A TWO-STAGE APPROACH FOR PROMOTING SUSTAINABLE INVESTMENT

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A two-stage approach for promoting sustainable investment

Abstract

The popularity of sustainable assets (stocks and bonds) has increased in recent years and especially since the launch of the 17 Sustainable Development Goals (SDGs) included in the UN 2030 Agenda. In that context, there are investors who want to make their conventional portfolios more sustainable but do not know how to obtain higher returns and less risk than in their previous portfolios. In this study, we show that the best way to improve portfolio performance is not simply to add sustainable assets to a conventional portfolio but rather to select the best ones and choose the right proportions for them. For that reason, we suggest a two-stage approach which combines a screening test and an optimization model. Our results, based on the use of indices that track conventional and sustainable stocks and bonds, show that the best performing portfolio is that in which sustainable assets account for the majority.

1. Introduction

Sustainable investment has increased significantly in recent years, especially since the launching of the United Nation's Sustainable Development Goals in September 2015. Nowadays, investors pay much more attention to climate change, the efficient use of resources and sustainable issues in general. In this context, different sustainable financial investment instruments have appeared such as investing in renewable energy or healthcare companies and also green bonds.

These assets are suitable for investors concerned about making green investments and wanting to incorporate ethical or social approaches, such as Environmental, Social and Governance (ESG) or Sustainable Responsibility Investing (SRI), in their portfolios. Baietti et al. (2012) and Voica et al. (2015) show that there are some non-financial and reputational reasons for choosing these assets. However, there are also some impediments such as fossil fuel subsidies, high costs and long payback periods for green investments and revenue risks due to uncertainty about new technologies, among others, and these could make green investments unattractive to investors. Furthermore, there is still the classical investment option of investing in conventional stocks and bonds which traditionally has been profitable for investors. Therefore, at this point there is a question about whether it is possible to create a portfolio of global (conventional and green) stocks and bonds which does not have lower returns and less risk than an equally weighted one (naïve) of conventional assets which has been the classic benchmark in previous empirical studies.

A crucial factor in achieving success and composing the best performing portfolio is defining the appropriate methodology. Previous studies have often employed complex methodologies that are not feasible for normal investors who commonly face serious restrictions in terms of analysis and technical approaches. In order to overcome that problem, we suggest the combination of screening and an optimization model (mean-variance) as the optimal way to identify the best assets for a portfolio and their proportions. Both approaches have been widely employed in the previous empirical literature, see Billio et al. (2015), Carneiro and Leal (2017), Leon et al. (2019) and Miralles-Quirós et al. (2019) among others. However, to the best of our knowledge they have not been combined in order to estimate the optimal weight of each asset in a portfolio.

We employ different indices for conventional and sustainable stocks and bonds and show that it is possible to obtain clear performance improvements, compared to the benchmark, when a combined screening and asset allocation procedure is employed. Furthermore, we show that the weight of sustainable investment in the most efficient portfolio is higher than that of conventional assets in most cases but that conventional assets must still be included in efficient portfolios, especially Treasury bonds. Therefore, investors have an incentive for investing in sustainable assets because this is profitable and also helps create a better world, always keeping conventional assets in mind and in their portfolios.

The rest of the paper is organized as follows. In Section 2, we describe the previous empirical evidence and theoretical background for this paper by explaining the methodology employed to construct and evaluate alternative portfolios. In Section 3, we define the database and analyze the descriptive statistics. In Section 4, we report the empirical results for the proposed portfolios. In Section 5, we show the robustness test results. Finally, Section 6 contains the main conclusions.

2. Literature review

Portfolios of conventional stocks and bonds have been commonly included in investors' asset allocations due to their low correlation. However, Gomes and Taamout

(2016), Perego and Vermeulen (2016), Cao et al. (2017) and, more recently, Miralles-Quirós et al. (2019) show that correlation varies over time so these conventional portfolios may not be as profitable as they once were. Additionally, in the transition to the new economy it is also interesting to consider green assets in investors' portfolios in order to achieve the Sustainable Development Goals established by the United Nations and, therefore, continue the economic and investment transformation towards a cleaner and, hopefully, a better performing portfolio.

MacAskill et al. (2021) point out that the introduction of the first green bond in 2007 was the start of the process connecting capital markets to green investments. In addition, the launch of the United Nations Principles for Responsible Investment in April 2006, as is pointed out by Cunha et al. (2020), and the first country-specific sustainability index launched by the London Stock Exchange in 2001, helped to develop empirical evidence on socially responsible investment, sustainable development goals and green investment and on analyzing the performance of these investments compared to conventional portfolios.

Ortas and Moneva (2013) show that the financial performance of clean technology equity indices is better than that of conventional ones. Reboredo (2018) states that green bonds are gaining popularity among environment-conscious investors and those who are concerned about climate change. However, Climent and Soriano (2011) and Reboredo et al. (2017) find evidence of underperformance by green investments compared to other alternatives and, more recently, Kanamura (2020) analyzes the performance of green bonds compared to conventional bonds and finds that the investment performance of green bonds is superior but decaying over time.

