07% *STD* = 3.05% *ESG Score average* = 50.00	*ER* = 0.09% *STD* = 3.01% *ESG Score average* = 31.55	-

The different characteristics of the clusters provide a framework for investor choice. Cluster 1 is characterized by high levels of expected return, risk and ESG scores. Cluster 3 has the lowest level of risk among the clusters, with an expected weekly return of 0.09% and very low ESG scores. Cluster 2 has the lowest return (among the clusters) and a risk level comparable to Cluster 3. However, it has higher ESG scores than Cluster 3. This shows that the investor has the possibility to choose between the three criteria "return-risk-ESG score", selecting an appropriate cluster.

Fig. 2 shows the core and fuzzy parts of Clusters 1 and 2, where the companies are presented on a 3-dimensional coordinate plane. Risk and expected return are plotted on the horizontal and vertical axes, respectively. The diameter of the points corresponds to their ESG scores. The third cluster has only one intersection point with another cluster (Cluster 2), so we do not show it on the Fig. 2.

The core of Cluster 1 consists of 17 companies, the fuzzy part contains 6 ones. The minimum risk portfolios are constructed by successively adding stocks from the fuzzy part. This is shown in Table 5.

Table 5

PROFILE OF THE PORTFOLIOS CONSTRUCTED AROUND THE CORE OF CLUSTER 1

Number of stocks	**17**	**18**	**19**	**20**	**21**	**22**	**23**
Portfolios with minimum risk characteristics	Core of Cluster 1	+ASML	+TTEF	+SASY	+MUVGn	+INGA	+BMVG
Portfolio Risk	2.093%	2.093%	2.066%	2.027%	1.983%	1.983%	1.983%
Portfolio Return	0.136%	0.136%	0.144%	0.134%	0.130%	0.130%	0.128%
Portfolio ESG Score	83.53	83.53	82.39	81.35	80.51	80.51	80.41

The core of Cluster 2 consists of 13 companies. The minimum risk portfolios are constructed by sequentially adding stocks from the fuzzy part, as shown in Table 6.

