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# Natural Resources Exchange Traded Funds: Performance Appraisal using DEA Modeling

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## Abstract

The purpose of this paper is to evaluate the performance of a sample of natural resources exchange traded funds (ETFs) by applying a two-stage procedure. In the first stage, the generalized proportional distance function (GPDF) in the data envelopment analysis (DEA) context is used for the first time to measure the relative efficiency of sectoral ETFs. In the second stage, a Tobit model is employed to identify the drivers of performance. The results indicate there is scope for efficiency improvement for about half or more of the sample funds depending on the variables used in the assessments, and fund performance can be explained by fund persistence and the beta coefficient.

*Keywords*: natural resources exchange traded funds, efficiency, data envelopment analysis, generalized proportional distance function

*JEL Classification codes*: C14, G20, G23

Exchange traded funds (ETFs) are similar to mutual funds, in other words, portfolios of stock-exchange securities and/or bonds consisting of shares (Chiodi, Mansini, & Speranza, 2003) in that they offer investors a proportionate share in a pool of stocks, bonds, and other assets (Investment Company Institute [ICI], 2009). In the study by ICI, ETFs are distinguished into four categories. One type of ETFs is index-based ETFs designed to track the performance of a specific index or an inverse of it and in some cases, a multiple or multiple inverse of indices. A second type are actively managed ETFs aimed to create a unique mix of investments to meet specific investment objectives and policies. A third are commodity-based ETFs invested in commodity futures and physical commodities. ETFs invested in particular market sectors and industries, for example, natural resources, technology, finance, health, real estate, and utilities are the final category.

Particular ETFs have proven to be popular with investors, both in terms of the number offered and assets gathered. Natural resources constituted 16% of the 231 funds by the end of 2008 and 13% of the total net assets of commodity and sector ETFs, valued at USD 94 billion by the end of 2008. Second, financial institutions constituted 12% of the total number of commodity and sector ETFs and 17% of total net assets of the commodity and sector ETFs.

One key difference between ETFs and mutual funds is ETFs are bought and sold on a stock exchange through a broker-dealer, whereas mutual funds are bought and sold through a financial adviser, broker-dealer, or directly from a fund company. Moreover, there are some advantages to ETFs over mutual funds. First, ETFs provide investors with high liquidity because investors can trade ETFs on the market whenever they want, while mutual funds are ‘forward priced,’ in other words, traded only at the close of the market. Second, investors can save tax by delaying capital gains up to the end to pay for redemption. Third, ETFs charge lower fees compared to mutual funds (ICI, 2009; Poterba & Shoven, 2002; Shin & Soydemir, 2010).

The performance evaluation of ETFs has become an important issue for both fund managers and researchers. Previous empirical studies rely on traditional evaluation measures, such as the capital asset pricing model (CAPM), that are quite sensitive to the benchmark selected. Moreover, these risk-adjusted measures might exclude other relevant factors such as the expense ratio (Chu, Chen, & Leung, 2010). Since the late 1990s, there is a growing body of research applying an operations research technique called data envelopment analysis (DEA) (Charnes, Cooper, & Rhodes, 1978) to mutual fund performance evaluation. DEA was proposed by Murthi, Choi, and Desai (1997) as a means to measure portfolio performance and capture the multidimensional aspect of mutual fund performance. Based on Farrell's (1957) method of efficiency measurement, DEA permits the appraisal and ranking of ETFs (Chu et al., 2010).

This study mainly makes two contributions to DEA applications in the finance literature. In a first stage, the performance of a sample of natural resources ETFs is assessed using DEA modeling. The study has an explicit focus on constructing a consolidated measure of the relative performance of 15 natural resources ETFs by employing a recent DEA model that can handle negative data occurring in a financial context in order to capture the multidimensional aspect of ETF performance using traditional performance indicators and fund characteristics. In a second stage, the DEA application identifies the drivers of fund performance using Tobit regression.

