No Gambling Here! A New Comprehensive Risk Index

Nico Rosamilia[§]

Politecnico di Milano, School of Management[‡]

Abstract

I create an index that measures the risk of investment funds using a traditional econometrics tool (PCA) and a machine learning algorithm (autoencoder). The composite index measure follows the classical signaling method of credit ratings. I include financial risk variables, ESG ratings, macroeconomic variables, and fund characteristics to obtain a composite measure to categorize fund risk. The customized autoencoder performs better than the PCA allowing us to convey an index that contains multiple sources of information and respects the correlation directionality between variables and risk. Therefore, I contribute to the risk management and decisional process for the investment funds evaluation by introducing a more complete and comprehensive measure of risk.

Keywords: Composite index, sustainable finance, risk management, fund performance.
JEL Classification: G11, G23, G32, C43.

[§]Email: nico.rosamilia@polimi.it

[‡]Via Raffaele Lambruschini, 20156 Milano, Italia

1 Introduction and Literature

ESG portfolios represent a subset of the overall market portfolio, affecting diversification Bauer et al. (2006). It follows that ESG investments may incur risk-reward challenges that affect long-term performance Cummings (2000) and Cortez et al. (2009). Fernández et al. (2019) and Wu et al. (2019) investigate the performance of the green mutual funds during the 2007-2009 financial crisis. These funds generate slightly higher risk-adjusted returns when compared to their conventional counterparts. There is an ongoing debate in the literature on the relationship between ESG and portfolio risk. Becchetti et al. (2018) shows that lower ESG ratings positively correlate with the number of future litigations faced by stakeholders. Pastor et al. (2020) and Albuquerque et al. (2019) prove that in equilibrium, investors reward firms with reduced systematic risk and high ethical scores. Pedersen et al. (2021) emphasize the role of ESG portfolios in forming the preferences of investors (see also Bougamont et al. (2014)). The shift in investors' preferences could serve as a parameter to direct investments for fund managers, which in turn can modify the overall risk-reward paradigm.

There is little evidence to support either of the claims that ESG funds are fundamentally less risky or consistently outperform non-ESG funds. Indeed, it appears that ESG funds report median risk-returns performance. Furthermore, data shows that sustainable funds do not display significantly higher or lower standard deviations than their peers. According to modern portfolio theory, ESG screening inevitably leads to a smaller number of eligible companies, therefore diminishing the number of stocks for portfolio diversification (see Rosamilia (2024) and Lanza et al. (2020) for a detailed discussion). Hoepner (2010) claims that the positive correlation among the remaining companies contributes to diversification issues. In contrast, according to Tim Verheyden and Andreas Feiner (2016), ESG screening does not affect diversification, and socially conscious investing does not reduce risk-adjusted returns (Iachini (2021)).

The dominance of modern portfolio theory established the relevance of the mean-variance paradigm, see Brandstetter and Lehner (2015). It is only recently, and still in a moderate fashion, that ESG consideration enters the portfolio construction strategies. One of the primary challenges of incorporating ESG factors into conventional valuation frameworks lies in the intrinsic limitations of these models, which are often not designed to capture non-financial indicators Sikken (2011). Aside from adhering to stringent legal and policy-related requirements, Brandstetter and Lehner (2015) claim that the commitment of pension funds to class-specific benchmarks for expected financial risk and return can be considered as a barrier for the inclusion of ESG criteria. Additionally, adding ESG involves additional costs, particularly if internal research is done. Drut (2010) give a straightforward solution to the problem of quantitative ESG incorporation into portfolio optimization and add a linear constraint to the traditional Markowitz model. When investors prioritize socially responsible investments, the optimization problem adapts to consider this score when constructing a portfolio. This modification leads to a refined objective function that seeks to enhance returns while being constrained by the socially responsible score. Recently, Rosamilia (2024) uses a customized random forest that creates efficient sustainable portfolios optimizing over single ESG indicators. Utility theory is another approach towards a quantitative integration of ESG factors into portfolio optimization, see Jessen (2012) and Pedersen et al. (2021) among others. This paper enters this strand of literature creating an index that evaluates the overall risk of a fund, and therefore offering a strategic variable for portfolio construction.