Most of the previous empirical evidence analyzing portfolio performance is focused on scrutinizing time varying correlations or employing, as was mentioned previously, complicated approaches that are not practical for normal investors. However, there are also studies proposing easier methodologies such as the study by Billio et al. (2015) who propose the use of optimal combinations of performance measures where the combination of weights is derived from an optimization problem. They also showed that their proposed composite performance index provided superior results in terms of realized returns than a naïve (equally weighted) portfolio. Carneiro and Leal (2017) formed equally weighted portfolios according to the lowest or highest values of different ratios, related to the Fama and French (1993) factors, for a previous period and found that these portfolios frequently outperformed the benchmark. León et al. (2019) also analyzed whether different portfolio measures generate different subsequent returns by using a fixed one-year rolling window of past returns to estimate the measures and then selecting the assets to create an equally weighted portfolio. Their results show that the screening rule influences portfolio returns.

More recently, Miralles-Quirós et al (2019) use a spanning strategy where different socially responsible assets are added to a stock-bond portfolio and they find that it is possible for investors to obtain benefits from investing in these companies. Finally, Cunha et al. (2020) analyze the performance of different sustainability indices and compare them with their respective benchmarks, concluding that investment performance is still heterogeneous worldwide. In view of this empirical evidence, there is a need to continue advancing in order to inform investors of the best way to improve their portfolio performance and contribute to a better and greener economy.

3. Theoretical background

We have followed the spirit of Billio et al. (2015), Carneiro and Leal (2017) and León et al. (2019) by proposing an approach where in the first stage investors evaluate the performance measures of a group of assets, ten in our case, at time t and use the outcome to select the best ones, five of them, to hold at time t+1.

The most widely used ratio is the Sharpe ratio, proposed by Sharpe (1966). This measures the relationship between excess return and standard deviation for an asset. The higher the Sharpe ratio, the better the return on the fund given the amount of risk taken. This ratio is calculated as follows:

$$\text{Sharpe} = \frac{E(R_i) - R_f}{\sigma_i} \tag{1}$$

where $E(R_i)$ denotes the expected return on asset i, R_f is the risk-free rate and σ_i is the standard deviation of the asset returns.

This ratio is an optimal performance measure under a normal distribution assumption. However, stock market assets, such as shares and funds, frequently generate returns that have non-normal distributions. Additionally, there are other ratios which differ from the Sharpe one in terms of the measure used to quantify risk, as was highlighted by Eling and Schuhmacher (2007), Bacon (2008) and Auer and Schuhmacher (2013). Examples include the Treynor, Omega, Sortino, Kappa and Calmar ratios. However, these ratios do not take extreme events into account because they occur very infrequently. Nonetheless, Value at Risk, which describes the possible loss of an investment over a given period for a given confidence interval, quantifies this risk. Following Dowd (2000), Favre and Galeano (2002), Alexander and Baptista (2003) and Eling and Schuhmacher (2007), among others, who propose the Excess Return on Value at Risk ratio as a performance measure, we also adopt it as a supplement to the Sharpe ratio.

$$\text{Excess return on VaR}\left(\text{Eron var}\right) = \frac{E(R_i) - R_f}{\text{VaR}_i} \tag{2}$$

In both cases we calculate the performance measures using a rolling window of 252 days (approximately one stock market year). Once these have been estimated for all assets, we select the best five for each performance measure. We opt for small portfolio sizes because we agree with Carneiro and Leal (2017) who use small portfolios due to their focus on individual investors. It is inappropriate for these investors to hold a well-diversified portfolio with a large number of assets, mainly because calculating this is not feasible for them. Additionally, it is important to point out that small portfolio sizes allow investors to reduce transaction costs.

The second stage of this procedure is to estimate the asset allocations in the portfolio for those assets selected in the first stage. Previous empirical evidence does not estimate any portfolio optimization weights for these assets. Instead, an equal weight system is commonly adopted. In contrast to that procedure, we opt for estimating a mean-variance optimization portfolio where the equally weighted portfolio (naïve) of the assets selected in the first stage is used as the target portfolio return constraint.

Therefore, the optimization problem, proposed by Markowitz (1952), is given by:

$$
\begin{aligned}
&\min_{w_t} \quad w_t' \, H_{t+1|t} \, w_t \\
&\text{s.t.} \quad w_t' E\{R_{t+1}\} \geq R^*
\end{aligned}
\tag{3}
$$

where R^* denotes the desired target return performance.

Moreover, following Santos et al. (2012), Harris and Mazibas (2013), Guidi and Ugur (2014), and Miralles-Quirós and Miralles-Quirós (2017), among others, short selling is excluded from the optimization problems. Therefore, we employ the following constraints:

$$
w_t' 1 = 1 \quad w_i \geq 0 \quad i = 1,2, \ldots, N \tag{4}
$$

where w_i is the weight of each asset in the portfolio vector, $w_t = [w_1, w_2, \ldots, w_N]$, and **1** is a vector of ones. Portfolios are rebalanced monthly, quarterly and annually. In all cases the vector of expected returns as well as the variance-covariance matrix are calculated using a rolling window of 252 days.