The following questions are addressed in the study:

1. What is the most efficient level of fund characteristics associated with ETF performance?
2. Which are the top performers, in other words, endogenous benchmarks, of the sampled ETFs?
3. Which are the drivers of the ETF performance?

The rest of the paper unfolds as follows. In Section 2, the literature on DEA-based ETF performance evaluation and DEA modeling in the presence of negative data is reviewed. In Section 3, the proposed model is outlined briefly. The data along with identification of inputs and outputs for the case of natural resources ETFs are reported in Section 4. In Section 5, the results of the two stages of the analysis are presented and discussed. In Section 6, some policy implications are provided, and the final section concludes the paper.

## Literature Review

The literature review is organized as follows: (a) A survey on DEA-based ETF performance evaluation and (b) a survey on DEA models to handle negative data.

### *Survey on DEA-Based ETF Performance Evaluation*

The only study that applies DEA to ETF performance evaluation is the work by Chu et al. (2010). Chu et al. employed the range directional measure (RDM) of Portela, Thanassoulis, and Simpson (2004) to deal with negative data using downside risk and expense ratio as inputs and monthly returns and upper deviation as outputs.

In recent years, a growing body of studies has applied the DEA to assess the performance of mutual funds. In the first research stream, the evaluation is conducted using models directly derived from the production context. In particular, the first use of the DEA to assess fund performance dates back to the pioneering work by Murthi et al. (1997), who developed the DEA portfolio efficiency index (DPEI) to evaluate the performance of mutual funds using costs (inputs) and returns (output). Murthi et al. modified the basic idea employed in the Sharpe index (Sharpe, 1966) by incorporating transaction costs. The motivation of Murthi et al. (1997) to use the DEA was to overcome a number of shortcomings of traditional two-dimensional (risk-return) performance measures. The DEA offers a multi-dimensional performance analysis compared to the above two-dimensional performance measures because it does not require any theoretical model as a benchmark, and the DEA-based performance is a combination of multiple fund attributes. The attributes include mean returns (outputs); total or systematic risk; expenses, in other words, transaction costs and administration fees; loads, such as subscription or/and redemption costs; minimum initial investment and net assets value (inputs). For recent reviews see Alexakis and Tsolas (2011) and Glawischnig and Sommersguter-Reichmann (2010).

In a second research stream based on portfolio theory, Morey and Morey (1999) proposed quadratic-constrained DEA models that use a mean–variance (MV) approach with variance as input and mean return as output. The analysis has been extended by Briec and Kerstens (2009) and Zhao Wang, and Lai (2011). In a third stream of research (Haslem & Scheraga, 2003, 2006), the Sharpe ratio is used as output and variables with positive user costs are identified as inputs. A recent paper by Kerstens, Mounir, and Van de Woestyne (2011) provided another option based on hedonic price theory.

In this paper, the performance of sample ETFs is assessed using the approach of Haslem and Scheraga (2003, 2006) for mutual fund performance and two new proposed DEA models based on the generalized proportional distance function (GPDF) (Kerstens & Van de Woestyne, 2011). The latter use either Jensen's alpha as a single output or both the Sharpe ratio and Jensen's alpha as outputs and some ETFs characteristics as inputs. See also Shin and Soydemir (2010) who employed Jensen's model to measure the performance of ETFs.

### *Survey on DEA Models to Handle Negative Data*

A great many models/measures have appeared in the DEA literature to address the issue of handling negative data including, among others, the range directional measure (RDM) (Portela et al., 2004), the modified slack-based measure (MSBM) of Sharp, Liu, and Meng. (2007), the semi-oriented radial measure (SORM) (Emrouznejad, Anouze, & Thanassoulis, 2010), and the generalized proportional distance function (GPDF) (Kerstens & Van de Woestyne, 2011). The MSBM is more limited in its application than are the RDM and the SORM. The disadvantage of the SORM is that because of the increase in dimensionality of the problem, it may not necessarily determine Pareto-efficient targets as happens with the standard radial models. The main drawback of the RDM is it cannot guarantee projections on the Pareto efficient frontier (Emrouznejad et al., 2010; Pastor & Ruiz, 2007). Chu et al. (2010) justified the use of RDM to ETF performance appraisal due to its ability to handle negative data. In the case study in this paper, the GPDF is used as the most recent DEA model developed to handle negative data.