The use of composite indices to combine parameters in a simpler and straightforward format has gained appreciation in recent years. These indices convey a compact representation of the characteristics or the performance of an entity through the numerical combination of various indicators, thus allowing monitoring of sparse information Nardo, Saisana, Saltelli, and Tarantola (2005). In essence, a composite indicator can represent complex and sparse data into synthesized indicators that simplify the overall understanding of data. Reisi et al. (2014) state that these compact tools are crucial in the communication gap between researchers, policy formulators, and society. The index-based technique spreads in different areas, including air quality evaluation Palit et al. (2013), quality of life Mederly et al. (2003), energy consumption of rural communities Doukas et al. (2012), and sustainability measurement Imberger et al. (2007) and Saisana et al. (2005). Indeed, the ESG scores of the rating agencies represent a synthetic and useful method to combine several sustainable indicators. The rating process involves multiple phases that lead to the creation of a composite index. Different research, see Escrig-Olmedo et al. (2014), Ilze Zumente (2021), and Berg et al. (2022) among others, analyze the rating structures, raising criticism for the transparent and fair aspect of compounded scores that involve possible loss of information. Therefore, Nardo, Saisana, Saltelli, Tarantola, et al. (2005) proposes a ten-step method known as a checklist that aims at establishing a uniform framework for more transparency in the creation of composite indices.

2 Data

Morningstar and FundFocus are the two datasets that I use for the financial year 2023. Numerous papers study funds characteristics and performances with the Morningstar investor platform[1]. FundFocus, accessible via the MoneyMate application, offers granular fund-specific information. I use data of funds from two sources to ensure reliability and to train the algorithms to generalize for data outside the dataset. Both datasets provide comprehensive coverage of financial and ESG metrics, allowing for a thorough examination of investment portfolios. Additionally, the inclusion of different methods for measuring ESG performance indicators, Sustainalytics for Morningstar and MSCI for FundFocus, enables a comprehensive comparative analysis.

I use three classical financial variables to gauge financial risk: standard deviation (σ), beta (β), and Maximum Drawdown (MDD). These variables fundamentally correlate with macroeconomic measures. Indeed, the complex relationships between macroeconomic dynamics and market behavior influence investment choices and asset pricing. In this paper, confidence and time horizon are two of the risk measures indicated by Burmeister et al. (2003) that capture a portion of the macroeconomic risk. Confidence measures the willingness of investors to undertake risky investments. It is the differential in returns between comparatively risky corporate bonds and more secure government bonds. This indicator expresses the premium that investors ask to assume extra risk, giving an idea about the general market sentiment. Time horizon risk measures the risk tolerance and the timeframe of payouts that investors are willing to bear. The measure considers the yield spread between government bonds and 3-month treasury bills. A higher spread shows that investors seek a higher reward for long-term investments than for short-term ones, indicating a perception of increasing uncertainty or volatility over the long term. Carboni (2017) calculates the Confidence Risk as the difference between the total return of the indices Merrill Lynch EMU Corporate Bonds, BBB rating, and the JPMorgan Global Bond Index EMU for 7-10 years. Time horizon risk is the change in the JPMorgan Global Bond Index EMU 10 years minus the one-month LIBOR rate. I measure these metrics in each geographic area of the Morningstar dataset. Table 1 shows the risky corporate bond interest rates, while Table 2 presents the rates for the government bonds. The dataset comprehends US funds (8,061), Global funds (1,115), and European funds (854).

[1] Babalos et al. (2015) examine the performance of US Equity mutual funds, Chang et al. (2012) studies green funds performances, Simons (1998) investigate risk-adjusted returns for mutual funds, and Svetina (2010) analyze the performance of ETFs.

