Portfolio management of ESG-labeled energy companies based on PTV and ESG factors

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Abstract

This paper evaluates a simple and cost-efficient investment strategy based on Prospect Theory Value (PTV) and Environmental, Social, and Governance (ESG). Monthly quartile portfolios of ESG-labeled companies are constructed based on their PTV and ESG scores in the closely monitored energy sector. Investing in ESG-labeled energy stocks can outperform a value-weighted global energy sector index, according to several out-of-sample performance analyses. The PTV strategy stands out over a sample period of more than twelve years. This strategy performs similarly to a fully diversified world market index and consistently outperforms a world energy index. Over the last five years, the simple strategy based on ESG scores performs similarly to the PTV strategy.

Keywords: prospect theory; ESG; energy; performance

JEL Classification: G11, G15, G41, Q56.

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Introduction

Active equity portfolio management typically involves considering various risk factors, including two that are derived from behavioral finance theory. The first risk factor arises from the application of prospect theory, which was initially proposed by Kahneman and Tversky in 1979, and further developed by Tversky and Kahneman in 1992. This theory aims to explain the decision-making behavior of individuals, going beyond the conventional analysis of risk aversion in modern portfolio theory as highlighted by Wakker (2010) and Barberis et al. (2016, 2021). The second risk factor has to do with the growing awareness among individual investors regarding environmental, social, and governance (ESG) issues. In response, many institutional investors have started to integrate ESG labels and rankings into their investment mandates. This trend has been explored by researchers such as Aouni et al. (2018), Melas et al. (2018), Daugaard (2019), Eccles and Klimenko (2019), and Hartzmark and Sussman (2019). ESG factors extend beyond the traditional models used to assess the future cash flows generated by a company. They encompass subjective elements, such as changes in investor attitudes and knowledge, which can have an impact on a company's value. These deviations from the assumptions of utility maximization can influence the prices of a company's securities, as discussed by Barberis and Thaler (2003), Fama and French (2007), and Huang (2022).

ESG considerations have become paramount in the energy sector due to its urgent need to address environmental challenges and meet global climate commitments. Energy companies recognize that embracing sustainability is not only essential for mitigating environmental impact but also for securing financial support, maintaining public trust, and driving innovation. By integrating ESG principles into their strategies, energy companies can adapt to the changing market dynamics, contribute to the transition towards a low-carbon future, and ultimately thrive in an economy that values sustainability. Consequently, the energy sector is highly affected by ESG trends. Renewable energy and oil and gas companies, in particular, are more likely to engage in activities with ESG implications. These companies are experiencing significant disruption due to technological innovations and evolving consumer preferences.

Furthermore, the activities of energy sector companies are under increased scrutiny by the public and regulators. Failure to comply with these regulations can result in substantial financial and reputational risks, impacting long-term sustainability (Mellahi et al., 2019). Given the growing demand for clean renewable energy, ESG investing has become particularly relevant. ESG scores and reports play a role in determining investment allocations to energy companies. ESG reports provide guidance for ESG investing in the energy sector.

Current paper presents a portfolio performance analysis over the past decade which aims to shed light on how results evolve with increased ESG engagement. Specifically, we study the ex-post performance of energy portfolio strategies in a behavioral finance context. The combination of the Prospect Theory Value (PTV) factor and the ESG factor can shed new light on the risk-adjusted performance of these strategies for practical applications. This analysis focuses on ESG-labeled companies in the global energy sector, providing robustness to the study. On the one hand, previous research exploring different investment strategies based on ESG scores faces a significant drawback. It stems from the fact that companies engaging in the same sustainable activities can obtain significantly different ESG scores based on their sector, known as sectoral bias. While some papers have attempted to rescale company scores based on their industry peers (Albuquerque et al., 2019; Alessandrini and Jondeau, 2020), this approach can be complex and not always effective. A simpler way to address this limitation is by examining only one sector. On the other hand, investor concerns regarding ESG scores span across all sectors; notwithstanding, it is important to note that the energy sector has a unique impact on the environment and society. This makes it a crucial area for ESG analysis. Energy companies face specific ESG risks, such as climate change and environmental pollution, which can have significant financial implications. The transition to a low-carbon economy introduces both risks and opportunities for energy companies.

The first risk factor we consider is the valuation based on prospect theory. Prospect theory provides insights into how individuals make decisions when faced with alternatives involving financial risk. Kahneman and Tversky (1979) and Tversky and Kahneman (1992) suggest that, overall, investors mentally conceptualize an investment's future returns distribution by examining the distribution of its past observations, considering it to be a reliable approximation. The investor's utility function is concave for gains and convex for losses, capturing risk aversion for moderate probability gains and risk seeking for moderate probability losses. Evidence from a wide range of empirical studies suggests that prospect theory captures individual investors' irrational attitudes toward risk, which often differ substantially from those predicted by expected utility theory. The application of this theory to financial markets has demonstrated its ability to predict future stock returns and to explain a number of stock market anomalies (Barberis and Huang, 2008; Barberis et al., 2016, Grishina et al., 2017; Guo and Schönleber, 2020; Barberis et al., 2021; Wang et al., 2021; Harris and Mazibas, 2022).

The second risk factor we incorporate into our analysis is the ESG scoring, which serves as a proxy for ESG investing and aligns with behavioral finance principles. Investors' preferences for ESG investing can be influenced by their emotions, values, and beliefs, which are all central to the field of behavioral finance. The integration of ESG factors in investment decision-making has gained traction in recent years. A growing body of literature suggests that incorporating ESG factors in portfolio construction not only contributes to better risk-adjusted returns (Chen et al., 2019), but it also aligns with investors' preferences and values (Oikonomou et al., 2012; Fatemi and Fooladi, 2013, Hartzmark and Sussman, 2019; Statman, 2020). Studies show that investors are increasingly motivated to invest in companies with good ESG performance (Fatemi et al., 2018), and that companies with high ESG scores exhibit lower costs of capital, better financial performance, and lower risk exposure (Eccles & Serafeim, 2013; Clark et al., 2015; Friede et al., 2015; Hartzmark and Sussman, 2019). Moreover, behavioral finance research provides additional support for the use of ESG factors in portfolio strategies. Behavioral biases, such as overconfidence and herding, can lead to suboptimal investment decisions. Notwithstanding, incorporating ESG criteria in portfolio construction can mitigate these biases by providing a framework for more disciplined and systematic investment processes (Barberis and Thaler, 2003; Statman, 2020). In addition, the incorporation of ESG factors may reduce investors' exposure to reputation risk and ethical concerns, which could impact portfolio performance in the long-term (Lajili et al., 2022).

Assets under ESG management have grown exponentially in recent years. Numerous institutional investors have clearly outlined their ESG requirements and guidelines within their investment mandates and policy statements. Additionally, there has been a proliferation of ESG rankings and lists. The rising demand for ESG investments stems from both financial and ethical motivations. Initially, from a financial standpoint, early empirical studies yielded discouraging results regarding the impact of ESG on a company's profitability. It was believed that engaging in socially responsible activities would put companies at a disadvantage as it diverted resources away from their core business (Aupperle et al., 1985). Existing empirical evidence suggested a negative relationship between ESG performance and firm financial performance, as documented in several studies (Bello, 2005; Renneboog et al., 2008; Margolis et al., 2007; Humphrey and Lee, 2011; Orlitzky et al., 2011; Friede et al., 2015). Interestingly, we find a turnaround in the relationship between ESG and performance in the most recent studies, which report a slightly positive or neutral relationship, and ESG strategies are shown to perform similarly or even better than traditional strategies (Kemptf and Osthoff, 2007; Auer and Schuhmacher, 2016; Alexopoulos, 2018; Joliet and Titova, 2018; Hang et al., 2019; Huang, 2019; Kaiser and Schaller, 2019; Chan et al., 2020; Vojtko and Hanicová, 2020; Naqvi et al., 2022; Yousaf et al., 2022). Nowadays, mixed evidence is also observed regarding this relationship, as other recent studies also suggest that investing in companies with higher ESG scores is associated with lower risk-adjusted returns, likely due to their lower levels of systematic risk and lower correlation with the business cycle (Albuquerque et al. 2019; Ciciretti et al., 2023). Investor and consumer preferences can also contribute to the negative ESG premium by influencing company policies and risk profiles. The negative performance of companies with higher ESG scores could be even worse if sudden shifts in demand towards ESG assets were included in the analysis. According to Hartzmark and Sussman (2019), the higher returns delivered by green assets are mainly due to an unexpected increase in environmental concerns, rather than high expected returns.

Sustainable finance and ethical or Socially Responsible Investing (SRI) consider ESG factors when making investment decisions. These are investors who make investment decisions in accordance with their own values and beliefs to facilitate social change (Statman, 2020). Portfolio managers develop strategies that enable them to meet their clients' value-based goals along with financial objectives (Haigh and Hazelton, 2004; Scholtens, 2006; Bollen, 2007; Dimson et al., 2015; Nath, 2021). This type of activism involves a group of conscientious individuals who adopt a form of investing to support social change, advocate against corporate social injustice and environmental damage, or encourage companies to make positive contributions to society. SRI financial portfolios can be constructed using a variety of management strategies, including exclusion or negative screening, selection or positive screening, consideration of ESG factors as part of portfolio construction, use of shareholder power to influence corporate behavior, etc. (Kempf and Osthoff, 2007; Statman and Glushkov, 2009; Berry and Junkus, 2013; Eding and Scholtens, 2017; Statman, 2020; Nath, 2021). Financial market regulators, as well as banks and investment fund managers, have encouraged the creation of ESG funds, in addition to promoting investment in companies that take ESG factors into account.

The aim of this study is to gain further insights into the impact of ESG scores and factor investing on investment performance. We are interested in providing international evidence on whether quartile strategies driven by PTV and ESG scores systematically outperform the full energy market. In recent years, different ESG ratings have been used to evaluate sustainable asset portfolios with mixed results (Melas et al., 2017; Bender et al., 2018; Giese et al., 2019; Kaiser and Schaller, 2019; Chan et al., 2020; Vojtko and Hanicová, 2020; Alessandrini and Jondeau, 2020 and 2021). We propose our portfolio construction strategy in the context of behavioral finance, where investors cannot be considered perfectly rational in the sense of modern portfolio theory. Currently, PTV is one of the most widely used methods to assess the peculiarities and uniqueness of financial investors. We analyze the ESG scores and the valuation of financial assets by PTV as criteria to construct portfolios of energy companies over a wide sample period.

