Instituto Superior de Contabilidade e Administração
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The efficiency of alternative and conventional energy ETFs: Are clean energy ETFs a safer asset?

Coimbra, Novembro de 2022

ISCAC|2022 João Augusto Martins Rendeiro Couceiro Jorge
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Dissertação submetida ao Instituto Superior de Contabilidade e Administração de Coimbra para cumprimento dos requisitos necessários à obtenção do grau de **Mestre em Análise Financeira**, realizada sob a orientação da Professora Carla Margarida Saraiva de Oliveira Henriques e coorientação da Professora Maria Elisabete Duarte Neves.

Coimbra, Novembro de 2022

TERMO DE RESPONSABILIDADE

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Agradecimentos

Agradeço principalmente aos meus pais, não só esta dissertação mas todo o meu trabalho e possível sucesso também é dedicado a vós. À minha namorada que me apoia incansávelmente. E às minhas orientadoras, Doutora Carla Henriques e Doutora Maria Elisabete Neves, pela disponibilidade, partilha e suporte extraordinários na elaboração deste trabalho.

Abstract

The relevance of alternative energy sources has been growing exponentially. Therefore, it becomes timely and relevant to explore the performance and diversification capability of financial instruments related to them, particularly during a market downturn. This dissertation assesses the efficiency of alternative energy equity Exchange-Traded Funds (ETFs) and conventional energy equity ETFs in two different time periods that include the COVID-19 pandemic. For that purpose, we employ an output-oriented slacks-based measure Data Envelopment Analysis (DEA) model combined with cluster analysis to determine the efficiency of 69 ETFs in the period 2018-2020. Our results show that alternative energy ETFs can outperform conventional energy ones in terms of efficiency in the long term; however, during a financial crisis period, the differences between the two types of ETFs attenuate, with neither of them significantly outperforming the other. The factors that most affect the efficiency of both ETF categories are the expense ratio and net asset value. Nevertheless, it is interesting to observe that environmental, social, and governance metrics positively affect much more conventional energy ETFs than alternative energy ones, highlighting the increasing importance of this factor in the performance of financial assets.

Keywords: ETFs; Energy; Efficiency; Covid-19; Diversification; Crisis

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List of acronyms and abbreviations

ETF – Exchange-traded fund

ESG - Environmental, social, and governance

AEE - Alternative energy ETFs

EE - Energy ETFs (conventional)

USD - United States dollar

US - United States

DEA - Data envelopment analysis

P/E - Price-To-Earnings

P/B - Price-To-Book

P/CF - Price-To-Cash Flow

P/S - Price-To-Sales

DMU - Decision-Making Unit

SBM - Slacks-Based Measure

CCR - Charnes, Cooper and Rhodes

BCC - Banker, Charnes and Cooper

CRS - Constants Returns to Scale

VRS - Variable Returns to Scale

TGR - Technology Gap Ratio

ER - Expense Ratio

NAV - Net Asset Value

MSCI - Morgan Stanley Capital International

YR - Year

VaR - Value at risk

DPEI - DEA portfolio efficiency index

RDM - Range Direction Model

SRI - Socially Responsible Investment

VAR-ADCC - Vector Auto-Regressive - Asymmetric Dynamic Conditional Correlation

CAPM - Capital Asset Pricing Model

Introduction

The renewable energy industry has observed extraordinary growth over the last decade due to environmental concerns and the volatility of gas and oil prices that cause many investors to shift their attention to other alternatives. Global investment in low-carbon energy totaled USD 595 billion in 2020, compared to just USD 264 billion in 2011 (BloombergNEF, 2022. Retrieved October 18, 2022)[1]. The most attractive low-carbon energy sector for investing in has always been the renewable energy sector, but over the last 5-6 years, other sectors have also shown fast growth, particularly electrified transportation, which reached an investment of USD 273 billion in 2021, according to BloombergNEF. Asia Pacific accounted for 49% of the world's investment in the energy transition in 2021, followed by Europe, the Middle East, and Africa, with 31%, and the Americas with 20% - data retrieved from BloombergNEF (2022). Over the last decade, alternative energy Exchange-Traded Funds (ETFs) also became an attractive investment tool for both institutional and retail investors. ETFs are open-end funds, which are defined as those that issue new fund shares and redeem existing shares on demand, counting for USD 63.1 trillion in total net assets worldwide by the end of 2020 (Investment Company Institute, 2021. Retrieved October 18, 2022)[2]. ETFs are open-end funds known for having lower costs, high transparency, and good flexibility in terms of trading. For this reason, this dissertation will focus on the assessment of the efficiency of energy ETFs, which are disaggregated into alternative and conventional energy ETFs for one year (2020) and three years (i.e., 2018, 2019, and 2020). By considering these two periods, it is possible to evaluate the behavior of the different types of ETFs before and during the economic crisis caused by COVID-19. Several authors have studied the performance of clean energy assets compared to conventional energy ones as well as the importance of environmental, social, and governance (ESG) investments during periods of financial crisis. In this context, Wei Kuang (2021) found that green bonds and clean energy stocks effectively mitigate the downside risks associated with conventional energy stocks, but they have different risk-reduction capabilities. Miralles-Quirós, J. L. and Miralles-Quirós, M. M. (2019) used a Vector Auto-Regressive – Asymmetric Dynamic Conditional Correlation (VAR-ADCC) approach to show that alternative energy ETFs can outperform energy ETFs, and Pavlova and Boyrie (2022) applied a five-factor model to report that ESG ETFs can outperform conventional ones but reached the same findings as Folger-Laronde (2020) who used ANOVA and multivariate regression models to conclude that higher levels of the sustainability performance of ETFs do not protect investments from periods of market downturns. However, during the COVID-19 period, they did not do better than match the performance of conventional ETFs. These last findings are contradicted Broadstock, Chan, Cheng and Wang (2021), who investigated the short-term cumulative returns of CSI300 and concluded that the ESG role had an incremental importance during times of crisis. When looking into past financial crises, Alexopoulos (2018) used the return and risk measures to find that the 2008 financial crisis affected more clean energy ETFs than the 2014 oil crisis did conventional energy ETFs, as the first ones were more sensitive to exogenous factors than the last ones. Dawar, Dutta., Bouri and Saeed (2021) provided evidence for the decreasing dependence of clean energy stock returns on crude oil returns, which strengthens the theory that these two assets react differently to market turmoil. Even if there are many studies assessing energy funds' performance, they mostly focus on indicators based on risk and return factors like Jensen's Alpha (Jensen, 1968), value at risk (VaR), or the Sharpe ratio (Sharpe, 1966). Other models, like the Carhart model (Carhart, 1997) and the Fama-French 5-factor model (Fama-French, 2015), added some other factors like momentum, investment, size, and value. In terms of evaluating the efficiency of a certain fund or portfolio, numerous authors have applied different DEA approaches to reach their findings, such as Murthi and Desai (1997), who used the original DEA model proposed by Charnes, Cooper, and Rhodes (1978) to evaluate the efficiency of mutual funds, or Basso and Funari (2016), who applied a DEA model with variable returns to scale to compare the results obtained from this model with traditional financial indicators. The most common outputs used in DEA models are relative to return (average return, Sharpe ratio, portfolio return), whereas the inputs can vary slightly more, ranging from the expense ratio, VaR, turnover, return standard deviation, and several others that will be discussed further. In this dissertation, we will use a Slack-Based Measure (SBM) DEA model combined with cluster analysis that contemplates two inputs and three outputs to assess the efficiency of 14 alternative energy equity ETFs and 55 conventional energy equity ETFs. The application of this model will allow us to evaluate and compare both ETF types during two time periods, as well as identify the inputs and outputs that may affect their efficiency. From an investor's perspective, this work is useful to identify the most relevant indicators for each ETF's category over shorter or longer periods and during periods of crisis. Furthermore, it assesses the importance of environmental factors over time and compares them to other well-known financial factors. The rest of the paper is organized as follows. Section 2 includes a review of other works that applied DEA to evaluate the efficiency or even other models used to analyze ESG or energy funds. Section 3 describes the DEA methodology followed. Section 4 provides information about the data used and the theory behind the choice of inputs and outputs. Section 5 examines the results obtained. Section 6 provides the main conclusions and proposes a possible investor's insight from the results obtained.

[1] Book "Energy Transition Investment Trends 2022". Available at: https://about.bnef.com/energy-transition-investment/
[2] Book " 2021 Investment Company Fact Book". Available at: https://www.icifactbook.

1. Literature Review

Table 1. Literature review on DEA models applied to the performance evaluation of mutual funds, ETFs, and portfolios.

Authors	Main Purpose	Methodologies	Inputs	Outputs
Murthi, Choi & Desai, 1997	Assess the performance of 2083 mutual funds divided into categories and compare the results with the traditional Jensen's alpha and the Sharpe index (1965-1993).	Charnes, Cooper and Rhodes (CCR) DEA model	Expense ratio; Load; Turnover and Standard Deviation.	Return
Allevi, Bonenti, Oggioni, & Riccardi, 2019	Evaluate the environmental and financial performance of European green mutual funds (2012-2015).	Banker, Charnes and Cooper (BCC) DEA model with four different groups of inputs and outputs (that focus on environmental and financial aspects or purely in financial indicators.	β-coefficient; Initial payout invested; Downside risk; Environmental consumption indicators	Final value; Environmental saving indicators; Green indicator
Zhang & Chen, 2018	Determine the performance of energy portfolios based on daily fossil-fuel future prices (2006-2015).	DEA window analysis method and DEA directional distance.	Return's standard deviation; VaR	Mean returns
Choi & Min, 2017	Evaluate the efficiency of eight ETF's and their benchmark index (KOSPI 200) and compare with the individual performance of the underlying stocks.	DEA portfolio efficiency index (DPEI); Range Direction Model (RDM)	Total risk; Systematic risk	Average portfolio return
Basso & Funari, 2016	Compare the results of DEA performance measure with traditional financial indicators for 312 mutual funds. (2006-2013)	BCC DEA model with variable returns to scale	Volatility; β-coefficient; Downside Risk	Monthly total returns
Tsolas & Charl 2015	Measure the performance of 16 green ETFs with DEA metrics. (2008-2010)	SBM DEA models	P/E; P/B; P/CF; P/S	Sharpe ratio; Jensen's alpha

Authors	Main Purpose	Methodologies	Inputs	Outputs
Basso & Funari, 2014	Evaluate the performance of 189 European socially responsible investment (SRI) funds and compare them with 90 non-SRI European funds. (2006-2009)	CCR DEA model; BCC DEA model	β-coefficient; Initial payout invested.	Final fund value; Ethical measure
Pavlova & Boyrie, 2022	Assess the risk-adjusted returns of ESG ETFs before and during the COVID-19 market crash. (2019-2020)	Capital Asset Pricing Model CAPM; Fama-French 3-factor model; Carhart; Fama-French 5-factor model; Fama-French 5-factor model plus momentum factor	Excess market return; size; value; profitability; investment.	Return
Martí-Ballester, 2019	Analyze the financial performance of 4496 energy and renewable energy mutual funds commercialized in Europe. (2007-2018)	Carhart's four-factor model	Size; Value; Momentum	Average daily fund return
Premachandra, Zhu, Watson, & Galagedera, 2012	Assess the relative performance of of 66 large mutual fund families in the US. (1993-2008)	Two-stage BCC DEA model	Management fees; Marketing and distribution fees; NAVL; Fund Size; Net Expense Ratio; Turnover Ratio; Standard Deviation	NAV; Average Return
Henriques, Neves, Castelão, & Nguyen, 2022	Assess the performance of 60 exchange traded funds in the energy sector (2014-2018)	DEA model – Weighted Russel Directional Distance model combined with a multiobjective interval portfolio model	Beta; Standard Deviation	Jensen's Alpha; Sharpe index; Mean annual return; Trailing total return

From Table 1, it is possible to verify that there is extensive literature about the performance evaluation of mutual funds, ETFs, and portfolios using DEA models that consider different inputs and outputs. However, it is also noticed that a reduced number of studies are conducted where the DEA approach is applied, specifically to assess the efficiency of energy ETFs or where environmental factors are used among the inputs and outputs. Allevi et al. (2019) employed a DEA model with environmental consumption and saving indicators as inputs/outputs to evaluate the performance of European green mutual funds, finding a positive relationship between the environmental factors and the efficiency of the funds. Tsolas (2015) also applied slack-based DEA models to appraise the performance of green ETFs, but in their paper, no environmental-based factors were considered as inputs/outputs. With the fast growth of investment in clean energy (see Figure 1) and the increasing popularity of the ETF industry (see Figure 2) for being accessible to every type of investor, it is important to start applying environmental and socially responsible factors when appraising any type of open-end fund, and particularly funds that focus on energy equities.