Table 1: **Risky corporate bonds interest rate**. The interest rate for the risky corporate bonds in each geographical area of the Morningstar dataset

Area	Risky corporate bonds	Value 2023 (%)
USA	MVIS Moody's Analytics US BBB Corporate Bond Index	7.20
Europe	iBoxx € High Yield Corporate Bond Index	9.81
Asia	J.P. Morgan Asia Credit Index (JACI) High Yield	6.00
Canada	MVIS Moody's Analytics US BBB Corporate Bond Index	7.20
Switzerland	SBI Foreign AAA-BBB 5-10 TR	5.27
China	W.I.S.E. CSI 300 China	-11.61
Japan	NOMURA-BPI (Nomura Bond Performance Index)	-14.40
Latin America	J.P. Morgan CEMBI Broad Diversified	8.07
UK	The FTSE Sterling High-Yield Bond Index	7.77
Global	Bloomberg Barclays Global High Yield Corporate Bond Index	8.40

Table 2: **Government bonds interest rate**. The interest rate for the government bonds in each geographical area of the Morningstar dataset

Area	Government bonds	Value 2023 (%)
USA	S&P U.S. Government Bond Index	2.47
Europe	Bloomberg Barclays Euro-Aggregate: Treasury Index	4.10
Asia	iShares Emerging Asia Local Govt Bond UCITS ETF	5.50
Canada	S&P Canada Government Bond Index	3.00
Switzerland	SBI® Domestic Government Total Return Index	3.44
China	S&P China Government Bond Index	5.94
Japan	S&P Japan Government Bond Index	-0.19
Latin America	J.P. Morgan Government Bond Index-Emerging Markets	12.1
UK	U.K. Government Bond Index Fund (VANUGSA)	3.35
Global	FTSE World Government Bond Index (WGBI)	-0.10

In Table 3, I calculate Confidence Risk as the difference between the rates of risky minus government bonds for 2023, and the time horizon risk as the difference between the government bond rates minus the LIBOR rate. The Confidence risk shows that China, Japan, and Latin America display lower risk premia, while the opposite is true for Europe, the UK, and the USA. The time horizon risk is relatively low for all regions, in particular for Japan. The 6.64% score in Latin America indicates that investors require higher returns for long-term investment.

2.1 Morningstar database

Morningstar contains over 3,396 ETFs, 10,500 Mutual Funds, and 650 CEFs. Among the 14,546 funds, the majority belong to the asset class US equity (3,623) and International Equity (2,236), but there is also space for Taxable Bonds (2,873). As for the management style, the dataset is almost balanced among active and passive funds, while only 483 are fund of funds. The prospectus objective of each fund is mainly on Growth and Income (5,081) and Asset Allocation (1,237). The prevalence of missing data regards ESG performance metrics, while there is a minor issue for the financial risk. The variable Carbon Risk Score counts 5,602 missing values. Corporate Sustainability Score and Morningstar Sustainability Rating have 3,000 and 2,917 missing values respectively. This study uses ESG, financial, and macroeconomic variables from Morningstar.

The Corporate Sustainability Score (CSS) of Morningstar is an asset-weighted average of company-level ESG risk rating from Sustainalytics. This ESG risk from Sustainalytics measures the extent to which ESG factors contribute to the economic value risk of a company. The ESG risk ratings and the portfolio CSS are on a 0-100 scale (with the lower score indicating better performance), using an asset-weighted average of all

Table 3: **Confidence and time horizon risk**. The Confidence risk is the difference between the interest rate of risky corporate bonds minus the interest rate of government bonds. The time horizon risk is the difference between the interest rate of government bonds minus the LIBOR rate

Area	Confidence risk (%)	Time horizon risk (%)
USA	4.73	-2.99
Europe	5.71	0.12
Asia	0.50	0.04
Canada	2.05	-2.46
Switzerland	1.83	-0.54
China	-2.22	0.48
Japan	3.29	-14.28
Latin America	-4.03	6.64
UK	4.42	-0.85
Global	8.50	-5.56

covered securities. I use the following ESG variables for Morningstar:

1. Carbon Risk Score (CRS): weighted average carbon risk score of corporate holdings in the portfolio. This score reflects the level of material risk that companies within the portfolio face in the context of transitioning to a low-carbon economy, with a lower score indicating a more favorable situation

2. Corporate Sustainability Score - Environmental (CSS - E): environmental contribution to the corporate sustainability score (a lower score indicates a better performance)

3. Corporate Sustainability Score - Social (CSS - S): social contribution to the corporate sustainability score (a lower score indicates a better performance)

4. Corporate Sustainability Score - Governance (CSS - G): governance contribution to the corporate sustainability score (a lower score indicates better performance)

5. Morningstar Sustainability Rating (MSR): considers the ESG risk of both companies and governments included in the investment. Higher ratings signify that a greater portion of the investments includes companies with lower ESG risk, as assessed by Sustainalytics

2.2 FundFocus database

FundFocus contains over 8,848 funds divided by 5,682 authorized foreign funds, 1,440 ETFs, and 1,074 italian mutual funds. Most of the missing data regards the two ESG metrics in FundFocus. The first, MSCI ESG Carbon Intensity (MECI) is defined as the amount of carbon dioxide emissions (CO_2e) produced by a company relative to its total revenue. This measure allows investors to evaluate and compare the carbon efficiency of companies. The formula for carbon intensity is: $\mathrm{CI} = \frac{\text{Metric tons of CO}_2\text{e}}{\text{Million dollars of revenue}} \left(\frac{\text{tCO}_2\text{e}}{\$M \text{ revenue}}\right)$, where hihg values of the measure indicate poor performances of the fund. The second ESG measure is the MSCI ESG Rating (MER). It evaluates the ability of companies to guard against long-term and other financial risks that are material and relevant to ESG. The rating uses a seven-point scale from CCC (highest risk) to AAA (lowest risk). To derive statistics, and to perform regression and clustering analysis, the 'MSCI ESG Rating' have been converted into numerical values from one to seven. Finally, FundFocus assesses financial risk metrics similarly to Morningstar. The only difference regards the beta calculation, determined as relative to a benchmark category and not relative to the general market benchmarking of Morningstar. The measure of risk from FundFocus may represent a more precise evaluation since it compares performances within the same category

3 Methodology

I create a composite risk index defined over a discrete interval where higher (lower) index values represent lower (higher) risk. I combine financial, macroeconomic, and ESG variables (input or index variables) into a synthetic measure representing risk information (output or composite index) in a compact fashion. The empirical strategy of this paper embraces different steps. I run simple regression models to capture the correlation between input variables and risk. These estimates allow us to understand whether linear models explain a relation between ESG variables and risk measures. Additionally, the sign of statistically significant coefficients in the regression indicates the direction of movement between the variables and financial risk. For example, a positive coefficient signals that the variable and financial risk are positively correlated. I then show the construction of the composite index. First, I run a Principal Component Analysis (PCA) to create a synthetic index measure through linear modeling. Finally, I use an unsupervised neural network algorithm to create the composite risk index with a model-free autoencoder. This model overcomes the limits of traditional linear methods allowing us to create the desired risk index measure. I determine the variables composing the index with lasso, a variables selection model, and explain the information sparsity with k-means clustering. In this section, I first introduce lasso and k-means clustering to select and describe the variables of interest. Following, I introduce the linear regressions to establish the existence of a correlation between funds variables and financial risk while understanding the direction of that possible correlation. Finally, I construct the index with the PCA and the autoencoder.

3.1 Feature selection with lasso

I use the Least Absolute Shrinkage and Selection Operator for feature selection and regularization when dealing with high-dimensional data. The model introduces a penalty term in the objective function that sets to zero the coefficients of the least important features. The conventional measure of risk uses modeling and evaluation of standard deviation, beta, and MDD. Therefore, I want to find the available funds data for Morningstar and FundFocus funds that are relevant for those measures of risk.