All portfolios are evaluated by calculating the cumulative return and the Sharpe and Omega ratios. It should be noted that the cumulative returns obtained from natural logarithm returns are transformed into simple returns by using the relationship $R_{pt} = e^{r_{pt}} - 1$ where R_{pt} is the simple return of the portfolio strategy and r_{pt} is the portfolio strategy return using natural logarithms.

Shadwick and Keating (2002) proposed the Omega ratio which is defined as:

$$
\text{Omega} = \frac{E(R_i) - R_f}{LPM_{1i}(\tau)} + 1 \tag{5}
$$

The numerator of this performance measure is different to the Sharpe ratio because Lower Partial Moment (LPM) is employed. This measure, which was first proposed by Bawa and Lindenberg (1977), only considers negative deviations of returns from a minimal acceptable return or threshold. This is different to standard deviation which considers both positive and negative deviations from the expected return.

$$
LPM_{ni}(\tau) = \frac{1}{T} \sum_{t=1}^{T} \max\left[\tau - r_{it}, 0\right]^n \tag{6}
$$

where τ is the minimum acceptable return (zero in our case) and n is the order of the lower partial moment which can be interpreted.

4. Database

The data used in this paper are daily returns from January 3, 2011 through September 30, 2020 (amounting to 2,453 usable observations) for ten S&P indices which provide liquid and tradable exposure to different companies involved in conventional, environmental, social and responsible businesses but also those which track the global green bond market and measure the performance of US Treasury bonds maturing in 5 to 10 years. The main reason for using indices is that they are all capable of being tracked by investors and additionally there are a large number of index-linked products that replicate them.

Table 1 shows the name and ticker of each index and Table 2 reports the summary statistics of their returns, calculated as the differences between two consecutive natural logarithms. In order to avoid different standards, all these indices are obtained from S&P Dow Jones Indices. Finally, Figure 1 displays the closing price graphs for the different indices over the sample period.

As shown in Table 1, the indices chosen to represent green investments are the following: S&P 500 ESG Index (SPXESUP), Health Care Select Sector (IXV), S&P Global Clean Energy Index (SPGTCED), S&P Global Water Index (SPGTAQD) and S&P Green Bond Index (SPUSGRN). All of these have strategies focused on investing in companies working to achieve the Sustainable Development Goals and, therefore, we can consider them to be green investments. On the other hand, we have included five indices that track major economic segments, those considered as conventional or traditional, and that are highly liquid benchmarks: Energy Select Sector (IXE), Financials Select Sector (IXM), Industrials Select Sector (IXI), Materials Select Sector (IXB) and S&P U.S. Treasury Bond 5-10 Year Index (SPBDUSBT).

Table 1: Indices

Index Type	Index Name	Ticker
Green Investment	S&P Green Bond Index	SPUSGRN
	S&P 500 ESG Index	SPXESUP
	Health Care Select Sector	IXV
	S&P Global Clean Energy Index	SPGTCED
	S&P Global Water Index	SPGTAQD
Conventional	Energy Select Sector	IXE
	Financials Select Sector	IXM
	Industrials Select Sector	IXI
	Materials Select Sector	IXB
	S&P U.S. Treasury Bond 5-10 Year Index	SPBDUSBT

From the results reported in Table 2 we can observe that the highest mean returns are provided by two green indices, namely the S&P 500 ESG Index (SPXESUP) and Health Care Select Sector (IXV), but in general the conventional indices provide higher mean returns than the green ones. There is only one index, Energy Select Sector (IXE), with a negative mean return due to the sharp upward and downward movements in this sector over the sample period. However, on the basis of the Anova test we do not reject the null hypothesis that all the series have the same mean so these differences cannot be considered to be statistically significant.

Table 2: Descriptive statistics

	SPUSGRN	SPXESUP	IXV	SPGTCED	SPGTAQD	IXE	IXM	IXI	IXB	SPBDUSBT	Eq Test
Mean	$7.57 \cdot 10^{-5}$	0.00040	0.00049	$6.09 \cdot 10^{-5}$	0.00027	-0.00031	0.00025	0.00032	0.00020	0.00016	0.8748 (0.5469)
Std. Dev.	0.00396	0.01098	0.01078	0.01432	0.00998	0.01742	0.01466	0.01270	0.01341	0.00302	9313.89 (0.0000)
Skewness	-0.33459	-0.91077	-0.47369	-0.78003	-0.93353	-1.38474	-0.71963	-0.72043	-0.66891	0.03239	
Kurtosis	9.28765	21.7584	12.7288	12.4830	17.6501	25.6699	18.5359	16.9758	13.1174	5.61558	
JB	4086.54 (0.0000)	36304.1 (0.0000)	9765.83 (0.0000)	9440.21 (0.0000)	22292.9 (0.0000)	53311.6 (0.0000)	24881.4 (0.0000)	20175.8 (0.0000)	10645.3 (0.0000)	699.663 (0.0000)	

This table contains the descriptive statistics for the daily return series for the sample period from January 3, 2011 through September 30, 2020 (amounting to 2,453 usable observations). The last column reports the mean and variance equality tests using the ANOVA and Levene statistics, respectively. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera statistic (JB) tests the normality of the series. This statistic has an asymptotic $\chi^2(2)$ distribution under the normal distribution hypothesis. The p values are reported in brackets.

