

Green Exchange-Traded Fund Performance Evaluation Using the EU-EV Risk Model

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Abstract. This work evaluates the performance of green exchange-traded funds (ETFs) using the expected utility, entropy and variance (EU-EV) risk model. Data from 14 green ETFs analysed in earlier literature in the in-sample period from January 2008 to December 2010 are used.

The green ETFs are ranked according to their risk, considering the returns' expected utility, entropy and variance, and the best-ranked ETFs are selected to construct equally weighted portfolios. Then, the performance of the green ETFs portfolios is evaluated and compared with those of the S&P500 Index. Cumulative returns in in-sample and out-of-sample periods and performance metrics, such as Maximum drawdown, Sharpe ratio, Sortino ratio, Beta and Alpha, are analysed. The results show that, in general, the equally weighted portfolios formed with half the number of best-ranked ETFs outperform the benchmark index in the in-sample period and for specific time ranges in the out-of-sample periods.

Keywords: ETF · Portfolio performance evaluation · EU–EV risk model

1 Introduction

Exchange-traded funds (ETFs) are popular financial instruments, made up of different securities (e.g. stocks, bonds), that can be traded on an exchange and that offer a great diversification, tax efficiency and low expenses (see e.g. [1], [2], [3]). Among these, green ETFs are funds that invest in companies that support environmentally responsible technologies or are involved with research, development, production and provision of alternative energy and possess positive environmental, social and corporate governance (ESG) characteristics. Due to the increasing interest in sustainable economic development and due to the increased financialization of green energy coupled with the interest of investors in this asset class, see e.g. the recent study in [4] and references therein, it is relevant to analyse in more detail the risk and performance of green ETFs, since one can find only few contributions addressing this issue. Sabbaghi [5] investigated the time-series behaviour of green exchange traded fund returns and their associated conditional volatility dynamics using the GARCH methodology. In [6],

Sabbaghi constructed an equally-weighted portfolio of green ETFs and analysed its return performance (using e.g. mean, standard deviation, Jensen's alpha) and compared it to that of the S&P500 index over different sub-periods in time from 2005 to 2010, before and after the financial market collapse of 2008. He found that the portfolio outperformed the S&P500 index prior to the financial collapse, however the portfolio was highly volatile and underperformed the S&P500 index in the period after the collapse. Tsolas and Charles [7] investigated the performance of green ETFs using data envelopment analysis. Rizvi et al. [4] studied the relationship between green and grey energy ETFs and concluded that green energy is more prominent in determining the returns in the US equity market.

The objective of the present work is to analyse the risk and performance of green ETFs using the recently proposed EU–EV risk model and evaluate their performance using different metrics. The EU–EV risk model, developed in [8],[9], can be used for classifying stock risks and for the preselection of the best ranked stocks in order to construct optimum portfolios with a reduced number of stocks (see [10],[11]). The aim is now to apply the EU–EV risk model to green ETFs in order to assess their risk (using expected utility, entropy and variance) and in order to investigate the capability of the risk model to select the efficient funds for investment purposes. Data of a sample of 14 green ETFs from 2008 to 2010 are used, that were analysed in earlier literature ([6],[7]). The ETFs are ranked according to their risk and different equally-weighted portfolios are formed. The portfolios' performances are analysed and compared with the S&P500 index considering different time periods.

This paper is structured as follows. Section 2 contains the definitions of the EU–EV risk model and of the performance measures and explains how the ETF portfolios are constructed and their performances are evaluated. In section 3, the proposed method is applied to the sample of 14 green ETFs. The risks of the ETFs are analysed, different portfolios are formed with the best ranked ETFs and their performances are compared with those of the benchmark in the in-sample period and in different out-of-sample time intervals. The paper ends with the Conclusions in section 4.

2 ETF Portfolio Construction and Performance Evaluation

In order to construct the ETF portfolios, the EU–EV risk model will be used to select the best ranked ETFs from an initial given set of ETFs. The selected ETFs will then be used to build equally weighted portfolios, whose performance is then analysed using different performance metrics.