3.2 K-means clustering

K-means clustering is a technique that divides a dataset into K non-overlapping groups, or clusters. The approach aims at reducing within-cluster variance by grouping similar data points. The K-means algorithm first assigns each data point to the nearest cluster centroid. Secondly, it updates the cluster centroids depending on the current cluster entities Kodinariya and Makwana 2013. K-means minimize the following objective function:

$$W(S,c) = \sum_{k=1}^{K} \sum_{i \in S_k} ||y_i - c_k||^2$$

where S_k is the set of points in cluster k, y_i is a data point in the cluster k, and c_k is the centroid of cluster k. The k-means clustering works sequentially and consists of a series of cycles that aim at dividing the dataset into k distinct clusters. K centroids are firstly put in different places arbitrarily within the data space. Each data point is then assigned to the nearest centroid to start the clusterization. At the end of each sequence, averaging the positions of the points in every cluster defines the centroids. The process of assigning points and calculating centroids is iterative and repeats until the centroids do not change and the clusters are optimal. To identify the optimal number of clusters, I use the elbow method. It creates a plot where the cost function, which is the sum of squared distances of data points to their closest cluster centers, is plotted against the number of clusters k. The optimal k is identified at the "elbow" point, where the rate of decrease sharply changes:

$$J(K) = \sum_{i=1}^{n} \min_{\mu_j \in C}(||x_i - \mu_j||^2)$$

where n is the number of data points, x_i is a data point, and μ_j is the centroid of cluster C_j. Silhouette analysis measures the quality of a clustering, where the silhouette score for a single sample is:

$$s = \frac{b - a}{\max(a, b)}$$

where a is the mean intra-cluster distance (the average distance between a sample and all other points in the same cluster), and b is the mean nearest-cluster distance (the average distance between a sample and the points in the nearest cluster that the sample is not a part of).

3.3 Regression models

The linear regression models shed light on the correlation between fund risk measures (σ, β, and MDD), sustainable performance, and the variables relevant to the risk measures defined with lasso. I regress each of the financial variables representing risk on the variables of the funds selected with lasso. Following the literature at the frontier I additionally include these control variables: fund size, age, turnover ratio, average manager tenure, net expense ratio, number of fund managers, potential capital gains exposure, and r-squared. The lasso selection of the variables considers correlation issues. Additionally, it allows us to avoid multicollinearity and therefore the possible partial loss of track of the independent effect of correlated left-hand side variables on the right-hand side variables. To avoid multicollinearity issues, I separate the Morningstar sustainable variables in two separate regressions with the first considering CSS-E, CSS-S, and MRS, and the second regressing CRS and CSS-G.

3.4 Principal Components Analysis (PCA)

Following Dunteman (1989), Giudici and Avrini (2002), and Mishra (2007), the best composite indicator would be the first principal component: $C_1 = \sum_{i=1}^{q} a_{1i}x_i$ where a_{1i} is the vector of weights (also called components or factors loading) of the original variables x_i where $i \in 1, ..., q$ is the number of original variables. The most important mathematical property of the composite indicator is that it explains the largest portion of the variance of the original indicators. However, the first principal component accounts for a limited part of the variance in the data, leading to possible relevant information loss. Additionally, S. K. Mishra (2008) and Mazziotta and Pareto (2019) underline that PCA-derived indexes focus primarily on closely interrelated indicators while disregarding others. It follows that PCA indexes may ignore relevant indicators because poorly inter-correlated.

An alternative method is the weighted mean of the principal components. The weights are proportional to the variance explained by each component. Therefore, the composite indicator is:

$$S = \frac{\sum_{j=1}^{p} C_j \lambda_j}{\sum_{j=1}^{p} \lambda_j}$$

where C_j is the principal component j, λ_j is the percentage of the variance explained by factor j, and $p \leq q$ is the number of principal components that explain the variance. This method assigns low relevance in the index for components explaining low variance.