In terms of standard deviations, we find that S&P Global Clean Energy Index (SPGTCED), Energy Select Sector (IXE) and Financials Select Sector (IXM) provide the highest values while both indices related to bonds, S&P Green Bond Index (SPUSGRN) and S&P U.S. Treasury Bond 5-10 Year Index (SPBDUSBT), provide the lowest. In this case, the null hypothesis of equality of variances is rejected so their differences are statistically significant. Additionally, we find that return series are negatively skewed, leptokurtic (meaning that there is a higher probability of finding extreme values which justifies the use of Value at risk as a performance measure) and the Jarque-Bera statistic rejects the null of a normal distribution for the returns in all cases.

In Figure 1 we mostly see upward trends since the sample covers the period following the record lows seen after the 2007 financial crisis, a period when the markets were recovering fast and forgetting economic concerns. There are only two indices that exhibit clear downward trends, S&P Global Clean Energy Index (SPGTCED) and Energy Select Sector (IXE). Both indices are related to the energy sector which suffered significant price changes over the sample period due to political and technical circumstances.

5. Empirical results

Having applied the proposed two-stage methodology, firstly a screening test and secondly an optimization approach, we report the results for this methodology in Table 3 where the equally weighted portfolio of the five conventional indices (labeled as Conv) is used as the benchmark. Additionally, we have also included a naïve portfolio of the ten indices (N10) to carry out an initial analysis of the effect of mixing conventional and green assets in a portfolio. It must be remembered that a rolling window of 252 days was used to estimate the two performance measures for the screening test and the vectors and matrices for the optimization approaches, so all the results in this section refer to the period from January 3, 2012 to October 30, 2020, which we can identify as the out of sample period.

We see some interesting results in Table 3. Firstly, there is a significant improvement in performance ratios when conventional and green investments are included in an equally weighted portfolio, meaning that adding green investments to a conventional portfolio is appropriate for investors. However, this portfolio is immediately outperformed when in an equally weighted portfolio of five assets we only include those indices selected in the first stage of screening for any rebalancing period (monthly, quarterly or annually). An annually rebalanced equally weighted portfolio of the best five assets following the Sharpe performance measure (N5A) gave us a 105.70% cumulative return in the out of sample period while the ten-asset equally weighted portfolio yielded a 73.45% cumulative return for the same period. Cumulative returns are similar but not better when the ERonVaR performance measure is used for the screening stage. In both cases, the use of the Sharpe and ERonVaR performance measures for screening result in better Sharpe and Omega ratios than using a ten-asset naïve portfolio and, by extension, the initial conventional portfolio.

Secondly, these five-asset naïve portfolios are clearly outperformed based on the Sharpe and Omega ratios when our proposed approach is used and monthly and annually rebalancing periods are considered (those portfolios are labeled as 2SM, 2SQ and 2SA which refer to the monthly, quarterly and annually rebalancing periods using the two-stage procedure). The combination of the Sharpe measure used for the first screening step and the mean-variance optimization model for the second step with monthly rebalancing periods allows us to obtain a Sharpe ratio of 0.6604, which is the best of the seven strategies followed. The same combination but using annual rebalancing periods yields an Omega ratio of 1.0653 which is also the highest.