This paper employs a factor-based strategy that has become increasingly popular in both the global asset management landscape and academic literature. This methodology has been previously explored by Koedijk et al. (2016); Israel and Ross (2017); Ang et al. (2017); Blitz and Vidojevic (2019); Dichtl et al. (2021); Flint and Vermaark (2022), among others. Our approach involves constructing quartile portfolios based on both PTV and ESG risk factors in a straightforward and intuitive manner. To construct factor portfolios, we implement a bivariate sorting approach, taking long positions in stocks that constitute each quartile. We construct quartile portfolios each month using monthly reported ESG scores and PTV calculated from the previous year's data. We then analyze the realized performance of each quartile portfolio one month after construction. Previous research examines financial performance of static investment strategies using portfolios constructed from companies ranked in different ESG score percentiles (e.g., De and

Clayman, 2015; Bender et al., 2018; Dorfleitner et al., 2020; Naffa and Fain, 2022 Sahin et al., 2022; Ciciretti et al., 2023). Several of these papers distinguish between different industries and consider industry-adjusted average scores (Auer and Schuhmacher, 2016, Albuquerque et al., 2019, Alessandrini and Jondeau, 2020). We examine monthly rebalanced quartile portfolios based on PTV ranking, ESG scores, and both factors combined. Each quartile portfolio is equally weighted and passively managed to isolate the impact of PTV and ESG factors from other variables, such as asset pricing models and portfolio optimization techniques. By using equal-weighted portfolios, we can measure the performance of these factors independently. To evaluate the performance of the constructed portfolios, we employ various performance analyses using observed returns from October 2009 to March 2022. Our analysis includes assessments of both raw returns and risk-adjusted returns, utilizing an AR-GARCH model for conditional volatility. Additionally, we employ an asset pricing model, such as the Fama-French four-factor model, to investigate whether the proposed portfolios generate excess returns beyond what can be explained by systematic factors. Furthermore, we conduct a comprehensive analysis of both traditional performance measures and downside risk measures.

Our main findings can be summarized as follows. First, we provide empirical evidence that sustainable investors can outperform fully diversified portfolios of energy stocks, including both "green" and "brown" energy companies, by investing in ESG-labeled energy stocks. Second, an equal-weighted portfolio investing in the first quartile of stocks ranked by PTV (PTV-Q1) can consistently outperform the value-weighted global energy index and perform very similarly to a broad stock market portfolio. Third, while the results consistently demonstrate a decline in performance and an increase in downside risk when utilizing the PTV and PTV-ESG criteria and transitioning from the top quartiles to the bottom quartiles, this clear consistency diminishes when employing the ESG criteria, particularly the ESG-PTV approach. Fourth, strategies based on ESG scores produce modest results throughout the study period, but in the latter part of the sample, they achieve a performance level similar to that of PTV strategies.

In summary, this paper makes a number of contributions to the sustainable and behavioral finance and factor investing literatures. First, we consider investors who simultaneously evaluate risk according to prospect theory and are ethically or socially responsible in their investment decisions. Second, we examine the impact of ESG labeling on energy companies worldwide by analyzing all energy companies with ESG scores from OWL ESG Analytics. This study focuses on the energy sector, which is likely to be most affected by ESG trends. Stakeholders are particularly concerned about the activities and sustainability of the energy sector. Examining only one sector helps to avoid sector biases in ESG scores. Third, we are the first to construct quartile portfolios of ESG-labeled energy companies according to rankings based on their monthly PTV and ESG scores. Fourth, our results are robust to a wide range of ex-post measures of financial performance.

The rest of the paper is organized as follows. In Section 1, we explain the procedure for determining the PTV. In Section 2, we describe the data and methodology used to construct the portfolio. An ex-post performance analysis is used to analyze the results in Section 3. Finally, Section 4 summarizes the main conclusions.

1. Prospect theory value

Prospect theory is a behavioral economic theory that describes how people make decisions under uncertainty or risk. It suggests that people evaluate potential losses and gains differently, and they are more sensitive to losses than gains. Specifically, people tend to experience more pain from losing a certain amount of money than pleasure from gaining the same amount. The model assumes that investors evaluate potential gains and losses using a utility function that is concave over gains and convex over losses, reflecting risk aversion over moderate-probability gains and risk-seeking over moderate-probability losses. This theory proposes that people do not evaluate outcomes in isolation but rather in relation to a reference point, which can be their current status quo or their expectations. People tend to take more risks when they are below their reference point (e.g., after a loss) and less risk when they are above it (e.g., after a gain). In addition, the model assumes that investors overweight small probabilities (tails of the distribution) and underweight large probabilities when evaluating potential outcomes, consistent with prospect theory's probability weighting function.

Mental accounting is the basis of the prospect theory (Kahneman and Tversky, 1979; Benartzi and Thaler, 1995), which describes an investor's mental process for encoding and evaluating financial assets. Investors use sample distributions of returns as the simplest, most intuitive information. In addition, Tversky and Kahneman (1992) develop the cumulative prospect theory, incorporating the rank dependence concept to address limitations in their original prospect theory. A value function, PTV, accounts for deviations from the benchmark, generally concave for gains, convex for losses, and steeper for losses than for gains.

To determine the allocation to a stock, investors evaluate the daily distribution of returns according to prospect theory, thereby determining the stock's PTV. We assume that investors construct the historical distribution of raw returns over the past year. Accordingly, they rank the gains and losses represented by r_t, i.e., the daily returns, over the last *n* = 252 business days in decreasing order along the moving window ($r_1 \geq \cdots \geq r_k \geq 0 \geq r_{k+1} \geq \cdots \geq r_n$, with probability $p_1, \ldots p_n$). As per Wakker (2010), the decision-maker's subjective parameters encompass the utility or value function, $v(r_t)$, along with the probability weighting functions, where w^+ corresponds to gain-ranked probabilities and w^- pertains to loss-ranked probabilities.[1]

The theoretical value of a stock, *PTV*, is calculated as the weighted average of the value function, $v(r_t)$, and the probability weighting function, $w(p)$,

$$PTV = \sum_{j=1}^{n} \pi_j \cdot v(r_j) \tag{1}$$

where the decision weights π_j are nonnegative,

$$\pi_j = \begin{cases} w^+(p_1 + \cdots + p_j) - w^+(p_1 + \cdots + p_{j-1}) & \text{, for } j \leq k \\ w^-(p_j + \cdots + p_n) - w^-(p_{j+1} + \cdots + p_n) & \text{, for } j > k \end{cases} \tag{2}$$

and w^+ and w^- are the probability weighting functions.

According to the cumulative prospect theory, Tversky and Kahneman (1992), the utility or value function is calculated as follows:

$$v(r_t) = \begin{cases} r_t^{\alpha} & \text{, for } r_t \geq 0 \\ -\lambda \cdot r_t^{\beta} & \text{, for } r_t < 0 \end{cases} \tag{3}$$

and

[1] Barberis et al. (2016, 2021) propose a slightly different process for constructing the PTV where returns are sorted in an increasing manner. Furthermore, in the specific case of Barberis et al. (2021), they introduce a single parameter δ (equal to γ), eliminating the distinction between probability weighting functions for gains and losses.

$$w^{+}(p) = \frac{p^{\gamma}}{\left(p^{\gamma}+(1-p)^{\gamma}\right)^{1/\gamma}} \;\; ; \;\; w^{-}(p) = \frac{p^{\delta}}{\left(p^{\delta}+(1-p)^{\delta}\right)^{1/\delta}} \quad (4)$$

where α and β are exponents for gains and losses, respectively, and λ is a parameter that captures the loss aversion of the investor. The shape of the value function is determined by parameters α and β. Tversky and Kahneman (1992) estimate values that make $v(r_t)$ a S-shaped function, meaning that investors tend to be risk-averse in the profit domain and risk-seeking in the loss domain. Based on this article, we assume $\alpha = \beta = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, and $\delta = 0.69$.

When $\lambda = 1$, $v(r_t)$ has the same value (absolute) regardless of the magnitude of the loss or gain, indicating investors' sensitivity is equally indifferent to losses or gains. The parameter λ is usually greater than 1, indicating that people are generally more sensitive to losses than to gains. A psychologically exaggerated loss penalty is estimated by Tversky and Kahneman (1992) to be $\lambda = 2.25$, meaning that the pain of losses is twice as great as the pain of gains of the same magnitude.

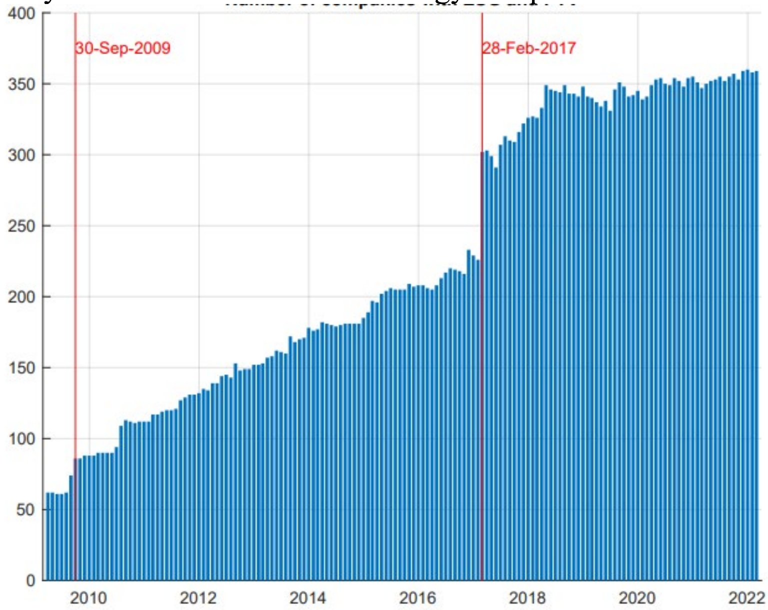
It is not the level of a payoff itself that determines the value of a payoff to an individual, but the difference between the payoff and some reference level. Also, the value of a payoff is not weighted by its probability, but by a function of the cumulative probability of the ranked payoffs. A relative payoff is defined with respect to a reference return level that is set to zero. By using the weighting functions, an individual is not using objective probabilities to evaluate a risk but is converting objective probabilities into transformed probabilities. The weighted or subjective probabilities are intended to reflect the actual behavior of investors, who systematically perceive objective probabilities in a biased manner, underestimating medium and high probabilities and overestimating low probabilities.

This inverse S-shaped weighting function overweights the probabilities of very large gains and very large losses. The tails of the distribution are overweighted based on experimental evidence that individuals prefer a positively skewed, lottery-like wealth distribution.