3.5 Unsupervised neural networks: the autoencoder

The autoencoder is an unsupervised neural network that adopts an encoder and a decoder. The former reduces input data in a lower-dimensional state (latent feature or encoded representation). From this condensed state, the latter reconstructs the original data minimizing the reconstruction error. In the decoding state, I customize the loss function to minimize information loss from initial data while assigning a precise directionality to the original variables. The resulting encoded features are the multidimensional and nonlinear composite index.

The encoder and decoder present two layers: a linear transformation and a non-linear activation. This setup processes data in three stages: dimensional reduction, use of nonlinear activation, and dimensional expansion. In the first layer, the encoder collapses the input variables (column vectors $\mathbf{x}$) into a 1-dimensional latent space representing the composite index. Therefore, it reduces the original data dimensionality. In the second layer, the encoder applies a Rectified Linear Unit activation function (ReLU), introducing nonlinearity into the model to capture complex patterns within the data. The mathematical definition of the encoder is the following:

$$h = \text{encoder}(\mathbf{x}) = \text{ReLU}(\mathbf{W} \cdot \mathbf{x} + \mathbf{b})$$

where $\mathbf{W}$ represents the weighting matrix connecting the input layer and hidden layer, $\mathbf{b}$ denotes the bias vector, and the ReLU function is $\text{ReLU}(\mathbf{y}) = \max(0, \mathbf{y})$. The number of nodes in the input layer matches the dimensionality of the input vector $\mathbf{x}$, and the number of nodes in the hidden layer equals the dimensionality of the output vector $\mathbf{h}$. The latter is the result of the ReLU activation function applied to the linear transformation of the input. Considering that a column vector of $\mathbf{x}$ has n elements, the number of input features, and $\mathbf{h}$ has m elements, the number of hidden units, then the weighting matrix $\mathbf{W}$ will have dimensions $m \times n$, allowing it to perform a linear transformation of the input vector to the hidden layer. The bias vector $\mathbf{b}$ dimension is $m \times 1$, allowing it to adjust the activation of each node in the hidden layer independently.

The decoder reversely mirrors the structure of the encoder, aiming to reconstruct the original data from the latent representation. The algorithm applies a non-linear activation to the encoded latent representation and then expands the dimensionality of the activated latent representation back to the original input dimension. A ReLU activation function precedes a linear transformation, expressed as:

$$\text{x}' = \text{decoder}(\mathbf{h}) = \text{ReLU}(\mathbf{W}' \cdot \mathbf{h} + \mathbf{b}')$$

where $\mathbf{W}'$ is the weight matrix and $\mathbf{b}'$ is the bias vector associated with the decoder. The inclusion of the ReLU activation function in the decoder is crucial for reconstructing non-linearly encoded inputs. The combination of these layers forms a three-stage architecture: encoding, activation, and decoding.

The proposed model has an 'input dimension-1-output dimension' structure, so it compresses the input data to a single value and then tries to rebuild the original data using the highly coded information. The simplicity of the model allows us to extract the mathematical formulation and understand the operating principle of the encoding and decoding processes. Finally, I customize the loss function to establish the desired directionality of the variables in the composite index (e.g. the volatility and the risk should move in the same direction). The traditional loss function considers only the MSE, while I introduce the correlation difference. This measure imposes penalties for the differences in correlations between the actual features and target versus the predicted features and target. If I call v the vector of correlation between the original variables and the index (the target in the latent space) and r the correlation vector between the decoder output and the target, I minimize the difference $v - r$ to preserve the statistical connection between the features and the target in its encoding. I add the correlation difference in the loss function to avoid loss of information in the encoded representations regarding the original data relation with risk and their effect on the risk mathematical formulation. The next section describes the use of the Least Absolute Shrinkage and Selection Operator (lasso) to reduce the dimensionality of the input vector fed in the algorithm. The lasso algorithm selects the most relevant variables for different risk measures in the neural network algorithm. Finally, I use K-means clustering to identify clusters among the input variables and understand the sparsity of information in the dataset.