Figure 1: Closing price graphs of the indices

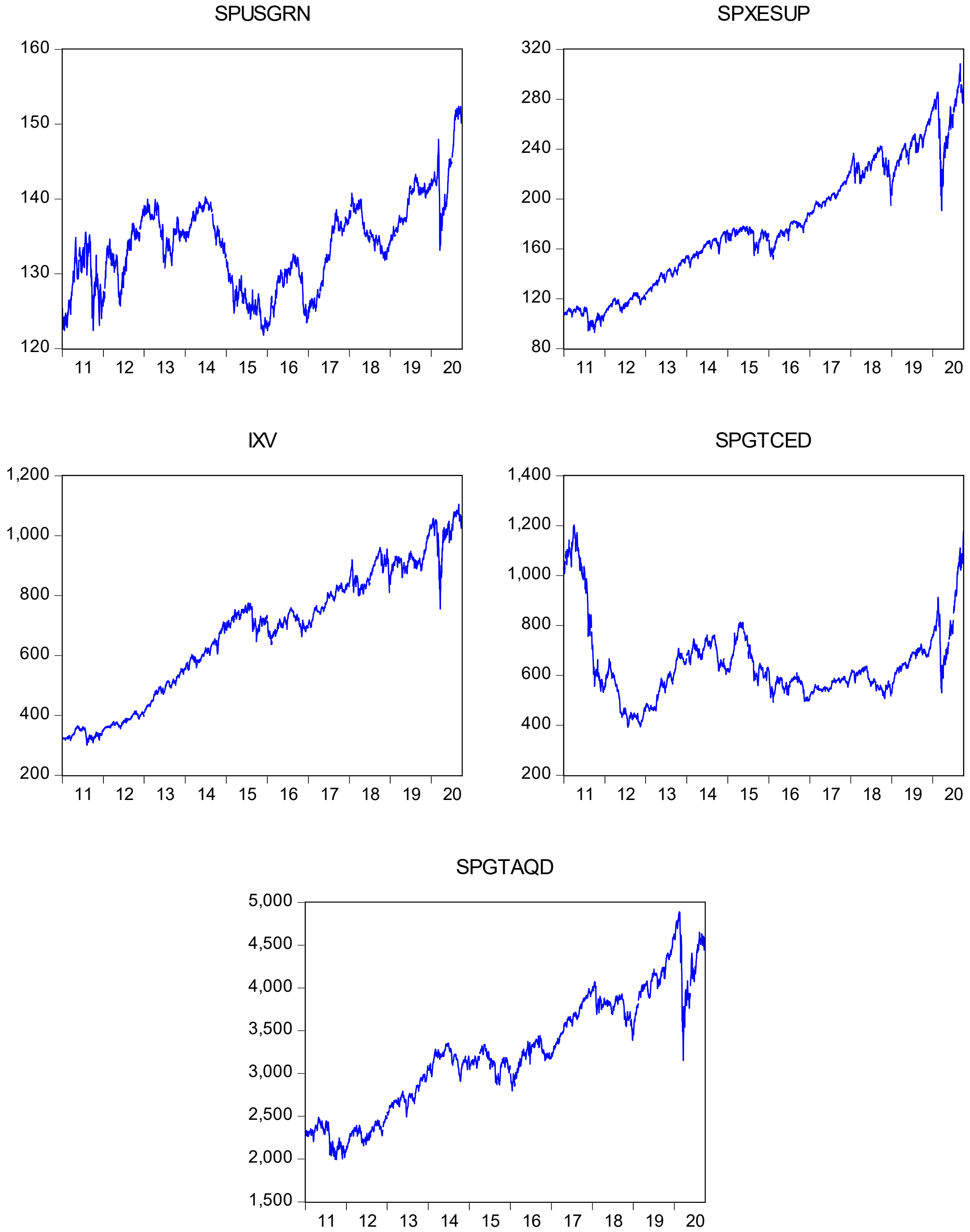

Figure 1: Closing price graphs of the indices (Continue)