## Conceptual Framework

### *The Generalized Proportional Distance Function*

More generally, in a DEA framework, the management of $n$ ETFs, $j=1,\ldots, n$, is characterized by a set of input-like values $X\in\Re^{m}_{+}$ to produce output-like values $Y\in\Re^{k}$; the amounts of the $i^{th}$ input-like and $r^{th}$ output-like values, used by the $j^{th}$ fund are denoted by $x_{ij}$ and $y_{rj}$, respectively. Kerstens and Van de Woestyne (2011) presented a slight variation of the shortage function, or directional distance function (see Chambers, Chung, & Färe, 1998), that offers a more general method to handle negative data values while maintaining a proportional interpretation. The directional distance function $D(x, y;-|x_{ijo}|,|y_{rjo}|) = \beta$ can be estimated non-parametrically using the DEA as follows (Kerstens et al., 2011):

$$
\begin{aligned}
&\text{Max } \beta \\
&\text{s.t.} \\
&\sum_{j=1}^{n}\lambda_j y_{rj} \geq y_{rj0} + \beta\left|y_{rj0}\right|,\ r = 1,2,\ldots,k, \\
&\sum_{j=1}^{n}\lambda_j x_{ij} \leq x_{ij0} - \beta\left|x_{ij0}\right|,\ i = 1,2,\ldots m, \\
&\sum_{j=1}^{n}\lambda_j = 1, \\
&\lambda \geq 0.
\end{aligned}
\tag{1}
$$

The solution to model (1) yields performance, in other words, inefficiency, measures $\beta \geq 0$ for each DMU, where 0 indicates an efficient DMU and a DMU with a score > 0 is defined as inefficient. Suppose that a DMU has an inefficiency score of $\beta > 0$; if this DMU were to operate efficiently, it would have been able to expand output-like values by the magnitude $\beta y_r, r = 1,2,\ldots,k$ while using fewer input-like values of the magnitude $\beta x_i, i = 1,2,\ldots,m$.

The assumption of VRS is deemed the most relevant assumption with regard to the nature of returns to scale when assessing mutual fund performance by means of the DEA (Kerstens et al., 2011). Moreover, this assumption is justified by the use of ratios as indicators of inputs and outputs (Hollingsworth & Smith, 2003).

## Data

### *Identification of Inputs and Outputs*

The input-output variables on 15 natural resources ETFs used in this study cover the three-year period between 2008 and 2010. The selected data set is publicly available on finance.yahoo.com and includes figures on returns, risk measures (standard deviation, beta coefficient), traditional performance indices (Sharpe ratio and Jensen's alpha), cost (i.e. total expense ratio [TER]), and other fund indices such as portfolio price/cash flow (P/CF) and portfolio price/book (P/B). The reason for considering only 15 ETFs in this study is the availability of complete information about the funds. The sample funds are the following: First Trust Materials AlphaDEX (FXZ), Guggenheim Timber (CUT), iShares Dow Jones US Basic Materials (IYM), iShares S&P Global Materials (MXI), iShares S&P North Amer Natural Resources (IGE), Market Vectors Agribusiness ETF (MOO), Market Vectors Glb Alternative Energy ETF (GEX), Market Vectors Steel ETF (SLX), Materials Select Sector SPDR (XLB), PowerShares Dynamic Basic Materials (PYZ), PowerShares Global Water (PIO), Rydex S&P Equal Weight Materials (RTM), SPDR S&P Metals & Mining (XME), Vanguard Materials ETF (VAW), and WisdomTree International Basic Materials (DBN).

### *Input and Output Variable Specification for DEA Runs*

No consensus exists among researchers and investors as to which input and output variables should be included in a DEA model. The input variables used in the DEA analysis are the following: (a) portfolio P/CF, (b) portfolio P/B, and (c) TER.