References

Albuquerque, Rui, Yrjö Koskinen, and Chendi Zhang (2019). "Corporate Social Responsibility and Firm Risk: Theory and Empirical Evidence". In: *Management Science* 65.10, pp. 4451–4469.

Babalos, Vassilios, Emmanuel C. Mamatzakis, and Roman Matousek (2015). "The performance of US equity mutual funds". In: *Journal of Banking Finance*.

Bauer, R., R. Otten, and A. T. Rad (2006). "Ethical investing in Australia: Is there a financial penalty?" In: *Pacific-Basin Finance Journal* 14, pp. 33–48.

Becchetti, Leonardo, Rocco Ciciretti, and Ambrogio Dalò (2018). "Fishing the Corporate Social Responsibility Risk Factors". In: *Journal of Financial Stability* 37, pp. 25–48.

Berg, Florian, Julian F Koelbel, and Roberto Rigobon (2022). "Aggregate confusion: The divergence of ESG ratings". In: *Review of Finance* 26.6, pp. 1315–1344.

Bougamont, M., A. L. Hubbard P. Christoffersen, A. A. Fitzpatrick, S. H. Doyle, and S. P. Carter (2014). "Sensitive response of the Greenland Ice Sheet to surface melt drainage over a soft bed". In: *Nature Communications* 5, p. 5052.

Brandstetter and Lehner (2015). "Opening the Market for Impact Investments: The Need for Adapted Portfolio Tools". In: *Entrepreneurship Research Journal* 5, pp. 87–107.

Burmeister, Edwin, Richard Roll, and Stephen Ross (2003). "Using macroeconomic factors to control portfolio risk". In: *A Practitioner's Guide to Factor Models* 9, pp. 1–27.

Carboni, Paolo (2017). "Modelli a fattori macroeconomici per i rendimenti azionari". In: *Final paper of the internship within the Financial Risk Management Direc- torate - Bank of Italy.*

Chang, C. Edward, Walt A. Nelson, and H. Doug Witte (2012). "Do green mutual funds perform well?" In: *Finance and General Business Department, Missouri State University, Springfield, Missouri, USA.*

Cortez, Silva, and Areal (2009). "Socially responsible investing in the global market: Performance of US and European funds". In: *Working Paper Series.*

Cummings, L. S. (2000). "The financial performance of ethical investment trusts: an Australian perspective". In: *Journal of Business Ethics* 25, pp. 79–92.

Doukas, Papadopoulou, Savvakis, Tsoutsos, and Psarras (2012). "Assessing energy sustainability of rural communities using Principal Component Analysis". In: *Renewable and Sustainable Energy Reviews* 16, pp. 1949–1957.

Drut (2010). *Social Responsibility and Mean-Variance Portfolio Selection.* Tech. rep. 10. Working papers CEB.

Dunteman (1989). "Principal Components Analysis." In: *Newbury Park: Sage Publications.*

Escrig-Olmedo, Elena, María Jesús Muñoz-Torres, María Ángeles Fernández-Izquierdo, and Juana María Rivera-Lirio (2014). "Lights and shadows on sustainability rating scoring". In: *Review of Managerial Science* 8.4, pp. 559–574.

Fernández, Abu-Alkheil, and Khartabiel (2019). "Do German Green Mutual Funds Perform Better Than Their Peers?" In: *Business and Economics Research Journal*, pp. 297–312.

Giudici and Avrini (2002). "Modelli statistici per la costruzione di indicatori della qualità della vita: aspetti metodologici". In: *Rivista di statistica ufficiale* 1, pp. 61–80.

Hoepner, Andreas (Mar. 2010). "Portfolio Diversification and Environmental, Social or Governance Criteria: Must Responsible Investments Really Be Poorly Diversified?" In: Unpublished manuscript.

Iachini, Michael (2021). "How Well Has Environmental, Social, and Governance Investing Performed?" In: *Charles Schwab.*

Ilze Zumente, Natalja Lace (2021). "ESG Rating—Necessity for the Investor or the Company?" In: *MDPI Sustainability* 37, pp. 1–14.