2.1 EU-EV Risk Model

Consider a set of ETFs $S = \{S_1, \dots, S_I\}$ and the action space $A = \{a_1, \dots, a_I\}$, where

$$a_i = (x_{i1}, p_{i1}; x_{i2}, p_{i2}; \dots; x_{iN}, p_{iN}) \in A$$

is the action of selecting the ETF S_i , $i = 1, \dots, I$, yielding the frequency distribution of returns, where x_{in} are the outcomes, occurring with probabilities p_{in} , $n = 1, \dots, N$, represented by the random variable X_i . The EU–EV risk of the action a_i depends on the corresponding returns' distribution with random variable X_i as follows.

Definition 1 (EU–EV risk). *The EU–EV risk for the action a_i with associated random variable X_i is defined by*

$$R_\lambda(X_i) = \frac{\lambda}{2} \left[H(X_i) + \frac{\text{Var}[X_i]}{\max_{a_i \in A} \{\text{Var}[X_i]\}} \right] - (1 - \lambda) \frac{\mathbb{E}[u(X_i)]}{\max_{a_i \in A} \{|\mathbb{E}[u(X_i)]|\}},$$

where $0 \leq \lambda \leq 1$, $u(x) = \begin{cases} \ln(1+x), & x \geq 0 \\ -\ln(1-x), & x < 0 \end{cases}$ is the utility function and $H(X_i) = -\sum_{n=1}^N p_{in} \ln p_{in}$ is the entropy.

The constant λ is a trade-off parameter that combines the expected utility and the uncertainty reflected by entropy [12] and variance [13] and it can be used to express the different risk attitudes of decision-makers (see [9] for more details). If $\lambda < 0.5$, then more weight is given to the expected utility term, which corresponds to a risk-averse attitude [14]. If $\lambda > 0.5$, more weight is given to the uncertainty component and this reflects a risk-seeking behaviour. The trade-off parameter is used in the model for: building portfolios that strike a balance between risk and return (portfolio risk models), understanding and navigating uncertainty in financial markets (entropy and uncertainty), evaluating the fluctuation and potential dangers associated with assets and derivatives (variance). Gaining a solid grasp of these concepts enables investors and financial professionals to make well-informed decisions, effectively manage risk, and maximise the potential of their portfolios.

The ETFs are classified with the EU–EV risk model by ranking them according to the following rule. Given two ETFs S_{i_1} and S_{i_2} , $i_1, i_2 \in \{1, \dots, I\}$, if

$$R_\lambda(X_{i_1}) < R_\lambda(X_{i_2}),$$

then S_{i_1} is preferred over S_{i_2} (which can be written as $S_{i_1} \succ S_{i_2}$), since S_{i_1} has lower EU–EV risk than S_{i_2} .

For $\lambda \in [0, 1]$, we will select from the set S the $I/2$ best ranked ETFs and form subsets (with the initial number of funds reduced to the half) for the different values of λ . With these subsets we will construct equally weighted portfolios, whose performance will then be compared with those of the equally weighted portfolio consisting of all I funds and with a benchmark portfolio. According to results presented in earlier literature, for example in [15], [16], using equal-weighted strategies lead to portfolios outperforming value-weighted strategies, therefore we opted to use equal weights in the portfolio construction.

2.2 Performance Measures

The following performance measures (see e.g. [17],[18]) will be used to analyse the performance of the portfolios in different time periods.

Definition 2 (Maximum Drawdown). *The Maximum Drawdown (MDD) is the largest percentage drop in total returns from the start to the end of a period, computed over all intervals of time that can be formed within a specified interval of time, and it is defined as follows. Let x_t , $t = 1, \dots, T$, represent the daily cumulative returns of the portfolio. The Maximum Drawdown is given by*

$$MDD = \frac{PV - LV}{PV},$$

where $LV = x_t^*$, the lowest point value (trough value), and $PV = x_{t,\max}^*$, the peak value, are the values that maximize the drawdown

$$DD_t = \frac{x_{t,\max} - x_t}{x_{t,\max}},$$

where $x_{t,\max} = \max\{x_s : s = 1, \dots, t\}$ for $t = 1, \dots, T$. A lower MDD value indicates a lesser degree of risk.

In the following definitions, r_P represents the expected return of the portfolio, σ_P is the standard deviation of the portfolio returns and r_f is the risk-free rate. We will consider $r_f = 0$, meaning that the rate of return of a zero risk benchmark investment is taken to be equal to zero.