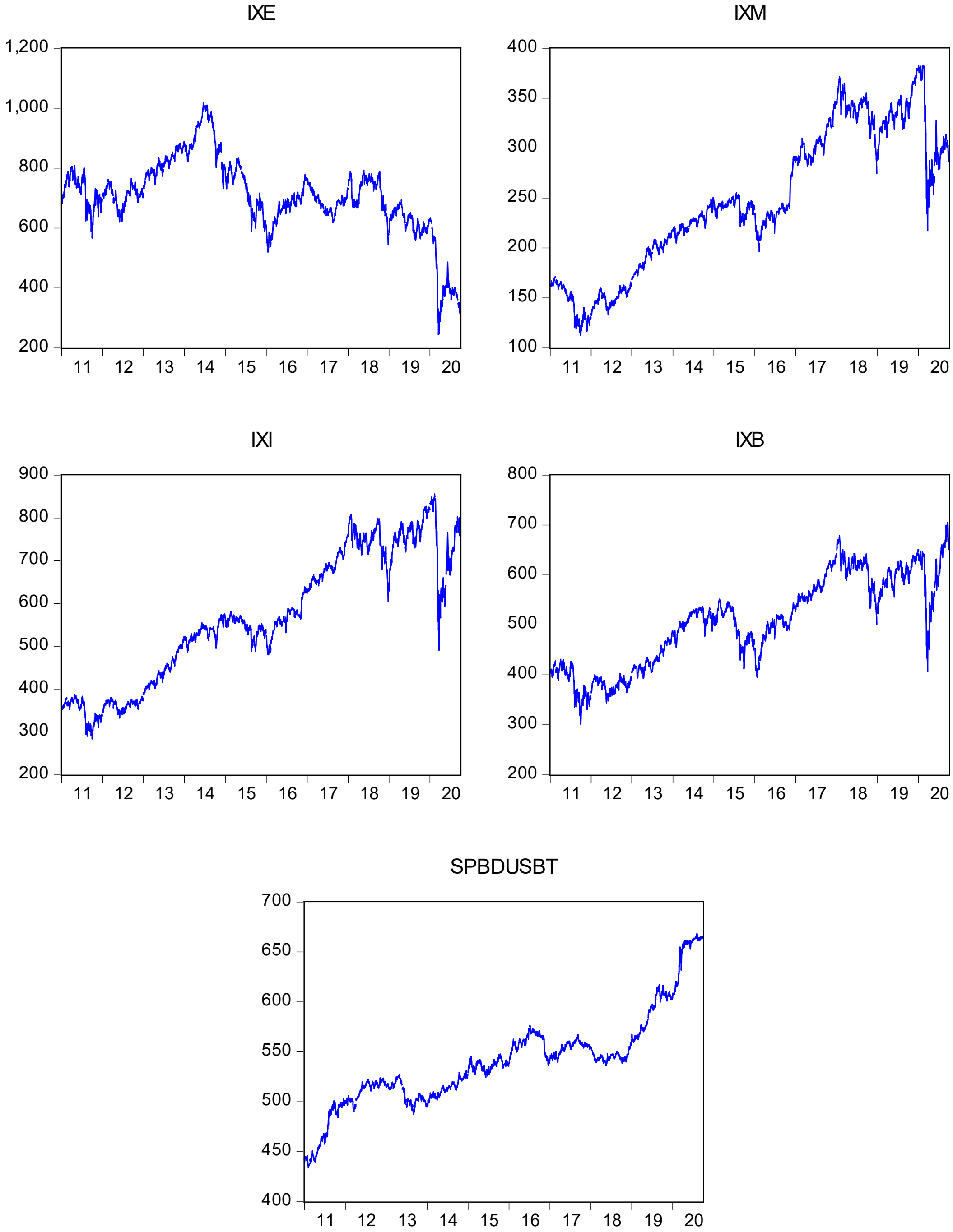

Table 3: Portfolio performances following different approaches

	CONV	N10	N5M	N5Q	N5A	2SM	2SQ	2SA
Panel A: First stage Sharpe								
Cumulative Return (%)	40,58	73,45	97,16	75,82	105,70	70,41	41,36	99,90
Sharpe	0,2041	0,4109	0,5957	0,4006	0,4903	0,6604	0,2841	0,5760
Omega	1,0197	1,0398	1,0539	1,0410	1,0502	1,0610	1,0332	1,0653
Panel A: First stage ERonVaR								
Cumulative Return (%)	40,58	73,45	99,35	78,12	97,18	68,13	42,54	96,61
Sharpe	0,2041	0,4109	0,6010	0,4107	0,4587	0,6341	0,2925	0,5641
Omega	1,0197	1,0398	1,0546	1,0423	1,0474	1,0585	1,0343	1,0639

This table contains the out-of-sample performance evaluation based on the cumulative returns, Sharpe and Omega ratios and for the conventional (Conv) and naïve (mixing conventional and green indices, N10) portfolios and the portfolios obtained following the screening test (those labeled as N5) and following the two-stage approach which combines the screening test and optimization for asset allocation (those labeled as 2S). M, Q and A refer to monthly, quarterly, and annually rebalancing periods respectively.

These two combinations are also the best when the ERonVaR performance measure is used in the first stage. In this case, values of 0.6341 and 1.0639 respectively are obtained for those performance ratios.

Finally, in accordance with León et al. (2019) we find that most of the best results are obtained using a monthly rebalancing period. However, it must also be pointed out that using annual rebalancing periods leads to notable positive returns while using quarterly rebalancing periods slightly improves the benchmark of the ten-asset naïve portfolio.

From the results shown in Table 3, we know that our approach outperforms previous classical methodologies, but we still have no information about the composition of the portfolios. Initial evidence about their structure is provide in Table 4 which contains the times and percentages for each index included in the portfolios, all of these referring to monthly data.

We can see that the top five assets in the naïve portfolios after the initial screening based on the Sharpe performance measure are the S&P 500 ESG Index (SPXESUP) which is included in 94.29% of portfolios (equivalent to 99 out of 105 months), the Health Care Select Sector (IXV) at 69.52%, the Industrials Select Sector (IXI) which stands at 62.86%, the Financials Select Sector (IXM) which is included a total of 58.10% and, finally, the S&P U.S. Treasury Bond 5-10 Year Index (SPBDUSBT) at 56.19%. The results after screening based on the ERonVaR measure are very similar. These percentages show that conventional indices have a greater presence than green ones after the first screening. This is because, even though the highest percentages belong to green assets, the following three large elements correspond to conventional assets.

However, once the second stage has been performed and, therefore, the mean-variance optimization model has been applied, most of the conventional assets disappear from the efficient portfolios meaning that green assets are now in the clear majority. In this case, the top five appearances after combining both screening measures and mean-variance optimization are the following in order of most frequent appearance: S&P 500 ESG Index (SPXESUP), Health Care Select Sector (IXV) and S&P U.S.