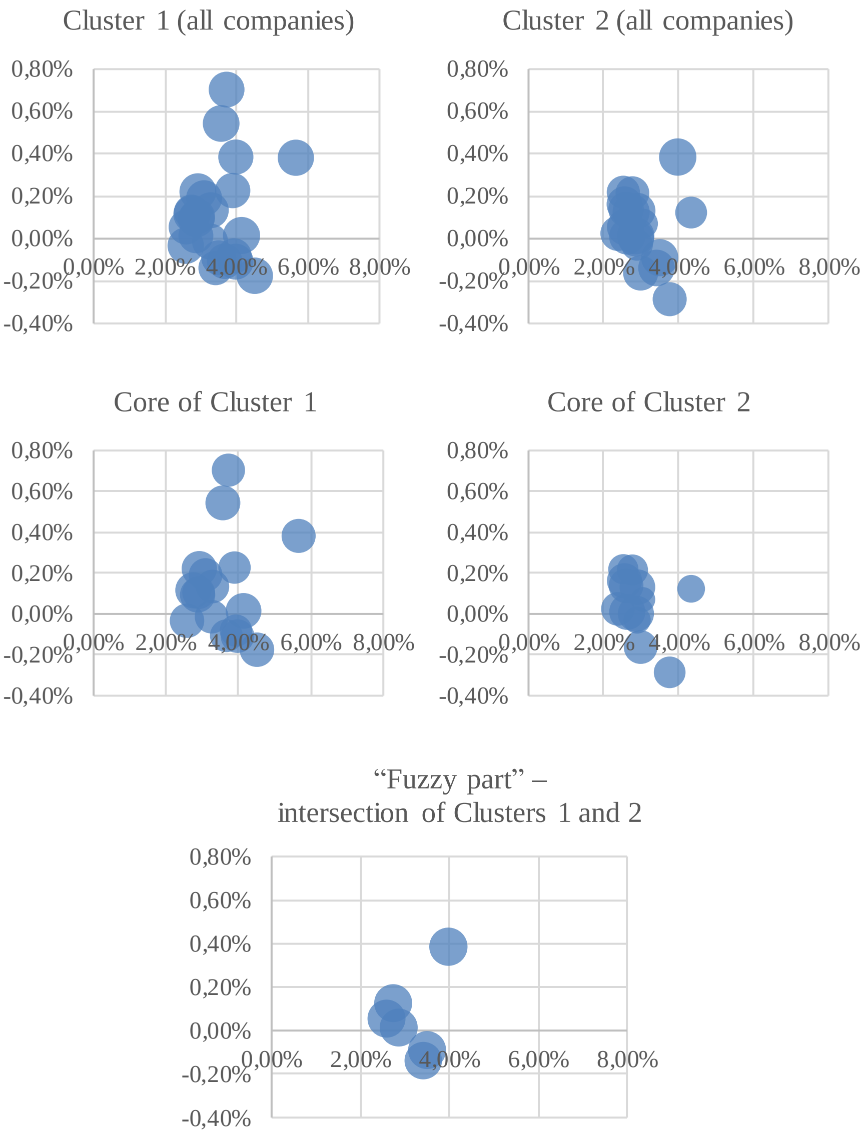

Fig. 2. Fuzzy and core components of Clusters 1 and 2

Table 6

PROFILE OF PORTFOLIOS CONSTRUCTED AROUND THE CORE OF CLUSTER 2

Number of stocks	**13**	**14**	**15**	**16**	**17**	**18**	**19**
Portfolios with minimum risk characteristics	Core of Cluster 2	+ASML	+INGA	+MUVGn	+SASY	+TTEF	+BMWG
Portfolio Risk	1.759%	1.759%	1.759%	1.751%	1.750%	1.750%	1.750%
Portfolio Return	0.104%	0.104%	0.104%	0.097%	0.097%	0.097%	0.097%
Portfolio ESG Score	66.26	66.26	66.26	67.31	67.49	67.49	67.49

Choosing the cluster based on ESG score, risk and return will be starting point of our algorithm to construct investment strategy.

The first step in our investment strategy lies in optimal portfolio construction for core of chosen cluster. The considered portfolio can be formed by naive diversification method or following to classical Markowitz approach. Other approaches can be grounded on Sharp ratio or other criteria. We demonstrate in this article approach based on risk minimizing within the framework of Markowitz portfolio theory.

The second step encompasses construction a number of portfolios by adding stocks into the portfolio basket. This is a sequential addition of one stock at a time from fuzzy part of chosen cluster. Portfolio design should follow the same algorithm as the portfolio optimization in the first step (for the core part).

The third step is dedicated to calculation of VAWI (1) for portfolios formed on previous steps. Thus, the cluster core and its “fuzzy” components generate family of VAWIs, which are visualized in Fig. 3 for Cluster 1.

The fourth step is to determine the portfolio for which the corresponding VAWI line is the top circumferential line at the moment *T*. According to our strategy, it is the best portfolio because at the moment its added value is the most. Over time, VAWI lines may intersect and the top line may correspond to another portfolio. This means that you need to change the portfolio to the one, which currently matches the top line.

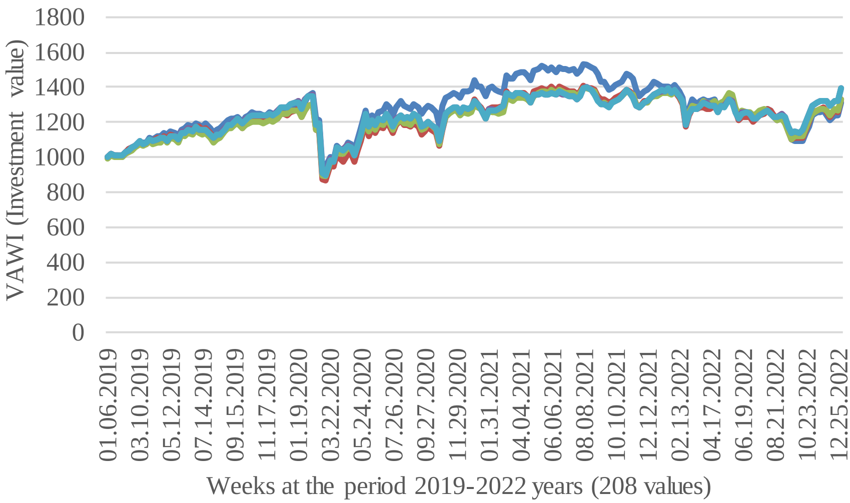

Fig. 3. VAWIs family for portfolios constructed on the base of Cluster 1

The changes happened 14 times for the period 2019-2022 for Cluster 1. It can be seen in Fig. 3. Upper circumferential line for VAWIs family of Cluster 1 is shown in the Fig. 4.