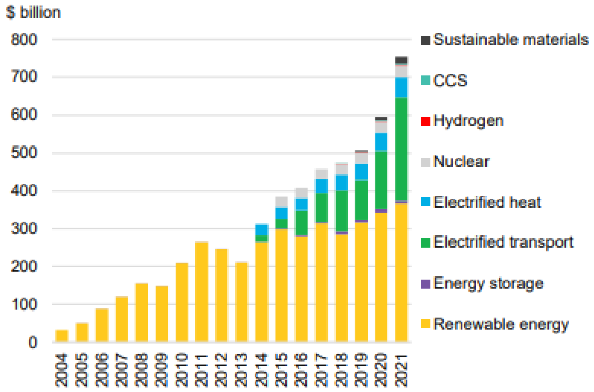


Figure 1. Global investment in energy transition by sector
Source: BloombergNEF

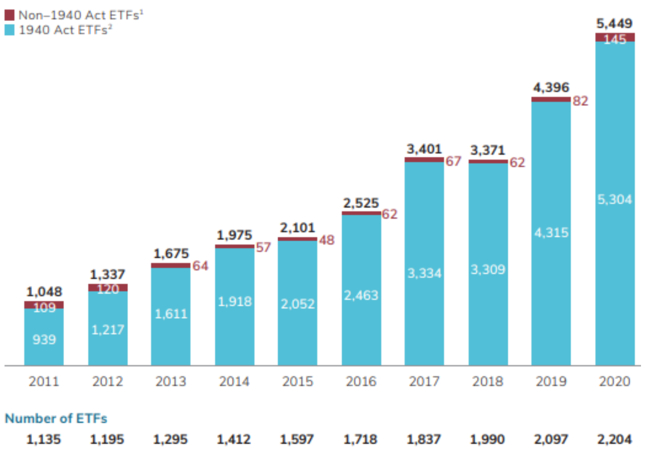


Figure 2. Total Net Assets in billions of dollars and Number of ETFs
Source: 2021 Investment Company Fact Book

2. Methodology

DEA was first proposed in a paper by Charnes, Cooper and Rhodes (1978). This model named CCR after the initials of its authors, estimates the efficiency of Decision-Making Units (DMUs) with constant returns to scale (CRS). Later, an extension of this model was proposed by Banker, Charnes and Cooper (1984), who formulated the BCC model that admits variable returns to scale (VRS). We use the Slacks-Based Measure model (SBM) proposed by Tone (2001), which provides a more suitable tool for efficiency assessment since it is non-radial (CCR and BCC models only allow assessing the proportional changes of either the inputs or outputs) and can be input-, output-, or non-oriented. The SBM model also provides information on the increase/decrease required for each input/output of inefficient DMUs so they can become efficient. Furthermore, this model can be combined with cluster analysis to evaluate the efficiency of DMUs based on the cluster frontier, thus enabling to account for the differences of the DMUs under evaluation (Tone and Tsutsui, 2014).

2.1 The SBM Model

Considering a set of n DMUs $(DMU_1, DMU_2, \dots, DMU_n)$, where $X = [x_{ij}, i = 1, 2, \dots, m, j = 1, 2, \dots, n]$ is the $(m \times n)$ matrix of inputs, $Y = [y_{rj}, r = 1, 2, \dots, s, j = 1, 2, \dots, n]$ is the vector of *outputs* $(s \times n)$ and the rows of these matrices corresponding to the inputs and outputs of DMU$_k$ are, respectively, given by $\boldsymbol{x}_k^T$ and $\boldsymbol{y}_k^T$, with ^{T} indicating the transpose of a vector. The SBM model is (Tone, 2001):

$$\underset{\boldsymbol{\lambda}, \boldsymbol{s}^-, \boldsymbol{s}^+}{Min} \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^-/x_{ik}}{1+\frac{1}{s}\sum_{r=1}^{s} s_r^+/y_{rk}}$$

s.t.

$$x_{ik} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^-, \ i=1, \dots, m$$

$$y_{rk} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_i^+, \ r = 1, \dots, s$$

$$\lambda_j \geq 0, j = 1, \dots, n,$$

$$s_i^- \geq 0, \ i=1, \dots, m,$$

$$s_i^+ \geq 0, \ r = 1, \dots, s. \quad (1)$$

From the first problem (1), we can perceive that an increase in s_i^- or s_i^+, *ceteris paribus*, will decrease the objective function value of the problem (1). Hence, it can be stated that $0 < \rho < 1$. ρ in (1) can also be formulated as:

$$\rho = \left(\frac{1}{m}\sum_{i=1}^{m}\frac{x_{ik}-s_i^-}{x_{ik}}\right)\left(\frac{1}{s}\sum_{r=1}^{s}\frac{y_{rk}+s_r^+}{y_{rk}}\right)^{-1} \tag{2}$$

The ratio $\frac{x_{ik}-s_i^-}{x_{ik}}$ evaluates the rate of reduction of input i and $\frac{1}{m}\sum_{i=1}^{m}\frac{x_{ik}-s_i^-}{x_{ik}}$ is the average reduction of inputs, in percentage. Likewise, the ratio $\frac{y_{rk}+s_r^+}{y_{rk}}$ measures the rate of increase of output r and $\frac{1}{s}\sum_{r=1}^{s}\frac{y_{rk}+s_r^+}{y_{rk}}$ is the average increase in outputs, in percentage. Hence, ρ is considered the ratio of average inefficiencies of inputs and outputs.

Model (1) is converted into model (3), using a positive scalar variable t:

$$\begin{aligned}
&\underset{t,\boldsymbol{\lambda},\boldsymbol{s}^-,\boldsymbol{s}^+}{Min}\ \tau = t - \frac{1}{m}\sum_{i=1}^{m} t s_i^-/x_{ik}\\
&\text{s.t. } t + \frac{1}{s}\sum_{r=1}^{s} t s_r^+/y_{rk} = 1,\\
&\boldsymbol{x}_k = X\boldsymbol{\lambda} + \boldsymbol{s}^-,\\
&\boldsymbol{y}_k = Y\lambda - \boldsymbol{s}^+,\\
&\boldsymbol{\lambda} \geq \mathbf{0},\ \boldsymbol{s}^- \geq \mathbf{0},\ \boldsymbol{s}^+ \geq \mathbf{0}, t > 0.
\end{aligned} \tag{3}$$

If $\boldsymbol{S}^- = t\boldsymbol{s}^-$, $\boldsymbol{S}^+ = t\boldsymbol{s}^+$ and $\boldsymbol{\Lambda} = t\boldsymbol{\lambda}$, problem (3) becomes:

$$\begin{aligned}
&\underset{t,\boldsymbol{\lambda},\boldsymbol{s}^-,\boldsymbol{s}^+}{Min}\ \tau = t - \frac{1}{m}\sum_{i=1}^{m} S_i^-/x_{ik}\\
&\text{s.t. } t + \frac{1}{s}\sum_{r=1}^{s} S_r^+/y_{rk} = 1,\\
&t\boldsymbol{x}_k = X\Lambda + \boldsymbol{S}^-,\\
&t\boldsymbol{y}_k = Y\Lambda - \boldsymbol{S}^+,\\
&\boldsymbol{\Lambda} \geq \mathbf{0},\ \boldsymbol{S}^- \geq \mathbf{0},\ \boldsymbol{S}^+ \geq \mathbf{0}, t > 0.
\end{aligned} \tag{4}$$

The optimal solution is formulated as:

$$\rho^* = \tau^*, \boldsymbol{\lambda}^* = \boldsymbol{\Lambda}^*/t^*,\ \boldsymbol{s}^{-*} = \boldsymbol{S}^- / t^*,\ \boldsymbol{s}^{+*} = \boldsymbol{S}^+ / t^*.$$

Definition 1. A DMU$_k$ is SBM-Efficient if $\rho^* = 1$. The previous condition can be equally defined as $\boldsymbol{s}^{-*} = \mathbf{0}$ and $\boldsymbol{s}^{+*} = \mathbf{0}$.

Definition 2. It is possible to obtain a set of efficient reference units for the SBM-inefficient DMU$_k$ by considering the indices of the DMUs related with $\lambda_j^* > 0$.

Consider the reference set of the SBM-inefficient DMU$_k$ as: E$_k$ = {j: $\lambda_j^* > 0$, j=1, …, n}. The point of the efficient frontier that can be considered as a reference DMU for the SBM-inefficient DMU$_k$ is:

$$(\hat{\boldsymbol{x}}_k, \hat{\boldsymbol{y}}_k) = (\boldsymbol{x}_k - \boldsymbol{s}^{-*}, \boldsymbol{y}_k + \boldsymbol{s}^{+*}) = \sum_{j \epsilon E_k} \lambda_j^* \boldsymbol{x_j}, \sum_{j \epsilon E_k} \lambda_j^* \boldsymbol{y}_j). \quad (5)$$

Model (1) uses the CRS assumption. To consider VRS, it is required to add the constraint $\boldsymbol{e}^T\boldsymbol{\lambda} = 1$ to model (1).

The output-oriented version of model (1) is (Tone and Tsutsui, 2015):

$$\underset{\boldsymbol{\lambda}, \boldsymbol{s}^-, \boldsymbol{s}^+}{Max} \ \rho' = \frac{1}{\rho} = 1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{rk}$$

s.t.

$$x_{ik} = \sum_{j=1}^{n} x_{ij} \lambda_j + s_i^-, i=1, \ldots, m$$

$$y_{rk} = \sum_{j=1}^{n} y_{rj} \lambda_j - s_i^+, r = 1, \ldots, s$$

$$\lambda_j \geq 0, j = 1, \ldots, n,$$

$$s_i^- \geq 0, i=1, \ldots, m,$$

$$s_i^+ \geq 0, r = 1, \ldots, s. \quad (7)$$

Definition 3. A DMU$_k$ is SBM-Output-Efficient if $\rho^* = 1$, which is equivalent to $\boldsymbol{s}^{+*} = \boldsymbol{0}$. Nevertheless, it is possible that $\boldsymbol{s}^{-*} \neq \boldsymbol{0}$.