Treasury Bond 5-10 Year Index (SPBDUSBT), all with a presence of around 56%-58%, and S&P Global Water Index (SPGTAQD) and S&P Green Bond Index (SPUSGRN) with a presence of around 40% and 27%-29% respectively. Therefore, this procedure of applying filters to select the variables to be included in a portfolio is profitable for investors but also sheds some light on the importance of green assets because it clearly shows that they are more efficient than conventional ones.

Table 4: Times and percentages of portfolio enrollments

MEASURE	SPUSGRN	SPXESUP	IXV	SPGTCED	SPGTAQD	IXE	IXM	IXI	IXB	SPBDUSBT
					SCREENING SHARPE					
TIMES	40	99	73	36	56	12	61	66	23	59
%	38,10	94,29	69,52	34,29	53,33	11,43	58,10	62,86	21,90	56,19
					SCREENING ERONVAR					
TIMES	38	99	74	34	56	11	63	68	22	60
%	36,19	94,29	70,48	32,38	53,33	10,48	60,00	64,76	20,95	57,14
					TWO STAGE SHARPE					
TIMES	31	61	61	30	42	9	26	27	5	59
%	29,52	58,10	58,10	28,57	40,00	8,57	24,76	25,71	4,76	56,19
					TWO STAGE ERONVAR					
TIMES	29	60	61	27	41	8	27	27	5	60
%	27,62	57,14	58,10	25,71	39,05	7,62	25,71	25,71	4,76	57,14

The monthly mean asset allocation of the indices used in this study is reported in Table 5. In keeping with the previous results, we observe that the top five weights are those referring to four green assets and conventional bonds. These green assets account for a mean weight of 47.57%, which increases to 52.36% when all green assets are considered, while the mean weight of conventional bonds is 37.23% (47.64% when all conventional assets are taken into account). This is after the Sharpe screening test and mean-variance model are combined. The equivalent weights are a total of 46.83% for green investments and 38.08% for conventional bonds when the combined ERonVaR and mean-variance model is employed (51.43% and 48.57% respectively when all green and conventional assets are considered). Hence, all these results reinforce the value of green investments compared to conventional assets.

Table 5: Monthly mean optimal allocations

	SPUSGRN	SPXESUP	IXV	SPGTCED	SPGTAQD	IXE	IXM	IXI	IXB	SPBDUSBT
SHARPE	6,97	14,91	16,80	4,78	8,90	0,84	4,05	5,14	0,39	37,23
ERONVAR	6,35	13,95	17,41	4,60	9,12	0,71	4,19	5,20	0,40	38,08

All data are in percentage

6. Robustness test

In order to reinforce the robustness of our results, we show in Tables 6 and 7 the mean performance ratios of the two stage approaches considering three rolling windows of one, two and three years, with the aim of proving that our suggested methodology is best not only for the whole sample but also for different sub-samples.

From the results reported in Table 6, where indices are screened using the Sharpe measure in the first stage, we observe that the mean cumulative return of the benchmark (the equally weighted portfolio of five conventional indices) is outperformed by the other investment options. In two out of the three cases the annually rebalanced portfolios estimated in the second stage show higher cumulative returns (only when a one-year rolling window is used does the annually rebalanced portfolio from the first stage report a higher cumulative return). When Sharpe and Omega ratios are compared, we clearly observe that portfolios obtained using the two-stage approach provide the best results compared to the rest for any rebalancing period and rolling window. Among these, we observe that the two-stage approach with an annual rebalancing period provides the best results in general.

Table 6: Mean portfolio performances following different rolling windows (Screening test: Sharpe)

	CONV	N10	N5M	N5Q	N5A	2SM	2SQ	2SA
				Panel A: One-year rolling window				
Cumulative Return (%)	4,24	6,13	6,82	5,95	7,54	5,50	4,59	7,32
Sharpe	0,4778	0,6675	0,6440	0,6435	0,7044	0,7018	0,6940	0,8994
Omega	1,0415	1,0572	1,0566	1,0555	1,0603	1,0651	1,0609	1,0788
				Panel A: Two-years rolling window				
Cumulative Return (%)	8,72	11,67	11,89	11,31	14,52	9,57	10,03	15,17
Sharpe	0,3968	0,5377	0,4875	0,5067	0,5986	0,5038	0,6219	0,8076
Omega	1,0338	1,0455	1,0416	1,0426	1,0504	1,0468	1,0555	1,0701
				Panel A: Three-years rolling window				
Cumulative Return (%)	14,14	17,61	17,86	17,81	21,82	15,12	17,30	25,18
Sharpe	0,3335	0,4489	0,4227	0,4346	0,5089	0,4966	0,6106	0,8058
Omega	1,0286	1,0389	1,0369	1,0378	1,0444	1,0460	1,0560	1,0714

This table contains the out-of-sample performance evaluation based on the cumulative returns, Sharpe and Omega ratios and for the conventional (Conv) and naïve (mixing conventional and green indices, N10) portfolios and the portfolios obtained following the screening test (those labeled as N5) and following the two-stage approach which combines the screening test and optimization for asset allocation (those labeled as 2S). M, Q and A refer to monthly, quarterly, and annually rebalancing periods respectively.