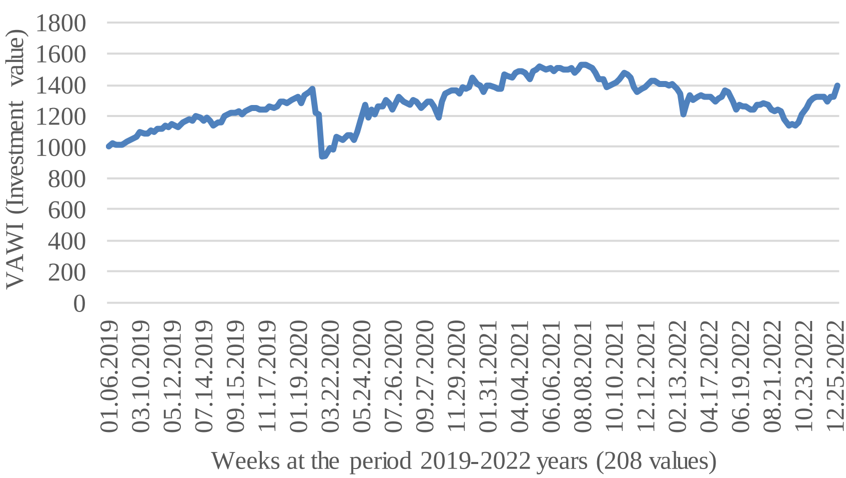

Fig. 4. Upper circumferential line for Cluster 1

Similar visualization for Cluster 2 presented in Figs. 5, 6. There were 16 changes in upper circumferential line.

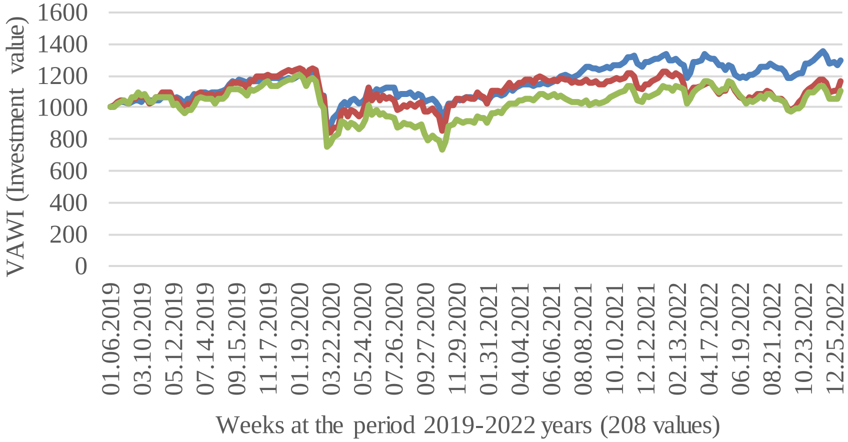

Fig. 5. VAWIs family for portfolios constructed on the base of Cluster 2

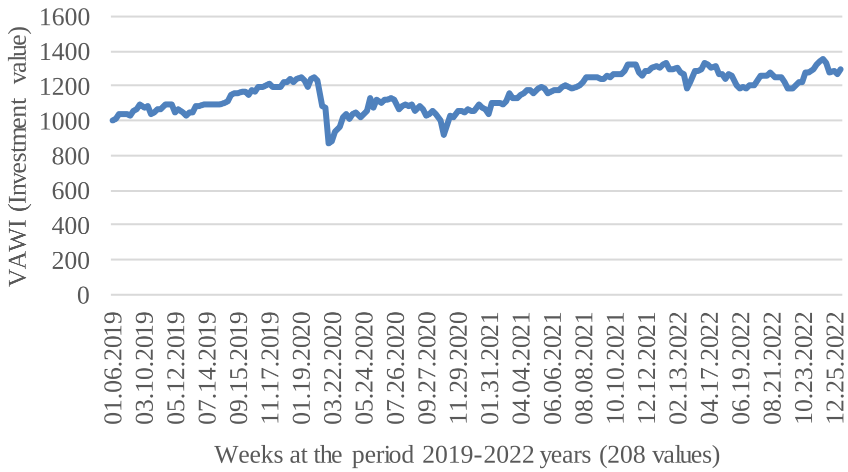

Fig. 6. Upper circumferential line for Cluster 2

Abovementioned four-step algorithm consists of following the portfolio investments along the upper circumferential line of VAWI curves of various portfolio structures (formed from shares of companies that meet the investor's ESG priorities).