2. Data and methodology

Our database contains daily quotes from Bloomberg from October 2008 through March 2022 for all ESG-rated energy companies according to the OWL ESG Analytics database. ESG scores are published at the end of each month. Figure 1 shows the evolution of the number of energy companies identified as ESG by OWL Analytics. Based on this evolution, we determine the starting point of our analysis and the division of the sample period into two subperiods. The analysis period begins when the number of rated energy companies reaches 86 in September 2009. We consider this to be a large enough number to construct quartile portfolios. We consider February 2017 as a breakpoint for ESG-rated energy companies. As shown in Figure 1, the number of rated energy companies increased by a third from the previous month, reaching 300 for the first time. The last portfolios are built from 359 ESG-labeled energy companies by the end of February 2022. Over the entire sample period, 1,130 ESG-rated energy companies from around the world are considered. Globally, 37% of the companies are from North America, while 21%, 16% and 16% are from Asia, Europe and Oceania, respectively.

Figure 1. Monthly number of ESG-labeled energy companies



Note: Among ESG-rated energy companies, only those with at least 90% of trading days in the previous 252-business day rolling window are included in each monthly analysis.

In each month, PTV are calculated based on daily logarithmic returns over 252-day rolling windows for all ESG-labeled energy companies reported by OWL Analytics. Only companies with an ESG label in that month and at least 90% of the trading days in the annual rolling window are included. Using the monthly PTV and ESG information, company rankings are calculated for each criterion and divided into quartiles. We consider quartile 1, Q1, to be the quartile containing the companies with the best score for the criterion (up to the 25th percentile), and quartile 4, Q4, to be the quartile containing the companies with the worst score (75th percentile or higher). For the PTV criterion, higher scores indicate a more desirable investment. Companies that exhibit favorable attributes such as low leverage, strong corporate governance, and high profitability typically provide more stable investment opportunities and are expected to outperform the market over time.

In the case of portfolios constructed using both factors simultaneously, they are first ranked by the PTV criterion into companies above the median, PTV-Q1 and PTV-Q2, and companies below the median, PTV-Q3 and PTV-Q4. Companies above the PTV median are re-sorted according to their ESG ranking into ESG companies above the median, PTV-ESG-Q1, and ESG companies below the median, PTV-ESG-Q2. The first quartile based on this dual criterion, PTV-ESG-Q1, is thus formed by the companies with the best ESG ranking within the companies with the best PTV rating. The PTV-ESG-Q2 quartile includes companies with ESG scores below the median of the companies with the best PTV scores. For companies with PTV scores below the median, the sample is again divided into those with better ESG scores, PTV-ESG-Q3, and those with worse ESG and PTV scores, PTV-ESG-Q4. As with these PTV-ESG portfolios, where PTV is the primary criterion, we also construct ESG-PTV portfolios, where ESG is the primary criterion.[2]

Equal-weighted portfolios are generated from these quartile portfolios of PTV, ESG, and both factors simultaneously. These simple equal-weighted portfolios have several advantages: they require no additional assumptions about an asset pricing model or optimization method, they do not have to deal with the problem of estimating the excess return and the covariance matrix of asset returns, and they do not have to be parameterized. Moreover, equal-weighted portfolios have been shown to be hard to beat (DeMiguel et al., 2009, Koedijk et al., 2016; Platanakis et al., 2020; Dichtl et al., 2021).

The portfolio construction process is repeated at the end of each month from September 2009 through February 2022. Based on the stock prices that make up each equal-weighted portfolio at the time of portfolio construction and one month later, realized returns are calculated. Therefore, we examine the monthly ex-post returns for each strategy over a 150-month period, from October 2009 to March 2022.

The performance analysis of the quartile portfolios is based on three benchmarks. The monthly ESG market portfolio is constructed by equally weighting all ESG energy companies included in the monthly quartile analysis. In addition, we consider two broad equity indices, the MSCI World Energy Index (WEI) and the MSCI All-Country World Index (WI).[3] The first index represents the global energy sector, including brown and green companies. The second index consists of companies from all sectors that make up a global market portfolio. Both indices are market capitalization weighted and free float adjusted.

[2] For brevity, the results of the ESG-PTV strategies are not presented in the main text but can be found in Appendix B.

[3] The MSCI World Energy Index comprises 23 developed countries, including large- and mid-capitalization companies. The MSCI All Country World Index is an equity index designed to track the broad performance of global equity markets. This index comprises nearly 3,000 companies from 23 developed countries and 25 emerging markets.

3. Results

3.1 Descriptive analysis

Table 1 shows the resulting statistics of the PTV and ESG scores of the stocks in each quartile and of the equal-weighted portfolio of all ESG-labeled energy companies. We distinguish between the full sample (Panel A) and the second part of the sample (Panel B). Using PTV to construct the portfolios (left panels), there is a large variation in the average PTV between the portfolios for Q1 and Q2, Q3 and Q4, but little variation between Q2 and Q3. These PTV-based portfolios do not differ significantly in their ESG scores. Portfolios constructed on ESG (middle panels) show large differences between quartiles on ESG, but not on PTV. A slight improvement in ESG scores is observed in all quartiles in the second period, Panel B.

Panel A of Table 2 shows the summary statistics of the monthly raw returns from the rolling step-ahead analysis over the period October 2009 to March 2022. For both PTV and PTV-ESG factors, there is a monotonic relationship between the quartile portfolios and their average returns and standard deviations. The Q1 portfolio, which consists of the stocks with the highest values, has the highest average return and the lowest standard deviation among the quartile portfolios. This implies that the Q1 portfolio has the best risk-return trade-off and dominates the other portfolios in terms of both performance and volatility. The Q2 portfolio, which consists of the stocks with the second highest values, has the second highest average return and the second lowest standard deviation among the quartile portfolios. The Q3 and Q4 portfolios have lower average returns and higher standard deviations than the Q1 and Q2 portfolios. These patterns are consistent across different percentiles of the return distribution, suggesting that they are robust and not driven by outliers or extreme events. In the case of the ESG quartile portfolios, and especially the ESG-PTV portfolios (Table B.1), the relationship between the quartile portfolios and their average returns and standard deviations is not as clear as in the case of the PTV and PTV-ESG quartile portfolios.

Table 1. Summary statistics of PTV and ESG scores

	PTV-Q1	PTV-Q2	PTV-Q3	PTV-Q4	ESG-Q1	ESG-Q2	ESG-Q3	ESG-Q4	PTV-ESG-Q1	PTV-ESG-Q2	PTV-ESG-Q3	PTV-ESG-Q4	ESG Energy
Panel A. Full sample (September 2009 – February 2022)													
PTV													
Mean	-0.0136	-0.0202	-0.0262	-0.0411	-0.0229	-0.0253	-0.0274	-0.0253	-0.0167	-0.0171	-0.0331	-0.0342	-0.0252
Standard deviation	0.0034	0.0051	0.0069	0.0115	0.0050	0.0071	0.0086	0.0068	0.0042	0.0042	0.0085	0.0100	0.0065
Median	-0.0128	-0.0190	-0.0249	-0.0384	-0.0224	-0.0234	-0.0257	-0.0241	-0.0158	-0.0161	-0.0311	-0.0321	-0.0240
ESG score													
Mean	51.26	51.41	50.16	49.97	64.18	53.50	47.13	37.90	60.04	42.51	57.34	42.75	59.40
Standard deviation	3.1769	3.1400	3.3560	2.8080	3.4513	2.6906	2.6183	2.7998	3.4926	2.8843	3.1767	2.8594	2.7570
Median	51.15	51.58	50.48	49.80	63.87	54.20	47.69	37.80	59.95	42.73	57.28	42.80	59.55
Panel B. From February 2017 to February 2022													
PTV													
Mean	-0.0135	-0.0209	-0.0279	-0.0443	-0.0219	-0.0258	-0.0303	-0.0285	-0.0171	-0.0173	-0.0340	-0.0381	-0.0266
Standard deviation	0.0031	0.0050	0.0072	0.0121	0.0043	0.0073	0.0089	0.0073	0.0040	0.0041	0.0088	0.0105	0.0068
Median	-0.0124	-0.0193	-0.0257	-0.0390	-0.0209	-0.0239	-0.0269	-0.0252	-0.0158	-0.0158	-0.0316	-0.0332	-0.0245
ESG score													
Mean	53.88	54.04	51.94	49.68	66.71	55.42	48.41	38.93	63.24	44.63	58.44	43.14	61.73
Standard deviation	2.5005	1.8316	2.0984	1.9816	2.7764	1.1614	1.6088	2.8674	2.3537	2.1289	2.1903	2.2740	1.7096
Median	53.70	54.03	51.40	49.43	65.47	55.35	48.51	39.24	62.77	44.79	58.14	42.94	61.74

Note: Q1 represents the first quartile for each strategy, showing the PTV and ESG scores of the top-ranked portfolios of stocks ranked by PTV, ESG, or both (PTV-ESG) among all ESG-rated global energy companies by OWL ESG Analytics. ESG-PTV portfolios are not included due to space limitations. All portfolios are equally weighted. PTV and ESG scores correspond to the end of each month from September 2009 to February 2022. Each quartile portfolio is created at the beginning of each month (October 2009-March 2022) based on the previous day's PTV and ESG scores.