The GPDF is used to examine whether input-like values, like portfolio P/CF and P/B as well as TER, represent an efficient user cost with respect to performance metrics, in other words, traditional indices such as Sharpe ratio and Jensen's alpha.

In the first stage of the analysis, three DEA runs are performed employing the GPDF using Equation 1. In the first DEA run, the three above input-like values, namely, portfolio P/CF and P/B, and TER, are used to produce a single output-like value, namely the Sharpe ratio. The second DEA run employs the same three input-like values to produce another single output-like value, namely the Jensen's alpha. The third DEA run employs the same three input-like values to produce two output-like values, namely the Sharpe ratio and Jensen's alpha. The input and output variables used in the DEA assessments and their descriptive statistics are presented in Table 1.

### *Variable Specifications for the Tobit Regression Models*

The second stage of analysis involves explaining the variation in the relative inefficiencies obtained from all the DEA runs with three Tobit regression models that include independent variables to proxy funds' characteristics. The variables include logarithm of funds' net assets that controls for fund size, fund persistence (1-year return), beta coefficient, and portfolio price to earnings (P/E) ratio.

## Results

In this section, the results of the DEA models (first stage) are first presented and discussed; thereafter, the second stage, namely, the Tobit regression results, are discussed.

Table 1
*Natural Resources ETFs Data and Descriptive Statistics*

| Ticker | Sharpe ratio | Jensen's alpha | Portfolio P/CF ratio | Portfolio P/B ratio | TER |
|---|---|---|---|---|---|
| FXZ | 0.23 | 13.83 | 5.56 | 2.21 | 0.70% |
| CUT | 0.00 | 5.38 | 3.36 | 0.98 | 0.70% |
| IYM | 0.15 | 10.42 | 7.85 | 2.71 | 0.47% |
| MXI | 0.03 | 5.68 | 8.05 | 2.16 | 0.48% |
| IGE | 0.07 | 5.97 | 9.79 | 2.00 | 0.48% |
| MOO | 0.16 | 9.70 | 7.35 | 1.83 | 0.59% |
| GEX | -0.55 | -18.13 | 6.48 | 1.44 | 0.65% |
| SLX | 0.10 | 11.40 | 7.73 | 1.56 | 0.55% |
| XLB | 0.03 | 5.37 | 8.69 | 2.80 | 0.22% |
| PYZ | 0.16 | 10.33 | 3.74 | 2.37 | 0.65% |
| PIO | -0.15 | -0.27 | 4.44 | 1.50 | 0.75% |
| RTM | 0.23 | 12.58 | 8.15 | 2.37 | 0.50% |
| XME | 0.18 | 14.19 | 11.95 | 1.90 | 0.35% |
| VAW | 0.06 | 6.72 | 6.62 | 2.40 | 0.24% |
| DBN | -0.02 | 4.20 | 5.87 | 1.85 | 0.58% |
| | | | Descriptive statistics | | |
| Mean | 0.05 | 6.49 | 7.04 | 2.01 | 0.53% |
| SD | 0.19 | 7.91 | 2.29 | 0.50 | 0.16% |
| Median | 0.07 | 6.72 | 7.35 | 2.00 | 0.55% |
| Q1 | 0.02 | 5.38 | 5.72 | 1.70 | 0.48% |
| Q3 | 0.16 | 10.91 | 8.10 | 2.37 | 0.65% |
| Min | -0.55 | -18.13 | 3.36 | 0.98 | 0.22% |
| Max | 0.23 | 14.19 | 11.95 | 2.80 | 0.75% |

*Notes: Sharpe* ratio: 3yr-Sharpe ratio, Jensen's alpha: 3yr- Jensen's alpha, TER: total expense ratio, SD: Standard deviation, Q1: first quartile, Q3: third quartile.

## *First Stage Analysis: GPDF Results*

The non-oriented inefficiency of the ETFs is assessed in the light of contrasting the P/CF and P/B ratios and TER and expanding their performance metrics such as Sharpe ratios and Jensen's alphas.