Conclusions

The paper presents an approach for integrating ESG criteria into the process of investment portfolio construction and further portfolio optimization in a dynamic way. Compared to other methods such as negative screening or positive screening, the proposed approach is characterized by its flexibility in finding an appropriate trade-off in the triple assessment "risk-return-ESG score". At the same time, the use of fuzzy cluster analysis allows the investor to dynamically manage the portfolio.

This approach has several advantages over the classic one, based on the Markowitz model, which is applied to a fixed stock basket. Let's briefly describe these advantages. First, the basis for portfolio management is a clear core of the formed cluster of companies chosen correspondingly to the investor's preferences across three criteria: minimizing risk and maximizing profitability and ESG score. Core of each cluster does not change over time. But, varying the portfolio components from "fuzzy" part of cluster provides management possibilities to ensure the optimal ratio "risk-return-ESG score".

The second advantage is the transparency of the optimal strategy for investors. The dynamics of the VAWIs clearly show which portfolio is currently generating the best investment value. This increases investor confidence because it eliminates the risk associated with delegating portfolio design to managers' discretion.

Third, the proposed approach clearly identifies the timing of portfolio rebalancing. This occurs when one of the VAWI lines crosses the upper circumferential line.

The fourth advantage is that there is a good opportunity to automate the proposed approach. The possibility to implement robo-advisers is an effective solution for retail investors because dynamic VAWIs provide good visualization and decision support.

The fifth advantage is that it can be easily implemented into practice through the Exchange Trade Funds (ETFs) scheme. Really, let's create an ETF, which correspond to chosen cluster. Since the cluster core is invariable, the corresponding ETF will have a constant positioning in the market. But, using fuzzy part of cluster it is possible to manage portfolio of ETF. It will be in accordance with the investor's preferences.

The sixth advantage is the relatively low transaction costs of portfolio rebalancing. As the calculations in the article show, this happens infrequently – 14 times for Cluster 1 and 16 times for Cluster 2 in the period 2019-2022.

However, the proposed approach has some limitations. The first of them is that there is no clear criterion for the formation of clusters. The larger number of clusters leads to a wider choice of the investor's "risk-return-ESG score" ratio. Investor`s preferences typically focus to average values of such metrics. Second limitation is based on the sizes of the clusters. Choosing small cluster may affect risk by reducing diversification. Third, ESG score has hierarchical structure and include different sub-criteria. The presence of many different sub-criteria gives a fairly wide choice for clustering. Fourth limitation reflects some delay in portfolio management decisions because it will be the consequence of changes in upper circumferential line. But our statistical analysis indicates that changes is not so often and chosen portfolio becomes optimal for a fairly long period (before the following changes in line).

Thus, we present a holistic model of investment strategy based on the application of fuzzy clustering. This strategy maximizes investment value within the selected cluster. It can be used by institutional investors who are oriented towards the implementation of ESG criteria in portfolio decisions.

References

1. Nasdaq. (2021, July 15). *What Is ESG Investing and Why Is it Worth Trillions?* https://www.nasdaq.com/articles/what-is-esg-investing-and-why-is-it-worth-trillions-2021-07-15

2. Statista. (2023, June 14). *Share of professional investors increasing their environmental, social, and governance (ESG) investments worldwide in 2023*. https://www.statista.com/statistics/1191755/esg-etf-increased-investment-next-year-worldwide/

3. Bernow, S., Klempner, B., & Magnin, C. (2017). *From 'why' to 'why not': Sustainable investing as the new normal*. McKinsey & Company. https://www.mckinsey.com/industries/private-equity-and-principal-investors/our-insights/from-why-to-why-not-sustainable-investing-as-the-new-normal

4. Kaminskyi, A., Nehrey, M., & Fedchun, A. (2022). ESG-score effect in risk assessment of direct and portfolio investment: evidence from CEE markets. *The Journal of V. N. Karazin Kharkiv National University. Series: International Relations. Economics. Country Studies. Tourism*, *15*, 38-44. https://doi.org/10.26565/2310-9513-2022-15-04

5. Kaminskyi, A. (2022). Investment risk management specifics in ESG investing: CEE stock markets examining. *Scientific Papers NaUKMA. Economics*, *7*(1), 54–60. https://doi.org/10.18523/2519-4739.2022.7.1.54-60