Definition 3 (Sharpe ratio, Sortino ratio, Beta). *The Sharpe ratio measures the excess return (the return of the portfolio less the risk-free rate of interest) per unit of total risk of the portfolio (the standard deviation of the portfolio's returns) and is defined by*

$$\text{Sharpe} = \frac{r_P - r_f}{\sigma_P}.$$

The Sharpe ratio with $r_f = 0$ quantifies the relation between the expected returns and the standard deviation of the returns of the portfolio. Portfolios with higher Sharpe ratios perform better according to this measure.

The Sortino ratio is a modification of the Sharpe ratio, where only the downside deviation is taken into account, and is expressed by

$$\text{Sortino} = \frac{r_P - r_f}{\sigma_P^-},$$

where σ_P^- represents the standard deviation of the negative portfolio returns. A higher Sortino ratio indicates a better performance.

The risk metric Beta determines the risk or volatility of a portfolio by comparing it to the market and is defined by

$$\text{Beta} = \frac{\text{Cov}(r_P, r_S)}{\sigma_S^2},$$

where $\text{Cov}(r_P, r_S)$ is the covariance between the expected return of the portfolio and the expected market return r_S of the benchmark S , and σ_S^2 corresponds to the variance of the market returns. Portfolios having $\text{Beta} > 1$ can be interpreted to be more volatile or riskier than the benchmark. If $\text{Beta} < 1$, the portfolio is less volatile than the benchmark. If $\text{Beta} = 1$, it has the same volatility as the benchmark.

Definition 4 (Alpha). *Jensen's Alpha is a performance metric that measures the portfolio return relative to the market return and is defined by*

$$\text{Alpha} = r_P - [r_f + \text{Beta}(r_S - r_f)],$$

where Beta is given in Definition 3. A value of $\text{Alpha} > 0$ indicates that the portfolio has performed better than the market index. If $\text{Alpha} < 0$, the portfolio has underperformed the market index. If $\text{Alpha} = 0$, the portfolio's performance is in line with that of the market.

3 Application to Green ETFs

The aim is to apply the EU-EV risk model to the selection of funds from a sample of 14 green ETFs in order to investigate if the EU-EV model adequately selects the relevant ETFs for an efficient portfolio construction with a reduced number of ETFs. Data of a sample of 14 green ETFs (with ticker symbols PBW, PHO, PUW, PKN, PIO, PZD, EVX, NLR, FIW, QCLN, CGW, DSI, KLD, PBD), described in [6] and [7], in the in-sample period from January 2008 to December 2010 are used.

3.1 Portfolio Construction

From each green ETF S_i , $i = 1, \dots, 14$, the daily closing prices $\{P_{i0}, \dots, P_{iT}\}$, $T + 1 = 756$, from January 2008 to December 2010 are collected. The daily returns are calculated by

$$r_{it} = \ln \left(\frac{P_{it}}{P_{i(t-1)}} \right); \quad i = 1, \dots, 14; \quad t = 1, \dots, 755.$$

The frequency distribution of returns is determined as follows. The interval $[r_{\min}, r_{\max}] = [-1.0114, 1.0205]$ where $r_{\min} = \min_{1 \leq i \leq 14} \{r_{i1}, \dots, r_{i755}\}$ and $r_{\max} = \max_{1 \leq i \leq 14} \{r_{i1}, \dots, r_{i755}\}$, is divided into $N = 19$ subintervals J_n , $n = 1, \dots, N$, of length $\Delta = \frac{r_{\max} - r_{\min}}{N} = 0.10694$. Then, the relative frequency of the return of S_i in the subinterval J_n is calculated by

$$p_{in} = \frac{|\{r_{it} \in J_n : t = 1, \dots, T\}|}{T}$$

and the expected return of S_i from the subinterval J_n is estimated by

$$x_{in} = \frac{1}{|\{r_{it} \in J_n : t = 1, \dots, T\}|} \sum_{\substack{r_{it} \in J_n \\ t=1, \dots, T}} r_{it},$$

where $|\cdot|$ represents the cardinality of a set.

The EU–EV risks for each fund S_i , $i = 1, \dots, 14$, will then be determined using the frequency distributions.

Table 1 contains the EU–EV risks for the 14 green ETFs for certain values of λ ($\lambda = 0, 0.5, 0.75, 0.85, 1$). For each value of λ , the 7 lower risk values are highlighted in bold.

Table 1. EU–EV risks for $\lambda = 0, 0.5, 0.75, 0.85, 1$.