2.2 SBM model with cluster benchmarking

Traditional DEA models consider data assumptions that can affect the accuracy of results. Corton and Berg (2009) state that the main factor that can affect the DEA's accuracy is the assumption of homogeneity of the DMUs, which implies that there are no outliers in the sample. Knowing this, clustering benchmarking is useful when dealing with heterogeneous data (Jiang, Hua, Zhang, Cheng, Ye, Huang and Jin, 2020). This technique consists of disaggregating a set of DMUs into groups where they are distinguished by a specific characteristic. Therefore, DMUs that belong to the same cluster are more alike than those that belong to different clusters. Hence, it is possible to take advantage of the homogeneity present within the clusters and the heterogeneity present in distinct clusters. When we compare the results of a DEA model without clustering benchmarking to another applying that feature, it is possible to obtain the technology gap ratio (TGR). The TGR_k of DMU_k is computed as follows (Battese, Rao, and O'Donnell, 2004):

$$TGR_k = \frac{\rho'_k{}^{meta\ (VRS)*}}{\rho'_k{}^{cluster\ (VRS)*}}, \tag{9}$$

where $\rho_k{}^{meta\ (VRS)*}$ is the SBM-output-efficiency value of DMU_k that corresponds to the the meta-frontier and $\rho_k{}^{cluster\ (VRS)*}$ is the SBM-output-efficiency value of DMU_k that corresponds to the cluster-frontier. The lower the TGR value, the higher the grouping requirement, and vice-versa. The value of TGR_k varies between 0 and 1, and a TGR_k closer to 1 suggests that there is a small gap between the meta-frontier and the cluster-frontier. Expression (10) allows obtaining the following decomposition of the efficiency of DMU_k for a particular input–output combination:

$$\rho'_k{}^{meta\ (VRS)*} = \rho'_k{}^{cluster\ (VRS)*} \times TGR_k, \tag{11}$$

The previous expression (11) shows that the efficiency of DMU_k measured for the meta-frontier can be obtained by the product of the efficiency of DMU_k measured for the cluster-frontier and the TGR.

3. Data and Assumptions

The data used in this paper refers to the period of 2018 – 2020 and considers the separate evaluation of alternative energy ETFs (AEEs) and conventional energy ETFs (EE). The available data led us to consider a total of 69 ETFs, of which 14 are AEEs and 55 are EEs.

Annualized Average Return

The average return is commonly used in the scientific literature as an output for DEA models and other methodologies (Murthi et al. 2017, Allevi et al. 2019, Yue-Jun Zhang 2018, Basso and Funari 2014) because it can be easily be applied from a portfolio point of view or specifically for one security and for any required time horizon. Nevertheless, when analyzing energy-related funds, this indicator may not be enough to get an appropriate and comprehensive performance evaluation.

Expense Ratio (ER)

The expense ratio is an indicator useful when evaluating a certain fund from an operational management perspective because it measures the total fund costs relative to the assets that it possesses for management. Premachandra et al. (2012) used ER as an input in a two-stage DEA model that evaluates the efficiency of a fund in an operational management function and a portfolio management function.

Environmental, Social, and Governance (ESG)

The application of ESG in the study of funds and portfolios' performance rose exponentially during and after the COVID-19 crisis as awareness of the influence that this indicator can have in worldwide markets became more visible among investors. Authors such as Singh (2020) and Broadstock et al. (2021) investigated the impact of the pandemic crisis on ESG-related portfolios and stocks producing findings that may change the investors' perceptions of company fundamentals. MSCI ESG ratings measure a company's resilience to relevant ESG (environment, social, and governance) risks and are divided into letter and numeric scores that vary from AAA to CCC and 0 to 10, respectively.

Beta

Beta is a market risk measure that determines the volatility of an asset relative to the market. This volatility is related to the tracking index for ETFs, and it is a very useful indicator from an investor's perspective because it allows them to verify how a certain asset reacts to market shocks. A higher Beta means that the security is riskier, but it also could provide higher returns relative to the market. For this reason, some questions might be raised on how to consider this indicator as an input or output. In this framework, Allevi et al. (2019) consider systematic risk (Beta) as an input for assessing the efficiency of ETFs compared to individual stocks.

Net Asset Value (NAV)

The net asset value (NAV) is more commonly used for evaluating the performance of mutual funds and ETFs because, similarly to what happens with ER, it gives a two-way perspective about the funds' management. Premachandra et al. (2012) used NAV as an output for a DEA approach based on the operational function and as an input for a DEA approach focused on the portfolio management function, showing the flexibility that this indicator could attain in different types of evaluations.

The input and output factors considered to evaluate the ETFs' efficiency were selected based on the characteristics of our data and to compare the results for both ETFs categories from a financial and environmental perspective. The description of the inputs and outputs used in our paper can be found in Table 2.

Table 2. Inputs and Outputs

	Return	**ER**	**ESG**	**BETA**	**NAV**
Description	Annualized total return (Calculated as an average)	Measure of operating costs relative to assets	MSCI rating based on environment; social responsibility; and corporate governance	Systematic risk of an ETF compared to the tracked index	Net value of fund's assets less its liabilities, per outstanding share
Type of factor	Output	Input	Output	Input	Output
Unit	%	%	0-10 units of score	-	Dollar

Source: lists of ETFs analyzed, and the corresponding data on the inputs and outputs are available online at: https://etfdb.com/ (accessed 17/11/2022)

Tables 3 and 4 summarize the descriptive statistics of all our observations, showing clear differences between the average values of all the indicators for AEEs and

EEs and the different periods. For the 1YR analysis, return is the indicator with a larger difference between the two categories of ETFs, with EEs showing an average value 83% higher than that of AEEs. In contrast, the indicator where the difference is almost null is beta, with a 2% difference favoring EEs. In the 3YR analysis, average returns were 45% higher in AEEs than in EEs, while NAV was the factor with the greatest difference (54% greater for EEs). Overall, the differences between the inputs and outputs are reduced over a longer period.

Table 3. Descriptive Statistic of the Inputs and Outputs – 1YR

Statistic	***Return***	***ER***	***ESG***	***BETA***	***NAV***
Number of Observations	69	69	69	69	69
Number of Observations (AEE)	14	14	14	14	14
Number of Observations (EE)	55	55	55	55	55
Mean	1.133653	0.006602	5.099855	6.266734	1.27E+09
Mean (AEE)	0.682153	0.006114	7.832857	6.157707	8.9E+08
Mean (EE)	1.248581	0.006726	4.404182	6.294486	1.37E+09
Standard Deviation	0.515168	0.002923	3.246057	1.682877	4.03E+09
Standard Deviation (AEE)	0.167837	0.001175	0.836452	0.510572	1.47E+09
Standard Deviation (EE)	0.510999	0.003217	3.266623	1.870746	4.46E+09
Minimum	0.000895	0.00084	0	0.00485	1419010
Minimum (AEE)	0.507796	0.0042	6.7	5.39485	1419010
Minimum (EE)	0.000895	0.00084	0	0.00485	2322090
Maximum	1.000396	0.0087	9.24	7.32485	5.08E+09
Maximum (AEE)	3.0079	0.0087	9.24	2.47	5.08E+09
Maximum (EE)	3.077696	0.0201	8.51	10.49485	3.21E+10

Table 4. Descriptive Statistic of the Inputs and Outputs – 3YR

Statistic	***Return***	***ER***	***ESG***	***BETA***	***NAV***
Number of Observations	69	69	69	69	69
Number of Observations (AEE)	14	14	14	14	14
Number of Observations (EE)	55	55	55	55	55
Mean	1.173944	0.006464	5.529565	2.38886	1.27E+09
Mean (AEE)	1.840840	0.006114	7.832857	2.279833	8.9E+08
Mean (EE)	1.004189	0.006553	4.943273	2.416612	1.37E+09
Standard Deviation	0.640938	0.0030074	4.339402	1.682876	4.03E+09
Standard Deviation (AEE)	0.838275	0.001175	0.836452	0.510572	1.47E+09
Standard Deviation (EE)	0.451089	0.003319	4.67102	1.870746	4.46E+09
Minimum	0.000976	0	0	-3.87302	0
Minimum (AEE)	0.976976	0.0042	6.7	1.516976	1419010
Minimum (EE)	0.000976	0	0	-3.87302	0
Maximum	3.275376	0.0201	29.65	6.616976	3.21E+10
Maximum (AEE)	3.275376	0.0087	9.24	3.446976	5.08E+09
Maximum (EE)	2.628876	0.0201	29.65	6.616976	3.21E+10

4. Results

This section presents the results obtained by the application of the DEA model proposed and computed with MaxDEA 8 Ultra software. Tables 5 and 6 display the descriptive statistics for the efficiency scores (cluster and meta-frontier) and TGR values obtained for EEs and AEEs in different time horizons.

Table 5. Descriptive statistics of the results obtained for each ETF category for the 1YR period

ETF Category	*Statistics*	*Efficiency scores (meta frontier)*	*Efficiency scores (cluster frontier)*	*TGR*
Alternative Energy	Mean	0.14	0.50	0.26
	Standard Deviation	0.27	0.40	0.31
	Minimum	0.00	0.01	0.00
	Maximum	1.00	1.00	1.00
	Count	14.00	14.00	14.00
Energy	Mean	0.28	0.28	0.98
	Standard Deviation	0.40	0.40	0.07
	Minimum	0.00	0.00	0.53
	Maximum	1.00	1.00	1.00
	Count	55.00	55.00	55.00

Table 6. Descriptive statistics of the results obtained for each ETF category for the 3YR period

ETF Category	*Statistics*	*Efficiency scores (meta frontier)*	*Efficiency scores (cluster frontier)*	*TGR*
Alternative Energy	Mean	0.29	0.55	0.38
	Standard Deviation	0.42	0.47	0.37
	Minimum	0.00	0.00	0.00
	Maximum	1.00	1.00	1.00
	Count	14.00	14.00	14.00
Energy	Mean	0.16	0.19	0.96
	Standard Deviation	0.30	0.33	0.16
	Minimum	0.00	0.00	0.06
	Maximum	1.00	1.00	1.00
	Count	55.00	55.00	55.00

The main results of the analysis are summarized in the previous tables, which report a higher room for improvement for the EEs in both time periods, more specifically 72% in the 1YR and 81% in the 3YR time periods, while the AEEs show only 50% in the 1YR and 45% in the 3YR time periods.

Figures 3 and 4 show the efficiency scores for the meta- and cluster-frontiers, where the AEEs are presented on the left and the EEs on the right.

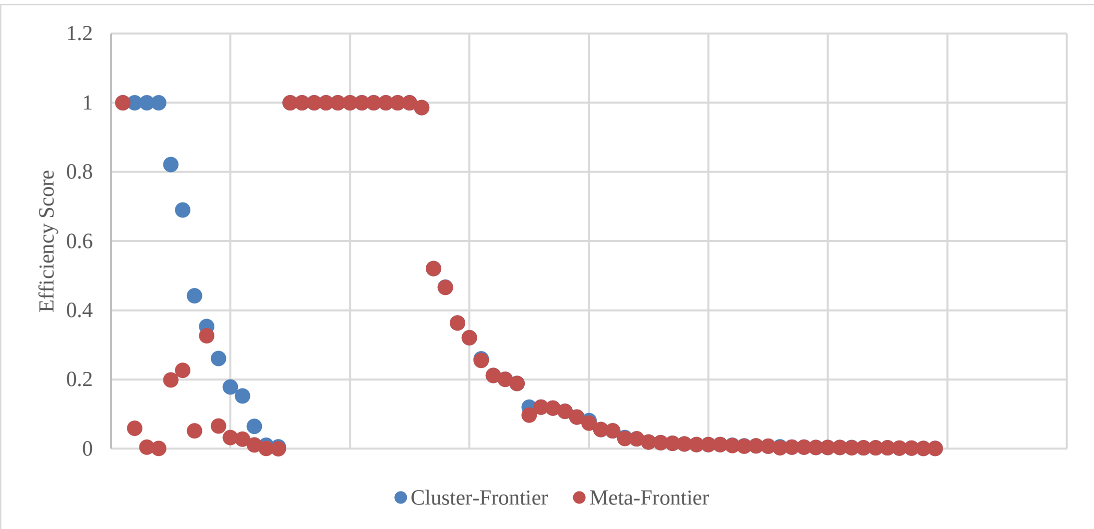


Figure 3. Efficiency Scores for 69 ETFs on meta- and cluster-frontier - 1YR analysis