These results are corroborated by those reported in Table 7, where the first stage is conducted based on the ERonVaR performance measure. Once again, the annually rebalanced portfolios estimated using a two-stage approach mostly provide the best results for any rolling investment window compared to the benchmark, the equally weighted portfolio of ten assets and the naïve portfolios obtained from the initial screening test.

Finally, Table 8 displays the one-year mean asset allocations of the two-stage portfolios shown in Tables 6 and 7. Once again, we observe that green assets have most of the larger means, more specifically the S&P Green Bond Index (SPUSGRN), S&P 500 ESG Index (SPXESUP) and Health Care Select Sector (IXV). However, this does not mean that the most efficient portfolios should only consist of green assets, largely because there is still a large percentage of these efficient portfolios that must be comprised of conventional assets, especially Treasury bonds (SPBDUSBT) but also the Industrial sector (IXI).

Table 7: Mean portfolio performances following different rolling windows (Screening test: ERonVaR)

	CONV	N10	N5M	N5Q	N5A	2SM	2SQ	2SA
				Panel A: One-year rolling window				
Cumulative Return (%)	4,24	6,13	6,97	6,13	6,99	5,32	4,70	7,09
Sharpe	0,4778	0,6675	0,6527	0,6592	0,6611	0,6680	0,6958	0,8869
Omega	1,0415	1,0572	1,0576	1,0574	1,0576	1,0615	1,0606	1,0773
				Panel A: Two-years rolling window				
Cumulative Return (%)	8,72	11,67	12,20	11,73	13,36	9,17	10,31	14,63
Sharpe	0,3968	0,5377	0,4952	0,5270	0,5632	0,4782	0,6346	0,7968
Omega	1,0338	1,0455	1,0425	1,0450	1,0483	1,0441	1,0564	1,0687
				Panel A: Three-years rolling window				
Cumulative Return (%)	14,14	17,61	18,27	18,43	19,94	14,32	17,60	24,26
Sharpe	0,3335	0,4489	0,4311	0,4529	0,4694	0,4680	0,6230	0,7943
Omega	1,0286	1,0389	1,0377	1,0398	1,0415	1,0432	1,0572	1,0697

This table contains the out-of-sample performance evaluation based on the cumulative returns, Sharpe and Omega ratios and for the conventional (Conv) and naïve (mixing conventional and green indices, N10) portfolios and the portfolios obtained following the screening test (those labeled as N5) and following the two-stage approach which combines the screening test and optimization for asset allocation (those labeled as 2S). M, Q and A refer to monthly, quarterly, and annually rebalancing periods respectively.

Table 8 One-year mean asset allocations of the two-stage portfolios

SCRE	REB	SPUSGRN	SPXESUP	IXV	SPGTCED	SPGTAQD	IXE	IXM	IXI	IXB	SPBDUSBT
SHARPE	**M**	6,77	16,11	17,88	4,61	9,63	0,97	4,60	5,70	0,42	33,32
	Q	6,63	17,24	16,37	3,44	9,68	1,02	5,49	6,65	0,00	33,48
	A	10,59	6,47	15,61	3,95	7,53	0,07	7,59	13,60	0,00	34,60
EOV	**M**	6,11	15,14	18,53	4,40	9,87	0,81	4,73	5,77	0,42	34,21
	Q	6,71	17,25	16,84	3,25	9,67	0,56	5,53	6,68	0,00	33,51
	A	10,59	3,63	15,77	3,14	11,03	0,07	7,67	13,39	0,00	34,70

M, Q and A refer to monthly, quarterly, and annually rebalancing periods respectively and EOV refers to ERONVAR.

7. Conclusions

Investing in green assets is now a reality rather than an option for the future. This can be seen in the recent momentum for issuing assets with the green label and the interest shown by companies in meeting the Sustainable Development Goals.

In that context, it is very important for investors to understand how to add these assets to their conventional portfolios and create a portfolio of global (conventional and green) assets which does not provide lower returns and less risk than their previous portfolios.

We have adopted different approaches, such as an equally weighted portfolio (naïve) of ten conventional and green indices and bonds, a naïve portfolio of five assets selected after a screening test and a portfolio of five assets selected after the previous screening test where their allocations were determined by an optimization model. From the results obtained we have shown that adding green assets is beneficial for investors, especially if they optimize the allocations of the assets selected after an initial screening test. These allocations show us that green assets form the majority of the best performing portfolios but also that conventional assets, particularly Treasury bonds, must be included in investors' portfolios. Therefore, investors are licensed to invest in green assets but without underweighting conventional assets in their portfolios.

These findings are relevant not only for active professionals but also for academics who could focus their future research on investigating the robustness of our findings and identifying alternative investment approaches to help investors improve the performance of their investments.

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