When the Sharpe ratio is used in the output side, the median inefficiency is of the order of 0.0031. The results indicate scope exists for efficiency improvement by contrasting input-like values and simultaneously expanding output-like values of approximately 5.1% (=0.051*100). When the Jensen's alpha is used in the output side, the median inefficiency is of the order of 0.0115. The results indicate scope exists for efficiency improvement by contrasting input-like values and simultaneously expanding output-like values of about 5.28% (=0.0528*100). When both the Sharpe ratio and Jensen's alpha are used in the output side, the median inefficiency is of the order of 0. The results indicate there is scope for efficiency improvement by contrasting input-like values and simultaneously expanding output-like values of approximately 4.76% (=0.0476*100) (see Table 2).

Table 2
*Inefficiency Scores, Descriptive Statistics, Number, and Percentage of Efficient ETFs*

| Ticker | β (DEA Run 1) | β (DEA Run 2) | β (DEA Run 3) |
|---|---|---|---|
| FXZ | 0.0000 | 0.0000 | 0.0000 |
| CUT | 0.0000 | 0.0000 | 0.0000 |
| IYM | 0.0808 | 0.0552 | 0.0530 |
| MXI | 0.1479 | 0.1479 | 0.1479 |
| IGE | 0.1225 | 0.1225 | 0.1225 |
| MOO | 0.0031 | 0.0680 | 0.0031 |
| GEX | 0.1012 | 0.1012 | 0.1012 |
| SLX | 0.0230 | 0.0000 | 0.0000 |
| XLB | 0.0000 | 0.0000 | 0.0000 |
| PYZ | 0.0000 | 0.0000 | 0.0000 |
| PIO | 0.1470 | 0.1470 | 0.1470 |
| RTM | 0.0000 | 0.0115 | 0.0000 |
| XME | 0.0000 | 0.0000 | 0.0000 |
| VAW | 0.0000 | 0.0000 | 0.0000 |
| DBN | 0.1392 | 0.1392 | 0.1392 |
| Descriptive statistics: GPDF efficient and inefficient ETFs | | | |
| Mean | 0.0510 | 0.0528 | 0.0476 |
| SD | 0.0634 | 0.0621 | 0.0638 |
| Median | 0.0031 | 0.0115 | 0.0000 |
| Q1 | 0.0000 | 0.0000 | 0.0000 |
| Q3 | 0.1118 | 0.1118 | 0.1118 |
| Min | 0.0000 | 0.0000 | 0.0000 |
| Max | 0.1479 | 0.1479 | 0.1479 |
| Efficient funds, number (%) | 7 (47%) | 7 (47%) | 8 (53%) |
| Descriptive statistics: GPDF inefficient ETFs | | | |
| Mean | 0.0956 | 0.0991 | 0.0031 |
| SD | 0.0562 | 0.0499 | 0.0530 |
| Median | 0.1118 | 0.1118 | 0.1012 |
| Q1 | 0.0664 | 0.0648 | 0.1225 |
| Q3 | 0.1411 | 0.1411 | 0.1392 |
| Min | 0.0031 | 0.0115 | 0.1470 |
| Max | 0.1479 | 0.1479 | 0.1479 |

*Note. SD:* standard deviation, Q1: first quartile, Q3: third quartile.

Results for the top efficient funds are included in Table 3. In DEA Run 1 the top funds that can be used as benchmarks are the following: FXZ, CUT, XLB, PYZ, RTM, XME, and VAW. With respect to DEA Run 2, the top funds that can be used as benchmarks are the following: FXZ, CUT, SLX, XLB, PYZ, XME, and VAW. In DEA Run 3, one more fund compared to DEA Run 2, namely RTM, is identified as efficient.