Fund Ticker	$R(a_i)$				
	$\lambda = 0$	$\lambda = 0.5$	$\lambda = 0.75$	$\lambda = 0.85$	$\lambda = 1$
S_1 PBW	1.0000	0.5934	0.3901	0.3088	0.1868
S_2 PHO	0.0894	0.0989	0.1037	0.1056	0.1085
S_3 PUW	-0.0072	0.0636	0.0991	0.1132	0.1345
S_4 PKN	0.1541	0.4380	0.5800	0.6367	0.7219
S_5 PIO	0.1917	0.1404	0.1147	0.1044	0.0890
S_6 PZD	0.2849	0.2022	0.1609	0.1443	0.1195
S_7 EVX	-0.0386	0.0147	0.0414	0.0521	0.0681
S_8 NLR	0.3383	0.2189	0.1593	0.1354	0.0996
S_9 FIW	-0.0410	0.0231	0.0551	0.0680	0.0872
S_{10} QCLN	0.6343	0.4011	0.2846	0.2380	0.1680
S_{11} CGW	0.2021	0.1407	0.1100	0.0977	0.0793
S_{12} DSI	0.0787	0.0757	0.0742	0.0736	0.0727
S_{13} KLD	0.0806	0.0657	0.0582	0.0552	0.0570
S_{14} PBD	0.8447	0.5029	0.3320	0.2636	0.1611

Considering the range of $\lambda \in [0, 1]$, one can form the following 5 different subsets

$$\begin{aligned}
G_{7,\lambda=0} &= \{\text{PHO, PUW, PKN, EVX, FIW, DSI, KLD}\}, & \lambda \in [0, 0.0561) \\
G_{7,\lambda=0.5} &= \{\text{PHO, PUW, PIO, EVX, FIW, DSI, KLD}\}, & \lambda \in [0.0561, 0.5175) \\
G_{7,\lambda=0.75} &= \{\text{PHO, PUW, EVX, FIW, CGW, DSI, KLD}\}, & \lambda \in [0.5175, 0.8139) \\
G_{7,\lambda=0.85} &= \{\text{PHO, PIO, EVX, FIW, CGW, DSI, KLD}\}, & \lambda \in [0.8139, 0.9655) \\
G_{7,\lambda=1} &= \{\text{PIO, EVX, NLR, FIW, CGW, DSI, KLD}\}, & \lambda \in [0.9655, 1],
\end{aligned}$$

where the best 7 funds with lower risk were selected, with λ belonging to the intervals $[0, 0.0561)$, $[0.0561, 0.5175)$, $[0.5175, 0.8139)$, $[0.8139, 0.9655)$, $[0.9655, 1]$. Each particular value of λ in Table 1 belongs to one of these intervals, so that the notations $G_{7,\lambda=0}$, $G_{7,\lambda=0.5}$, $G_{7,\lambda=0.75}$, $G_{7,\lambda=0.85}$ and $G_{7,\lambda=1}$ are used to represent the different sets.

The portfolios are constructed as equal weighted combinations of the seven best ranked funds from the five sets. The portfolios will be denoted by $G_{7,\lambda=0}$, $G_{7,\lambda=0.5}$, $G_{7,\lambda=0.75}$, $G_{7,\lambda=0.85}$ and $G_{7,\lambda=1}$.

In the following analysis, we will use the S&P500 index as benchmark portfolio. We will also consider the equal-weighted portfolio G_{14} formed with all 14 green ETFs

$$G_{14} = \{\text{PBW, PHO, PUW, PKN, PIO, PZD, EVX, NLR, FIW, QCLN, CGW, DSI, KLD, PBD}\}$$

and the equal-weighted portfolio G_4 formed with the green ETFs of the set

$$G_4 = \{\text{EVX, NLR, FIW, CGW}\},$$

These ETFs were identified in an earlier study (see [7]) as top efficient ETFs using data envelopment analysis.

3.2 Performance Evaluation

The performance of the five portfolios constructed with the best ranked ETFs will be analysed and compared with the performance of the G_{14} and G_4 portfolios and with the S&P500 benchmark portfolio, first in the in-sample period from January 2008 to December 2010 and then in different out-of-sample periods, from January 2011 to December 2020, with one-year, two-year, five-year and ten-year time horizons. For that puprpose, the cumulative returns are calculated in the mentioned time periods, along with the metrics presented in Section 2.2, using the S&P500 index as benchmark S .