Table 2. Summary statistics of monthly raw returns

	PTV-Q1	PTV-Q2	PTV-Q3	PTV-Q4	ESG-Q1	ESG-Q2	ESG-Q3	ESG-Q4	PTV-ESG-Q1	PTV-ESG-Q2	PTV-ESG-Q3	PTV-ESG-Q4	ESG Energy	World Energy	World
Panel A. Full sample (October 2009-March 2022)															
Mean	0.0043	-0.0025	-0.0020	-0.0222	-0.0007	-0.0081	-0.0059	-0.0076	0.0021	-0.0003	-0.0102	-0.0140	-0.0056	0.0005	0.0060
Std. Dev.	0.0477	0.0677	0.0856	0.1273	0.0666	0.0865	0.0943	0.0789	0.0557	0.0593	0.1034	0.1101	0.0788	0.0692	0.0412
5^{th} Percentile	-0.0673	-0.1164	-0.1447	-0.1920	-0.1110	-0.1388	-0.1405	-0.1367	-0.0831	-0.0972	-0.1646	-0.1820	-0.1333	-0.1049	-0.0738
Q1	-0.0145	-0.0385	-0.0391	-0.0931	-0.0290	-0.0519	-0.0524	-0.0508	-0.0260	-0.0288	-0.0603	-0.0579	-0.0483	-0.0371	-0.0172
Median	0.0098	0.0031	0.0019	-0.0207	0.0016	-0.0026	-0.0013	0.0047	0.0073	0.0096	-0.0068	-0.0066	0.0055	0.0049	0.0109
Q3	0.0317	0.0419	0.0451	0.0474	0.0390	0.0434	0.0517	0.0371	0.0344	0.0345	0.0492	0.0457	0.0363	0.0394	0.0271
95^{th} Percentile	0.0677	0.0831	0.1164	0.1428	0.0901	0.1027	0.1053	0.1008	0.0856	0.0756	0.1221	0.1448	0.0991	0.0957	0.0694
Ann. Return	0.0515	-0.0301	-0.0245	-0.2667	-0.0079	-0.0974	-0.0708	-0.0908	0.0257	-0.0035	-0.1222	-0.1682	-0.0667	0.0064	0.0726
Cum. Return	0.6439	-0.3756	-0.3061	-3.3334	-0.0990	-1.2171	-0.8847	-1.1352	0.3207	-0.0433	-1.5279	-2.1027	-0.8339	0.0801	0.9072
%month beats ESG Energy	0.6333	0.6067	0.5800	0.3600	0.5533	0.4267	0.4733	0.4667	0.6333	0.6400	0.4200	0.3867	--	0.6000	0.5667
Panel B. From March 2017 to March 2022															
Mean	0.0024	-0.0011	-0.0015	-0.0198	0.0029	-0.0058	-0.0092	-0.0077	0.0017	-0.0004	-0.0047	-0.0166	-0.0050	0.0015	0.0077
Std, Deviation	0.0557	0.0747	0.0962	0.1415	0.0629	0.0941	0.1102	0.0952	0.0617	0.0681	0.1102	0.1284	0.0879	0.0854	0.0437
5^{th} Percentile	-0.0770	-0.1155	-0.1060	-0.1829	-0.0814	-0.1141	-0.1383	-0.1470	-0.0816	-0.1158	-0.1331	-0.1788	-0.1202	-0.1062	-0.0744
Q1	-0.0111	-0.0277	-0.0363	-0.0828	-0.0253	-0.0417	-0.0627	-0.0519	-0.0160	-0.0105	-0.0565	-0.0719	-0.0344	-0.0400	-0.0070
Median	0.0087	0.0080	-0.0001	-0.0274	-0.0009	-0.0025	-0.0050	0.0047	0.0011	0.0108	-0.0064	-0.0207	0.0032	0.0100	0.0139
Q3	0.0315	0.0438	0.0403	0.0453	0.0381	0.0379	0.0538	0.0325	0.0327	0.0430	0.0292	0.0536	0.0312	0.0421	0.0285
95^{th} Percentile	0.0658	0.0854	0.1231	0.1432	0.0844	0.0978	0.1081	0.1062	0.0869	0.0757	0.1324	0.1568	0.1078	0.1433	0.0617
Ann. Return	0.0287	-0.0137	-0.0176	-0.2380	0.0345	-0.0695	-0.1103	-0.0926	0.0209	-0.0046	-0.0564	-0.1990	-0.0596	0.0177	0.0926
Cum. Return	0.1460	-0.0695	-0.0896	-1.2098	0.1751	-0.3535	-0.5609	-0.4708	0.1061	-0.0233	-0.2869	-1.0114	-0.3030	0.0900	0.4705
%month beats ESG Energy	0.6290	0.6290	0.5000	0.3226	0.5323	0.4516	0.3871	0.4032	0.5968	0.6290	0.4032	0.3226	--	0.5806	0.5806

Note: Q1 represents the first quartile for each strategy, showing the logarithmic returns of the top-ranked portfolios of stocks ranked by PTV, ESG, or both (PTV-ESG) among all ESG-rated global energy companies by OWL ESG Analytics. ESG-PTV portfolios are presented in the Appendix B. All portfolios are equally weighted. The MSCI World Energy Index and the MSCI World Index are benchmarks for the global energy industry and the global equity market, respectively. *Ann.Return* and *Cum.Return* are annualized and cumulative returns, respectively.

Examining the number of months in which each strategy beats the ESG energy market, we find that the strategies based on the best PTV and the best PTV-ESG and ESG-PTV combinations outperform the market in approximately two out of three months. The second-best portfolios, Q2, also beat the market in more than 60% of the months for PTV and PTV-ESG strategies. However, it is important to note that this percentage is only observed in Q3 and not in Q2 for the ESG-PTV strategies. In the case of ESG-based strategies, only those in the first ESG quartile outperform the market in more than half of the months. Analyzing the time evolution of these results can be useful to identify trends over time.

Panel B of Table 2 presents summary statistics for strategies formed since the beginning of March 2017, which corresponds to the hatching of ESG-rated companies in our database. This subsample consists of 61 months. The results for PTV-based strategies are still notable, albeit with more modest values than for the full sample period. However, in this second part of the sample, the results for ESG strategies improve significantly, especially for ESG-Q1. Looking at the annualized return, the global ESG-labeled energy portfolio remains stable at around -6%. However, when only the second part of the sample period is considered, this value almost halves for PTV-Q1, from 5.15% for the full sample to 2.87% for the second part, and jumps for ESG-Q1, from -0.79% for the full sample to 3.45% for the second part. This indicates a significant improvement in the raw return of stocks with the best ESG ratings.

The two right columns of Table 2 show statistics for the MSCI indices for the world energy sector and the world market portfolio. At first glance, the raw returns of the WEI outperform those of the ESG energy portfolio. Raw returns are higher when non-green or brown energy companies are included in the investment strategies than when only ESG-labeled energy companies are considered. The second part of the sample illustrates this more clearly. In contrast, the highest quartiles of PTV and PTV-ESG offer higher returns than the WEI. According to the ESG factor in the second part of the sample, the Q1 performs on average twice as well as the WEI. Finally, the greater portfolio diversification of the WI, which includes all sectors of the economy, is reflected in higher average returns and lower standard deviations compared to our ESG energy sector portfolio.

Figure 2 shows the daily evolution of the cumulative returns of the first quartile strategies and the three benchmarks. In particular, the first quartile portfolios based on the PTV ranking, the ESG score ranking or the PTV-ESG and the ESG-PTV iterations outperform the ESG energy market with cumulative returns of 64.4%, -9.9%, 32.8% and 32.1%, respectively, compared to cumulative losses of 83.4% for the ESG energy portfolio. Compared to naïve investments in ESG energy companies, the energy sector and the total market portfolio have significantly better cumulative returns. The PTV-Q1 portfolio outperforms both the WEI over the entire sample and the WI through the end of 2018.

Figure 3 depicts the cumulative excess returns of the quartile portfolios over the ESG energy market. The portfolios based on the PTV criterion exhibit positive excess returns for the first three quartiles, while they are significantly negative for PTV-Q4. In the case of the ESG criterion, only Q1 and Q3 show excess returns, although those of ESG-Q3 become negative since the outbreak of the COVID-19 pandemic. Only the portfolio with the highest ESG scores systematically outperforms the ESG energy market. This evidence agrees with recent literature (Alessandrini and Jondeau, 2020; Maiti, 2020; Pedersen *et al.*, 2021), which highlights that active management of portfolios based on high ESG ratings overperforms both traditional active investment and passive management of the ESG benchmarks (MSCI indices, etc.). After a gradual widening of the spreads for PTV-Q1 and ESG-Q1 through March 2020, these spreads narrow for the former and widen for the latter. Figure 2 provides context for this finding. The cumulative returns for PTV-Q1 and ESG-Q1 decline through March 2020, but less than in the case of the ESG energy market. From April 2020, the cumulative returns of ESG-Q1 and the ESG energy market grow similarly, outperforming PTV-Q1 and even the WI.

To empirically analyze the observed discrepancies between the quartile strategies for each risk factor and between Q1 and the three benchmark portfolios considered, descriptive statistics are used to analyze the statistical significance of the observed differences. We use a standard t-test for equality of means and a Wilcoxon-Mann-Whitney test for equality of medians to compare monthly raw returns. The null hypothesis to be tested is that the means and medians of the paired raw return series are equal.

Figure 2. Daily evolution of the cumulative return for the best portfolios (Q1) by each criterion and the three benchmarks