Table 3
*The Top Efficiency ETFs*

| Ticker | DEA Run 1 | DEA Run 2 | DEA Run 3 |
|---|---|---|---|
| FXZ | n | n | n |
| CUT | n | n | n |
| SLX | | n | n |
| XLB | n | n | n |
| PYZ | n | n | n |
| RTM | n | | n |
| XME | n | n | n |
| VAW | n | n | n |

## *Second Stage Analysis: Tobit Regressions*

The DEA measures that stem from Equation 1 yield only first-stage measures of fund performance. What is unknown is the reason for the variations in such performance patterns, and that GPDF metrics may not be enough for both consulting purposes and policy analysis is evident. Therefore, a second stage analysis is called for because performance may be affected by other explanatory variables. In this study, the Tobit regression model is used to explore some fund-specific factors which are likely to interfer with the determination of efficiency. Tobit regression is employed as an alternative to ordinary least squares regression (OLS) when the dependent variable is bounded from below or above or both. The Tobit regression is employed often in a next stage that follows DEA, in other words, when the relationship between explanatory (control) variables and DEA efficiency scores is assessed (Hoff, 2007). In the sequential stage that follows the DEA, the fund performance measures are regressed using the Tobit regression method to identify the impact of a series of explanatory variables listed in Table 4.

Table 4
*Explanatory Variables and Descriptive Statistics*

| Ticker | Portfolio P/E ratio | Beta coefficient | Persistence | SIZE |
|---|---|---|---|---|
| FXZ | 13.04 | 1.53 | 24.97% | 5.85 |
| CUT | 12.96 | 1.54 | 11.54% | 4.81 |
| IYM | 16.90 | 1.43 | 21.85% | 6.90 |
| MXI | 13.70 | 1.32 | 10.62% | 6.53 |
| IGE | 14.27 | 1.08 | 14.11% | 7.55 |
| MOO | 14.78 | 1.14 | 16.16% | 7.69 |
| GEX | 16.22 | 1.74 | -19.84% | 4.86 |
| SLX | 13.30 | 1.83 | 11.94% | 5.59 |
| XLB | 16.62 | 1.26 | 11.74% | 7.64 |
| PYZ | 14.63 | 1.40 | 26.45% | 4.16 |
| PIO | 15.64 | 1.21 | 4.67% | 5.76 |
| RTM | 17.27 | 1.40 | 17.83% | 3.62 |
| XME | 22.52 | 1.61 | 25.75% | 7.06 |
| VAW | 15.73 | 1.32 | 16.46% | 6.46 |
| DBN | 12.23 | 1.42 | 9.04% | 3.73 |
| | | Descriptive statistics | | |
| Mean | 15.32 | 1.42 | 13.55% | 5.88 |
| SD | 2.53 | 0.21 | 11.28% | 1.40 |

| | | | | |
|---|---|---|---|---|
| Median | 14.78 | 1.40 | 14.11% | 5.85 |
| Q1 | 13.50 | 1.29 | 11.08% | 4.83 |
| Q3 | 16.42 | 1.54 | 19.84% | 6.98 |
| Min | 12.23 | 1.08 | -19.84% | 3.62 |
| Max | 22.52 | 1.83 | 26.45% | 7.69 |

*Notes: SIZE:* logarithm of funds' net assets; Persistence: funds' annualized 1year-return.

Between the DEA and Tobit regression, this study uses the performance metric derived from Equation 1 as the dependent variable. For computational purposes, Greene (1993) suggested the use of censoring at zero for the Tobit regression; see also Sueyoshi, Goto, and Omi (2010). The results of the analyses explaining the performance scores derived by the three DEA runs are given in Table 5.