Imberger, Mamouni, Anderson, Nicol, and Veale (2007). "The index of sustainable functionality: a new adaptive, multicriteria measurement of sustainability? Application to Western Australia". In: *International Journal of Environmental and Sustainable Development* 6, pp. 323–355.

Jessen (2012). "Optimal Responsible Investment". In: *Applied Financial Economics* 22, pp. 1827–1840.

Kodinariya, Trupti M. and Dr. Prashant R. Makwana (2013). "Review on determining number of Cluster in K-Means Clustering". In: *International Journal of Advance Research in Computer Science and Management Studies* 1.6, pp. 90–95.

Lanza, Ariel, Enrico Bernardini, and Ivan Faiella (2020). "Mind the gap! machine learning, esg metrics and sustainable investment". In: *Machine Learning, ESG Metrics and Sustainable Investment (June 26, 2020). Bank of Italy Occasional Paper* 561.

Mazziotta, Matteo and Adriano Pareto (2019). "Use and misuse of PCA for measuring well-being". In: *Social Indicators Research* 142, pp. 451–476.

Mederly, Novacek, and Topercer (2003). "Sustainable development assessment: quality and sustainability of life indicators at global, national, and regional level". In: *Foresight* 5, pp. 42–49.

Mishra (2007). "A Comparative Study of Various Inclusive Indices and the Index Constructed by the Principal Components Analysis." In: *MPRA.*

Mishra, Sudhanshu K (2008). "On construction of robust composite indices by linear aggregation". In: *Available at SSRN 1147964.*

Nardo, Saisana, Saltelli, and Tarantola (2005). *Tools for Composite Indicators Building.* Technical Report. Ispra, Italy: Institute for the Protection and Security of the Citizen.

Nardo, Saisana, Saltelli, Tarantola, Hoffman, and Giovannini (2005). *Handbook on Constructing Composite Indicators: Methodology and User Guide*. OECD Statistics Working Papers.

Palit, Kar, Misra, and Banerjee (2013). “Assessment of air quality using several biomonitors of selected sites of Durgapur, Burdwan district by air pollution tolerance index approach”. In: *Indian Journal of Scientific Research* 1, pp. 149–152.

Pastor, Lubos, Robert Stambaugh, and Lucian A. Taylor (2020). “Sustainable Investing in Equilibrium”. In: *Journal of Financial Economics*. In press.

Pedersen, Fitzgibbons, and Pomorski (2021). “Responsible investing: The ESG-efficient frontier”. In: *Journal of Financial Economics* 142.2, pp. 572–597.

Reisi, Aye, Rajabifard, and Ngo (2014). “Transport sustainability index: Melbourne case study”. In: *Ecological Indicators* 43, pp. 288–296.

Rosamilia, Nico (2024). “Beyond the E$Ch$$O_2$ Chamber:
Efficient Sustainable Portfolios”. School of Management, Politecnico di Milano Working Paper.

Saisana, Saltelli, and Tarantola (2005). “Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators”. In: *Journal of the Royal Statistical Society* 168, pp. 307–323.

Sikken (2011). *Accelerating the Transition Towards Sustainable Investing-Strategic Options for Investors, Corporations, and Other Key Stakeholders*. SSRN Working Paper Series.

Simons, Katerina (1998). “Risk-Adjusted Performance of Mutual Funds”. In: *New England Economic Review*.

Svetina, Marko (2010). “Exchange Traded Funds: Performance and Competition”. In: *The joutnal of applied finance*.

Tim Verheyden, Robert G. Eccles and Arabesque Partners Andreas Feiner (2016). “ESG for All? The Impact of ESG Screening on Return, Risk, and Diversification”. In: *Applied corporate finance* 47-56.

Wu, Lodorfos, Dean, and Gioulmpaxiotis (2019). “The Market Performance of Socially Responsible Investment during Periods of the Economic Cycle—Illustrated Using the Case of FTSE.” In: *Managerial and Decision Economics*, pp. 238–251.