Considering the in-sample period from January 2008 to December 2010, Figure 1 contains the cumulative returns in that time interval and Table 2, the results of the different metrics (where in the following tables the values corresponding to the best performances are highlighted in bold). One can observe that $G_{7,\lambda=0}$ is the best performing portfolio according to all performance indicators, yielding the highest cumulative returns and this with the lowest volatility according to Beta. The G_{14} portfolio is the second best performing portfolio taking into account the cumulative returns, the Alpha, Sharpe and Sortino metrics, however, achieved with the highest volatility in terms of Beta and it has the highest maximum drawdown. The evolution of the cumulative returns of the remaining portfolios is very similar to the evolution of the benchmark's cumulative returns. Since the ETFs of $G_{7,\lambda=0}$ were selected with the EU-EV model privileging higher expected utility and almost ignoring variance and entropy in the given period, one would expect a better performance this portfolio in terms of higher returns with respect to the other portfolios in the same period and this is consistent with the obtained results.

In the one-year and two-year out-of-sample periods from 2011 to 2012, the results seem to indicate that $G_{7,\lambda=0}$ followed by S&P500 are the best performing portfolios. This is evident from the performance measures in Table 3 and Table 4,

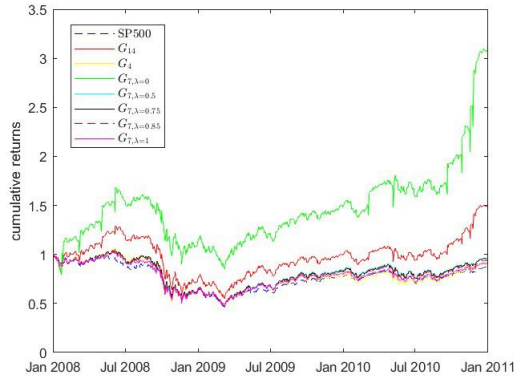


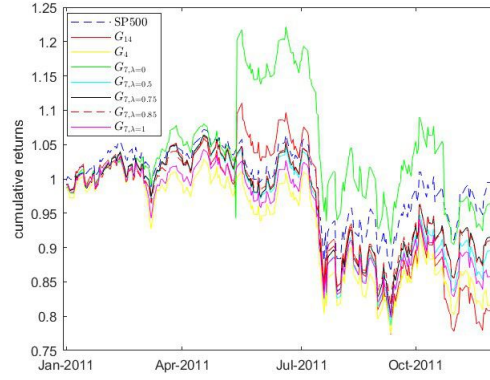
Fig. 1. Cumulative returns from January 2008 to December 2010.

Table 2. Performance measures from January 2008 to December 2010.

	MDD	Sharpe	Sortino	Beta	Alpha
S&P500	0.5325	-0.0019	-0.0024	1.0000	0.0000
G_{14}	0.5704	0.5363	0.7863	1.0164	0.2402
G_4	0.5647	0.0510	0.0632	0.9447	0.0168
$G_{7,\lambda=0}$	0.4890	0.9670	1.6931	0.8925	0.6630
$G_{7,\lambda=0.5}$	0.5522	0.1161	0.1480	0.9771	0.0381
$G_{7,\lambda=0.75}$	0.5514	0.1111	0.1396	0.9798	0.0365
$G_{7,\lambda=0.85}$	0.5480	0.0807	0.1035	0.9409	0.0255
$G_{7,\lambda=1}$	0.5504	0.0425	0.0538	0.9779	0.0133

where only the maximum drawdown is now the lowest one for S&P500. The portfolio $G_{7,\lambda=0}$ achieves higher cumulative returns for a larger time interval in 2011 (see Figure 2). However, there are also time periods where S&P500 exhibits higher returns (in the first quarter and in the last quarter of that year). In 2012 (see Figure 3), the S&P500 benchmark portfolio outperforms the other portfolios in terms of cumulative returns for a wider time range in 2012 (only in the last quarter of 2012 the portfolio $G_{7,\lambda=0}$ surpasses again the benchmark). Both in the one-year and two-year periods, the portfolios G_{14} , G_4 and $G_{7,\lambda=1}$ underperform the remaining portfolios. All portfolios are more volatile than S&P500.

In the five-year out-of-sample period from 2011 to 2015, now, in contrast to the other out-of-sample periods, it is S&P500 that exhibits the best Sharpe and Sortino ratios and the lowest maximum drawdown (see Table 5), only the Alpha value is higher for $G_{7,\lambda=0}$, which also yields the higher cumulative returns (see Figure 4).