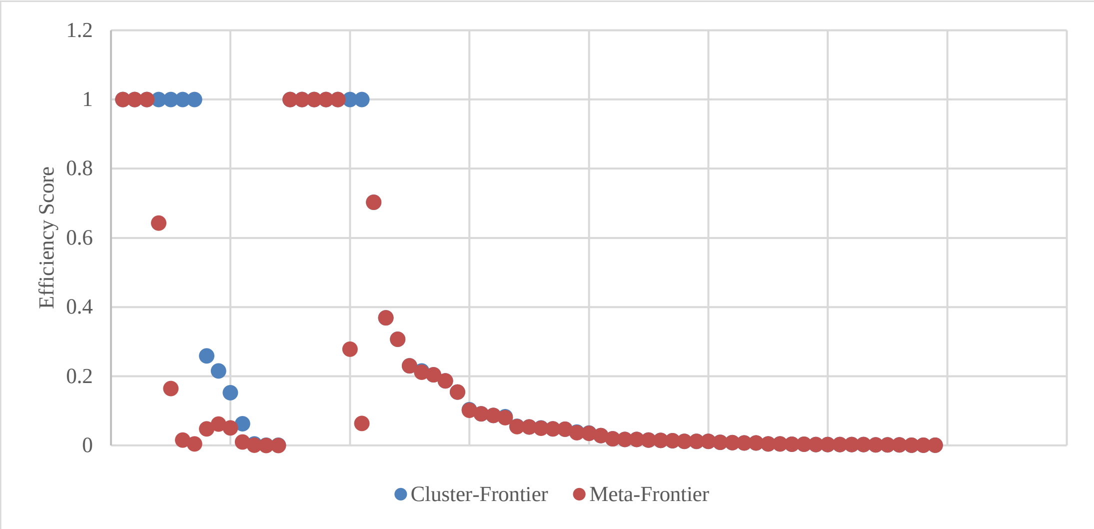
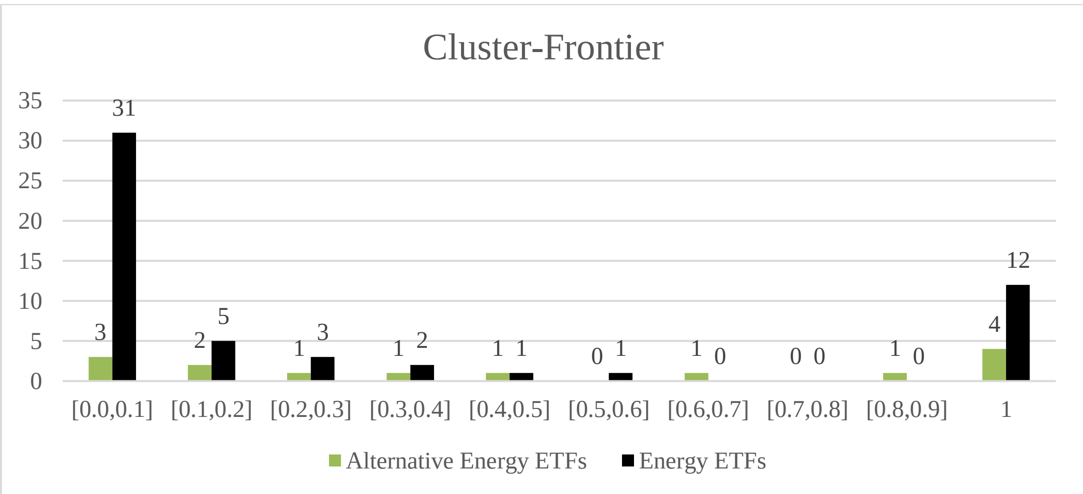


Figure 4. Efficiency Scores for 69 ETFs on meta- and cluster-frontier - 3YR analysis

From the analysis of Figures 3 and 4, it seems clear that AEEs have a larger difference between the meta- and cluster-frontiers when contrasted with the EEs in the two periods. The values for the average TGRs are much lower for AEEs (a minimum of 0.26 in the 1YR period) than for EEs (a minimum of 0.96 in the 3YR period), meaning that for the first type of ETF there is a larger gap between the two frontiers. It is also worth noting that the average TGR values for AEEs increased over the 3YR period, whereas EEs slightly decreased.



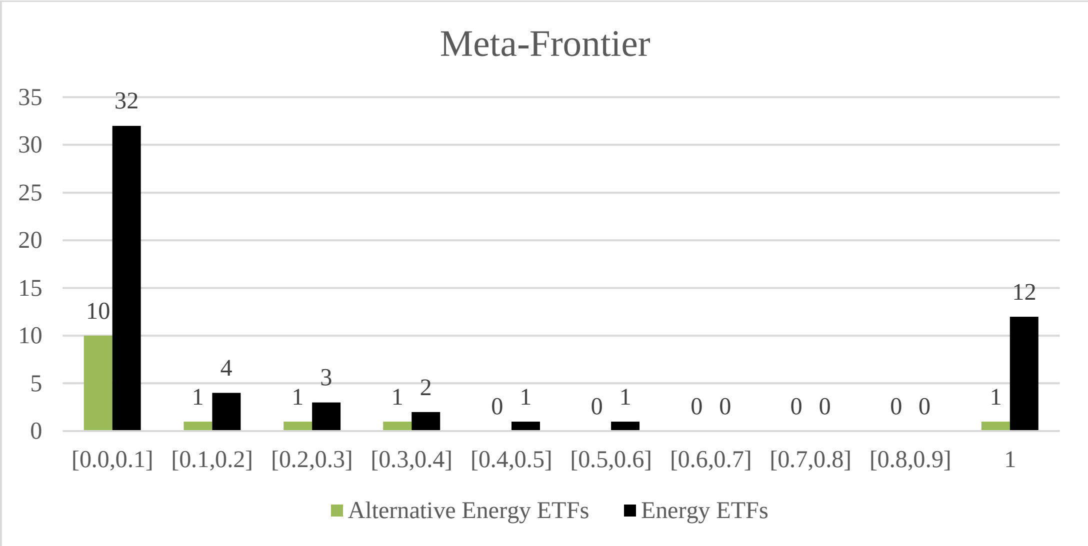
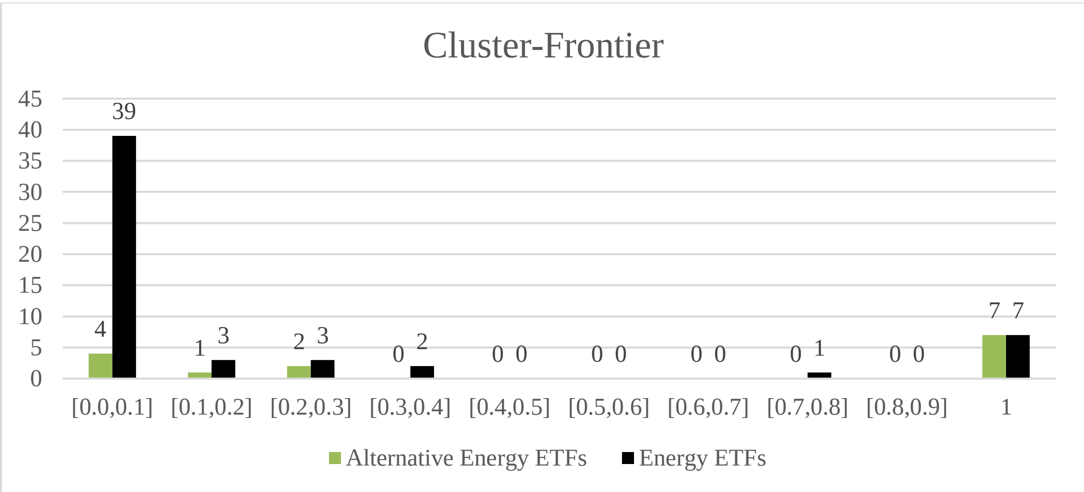


Figure 5. Number of ETFs in different intervals of efficiency scores

In the 1YR period, the number of efficient AEEs decreased from the cluster (4 ETFs) to the meta-frontier (1 ETF), while the number of efficient EEs remained constant for the two frontiers (12 ETFs) – see Figure 5.



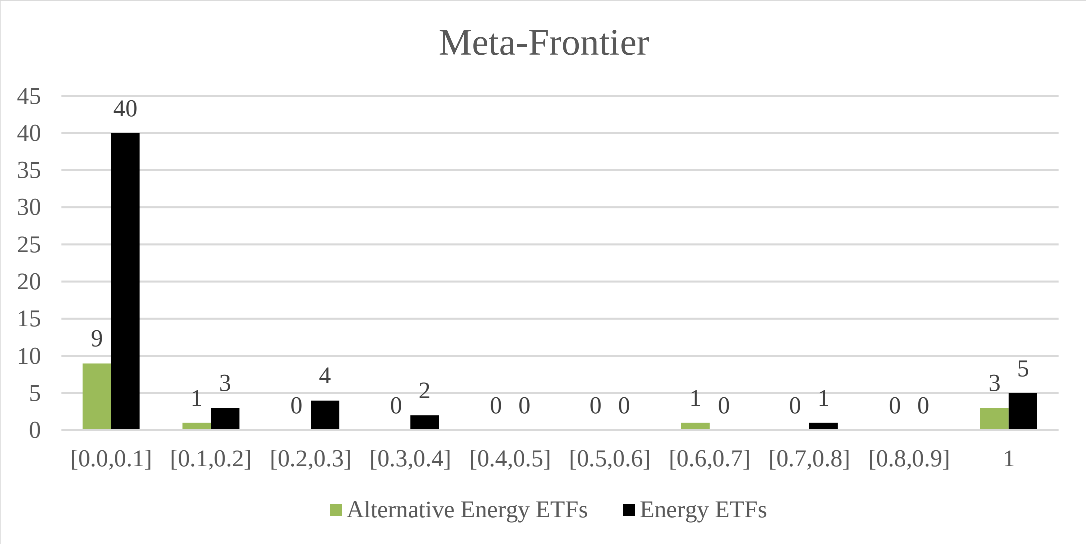


Figure 6. Number of ETFs in different intervals of efficiency scores

For the 3YR period, there was a decrease in the number of efficient AEEs and EEs from the cluster to the meta-frontier, which was more pronounced in the first, where the number decreased from 7 to 3 efficient ETFs. From the combined analysis of the two periods, it is also possible to state that the number of efficient AEEs is higher in the 3YR period, while the number of efficient EEs is higher in the 1YR period (see Figure 6). These results are in line with Pavlova and Boyrie (2022), who found that ESG ETFs outperformed the market pre-crisis but did not perform any better during the COVID-19 crash, and Demers, Hendrikse, Joos and Lev (2021), whose results reported that firms with higher ESG scores did not experience superior returns during the period of the COVID-19 crisis. However, Nofsinger (2014) reported different findings for the period of 2000-2011, where socially responsible investing (SRI) outperformed conventional funds during the crisis period (2007-2009).

Table 7. Percentage of efficient ETFs for meta- and cluster-Frontiers – 1YR and 3 YR periods

	Meta-Frontier	Cluster-Frontier
1YR		
Percentage of efficient AEEs	7.14%	28.57%
Percentage of efficient EEs	21.82%	21.82%
3YR		
Percentage of efficient AEEs	21.43%	50.00%
Percentage of efficient EEs	9.09%	12.73%

Table 7 reports the percentage of efficient ETFs per type. As we can see, for the cluster-frontier, the percentage of efficient AEEs is higher than that of efficient EEs for both periods, which means that a larger number of AEEs can maximize their outputs.