Table 5
*Results of Tobit Regression for Fund Efficiency*

| Variable | Coefficient | Standard error | *t*-value |
|---|---|---|---|
| Panel A: Censored Tobit model (dependent variable (DEA Run 1) = β) | | | |
| Constant | 0.330 | 0.1629 | 2.03(0.063) |
| BETA | -0.168 | 0.1084 | -1.55(0.145) |
| PERSISTENCE | -0.551 | 0.2209 | -2.49**(0.027) |
| Sigma | 0.0764 | 0.0209 | |
| Log likelihood = 4.955 | | | |
| Panel B: Censored Tobit model (dependent variable (DEA Run 2) = β) | | | |
| Constant | 0.517 | 0.1675 | 3.09 (0.009) |
| BETA | -0.300 | 0.1146 | -2.59**(0.022) |
| PERSISTENCE | -0.577 | 0.1940 | -2.97** (0.011) |
| Sigma | 0.0625 | 0.0168 | |
| Log likelihood = 7.24 | | | |
| Panel C: Censored Tobit model (dependent variable (DEA Run 3) = β) | | | |
| Constant | 0.530 | 0.2167 | 2.44(0.030) |
| BETA | -0.311 | 0.1490 | -2.09*(0.057) |
| PERSISTENCE | -0.682 | 0.2568 | -2.65**(0.020) |
| Sigma | 0.0771 | 0.0224 | |
| Log likelihood = = 4.509 | | | |

*Notes: BETA:* beta coefficient; PERSISTENCE: funds' 1yr-return. t-ratios followed by * and ** are significant at a level of 1% and 5%, respectively. *p*-values in parentheses.

The effect of funds' persistence, defined as the funds' 1-year return, is significant in explaining fund efficiency at the 0.05 level in all the DEA runs. The effect of the beta coefficient is significant in explaining the fund's efficiency at the 0.05 level in DEA Run 2 and at the 0.1 level; in DEA Run 3, the signs of variables are negative as expected.

## Policy Implications

The models above can be used by (a) financial analysts to monitor the performance of natural resources ETFs at a sectoral level, (b) financial investors to appraise their investments and obtain more information using the derived metrics, and (c) fund managers to monitor the performance of their funds along with their efficiency.

The general implications of the non-parametric approach employed in this study are worth pointing out. First, in the GPDF, the sample of observed ETFs can be classified in terms of those located on an efficient (in the DEA context) frontier and those that fall below the frontier. Second, the non-parametric clustering of sample ETFs into subsets of efficient and inefficient ETFs provides an analysis of the sample funds against the best-in-class funds defined by the GPDF optimization process. The results of the non-parametric approach can be compared with those of other approaches included as tandem of methods.

From the investor's perspective, evidence supporting links between fund performance and fund attributes is provided. The findings from the Tobit regression analysis provide evidence suggesting persistence and beta coefficient are significant in explaining performance. In general, investors should take into account these relations before investing.

The managerial implications are clear. The DEA determines the current performance level of each individual fund in the sample. Fund managers can greatly benefit from the information provided by GPDF performance scores. The information is useful for knowing the performance rating of each individual fund, and for DEA-inefficient funds. The information can also be used to plan some corrective actions to increase funds' performance.

## Conclusions

In this paper, a study that employed the DEA to monitor the performance of a sample of natural resources ETFs was conducted. The DEA is a non-parametric methodology with the advantage of allowing the evaluation of the performance of funds along a multitude of dimensions and provides a performance metric for each fund under evaluation relative to the best set of funds.

A series of research questions presented in Section 1 were addressed in this study. In order to address the questions three different DEA runs based on the GPDF were performed for assessing fund performance. The DEA was applied under the assumption of VRS. With respect to Question 1, the empirical results indicated scope exists for efficiency improvement for about 47% or 53% of the sample funds, depending on the input and output-like values used in the assessments; the decreasing of input-like values, namely, P/CF and P/B ratios and TER, and the simultaneous expansion of output-like values range from 4.76% to 5.3%. With respect to Question 2, the derived GPDF metrics can be used to discriminate among funds that have excelled in performance and therefore could be proposed to benchmark funds across the funds of the sample. To provide an answer to Question 3, the Tobit regression model was used to examine factors significantly influencing fund performance. A series of variables were examined with the model. The results revealed fund performance can be explained by fund persistence (1-year return) in all the DEA runs and by the beta coefficient only in DEA Runs 2 and 3. An understanding of the GPDF-based performance for the sample funds and the factors that affect it can be extremely beneficial to both practitioners and investors, and can provide helpful references for future studies.

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