**Fig. 2.** Cumulative returns for 2011.**Table 3.** Performance measures for 2011.

	MDD	Sharpe	Sortino	Beta	Alpha
S&P500	0.1939	0.0663	0.0850	1.0000	0.0000
G_{14}	0.3032	-0.5402	-0.7855	1.1621	-0.1742
G_4	0.2492	-0.6656	-0.0159	1.0523	-0.1741
$G_{7,\lambda=0}$	0.2594	0.0820	0.1309	1.0721	0.0165
$G_{7,\lambda=0.5}$	0.2606	-0.3128	-0.4320	1.0934	-0.0947
$G_{7,\lambda=0.75}$	0.2476	-0.2355	-0.3283	1.0820	-0.0752
$G_{7,\lambda=0.85}$	0.2326	-0.2671	-0.3708	1.0514	-0.0803
$G_{7,\lambda=1}$	0.2349	-0.5135	-0.6958	1.0249	-0.1337

Table 4. Performance measures from January 2011 to December 2012.

	MDD	Sharpe	Sortino	Beta	Alpha
S&P500	0.1939	0.3610	0.4598	1	0
G_{14}	0.3090	0.0110	0.0159	1.1402	-0.0714
G_4	0.2492	-0.1570	-0.2143	1.0661	-0.1003
$G_{7,\lambda=0}$	0.2594	0.5742	0.9511	1.0131	0.1265
$G_{7,\lambda=0.5}$	0.2606	0.1333	0.1797	1.0925	-0.0443
$G_{7,\lambda=0.75}$	0.2476	0.1929	0.2620	1.0814	-0.0318
$G_{7,\lambda=0.85}$	0.2326	0.1910	0.2595	1.0489	-0.0325
$G_{7,\lambda=1}$	0.2349	-0.0527	-0.0707	1.0328	-0.0772

Considering the evolution of the cumulative returns in the ten-year out-of-sample period from 2011 to 2020 (see Figure 5), one can observe that from 2016 onwards the cumulative returns of $G_{7,\lambda=0}$ increase notably. The portfolio G_{14}

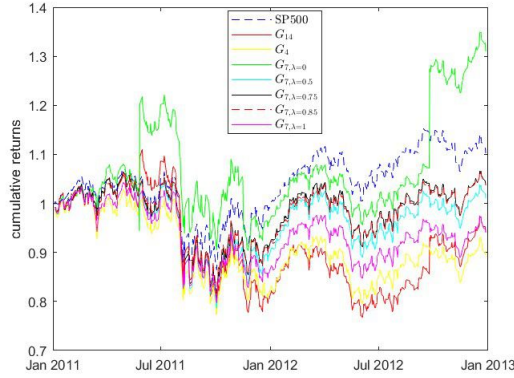


Fig. 3. Cumulative returns from January 2011 to December 2012.

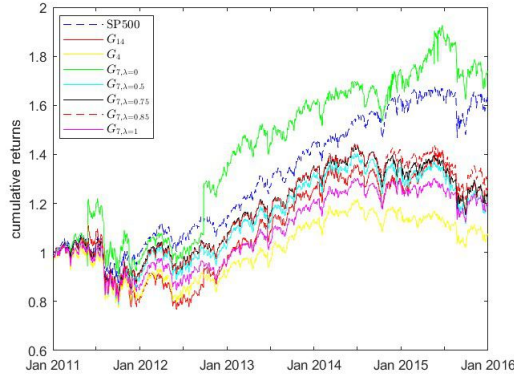


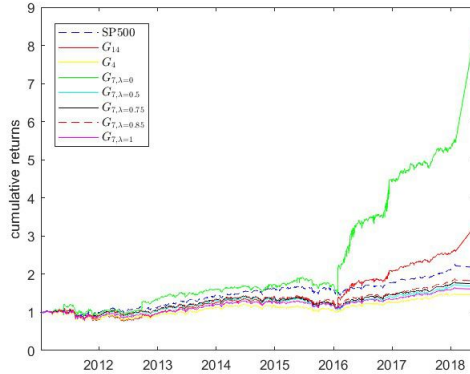
Fig. 4. Cumulative returns from January 2011 to December 2015.