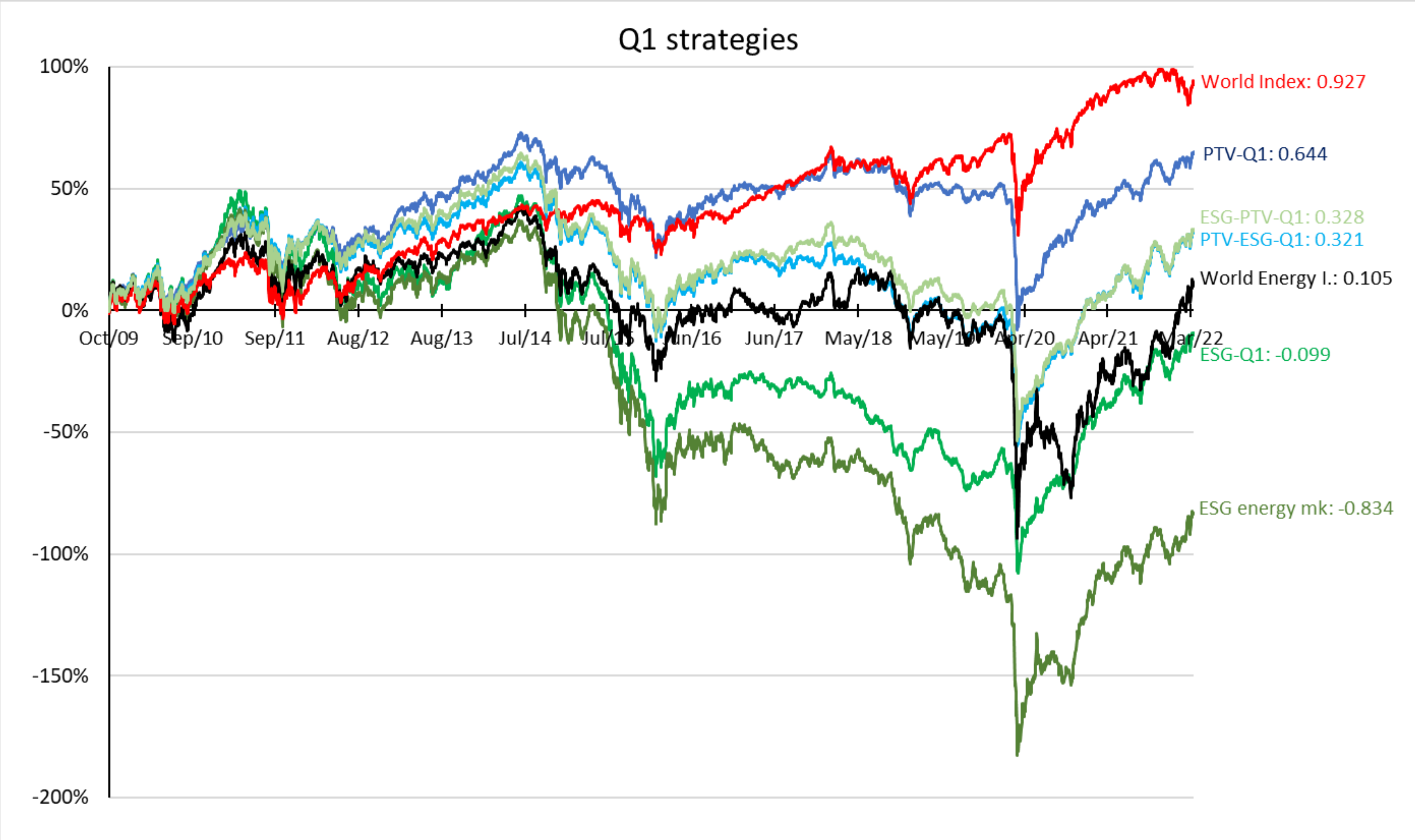
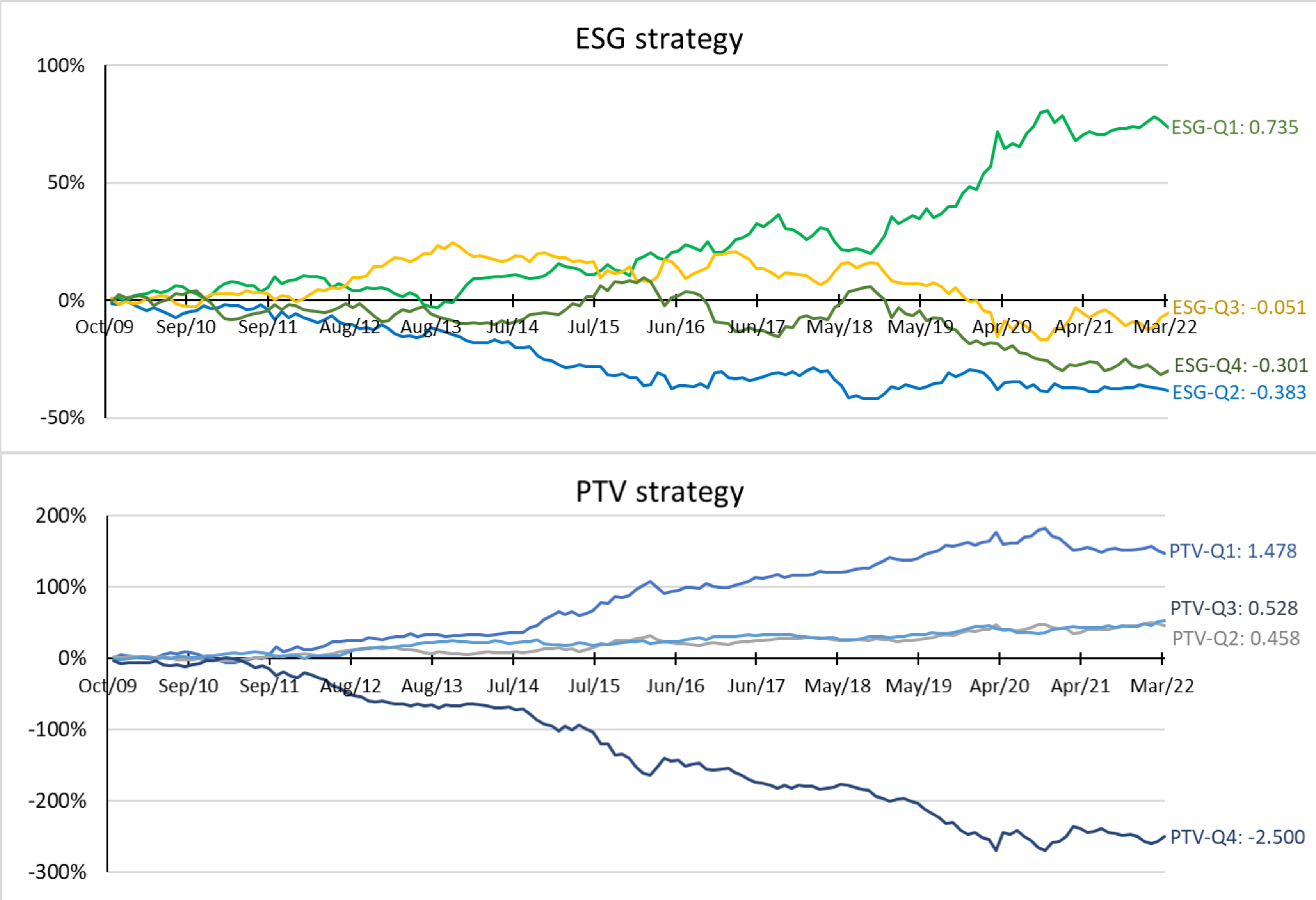


Figure 3. Monthly evolution of the cumulative excess return over the ESG energy market for the PTV and ESG portfolios



As shown in Panel A of Table 3 (full sample), all Q1 portfolios show positive and statistically significant return differences relative to Q4 and the ESG energy portfolio. PTV-Q1 achieves notable monthly excess returns, averaging 2.65% and 0.99% over Q4 and ESG energy, respectively. However, the differences in returns between the different Q1 strategies are only statistically significant at low levels. Even the differences between PTV-ESG-Q1 and ESG-Q1 are not statistically significant.

In the bottom rows of Table 3, we analyze the statistical significance of the excess returns of Q1 strategies relative to the WEI, which includes both green and brown companies, and relative to the WI, which includes all industries. It is noteworthy that all Q1 strategies, except ESG-Q1, show a positive excess return relative to the WEI over the entire sample period. However, this difference is only significant at the median level for PTV-Q1. As expected, the excess return of these strategies over the WI, which represents maximum diversification, is negative, although it is not always statistically significant.

Panel B of Table 3 shows the results for the second part of the sample period. In general, the median excess return between Q1 and Q4 portfolios and between Q1 and the ESG energy universe remains significant. However, the difference between Q1 portfolios for the different strategies is no longer significant, and the same is true for Q1 portfolios and the energy market. The market portfolios significantly outperform the strategies based on PTV when only the second part of the sample is considered. Finally, the excess return for the ESG Q1 strategy improves relative to the other portfolios.

Table 3. Test results for statistical differences in monthly raw returns across quartile strategies and between Q1 and various indices

	Panel A. Full sample			**Panel B. Mar17 to Mar22**		
	Mean	Median	% > 0	Mean	Median	% > 0
PTV-Q1 minus Q4	0.0265***	0.0327***	63.33	0.0222	0.0434***	65.57
ESG-Q1 minus Q4	0.0069**	0.0044**	57.33	0.0106	0.0059	63.93
PTV-ESG-Q1 minus Q4	0.0162***	0.0136***	60.67	0.0183*	0.0278*	65.57
PTV-Q1 minus ESG Energy	0.0099***	0.0107***	63.33	0.0074	0.0140**	67.21
ESG-Q1 minus ESG Energy	0.0049***	0.0037**	55.33	0.0078	0.0103*	59.02
PTV-ESG-Q1 minus ESG En.	0.0077***	0.0071***	63.33	0.0067	0.0810*	63.93
PTV-Q1 minus ESG-Q1	0.0050*	0.0053*	56.00	-0.0005	0.0033	52.46
PTV-Q1 minus PTV-ESG-Q1	0.0022	0.0042*	58.67	0.0007	0.0014	55.74
ESG-Q1 minus PTV-ESG-Q1	-0.0028	-0.0035	46.67	0.0012	-0.0003	49.18
PTV-Q1 minus World Energy	0.0038	0.0075**	59.33	0.0009	0.0040	52.46
ESG-Q1 minus World Energy	-0.0012	-0.0011	45.33	0.0014	0.0026	50.82
PTV-ESG-Q1 minus World En.	0.0016	0.0024	54.00	0.0003	0.0014	50.82
PTV-Q1 minus World	-0.0018	-0.0011	46.66	-0.0053	-0.0095*	34.43
ESG-Q1 minus World	-0.0067*	-0.0059*	43.33	-0.0048	-0.0077	36.07
PTV-ESG-Q1 minus World	-0.0039	-0.0040*	44.66	-0.0060	-0.0094**	37.70

Note: This table shows the results of statistical tests of equality of monthly raw returns between Q1 and Q4 portfolios for each factor, Q1 portfolios and the ESG energy portfolio, Q1 from different factors, Q1 and both the global energy industry and the global equity market (MSCI World Energy Index and MSCI All Countries World Index). The hypothesis of equality of means of each pair of portfolios is tested using a standard t-test. The non-parametric Wilcoxon signed-rank test is used to test the equality of the medians. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively, in a two-tailed test.

3.2 Risk-adjusted returns

In this section, we analyze the risk-adjusted returns of our monthly-rebalanced portfolios. Firstly, we interpret the risk-adjusted returns as the observed return-to-risk ratio using a conditional volatility model that aligns with past return performance, without relying on a specific valuation model. Secondly, we assess "alphas" as a measure of excess returns compared to a selected systematic risk metric. Specifically, we employ the Carhart (1997) four-factor model to estimate abnormal returns for ESG, PTV, and a combination of both portfolios, following established research practices. These alphas enable us to evaluate the potential to generate returns attributed to factors beyond what can be explained by systematic factors alone.

3.2.1. Model-free risk-adjusted returns

This section analyzes a ratio of observed return to time-varying risk as a proxy for realized risk-adjusted return. Portfolios that invest only in energy stocks, and even more so, only in stocks with ESG labels, limit diversification opportunities. As a result, these portfolios bear both sector risk and idiosyncratic risk if there is insufficient diversification among energy companies. In portfolio management, observed returns are not analyzed in isolation, but are relativized according to the risk taken. Risk refers to the statistically quantifiable probability of obtaining returns different than expected from an investment strategy. Thus, risk includes not only poor performance (i.e. lower than expected returns) but also overperformance scenarios (i.e. higher than expected returns). From this basis, a reasonable starting point for assessing financial risk is provided by accurately fitting the volatility of asset prices over the investment decision period. Historical volatility estimates the current risk exposure by considering past events and assumes that the pattern followed by such volatility will continue in the future. Statistically estimated as the standard deviation (i.e., the square root of the variance or the second moment of the return distribution) of all observed returns up to the valuation date, historical volatility is considered as a benchmark in diverse seminal studies (French et al., 1987; Schwert, 1990; Hull and White, 1998).