Figures 7 and 8 show that the average values of the outputs (NAV, ESG, and return) are significantly higher for efficient ETFs than for inefficient ones, particularly in the 3YR period, where NAV, ESG, and return were higher for efficient funds by 341%, 78%, and 66%, respectively. On the other side, the average values of the inputs (Beta and ER) are lower for efficient ETFs than for inefficient ones in both periods, but this is more visible in the 3YR period, where beta and ER were lower for efficient funds by 58% and 22%, respectively.

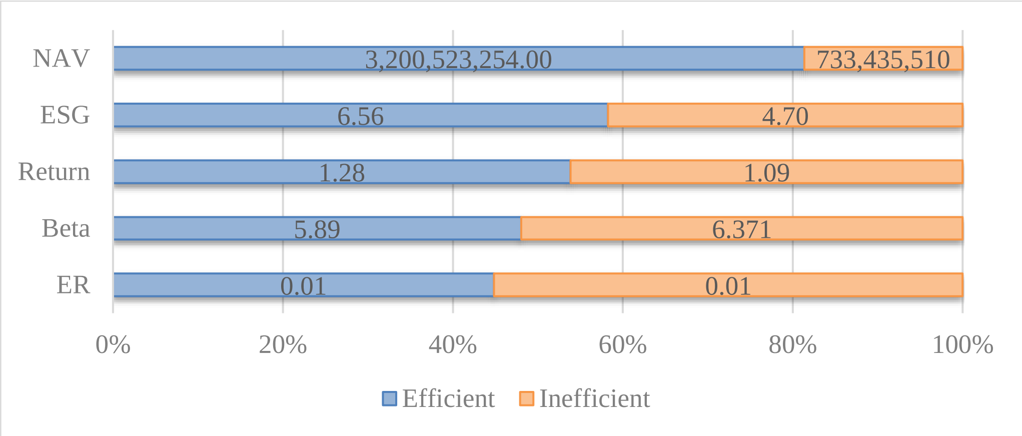


Figure 7. Average input and output values for efficient and inefficient ETFs - 1YR period

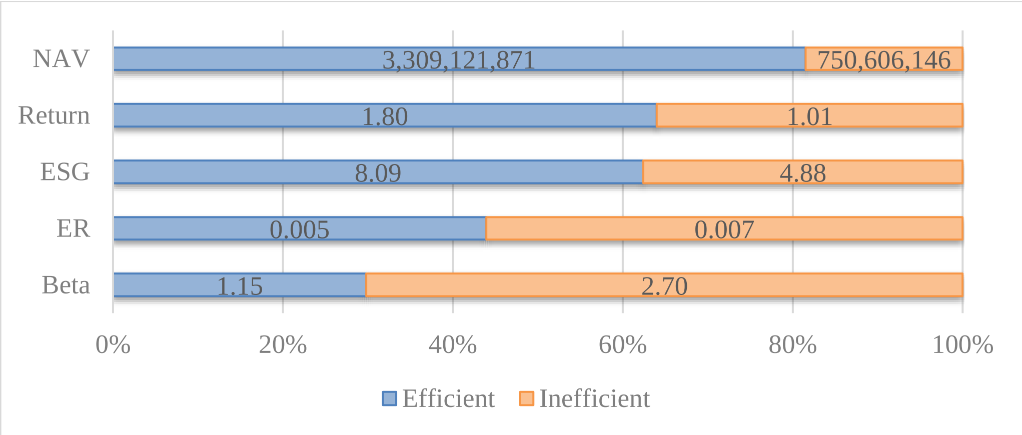
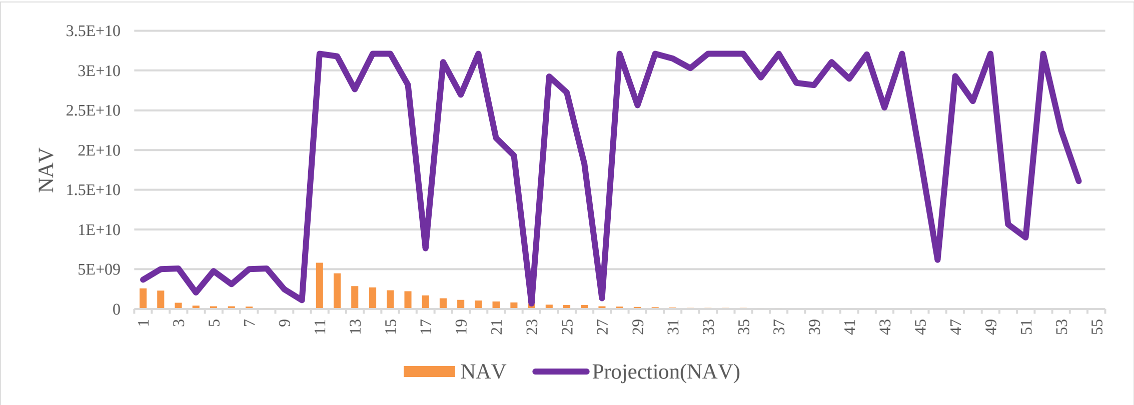


Figure 8. Average input and output values for efficient and inefficient ETFs - 3YR period

4.1 Potential Improvements

4.1.1 One Year Analysis

Figures 9 and 10 show the potential improvement for every input and output that inefficient ETFs should attain to become efficient from the analysis of cluster-frontier results. The results shown are for a 1YR period and are structured by indicator and ETF category. The indicator that reports the highest improvement potential is the ER (-137%), which suggests a reduction of the average ER from 0.0069 to 0.0029. The improvement potential that results from the ER decrease is much more evident for EEs (-182%) than for AEEs (-32%). NAV also exhibits a great improvement potential average of 97%, with a higher value for EEs (97%) than for AEEs (81%). ESG shows a reasonable average improvement potential of 36%, particularly for EEs (43%), rather than AEEs (13%), therefore showing much more relevance for conventional energy funds (EEs) than for alternative energy ones (AEEs). Return and beta are the indicators that report the lowest improvement potential, with averages of 14% and -5%, respectively. It is also worth noting that there is almost no room for improvement potential in the return of AEEs (0.4%), but beta shows a more relevant value of 10%. The opposite occurs for EEs, where return reveals an improvement potential of 15% and beta has a much lower value of -4%. Overall, to improve the efficiency of EEs and AEEs over the 1YR period, the ER should be reduced, and the NAV increased.



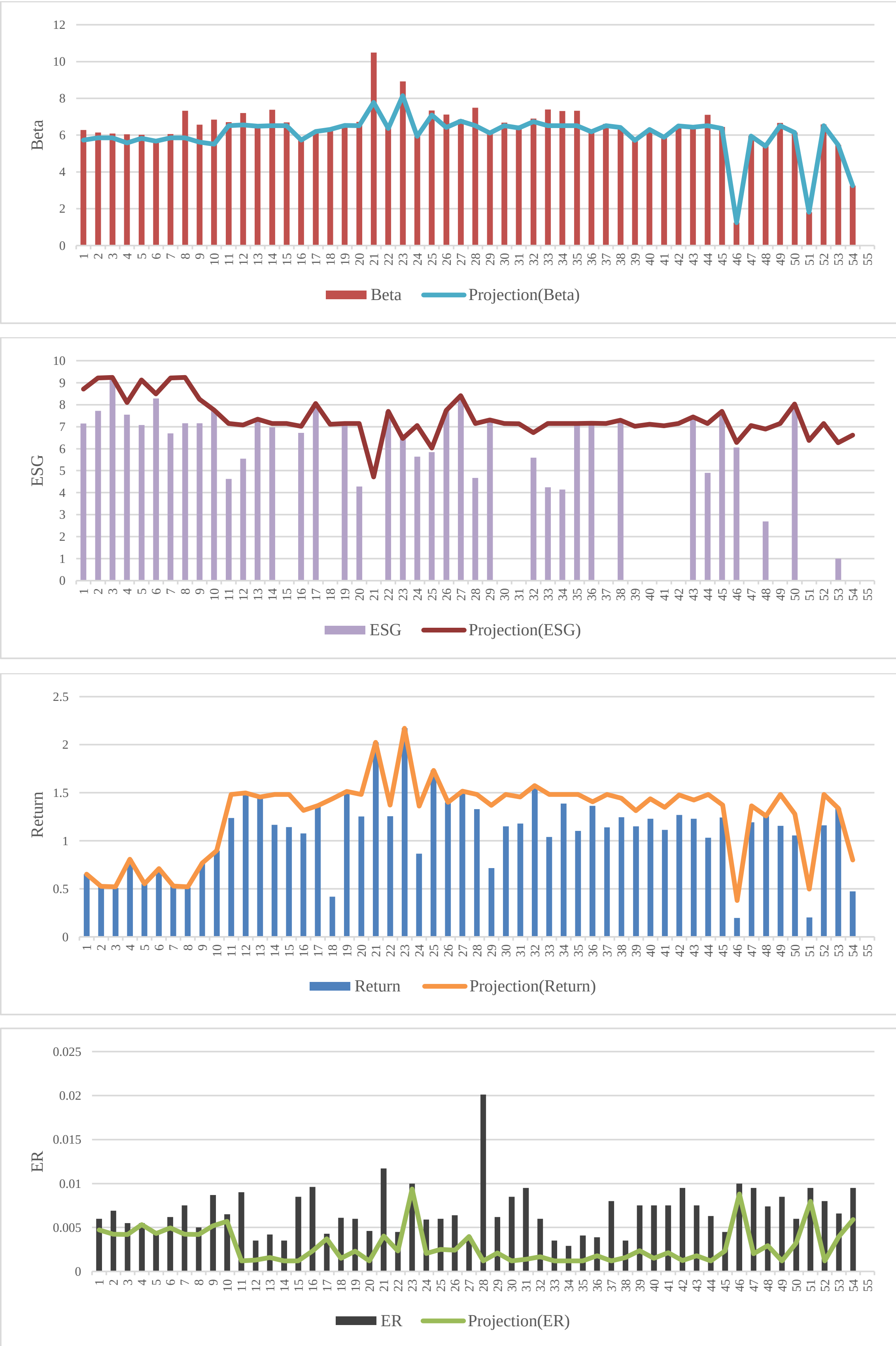


Figure 9. Potential improvement for each input and output for inefficient ETFs - 1YR Analysis