replicates this behaviour in the same period with a lower increasing rate and its cumulative returns surpass the S&P500 returns. Therefore, from 2016 to 2020 the best performing portfolios are $G_{7,\lambda=0}$ and G_{14} , followed by S&P500. The other portfolios underperform the benchmark in this time interval. The performance measures indicate that $G_{7,\lambda=0}$ is in fact the best performing portfolio (see Table 6). The portfolio G_{14} has the second best Sortino and Alpha, whereas S&P500 has the lowest maximum drawdown and the second best Sharpe ratio. In all time periods, G_4 is the poorest performing portfolio. Although this portfolio contains the most relevant ETFs, a higher number of ETFs is necessary to build a sufficiently diversified portfolio in order to improve the performance.

Table 5. Performance measures from January 2011 to December 2015.

	MDD	Sharpe	Sortino	Beta	Alpha
S&P500	0.1939	0.7124	0.9211	1	0
G_{14}	0.3090	0.3326	0.4706	1.0583	-0.0492
G_4	0.2492	0.1660	0.2187	0.9333	-0.0726
$G_{7,\lambda=0}$	0.2594	0.5777	0.9091	0.9348	0.0356
$G_{7,\lambda=0.5}$	0.2606	0.2972	0.3989	1.0178	-0.0601
$G_{7,\lambda=0.75}$	0.2476	0.3382	0.4553	1.0053	-0.0530
$G_{7,\lambda=0.85}$	0.2326	0.4167	0.5622	0.9838	-0.0403
$G_{7,\lambda=1}$	0.2349	0.3090	0.4074	0.9523	-0.0546

In general, since the portfolio $G_{7,\lambda=0}$ is the best performing portfolio for short-term and long-term investments, the results suggest that successful portfolios can be built by selecting half the number of the best ETFs in terms of EU-EV risk by weighting more the expected utility (using a trade-off factor close to zero).

**Fig. 5.** Cumulative returns from January 2011 to December 2020.

4 Conclusions

In this paper, we have applied the EU–EV risk model to a set of 14 green ETFs and selected the best classified funds to build equally weighted ETF portfolios with half of the funds of the initial set. The EU–EV risk model assesses the funds by weighting differently through a trade-off parameter the expected utility, entropy and variance of the corresponding returns. Based on daily return

Table 6. Performance measures from January 2011 to December 2020.

	MDD	Sharpe	Sortino	Beta	Alpha
S&P500	0.1939	0.8585	1.0847	1	0
G_{14}	0.3090	0.8241	1.4012	1.0155	0.0761
G_4	0.2492	0.4417	0.5749	0.9064	-0.0437
$G_{7,\lambda=0}$	0.2594	0.9533	2.0308	0.8717	0.2990
$G_{7,\lambda=0.5}$	0.2606	0.5360	0.7419	1.0168	-0.0358
$G_{7,\lambda=0.75}$	0.2476	0.5985	0.7906	1.0062	-0.0302
$G_{7,\lambda=0.85}$	0.2326	0.6575	0.8687	0.9797	-0.0217
$G_{7,\lambda=1}$	0.2349	0.5499	0.7117	0.9381	-0.0349

data from January 2008 to December 2010, five portfolios were constructed for different values of the trade-off factor. The performance of these portfolios has been analysed and compared with the benchmark S&P500 portfolio and with two other green ETF portfolios, one built with the entire set of green ETFs and another consisting of only four green ETFs. The performance analysis was carried out for the in-sample period and for different out-of-sample periods, starting in January 2011 with one-year, two-year, five-year and ten-year time horizons.

The results of the performance evaluation show that the portfolio built with the seven best classified green ETFs according to the EU–EV risk model with very low values of the trade-off factor, thus weighting very more the expected utility and almost devaluing the variance and entropy, outperforms the benchmark in terms of cumulative returns, Sharpe, Sortino and Alpha in the in-sample period and in the out-of-sample periods of one year, two years and 10 years. Only the maximum drawdown in the out-of-sample periods was lower for the benchmark portfolio, which exhibited better Sharpe and Sortino ratios in the five-year out-of-sample period.

The results indicate that the methodology of constructing ETF portfolios using the best ranked ETFs with to the EU–EV risk model can be useful for investment objectives. A more thorough analysis should however be conducted in the future by applying the methodology to markets with more ETFs, considering different in-sample periods and different time horizons for the out-of-sample period.

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