Notwithstanding, numerous papers in the financial literature provide evidence that financial uncertainty and therefore, risk exposure, does not remain static or invariant to market changes (Engle, 1982; Bollerslev, 1986; Schwert, 1989; Harvey and Whaley, 1992). At this point, autoregressive volatility emerges to account that risk exposure changes over time. Specifically, this paper implements the Autoregressive Conditional Heteroskedasticity Generalized Autoregressive Conditional Heteroskedasticity (AR-GARCH) specification on portfolio returns to account for the presence of volatility clustering and time-varying volatility in financial data. Financial time series data often exhibit periods of high volatility followed by periods of low volatility, and AR-GARCH models capture this clustering effect by incorporating lagged conditional variances and error terms (Bollerslev, 1986). Additionally, financial markets are dynamic, and the level of volatility changes over time, making traditional constant volatility assumptions unrealistic (Engle, 1982). Understanding and managing risk is crucial for investors and portfolio makers, and AR-GARCH models provide insights into the risk profile of a portfolio by estimating the conditional variance or volatility as a function of past information and innovations. The Sharpe ratio, a key metric for evaluating portfolio performance, incorporates volatility and risk, making it important to account for the risk-adjusted returns. By incorporating AR-GARCH, portfolio managers can assess how a portfolio performs relative to its risk exposure, enhancing their understanding of risk profiles and risk-adjusted returns. In summary, implementing an AR-GARCH specification on portfolio returns is essential for capturing volatility clustering, time-varying volatility, managing risk, assessing portfolio performance accurately and subsequently making informed decisions.

We examine daily returns based on the full sample of data, as conditional volatility models may require long samples to accurately estimate the parameters. With the estimated daily volatilities, we transform them into monthly volatilities and maintain the monthly periodicity of returns as in the previous analyses.

To model the conditional heteroskedasticity, we first fit the residuals (innovations in the subsequent GARCH models) of an AR(1) specification. The daily return of the portfolio j at a given time t, $r_{j,t}$, are modeled as follows:

$$r_{j,t} = \phi_j r_{j,t-1} + \varepsilon_{j,t} \tag{4}$$

$$\varepsilon_{j,t} = \sigma_{j,t} \eta_{j,t} \tag{5}$$

where ϕ_j are the parameters of the AR(1) structure, $\varepsilon_{j,t}$ are the current period residuals, $\sigma_{j,t}$ is the return volatility, and $\eta_{j,t}$ are the standardized innovations for each univariate j series. The model assumes that $\eta_{j,t}$ are *i.i.d.* random variables which conditionally follow the univariate standardized skewed Student's t distribution, $\eta_{j,t} \sim f_{j,t}(0,1,\xi_{j,t},\nu_{j,t})$, introduced by Fernández and Steel (1998), with skew and shape parameters $\xi_{j,t}$ and $\nu_{j,t}$, respectively, for each univariate j series.

The conditional variance $\sigma_{j,t}^2$ follows a GARCH process (Bollerslev, 1986), which states that the current variance depends not only on its past variance, but also on the past squared innovations:

$$\sigma_{j,t}^2 = \omega_j + \alpha_j \varepsilon_{j,t-1}^2 + \beta_j \sigma_{j,t-1}^2 \tag{6}$$

where ω_j is the model constant, α is the ARCH component parameter, and β_j is the GARCH component parameter.

The estimation results of the AR(1)-GARCH(1,1) model are presented in Appendix Table A. Given the high statistical significance of most of the calibrated parameters, this model is relevant and necessary to properly represent the variance of the financial portfolios under study. Overall, the univariate portfolio processes show high persistence in variance, with β in the range of 0.86-0.93, and low impact of new information shocks on conditional heteroskedasticity (α between 0.07-0.13). Thus, shocks have little impact on variance processes, but their effects are persistent in the long-term. Moreover, the parameters ξ and ν capture the highly asymmetric and jumpy nature of the financial time series. The LM test on squared innovations shows that the GARCH model has succeeded in mitigating the second-order autocorrelation for most portfolios, except for PTV-Q4 and WI, which may indicate the need to adjust these specific processes by increasing the lag, both in terms of shocks and persistence.

Table 4 shows the summary statistics of the realized risk-adjusted return measures. The high value achieved by the PTV-Q1 portfolio is more than remarkable, as it is far superior to any other portfolio. This portfolio outperforms the ESG energy market on a risk-adjusted basis in three out of four months. The ESG strategies show modest values, despite the good performance of the ESG-Q1 portfolio. This portfolio improves in the second part of the sample (Table 4, Panel B). In two out of three months, the ESG-Q1 portfolio outperforms the ESG energy market over the last five years. The risk-adjusted returns in this second subsample exceed those of the WEI.

Regarding the combined PTV-ESG and ESG-PTV strategies, the results for the best portfolio, Q1, are very similar. The same holds true for the worst portfolio, Q4. What is remarkable is that while the observed trend of deteriorating performance as the quartile worsens is maintained in the PTV-ESG portfolios, the same does not occur in the ESG-PTV portfolios (Table B.1). Under this dual criterion ESG-PTV, portfolios Q2 and Q4 are clearly inferior to portfolios Q1 and Q3. This behavior suggests that when the first criterion applied in portfolio formation is PTV, and then within the top PTV-ranked companies, they are sorted by ESG score (PTV-ESG-Q1 and PTV-ESG-Q2), the result is significantly better than when the first criterion is ESG score and then sorted by PTV (ESG-PTV-Q1 and ESG-PTV-Q2). This indicates that the PTV criterion dominates over ESG.

Table 4. Summary statistics of monthly risk-adjusted returns (AR(1)-GARCH(1,1) volatility)

	PTV-Q1	PTV-Q2	PTV-Q3	PTV-Q4	ESG-Q1	ESG-Q2	ESG-Q3	ESG-Q4	PTV-ESG-Q1	PTV-ESG-Q2	PTV-ESG-Q3	PTV-ESG-Q4	ESG Energy	World Energy	World
Panel A. Full sample (October 2009-March 2022)															
Mean	0.2082	0.0296	0.0213	-0.2238	0.0428	-0.0779	-0.0391	-0.0525	0.1135	0.0944	-0.1181	-0.1113	-0.0408	0.0381	0.2632
Std. Deviation	1.0228	1.0447	1.0218	1.0815	1.1020	1.0579	1.0214	1.0108	1.0532	1.0240	1.0814	1.0226	1.0599	1.0318	0.9901
5th Percentile	-1.5509	-1.9398	-1.8676	-2.0203	-1.8721	-1.9176	-1.8572	-1.8229	-1.6810	-1.8259	-1.9888	-1.9413	-1.9841	-1.7156	-1.5300
Q1	-0.4262	-0.6553	-0.5932	-0.9887	-0.7414	-0.8962	-0.6337	-0.7918	-0.5965	-0.6991	-0.8891	-0.7434	-0.8006	-0.6770	-0.4428
Median	0.2866	0.0580	0.0336	-0.1998	0.0414	-0.0342	-0.0202	0.0679	0.1887	0.2205	-0.0952	-0.0764	0.0972	0.0987	0.2996
Q3	0.9468	0.7962	0.7462	0.5733	0.7796	0.6757	0.7201	0.6274	0.8485	0.7752	0.6565	0.6492	0.7360	0.6917	0.9255
95th Percentile	1.7935	1.6001	1.4118	1.3931	1.7828	1.5443	1.5445	1.4569	1.7261	1.5881	1.5922	1.4033	1.5671	1.6040	1.7411
%month beats ESG Energy	0.7600	0.5733	0.6133	0.2600	0.6000	0.4333	0.5000	0.4733	0.6933	0.6867	0.3667	0.3600	--	0.6000	0.6447
Panel B. From March 2017 to March 2022															
Mean	0.1886	0.0450	-0.0016	-0.2758	0.0681	-0.1054	-0.1266	-0.0527	0.0925	0.1191	-0.1525	-0.1571	-0.0788	0.0292	0.3283
Std, Deviation	1.1497	1.1698	1.1139	1.1467	1.1663	1.1537	1.0807	1.1298	1.2014	1.1422	1.1296	1.1011	1.1536	1.1375	1.0431
5th Percentile	-2.0650	-1.9748	-1.9121	-2.0139	-1.8765	-1.9428	-1.8689	-2.0379	-1.9489	-1.9064	-2.0248	-1.8955	-2.0104	-1.9833	-1.5891
Q1	-0.3627	-0.8002	-0.5697	-1.2261	-0.7637	-0.9450	-0.9359	-0.8700	-0.6031	-0.2665	-0.9982	-1.0873	-0.8084	-0.6464	-0.2597
Median	0.2982	0.1103	-0.0014	-0.2370	-0.0207	-0.0330	-0.0649	0.0919	0.0345	0.2400	-0.0800	-0.2384	0.0805	0.1807	0.4716
Q3	0.9551	0.9131	0.6895	0.5650	0.9080	0.6790	0.7045	0.6248	0.8666	0.8936	0.5537	0.4897	0.5810	0.6688	0.9381
95th Percentile	1.8176	1.6671	1.6220	1.7959	1.9922	1.6498	1.7220	1.7478	2.0226	1.7282	1.7899	1.9144	1.7133	1.8614	1.9841
%month beats ESG Energy	0.7377	0.6393	0.6066	0.3115	0.6721	0.4262	0.4754	0.5082	0.6721	0.7213	0.3934	0.3934	--	0.5738	0.6885

Note: Q1 represents the first quartile for each strategy and shows the risk-adjusted returns of the top-ranked portfolios of stocks ranked by PTV, ESG, or both (PTV-ESG) among all ESG-rated global energy companies by OWL ESG Analytics. Risk-adjusted returns are measured by relating each portfolio's mean to its standard deviation. Monthly volatility is calculated from daily AR(1)-GARCH(1,1) volatility assuming an asymmetric t-student distribution. ESG PTV portfolios are presented in the Appendix B. All quartile portfolios are created at the beginning of each month and returns are calculated through the end of the month. The MSCI World Energy Index and the MSCI World Index are benchmarks for the global energy industry and the global equity market, respectively.

As shown in Table 5, risk-adjusted returns show greater statistical significance between strategies and indices than raw returns. Panel A shows that all Q1 strategies outperform both the Q4 strategies and the ESG energy market throughout the sample period. The PTV-Q1 strategy dominates the other Q1 portfolios as well as the WEI. Its risk-adjusted return is not significantly different from the WI. Moreover, the PTV-ESG-Q1 portfolio outperforms the ESG-Q1 portfolio. Notwithstanding, both strategies are outperformed by the WEI and WI portfolios, with only the difference with the WI portfolio being statistically significant.