6. UNCTAD. (2021). *The rise of the sustainable fund market and its role in financing sustainable development*. https://unctad.org/system/files/official-document/diae2021d1_en.pdf

7. Gond, J-P., O'Sullivan, N., Slager, R., Homanen, M., Viehs, M., & Mosony, S. (2018). *How ESG engagement creates value for investors and companies*. UNEP Finance Initiative. https://www.unpri.org/download?ac=4637

8. Zeidan, R. (2022). Why don't asset managers accelerate ESG investing? A sentiment analysis based on 13,000 messages from finance professionals. *Business Strategy and the Environment*, *31*(7), 3028-3039. https://doi.org/10.1002/bse.3062

9. Meira, E., Cunha, F. A. F. D. S., Orsato, R. J., Miralles-Quirós, M. M., & Miralles-Quirós, J. L. (2023). The added value and differentiation among ESG investment strategies in stock markets. *Business Strategy and the Environment*, *32*(4), 1816-1834. https://doi.org/10.1002/bse.3221

10. Cerqueti, R., Ciciretti, R., Dalò, A., & Nicolosi, M. (2021). ESG investing: A chance to reduce systemic risk. *Journal of Financial Stability*, *54*, Article 100887. https://doi.org/10.1016/j.jfs.2021.100887

11. Jin, I. (2022). Systematic ESG risk and passive ESG investing. *The Journal of Portfolio Management*, *48*(5), 71-86. https://doi.org/10.3905/jpm.2022.1.344

12. Cesarone, F., Martino, M. L., & Carleo, A. (2022). Does ESG Impact Really Enhance Portfolio Profitability? *Sustainability*, *14*(4), Article 2050. https://doi.org/10.3390/su14042050

13. Kaiser, L., & Welters, J. (2019). Risk-mitigating effect of ESG on momentum portfolios. *The Journal of Risk Finance*, *20*(5), 542-555. https://doi.org/10.1108/JRF-05-2019-0075

14. Tiwari, A. K., Abakah, E. J. A., Gabauer, D., & Dwumfour, R. A. (2022). Dynamic spillover effects among green bond, renewable energy stocks and carbon markets during COVID-19 pandemic: Implications for hedging and investments strategies. *Global Finance Journal*, *51*, Article 100692. https://doi.org/10.1016/j.gfj.2021.100692

15. Cagli, E. C. C., Mandaci, P. E., & Taşkın, D. (2022). Environmental, social, and governance (ESG) investing and commodities: dynamic connectedness and risk management strategies. *Sustainability Accounting, Management and Policy Journal*, *14*(5), 1052-1074. https://doi.org/10.1108/SAMPJ-01-2022-0014

16. Alessandrini, F., & Jondeau, E. (2021). Optimal strategies for ESG portfolios. *The Journal of Portfolio Management*, *47*(6), 114-138. https://doi.org/10.3905/jpm.2021.1.241

17. Ielasi, F., Ceccherini, P., & Zito, P. (2020). Integrating ESG analysis into smart beta strategies. *Sustainability*, *12*(22), Article 9351. https://doi.org/10.3390/su12229351

18. Abhayawansa, S., & Tyagi, S. (2021). Sustainable investing: The black box of environmental, social, and governance (ESG) ratings. *The Journal of Wealth Management*, *24*(1), 49-54. https://doi.org/10.3905/jwm.2021.1.130

19. Lee, T. K., Cho, J. H., Kwon, D. S., & Sohn, S. Y. (2019). Global stock market investment strategies based on financial network indicators using machine learning techniques. *Expert Systems with Applications*, *117*, 228-242. https://doi.org/10.1016/j.eswa.2018.09.005

20. Kaminskyi, A., & Nehrey, M. (2023). Clustering Stocks by ESG Score Values, Risks and Returns: Case of Expanded German Index DAX. In Z. Hu, Z. Ye, & M. He (Eds.), *Lecture Notes on Data Engineering and Communications Technologies: Vol. 159. Advances in Artificial Systems for Medicine and Education VI (AIMEE 2022)* (pp. 264–276). Springer, Cham. https://doi.org/10.1007/978-3-031-24468-1_24

21. Chourmouziadis, K., & Chatzoglou, P. D. (2016). An intelligent short term stock trading fuzzy system for assisting investors in portfolio management. *Expert Systems with Applications*, *43*, 298-311. https://doi.org/10.1016/j.eswa.2015.07.063