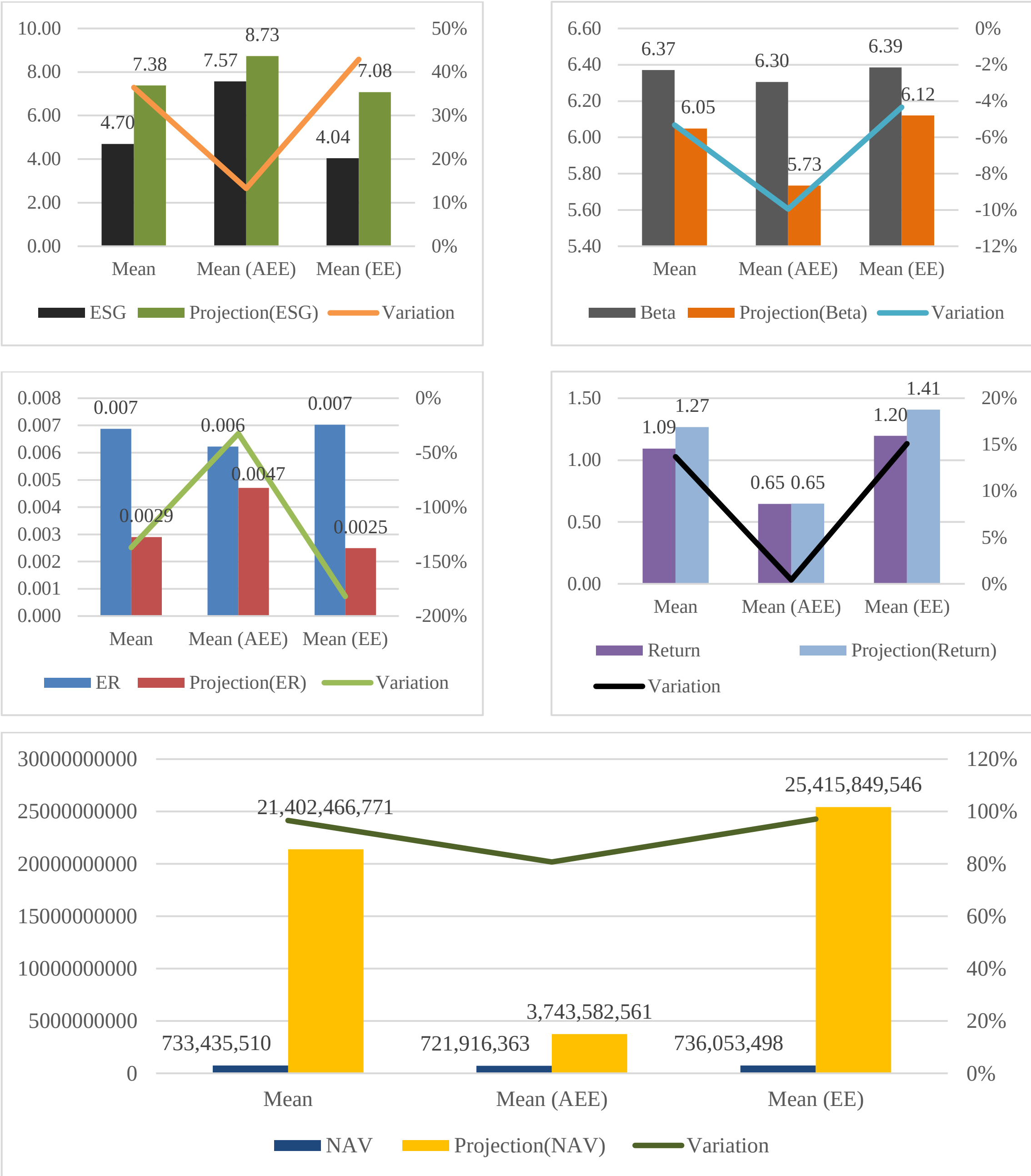
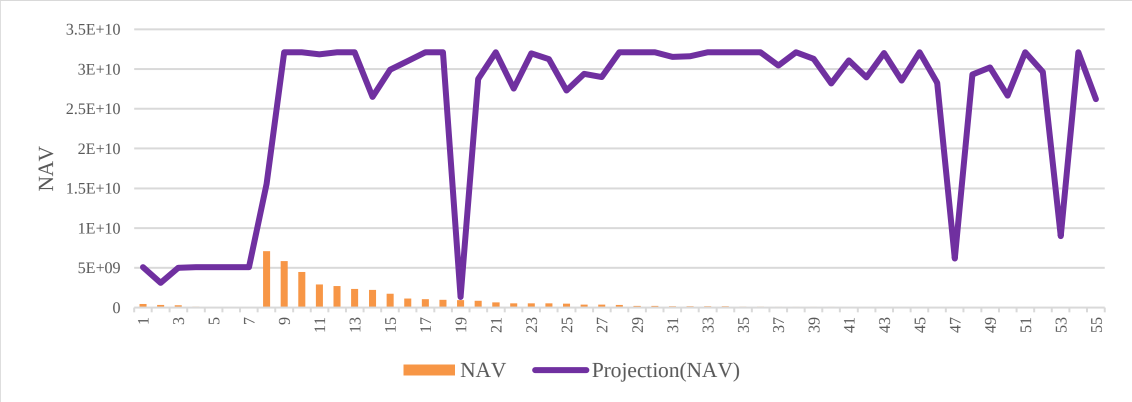
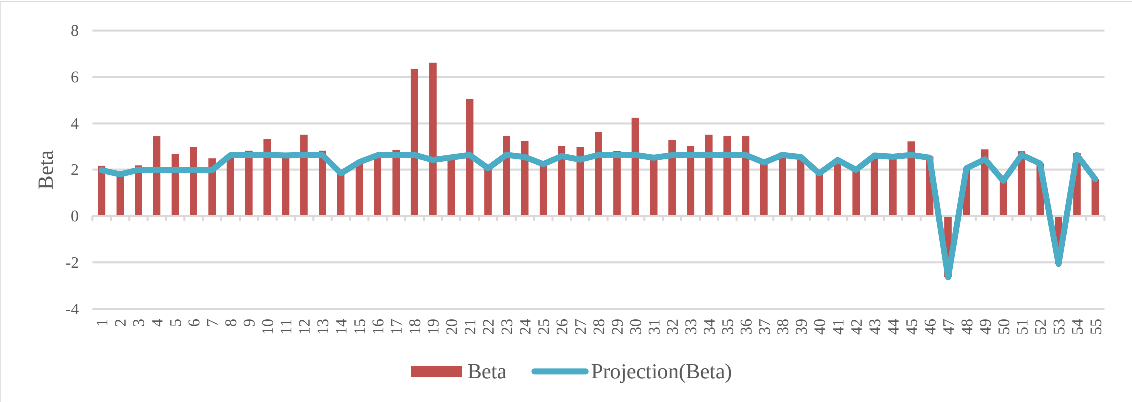


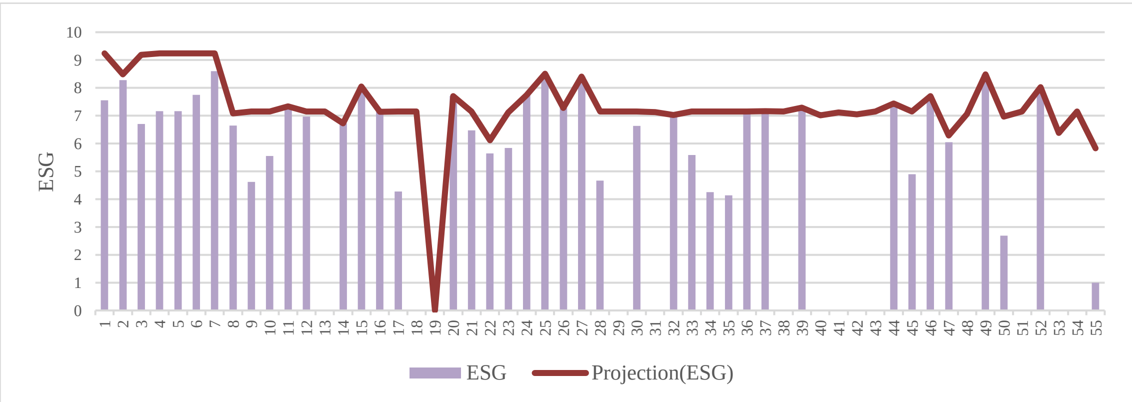
Figure 10. Average potential improvement for each input and output for inefficient ETFs - 1YR Analysis

4.1.2 Three Year Analysis

The analysis shown previously is also applied to a 3YR period (see Figures 11 and 12) to observe the time effect on the results. The indicator that reports the highest improvement potential is the ER (-212%), which suggests a reduction of the average ER from 0.0068 to 0.0022. As observed for the 1YR period, the improvement potential that results from the ER decrease is much more evident for EEs (-267%) than for AEEs (-52%). NAV exhibits the same improvement potential observed in the 1YR period, but this time with almost identical values for EEs (97%) and AEEs (96%). ESG values are similar to those for the 1YR period, with an average improvement potential of 33%, but with a smaller gap between EEs (37%) and AEEs (17%). Return and beta have much more room for improvement when compared to the 1 YR period, with average values of 23% and -22%, respectively. In comparison to the 1YR period results, the return from AEEs has a higher improvement potential (35% versus 20%) than the return from EEs (20%) in the 3YR period. Hence, it is possible to state that the average absolute values for improvement potential increase over a longer period (except for ESG), but the most relevant ones to strive for a higher efficiency remain the same for both ETF categories (ER and NAV).







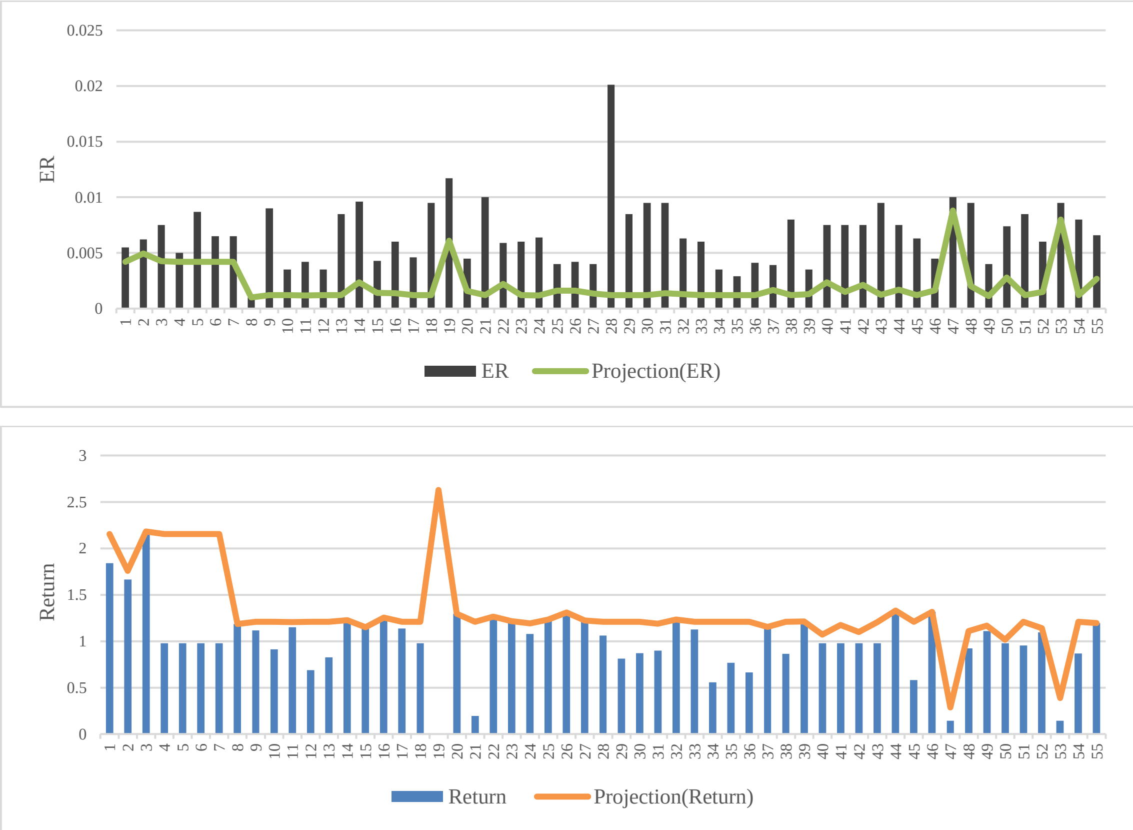
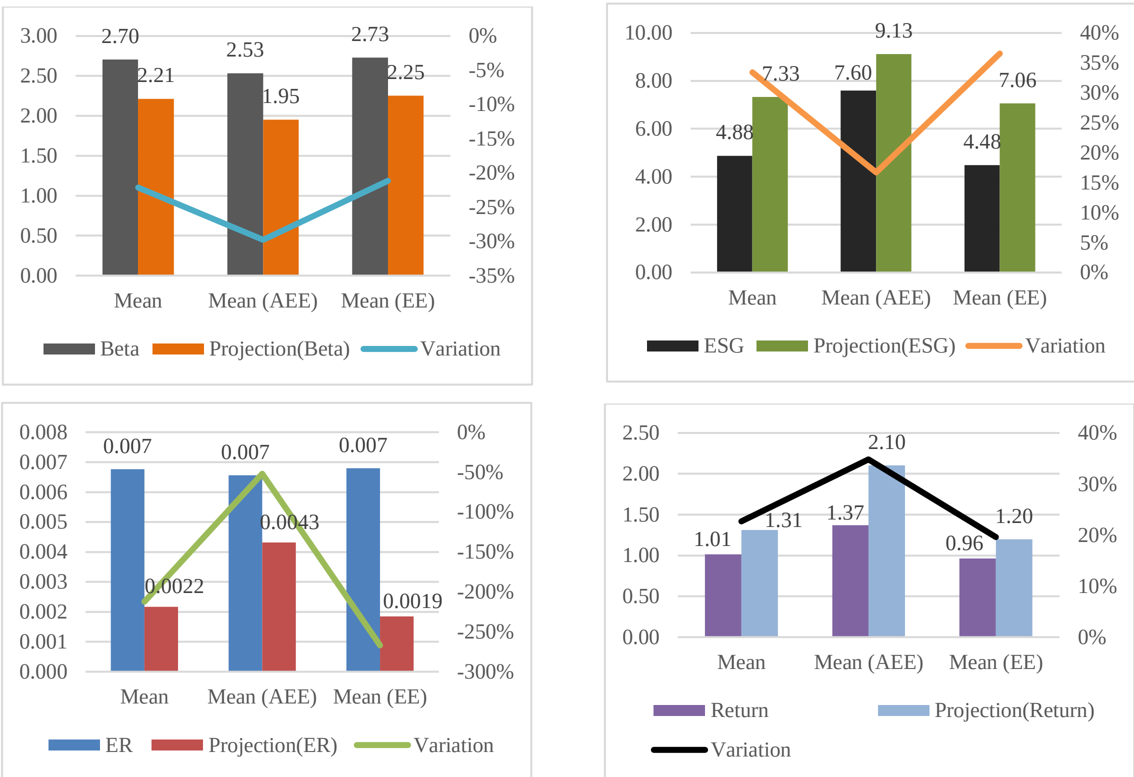