The results in Panel B of Table 5 are based on the sample period of the last five years. The risk-adjusted return differences between Q1 and Q4 strategies, and between Q1 strategies and the ESG energy universe, have increased slightly at the mean and median and remain statistically significant. Although there is a larger difference in risk-adjusted return between ESG-Q1 and ESG-Q4, these differences are not statistically significant. In this second subsample, the differences between the Q1 portfolios are smaller. The differences between the Q1 strategies and the two global indices remain constant. Accordingly, the positive differences between PTV-Q1 and WEI remain statistically significant.

There are two main results to highlight from this section. First, the differences between the Q1 strategies and both the ESG energy universe and the WEI, which are barely statistically significant in terms of raw returns (Table 3), become statistically significant when risk-adjusted returns are considered (Table 5). This finding suggests that portfolios constructed by Q1 on the basis of PTV, ESG or both factors have a relatively low level of risk. Second, in the second subperiod of our sample (from March 2017 to March 2022), the risk-adjusted returns of the energy market, and in particular the ESG energy universe, significantly underperformed the WI. Notably, the PTV-Q1 strategy outperforms the value-weighted energy portfolio (WEI) in a statistically significant manner and does not underperform the WI despite this adverse environment. Third, there is a consistent performance trend observed among quartiles when PTV is either the sole or primary criterion in portfolio formation (PTV and PTV-ESG portfolios). However, the lack of consistency in the case of ESG-PTV portfolios suggests that the PTV criterion dominates over the ESG criterion.

Table 5. Test results for statistical differences in monthly risk-adjusted returns across quartile strategies and between Q1 and various indices

	Panel A. Full sample			Panel B. Mar17 to Mar22		
	Mean	Median	% > 0	Mean	Median	% > 0
PTV-Q1 minus Q4	0.4320***	0.4573***	78.00	0.4644***	0.5357***	73.77
ESG-Q1 minus Q4	0.0953*	0.0757**	56.00	0.1207	0.1182	59.02
PTV-ESG-Q1 minus Q4	0.2248***	0.2995***	66.00	0.2496**	0.3431**	65.57
PTV-Q1 minus ESG Energy	0.2490***	0.3063***	76.00	0.2674***	0.3546***	73.77
ESG-Q1 minus ESG Energy	0.0835**	0.0840**	60.00	0.1468*	0.2113**	67.21
PTV-ESG-Q1 minus ESG En.	0.1543***	0.1590***	69.33	0.1712**	0.2106**	67.21
PTV-Q1 minus ESG-Q1	0.1654***	0.2047***	66.00	0.1205	0.0903	60.66
PTV-Q1 minus PTV-ESG-Q1	0.0947***	0.0907***	67.33	0.0961*	0.0818*	65.57
ESG-Q1 minus PTV-ESG-Q1	-0.0707**	-0.0885***	39.33	-0.0244	-0.0304	49.18
PTV-Q1 minus World Energy	0.1701***	0.1574***	66.00	0.1594*	0.1535*	60.66
ESG-Q1 minus World Energy	0.0047	-0.0431	47.33	0.0388	-0.3043**	36.07
PTV-ESG-Q1 minus Wd. En.	0.0754	0.0351	54.00	0.0632	0.0464	54.10
PTV-Q1 minus World	-0.0550	-0.0794	46.66	-0.1397	0.0368	50.82
ESG-Q1 minus World	-0.2204***	-0.2939***	34.67	-0.2603**	-0.3322**	36.07
PTV-ESG-Q1 minus World	-0.1497**	-0.1267***	42.67	-0.2359*	-0.3322***	39.34

Note: This table shows the results of statistical tests of equality of monthly risk-adjusted returns between Q1 and Q4 portfolios for each factor, Q1 portfolios and the ESG energy portfolio, Q1 across factors, Q1 and both the global energy industry and the global equity market (MSCI World Energy Index and MSCI All Countries World Index). Risk-adjusted returns are measured by relating the mean of each portfolio to its standard deviation. Monthly volatility is computed from a daily AR(1)-GARCH(1,1) volatility assuming an asymmetric t-student distribution. The hypothesis of equality of means of each pair of portfolios is tested using a standard t-test. The non-parametric Wilcoxon signed-rank test is used to test the equality of the medians. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively, in a two-tailed test.

3.2.2. Four factor risk-adjusted returns

In this section, we employ the four-factor model of Fama and French (1993) and Carhart (1997) to assess the exposure to risk factors and calculate risk-adjusted abnormal returns (Kempf and Osthoff, 2007; Halbritter and Dorfleitner, 2015). The exposure to risk factors can manifest in various ways. Firstly, the market risk factor (Mkt), which measures the excess return of the market over the risk-free rate, captures the systematic risk associated with investing in the overall market rather than specific factors. Low market beta would suggest that PTV or ESG portfolios may have a lower exposure to systematic market risk. Secondly, the size factor (Small Minus Big, SMB), which captures the excess return of small-cap stocks over large-cap stocks, reflects the potential bias towards large and well-established companies in the portfolio. These companies typically have more resources to dedicate to ESG reporting, potentially leading to an imbalance in representation across companies of different sizes.

Thirdly, the value factor (High Minus Low, HML) reflects the excess return of value stocks over growth stocks. Value stocks are those with high book-to-market ratios, while growth stocks are those with low book-to-market ratios. In the literature, it is commonly assumed that value stocks tend to outperform growth stocks. Given that value stocks are often associated with smaller market capitalization, an equal-weighted scheme can lead to a higher representation of value stocks in the PTV and ESG portfolios (Swade et al., 2023). Consequently, the portfolio is more likely to exhibit a significant positive exposure to the value factor. Lastly, the momentum factor (MOM) represents the excess return of stocks with high past returns over stocks with low past returns. It captures the dynamic effects of SRI, which can result in significant financial flows that may temporarily impact companies with improving or deteriorating ESG scores. This dynamic can introduce correlations with the momentum factor, as investor sentiment and market movements react to changing ESG performance of companies (Hong and Kacperczyk, 2009). We need to consider the potential exposure to these risk factors that may not align with investors' preferences when evaluating the PTV and ESG portfolios and interpreting their performance in relation to systematic factors.

In our analysis, the dependent variable is the monthly excess return of each portfolio, while the 1-month US Treasury Bill return serves as the risk-free rate. Throughout 69% of the months in our sample period, the risk-free rate is nearly negligible, ranging from 0 to 1 basis point. The highest observed value is 21 basis points, occurring at the beginning of 2019. The four factors act as independent variables, with the intercept representing the alpha.[4] The risk-adjusted returns, or alphas, allow us to gauge return outcomes attributable to idiosyncratic opportunities or those associated with non-beta factors.

Table 6 presents the regression results for the four-factor model. The findings reveal that all portfolios, including the market benchmarks (ESG Energy, WEI, and WI portfolios), exhibit negative alpha values.[5] Notably, during the entire sample period, the PTV-Q1 portfolios display the highest alpha among all the portfolios and market indices. Despite

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[4] We collect our monthly data from Kenneth French's website, which provides comprehensive information on these factors. The factors are calculated based on the value-weighted returns of all firms listed in the CRSP database, including those incorporated in the United States and listed on the NYSE, AMEX, or NASDAQ exchanges.

[5] The risk factors utilized in our analysis are computed specifically for companies based in the United States. However, it's important to note that our three benchmark portfolios encompass companies from various regions worldwide.

its negative value (-0.52), it is comparable to the alpha of the fully diversified global market portfolio, WI (-0.55), and significantly outperforms the alpha of the WEI portfolio (-1.00) and the ESG universe portfolio (-1.76). This implies that the PTV-Q1 portfolios have the potential to generate additional returns beyond what can be attributed to systematic factors, despite focusing solely on the energy sector and employing a simple equally weighted scheme. Supporting this finding, the alpha of the PTV and PTV-ESG portfolios consistently deteriorates across quartiles.

The explanatory power of the four-factor model for the PTV-Q1 and ESG-Q1 portfolios is markedly lower than that of the benchmark portfolios, indicating the presence of additional risk factors not considered in the model. Additionally, in both portfolios, the coefficients associated with the size (SMB) and momentum (MOM) variables are not significant. The results suggest that the higher PTV or ESG score that exhibit first quartile portfolios are not related with large and well-established companies.

When conducting a common risk factor analysis across different PTV quartile portfolios, a consistent trend is observed in the factor-loadings. The factor-loading on market risk premium increases from 0.83 (Q1) to 1.06 (Q2), 1.20 (Q3), and 1.53 (Q4). A similar increasing trend is observed for the factor-loadings on SMB and HML, while a decreasing trend is observed for the factor-loading on MOM.

As for the ESG and ESG-PTV portfolios, the first quartile portfolio stands out with the highest alpha among the ESG portfolios. Although the majority of the literature suggests that investing in companies with higher ESG scores tends to yield lower alphas (Renneboog et al., 2008; Hong and Kacperczyk, 2009; Albuquerque et al., 2019; Ciciretti et al., 2023), there are other studies that support the inverse relationship (Kempf and Osthoff, 2007; Statman and Glushkov, 2009). The negative alpha of the ESG-Q1 portfolio is higher than that of our universe of ESG Energy companies but lower than the WEI and the WI. On a different note, the alpha values for the other quartiles do not display consistent patterns (Naffa and Fain, 2022). Moreover, the factor-loadings of the various systematic risk factors across the different quartiles in the ESG and ESG-PTV portfolios do not exhibit as clear trends as those observed in the PTV and PTV-ESG portfolios. Notwithstanding, it is worth noting that in the second part of the sample period (Table 6, Panel B), there is a notable improvement in the alpha level for the ESG-Q1 portfolio. This suggests that the ESG-Q1 portfolio shows promising results during that specific period.