22. Nguyen, T. T., Gordon-Brown, L., Khosravi, A., Creighton, D., & Nahavandi, S. (2015). Fuzzy portfolio allocation models through a new risk measure and fuzzy Sharpe ratio. *IEEE Transactions on Fuzzy Systems*, *23*(3), 656-676. https://doi.org/10.1109/TFUZZ.2014.2321614

23. Wang, B., Li, Y., & Watada, J. (2017). Multi-period portfolio selection with dynamic risk/expected-return level under fuzzy random uncertainty. *Information Sciences*, *385-386*, 1-18. https://doi.org/10.1016/j.ins.2016.12.033

24. Bielinskyi, A., Soloviev, V., Solovieva, V., & Velykoivanenko, H. (2022). Fuzzy time series forecasting using semantic artificial intelligence tools. *Neuro-Fuzzy Modeling Techniques in Economics, 11*, 157-198. http://doi.org/10.33111/nfmte.2022.157

25. Matviychuk, A. (2006). Fuzzy logic approach to identification and forecasting of financial time series using Elliott wave theory. *Fuzzy economic review*, *11*(2), 51-68. https://doi.org/10.25102/fer.2006.02.04

26. Bondarenko, M. (2021). Modeling relation between at-the-money local volatility and realized volatility of stocks. *Neuro-Fuzzy Modeling Techniques in Economics*, *10*, 46-66. http://doi.org/10.33111/nfmte.2021.046

27. Tkachenko, R., Tkachenko, P., Izonin, I., Vitynskyi, P., Kryvinska, N., & Tsymbal, Y. (2019). Committee of the Combined RBF-SGTM Neural-Like Structures for Prediction Tasks. In I. Awan, M. Younas, P. Ünal, & M. Aleksy (Eds.), *Lecture Notes in Computer Science: Vol. 11673. Mobile Web and Intelligent Information Systems (MobiWIS 2019)* (pp. 267–277). Springer, Cham. https://doi.org/10.1007/978-3-030-27192-3_21

28. Derbentsev, V., Velykoivanenko, H., & Datsenko, N. (2019). Machine learning approach for forecasting cryptocurrencies time series. *Neuro-Fuzzy Modeling Techniques in Economics*, *8*, 65-93. http://doi.org/10.33111/nfmte.2019.065

29. Fadilah, I., & Witiastuti, R. (2018). A Clustering Method Approach for Portfolio Optimization. *Management Analysis Journal*, *7*(4), 436-447. https://doi.org/10.15294/maj.v7i4.23378

30. Gularte, A. P. D. S., Feitosa, F. D. S. A., Pacheco, V. H. P., & Curtis, V. V. (2023). Clustering Approach for Portfolio Optimization. *SSRN*, Article 4474899. http://dx.doi.org/10.2139/ssrn.4474899

31. Kaminskyi, A., Miroshnychenko, I., & Pysanets, K. (2019). Risk and return for cryptocurrencies as alternative investment: Kohonen maps clustering. *Neuro-Fuzzy Modeling Techniques in Economics*, *8*, 175-193. http://doi.org/10.33111/nfmte.2019.175

32. Kaminskyi, A., Butylo, D., & Nehrey, M. (2021). Integrated approach for risk assessment of alternative investments. *International Journal of Risk Assessment and Management*, *24*(2-4), 156-177. https://doi.org/10.1504/IJRAM.2021.126413

33. Lovas, G. (2023). *The top ESG rating providers and how to use them*. Broker Chooser. https://brokerchooser.com/education/investing/top-esg-rating-providers

34. Bede, B. (2013). Fuzzy Clustering. In *Studies in Fuzziness and Soft Computing: Vol. 295. Mathematics of Fuzzy Sets and Fuzzy Logic* (pp. 213-219). Springer. https://doi.org/10.1007/978-3-642-35221-8_12

35. Ganti, A. (2022, April 30). *Value Added Monthly Index (VAMI): What It Is, How It Works*. Investopedia. https://www.investopedia.com/terms/v/vami.asp

36. Investing.com. (2023). *Euro Stoxx 50 (STOXX50E)* [Data set]. Retrieved January 15, 2023, from https://www.investing.com/indices/eu-stoxx50

37. Liu, D., & Graham, J. (2017). *Simple Measures of Individual Cluster-Membership Certainty for Hard Partitional Clustering*. arXiv. https://doi.org/10.48550/arXiv.1704.00352

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