Figure 11. Potential improvement for each input and output for inefficient ETFs - 3YR period



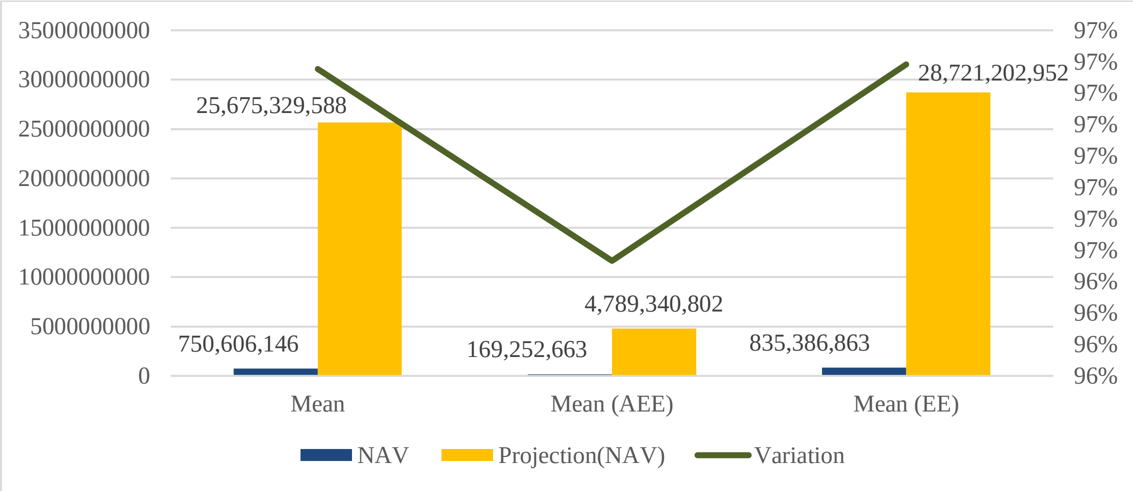


Figure 12. Average potential improvement for each input and output for inefficient ETFs - 3YR period

4.2 Correlation analysis

Table 8 shows the correlation values between the efficiency scores and the indicators of both categories for the two periods. From the analysis of this table, it seems clear that there is a positive correlation between the outputs (return, ESG, and NAV) and the efficiency scores, as well as a negative (or null) correlation between the inputs (ER and beta) and the efficiency scores. It is also noticed that the absolute values of the correlations are stronger over a longer period, except for ESG, which attains more relevance over the shorter period, particularly for AEEs. The indicator with a stronger correlation to efficiency scores in the 1YR period is beta (-0.572) for AEEs and ESG (0.330) for EEs, whereas in the 3YR period it is return (0.628) for AEEs and NAV (0.403) for EEs.

Table 8. Correlation between the efficiency scores and the input and output factor for each ETF category – 1YR and 3 YR periods

	1YR Scores		3YR Scores	
	AEE	EE	AEE	EE
Return	0.199	0.318	0.628	0.271
ER	-0.210	-0.189	-0.423	-0.263
ESG	0.468	0.330	0.285	0.294
Beta	-0.572	0.005	-0.595	-0.398
NAV	0.446	0.310	0.516	0.403

4.3 Robustness Analysis

The DEA method is a linear programming technique used to evaluate the efficiency of DMUs. As we know, in several real-world applications, the input and output factors cannot be precisely measured, and this is very important when using DEA since the efficiency of DMUs is sensitive to possible data errors (Zerafat, Emrouznejad and Mustafa, 2012). Several approaches have been proposed to incorporate fuzziness into the DEA models by defining tolerance levels. One of the most popular approaches is the α-level approach, which consists of converting the fuzzy DEA model into a pair of parametric programs to find the lower and upper bounds of the efficiency scores (Hatami-Marbini, Emrouznejad and Tavana, 2011). The MaxDEA software allows introducing fuzzy inputs and outputs into the model and computes the lower and upper bounds of the efficiency scores. In this way, it is possible to evaluate the impact that changes in the inputs and outputs might have on the efficiency scores. The lower and upper bounds of the inputs and outputs are given as follows:

$$x_{ij}^L = x_{ij} \leq x_{ij} \leq x_{ij} = x_{ij}^U$$

$$y_{ij}^L = y_{ij} \leq y_{ij} \leq y_{ij} = y_{ij}^U$$

where $[x_{ij}^L, x_{ij}^U]$ and $[y_{ij}^L, y_{ij}^U]$ are the α-level form of the fuzzy inputs and fuzzy outputs, and L and U designate the lower and upper bounds, respectively. By applying a tolerance δ to these inputs and outputs it is possible to obtain the new following intervals:

$$x_{ij}^L = x_{ij}\,(1-\delta) \leq x_{ij} \leq x_{ij}\,(1+\delta) = x_{ij}^U$$

$$y_{ij}^L = y_{ij}\,(1-\delta) \leq y_{ij} \leq y_{ij}\,(1+\delta) = y_{ij}^U$$

4.3.1 One-year Analysis

For a tolerance of δ = 5% applied to the current inputs and outputs according to the cluster-frontier, 7 ETFs remain robustly efficient (2 AEEs and 5 EEs), 37 remain robustly inefficient, and 25 are potentially efficient. For a tolerance of δ = 10%, 7 ETFs remain robustly efficient (2 EEs and 5 AEEs), 24 remain robustly inefficient, and 38 are potentially efficient (see Figure 13). If the factors suffer an increase of 5% to 10%, AEEs will have a potential improvement of 58% to 77%, while EEs have a greater potential improvement that can vary from 64% to 122% (see Figure 14). On the other hand, if all the factors suffer a decrease of 5% to 10%, AEEs get a potential worsening of -32% to -

37%, and EEs will have a higher potential worsening of -47% to -50% (see Figure 15). Overall, the efficiency of AEEs is more immune to potential variations in the inputs and outputs than that of EEs, which show a stronger reaction in terms of efficiency.

4.3.2 Three-year Analysis

For a tolerance of δ = 5% applied to the current inputs and outputs, according to the cluster-frontier, 8 ETFs remain robustly efficient (3 AEEs and 5 EEs), 52 remain robustly inefficient, and 9 are potentially efficient. For a tolerance of δ = 10%, 6 ETFs remain robustly efficient (2 EEs and 4 AEEs), 50 remain robustly inefficient, and 13 are potentially efficient (see Figure 14). If the factors increase by 5% and 10%, AEEs have a potential improvement of 23% to 47%, respectively, and EEs have a lower potential improvement of 7% to 14% (see Figure 15). With a decrease in the factors of 5% and 10%, AEEs have a potential worsening of -23% to -41%, respectively, and EEs have a slightly lower potential worsening of -15% to -32% (see Figure 16). In contrast to what was observed over the one-year period, EEs show more immunity in terms of efficiency variations in the longer term than AEEs when the tolerance is applied to the inputs and outputs.

Hence, when inputs and outputs are perturbed, AEEs show better improvement potential than EEs over the longer term, while in the short term, EEs attain a much higher room for improvement than AEEs. It can also be ascertained that the absolute values regarding the potential worsening are smaller than the potential improvement ones in both periods for AEEs; however, for EEs, the potential worsening is higher in a longer period.

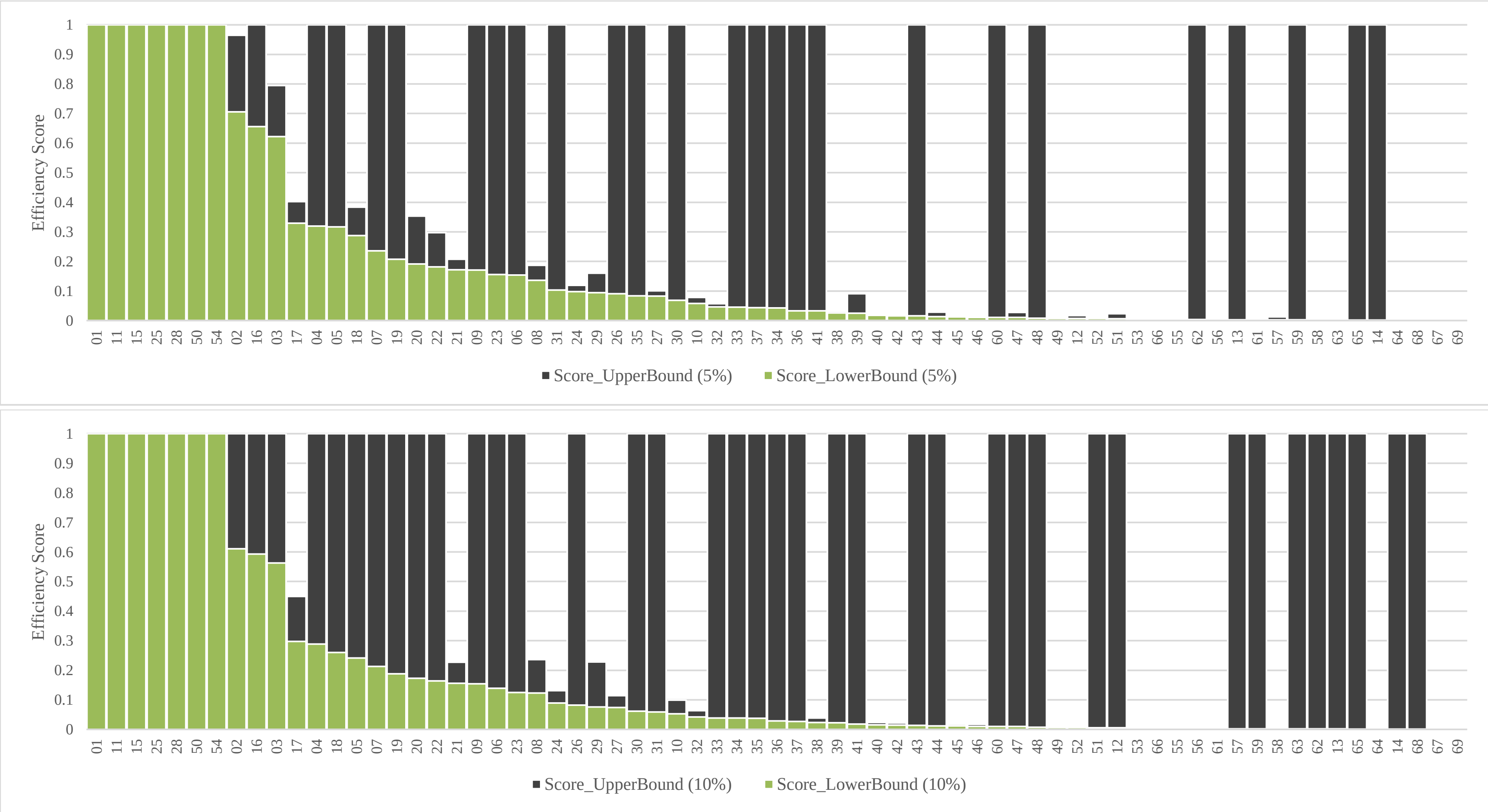


Figure 13. Upper and lower bounds of efficiency scores for each ETF - 1YR period

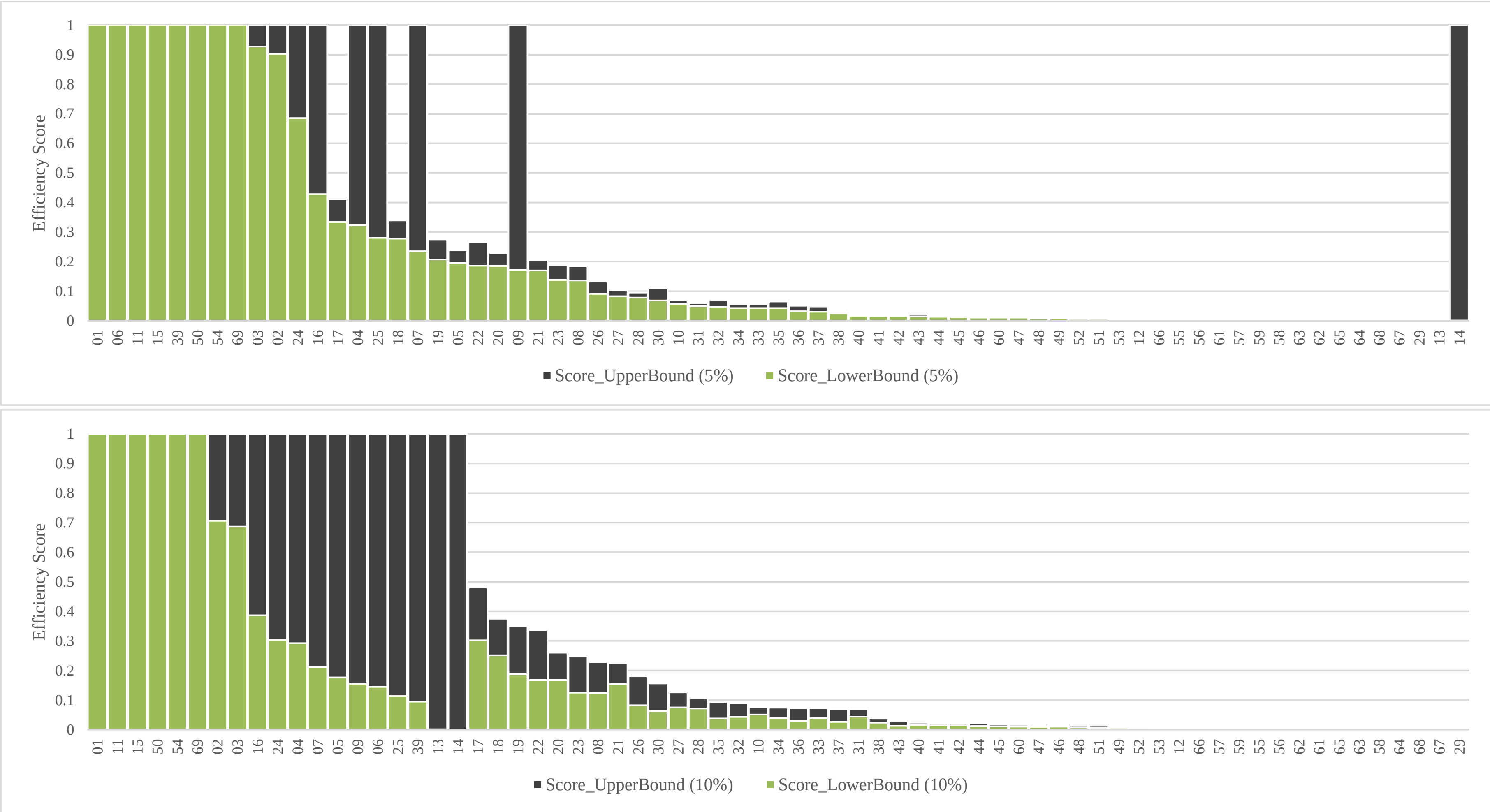


Figure 14. Upper and lower bounds of efficiency scores for each ETF - 3YR period

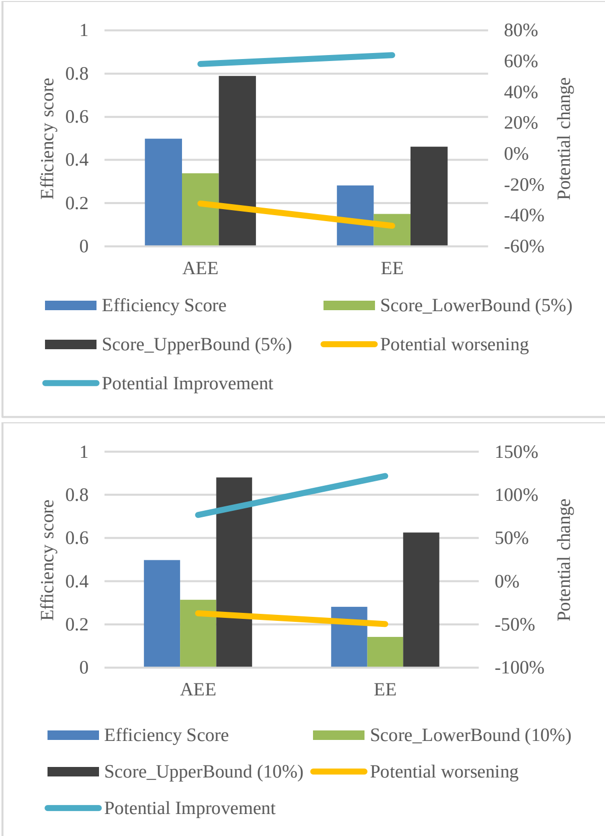


Figure 15. Average Upper and lower bounds of efficiency scores for each ETF - 1YR period

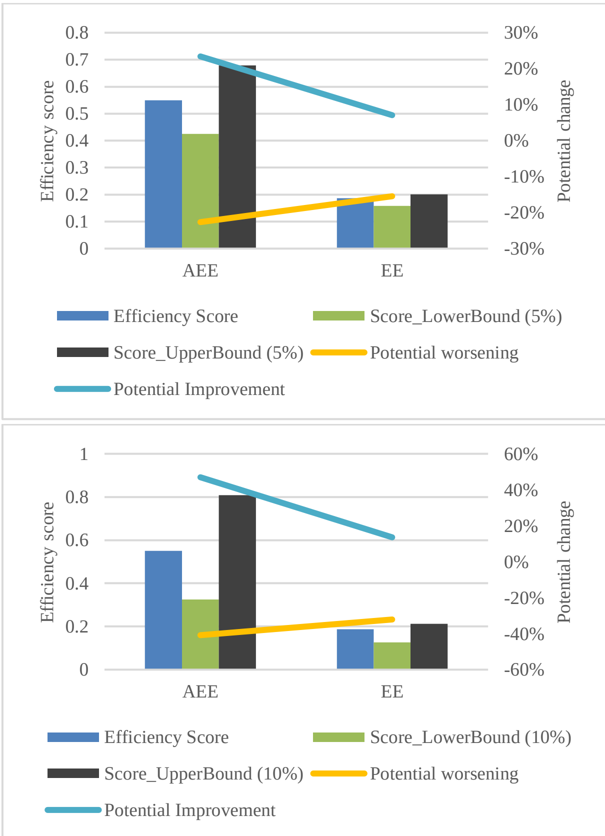


Figure 16. Average Upper and lower bounds of efficiency scores for each ETF - 3YR period

5. Conclusion

The exceptionally fast growth of clean energy allows investors and fund managers to diversify their portfolios by investing in firms that focus on sustainable energy sources. This paper investigates the efficiency of alternative energy ETFs when compared to conventional energy ones, considering financial and environmental factors. The performances of 14 alternative energy ETFs and 55 conventional energy ETFs were evaluated using an SBM-DEA model over one year (2020) and three years (2018, 2019, and 2020). This modeling approach is non-radial and gives us information on the required adjustments that inefficient ETFs should undergo to reach efficiency. When combining the SBM model with cluster analysis, it is also possible to group the ETFs according to the type of energy considered, i.e., AEEs or EEs. Finally, the robustness analysis allows us to anticipate the influence on efficiency from possible changes in the factors, that can arise in real-world situations, such as during periods of market turmoil. After conducting the literature review on the performance assessment of energy ETFs, it can be concluded that despite the advantages offered by the DEA model, the literature is not prolific. Besides, to the best of our knowledge, this is the first time that the SBM model coupled with cluster analysis has been used in the assessment of energy ETFs.

The key findings of our study show that the efficiency of AEEs is much more sensitive to cluster analysis than the efficiency of EEs. When the data is divided into groups according to the ETF type, the percentage of efficient AEEs rises significantly, while EEs do not show a strong reaction. TGR values are also substantially lower for AEEs, indicating that these ETFs only produce, on average, 26% and 38% of their potential output in 1YR and 3YR periods, respectively. Hence, there is stronger connectivity between the inputs and outputs used in the assessment and conventional energy ETFs. These results can be a consequence of the lack of environmental and socially responsible factors that would probably show a better association with alternative energy funds, instead of performance indicators that can be more suitable for consolidated and highly valued ETFs. The introduction of 5% and 10% perturbations in the evaluation factors will have little impact on efficiency, especially over the longer term, because more than 50 ETFs are robustly inefficient over this period. However, in the short term, some variations in the indicators could lead to a potential efficiency that expands to more ETFs when the tolerance considered is increased. From our results, it is also clear that the factors that most affect the efficiency of both categories of ETFs are the ER and NAV. Therefore, a reduction in operational expenses would be one of the most important actions that fund managers should consider improving the efficiency of ETFs, along with increasing the assets/liabilities ratio. It is also interesting to see that an increase in the ESG factors would affect conventional energy ETFs more positively than alternative energy ones and would have an even greater impact when compared to return or beta. From an investor's perspective, it is important not to overlook how different alternative and conventional energy ETFs react to changes in the same indicators, especially in a market crisis period, such as the one covered by our work. The rapid growth of the clean energy industry and the diversity that AEEs could offer are relevant arguments for the introduction of this type of security in any investor's portfolio. In this dissertation, we have striven to provide a group of inputs and outputs that could better assess the efficiency of the ETFs' categories from financial- and environmental-oriented perspectives. Although, we consider that the data reported is lacking a significant sample of alternative energy ETF's that would probably lead to more relevant and comprehensive results.

Future work should contemplate other indicators to evaluate the efficiency of AEEs and EEs, particularly more specific indicators based on environmental and socially responsible attributes, in addition to significant data for alternative energy ETFs.

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