Table 6. Analysis of the Four-Factor Model (all loadings multiplied by 100)

	PTV-Q1	PTV-Q2	PTV-Q3	PTV-Q4	ESG-Q1	ESG-Q2	ESG-Q3	ESG-Q4	PTV-ESG-Q1	PTV-ESG-Q2	PTV-ESG-Q3	PTV-ESG-Q4	ESG Energy	World Energy	World
Panel A. Full sample (October 2009-March 2022)															
Alpha	-0.52*	-1.39***	-1.44***	-3.72***	-1.14***	-2.13***	-1.76***	-2.01***	-0.83***	-1.09***	-2.40***	-2.75***	-1.76***	-1.00***	-0.55***
Mrkt	0.83***	1.06***	1.20***	1.53***	1.00***	1.25***	1.18***	1.17***	0.93***	0.96***	1.36***	1.36***	1.15***	1.04***	0.96***
SMB	0.00	0.37***	0.63***	1.24***	0.17	0.63***	0.88***	0.55***	0.09	0.27***	0.83***	1.04***	0.56***	0.13	-0.13***
HML	0.51***	0.65***	0.70***	0.62***	0.43***	0.68***	0.80***	0.56***	0.58***	0.58***	0.54***	0.77***	0.62***	0.80***	0.03
Mom	0.06	-0.08	-0.31*	-0.81***	-0.25	-0.25	-0.41**	-0.23	0.02	-0.03	-0.57**	-0.55**	-0.28*	-0.25**	-0.07**
Ad.R^2	0.6502	0.6912	0.6772	0.6344	0.5867	0.6764	0.6789	0.6738	0.6584	0.6959	0.6350	0.6543	0.7014	0.6928	0.9290
Panel B. From March 2017 to March 2022															
Alpha	-0.67	-1.17**	-1.20*	-3.38***	-0.63	-1.80***	-2.06***	-1.91***	-0.74*	-1.08**	-1.75**	-2.84***	-1.60***	-0.72	-0.39***
Mrkt	0.87***	1.09***	1.19***	1.60***	0.89***	1.29***	1.33***	1.24***	0.91***	1.05***	1.36***	1.43***	1.19***	1.03***	0.91***
SMB	0.17	0.62***	1.02***	1.82***	0.34**	0.87***	1.35***	1.06***	0.30*	0.48***	1.13***	1.72***	0.91***	0.41*	-0.05
HML	0.75***	0.92***	0.91***	1.02***	0.62***	0.92***	1.12***	0.93***	0.79***	0.87***	0.77***	1.17***	0.90***	0.97***	0.09**
Mom	0.33*	0.37***	0.10	0.04	0.16	0.20	0.27*	0.21	0.33**	0.35***	-0.04	0.20	0.21*	-0.13	-0.02
Ad.R^2	0.7166	0.8015	0.7675	0.7288	0.6619	0.7735	0.7826	0.8041	0.6964	0.8317	0.7218	0.7613	0.8106	0.7348	0.9635

Note: This table shows the results from the four-factor regression analysis. ***, ** and * indicates statistical significance at the 1%, 5% and 10% levels, respectively. The t-statistics are calculated by robust standard errors. Q1 represents the first quartile for each strategy and shows the risk-adjusted returns of the top-ranked portfolios of stocks ranked by PTV, ESG, or both (PTV-ESG) among all ESG-rated global energy companies by OWL ESG Analytics. ESG PTV portfolios are presented in the Appendix B. All quartile portfolios are created at the beginning of each month and returns are calculated through the end of the month. The MSCI World Energy Index and the MSCI World Index are benchmarks for the global energy industry and the global equity market, respectively.

From this section, several key results emerge. Firstly, the PTV-Q1 portfolio has the highest alpha among the PTV and ESG portfolios and is comparable to the global market portfolio, suggesting that it can generate additional returns beyond systematic factors despite being focused on the energy sector and using an equally weighted scheme. Secondly, the PTV portfolios have consistent increasing exposure to market risk, size factor, and value factor, and decreasing exposure to momentum factor across quartiles. Thirdly, the ESG-Q1 portfolio has the highest alpha among the ESG portfolios, suggesting that it can benefit from investing in companies with higher ESG scores contrary to some literature findings. Fourthly, the ESG and ESG-PTV portfolios do not show consistent patterns in alpha values or factor-loadings across quartiles. Finally, there is a noticeable improvement in the alpha level for the ESG-Q1 portfolio during the second part of the sample period.

3.3 Performance analysis

In the final step, we use several formal risk-adjusted performance measures to evaluate the ex-post financial performance of the portfolio. Because of the wide range of performance measures and the fact that their appropriateness depends on the type of investor and the distribution of portfolio returns, we use several alternative standard measures. Specifically, we consider Jensen's alpha and beta for each of the three benchmark indices, i.e., the equal-weighted ESG energy universe and the value-weighted WEI and WI, as well as Treynor and Sharpe ratios assuming normally distributed returns. Most of these measures rely on the assumptions of the CAPM and primarily focus on analyzing systematic risk, measured by beta, relative to a market index. As a result, these measures are well-suited for investors with a well-diversified portfolio. However, our ESG energy universe imposes restrictions on investment options, potentially exposing portfolio strategies to idiosyncratic (unsystematic) risk. While the Sharpe ratio considers total risk rather than just market risk, its conventional use assumes asymptotic normality in statistical inference, which may not accurately capture the characteristics of our data. In Section 3.2.1, we propose a risk-adjusted return measure derived from an AR(1)-GARCH(1,1) conditional volatility model that incorporates a skewed Student's t distribution. This model better accounts for the skewness and kurtosis observed in our data compared to a normal distribution. Furthermore, in Section 3.2.2, we explore an alternative alpha derived from a multifactor model, specifically the one suggested by Fama and French (1993) and Carhart (1997). This alternative approach offers a more appropriate methodology for evaluating systematic risk.

Compared to traditional performance measures, downside risk measures provide a more realistic assessment of risk. They consider the asymmetric nature of investment returns, where investors prioritize downside risk (losses) over upside potential (gains). This is particularly crucial for risk-averse investors concerned with capital preservation and sensitive to downside volatility. Measures like the Sortino ratio or Omega ratio offer a comprehensive assessment of a portfolio's risk-adjusted returns by explicitly incorporating downside volatility and losses. Additionally, downside risk measures such as Value at Risk (VaR) provide a clearer understanding of potential losses beyond a specified confidence level. Due to the prevalent negative skewness observed in financial time series, we consider the VaR-adjusted Sharpe ratio (Dowd, 2000; Favre and Galeano, 2002) as a comprehensive performance measure. By incorporating the lower bound of a confidence interval, the VaR-adjusted Sharpe ratio improves upon the traditional Sharpe ratio, providing a more robust assessment of performance (Deng et al., 2013). Finally, the Maximum Drawdown (MDD) complements this by revealing the largest peak-to-trough decline experienced within a specific time period, helping investors assess worst-case scenarios in terms of loss (Magdon-Ismail and Atiya, 2004).

Most performance measures take into account the excess return over a risk-free rate, while downside measures consider a minimum acceptable return. In our analysis, we utilize the 1-month US Treasury Bill return as both the risk-free rate and the minimum acceptable rate of return. However, it is important to acknowledge that this assumption may have limitations, particularly when considering companies on a global scale.

Table 7 and the left panel of Table B.2 present the performance measures for the investment strategies and the three benchmark indices. The findings for the PTV strategies align with the results discussed in the previous sections, demonstrating consistent patterns in terms of raw return, risk-adjusted return, and alpha derived from the four-factor model. The PTV-Q1 portfolios consistently outperform the other strategies, the ESG-labeled universe of energy companies, and the WEI. This strategy has the highest Jensen's alpha (systematic risk-adjusted return), Treynor ratio (excess return per unit of systematic risk), Sharpe ratio (excess return per unit of total risk), Omega ratio (gain-loss ratio), Sortino ratio (excess return per unit of downside risk), and VaR-adjusted Sharpe ratio (excess return per unit of downside risk). Similarly, the MDD and VaR at the 95% and 99% confidence levels (losses for these percentiles) of PTV-Q1 are the lowest among all portfolios and the WEI. The largest performance differences between PTV-Q1 and the ESG energy universe and the WEI are in the Omega ratio and MDD. Investors concerned with downside risk find these performance measures particularly attractive. According to the prospective theory, investors are not only risk-averse, but also loss-averse.

The PTV-ESG-Q1 strategy also outperforms the ESG energy universe portfolio and the WEI, but with less favorable values than PTV-Q1. ESG-Q1 only outperforms the ESG energy portfolio over the entire sample period. None of the strategies analyzed outperform the WI, which represents the market portfolio. However, all Q1 strategies have low betas with respect to the energy sector, suggesting a lower cost of capital than the rest of the companies in the sector.

The performance measures for PTV-ESG show a high level of consistency within quartiles, with one quartile consistently outperforming the next quartile. However, the PTV strategy does not exhibit the same pattern, as the results for Q2 and Q3 are similar, and Q2 does not consistently outperform Q3. In terms of the ESG score and the ESG-PTV combination criterion, the Q1 portfolios demonstrate superior performance, while the Q2 portfolios perform similarly to Q4 and worse than Q3. It is worth noting that regardless of the criteria used to construct the portfolios, the Q1 strategies consistently outperform the Q4 strategies. Based on these findings, constructing self-financing portfolios with long positions in Q1 and short positions in Q4 could be a favorable approach.

Table 7. Performance and downside risk analysis. Full sample period

	PTV-Q1	PTV-Q2	PTV-Q3	PTV-Q4	ESG-Q1	ESG-Q2	ESG-Q3	ESG-Q4	PTV-ESG-Q1	PTV-ESG-Q2	PTV-ESG-Q3	PTV-ESG-Q4	ESG Energy Ind.	World Energy Ind.	World Ind.
Beta (ESG-En.)	0.5436	0.8341	1.0653	1.5582	0.7924	1.0759	1.1691	0.9621	0.6625	0.7154	1.2686	1.3577	1	0.8085	0.4069
Beta (Wld En.)	0.5922	0.8890	1.1203	1.5957	0.8098	1.1313	1.2278	1.0267	0.7098	0.7734	1.2964	1.4205	1.0490	1	0.4518
Beta (World)	0.9356	1.2982	1.5644	2.1451	1.2543	1.6049	1.6166	1.4667	1.0913	1.1475	1.8345	1.8738	1.4856	1.2714	1
Alpha (ESGEn)	0.0073	0.0021	0.0039	-0.0136	0.0037	-0.0021	0.0006	-0.0022	0.0058	0.0037	-0.0031	-0.0065	0	0.0050	0.0083
Alpha (Wld En)	0.0040	-0.0030	-0.0026	-0.0231	-0.0011	-0.0087	-0.0066	-0.0081	0.0018	-0.0007	-0.0109	-0.0148	-0.0061	0	0.0058
Alpha (World)	-0.0014	-0.0104	-0.0115	-0.0352	-0.0082	-0.0178	-0.0157	-0.0164	-0.0045	-0.0072	-0.0213	-0.0254	-0.0145	-0.0072	0
Treynor ratio	0.0079	-0.0030	-0.0019	-0.0143	-0.0008	-0.0075	-0.0050	-0.0079	0.0032	-0.0004	-0.0080	-0.0103	-0.0056	0.0007	0.0149
Sharpe ratio	0.0900	-0.0370	-0.0238	-0.1746	-0.0099	-0.0938	-0.0625	-0.0959	0.0383	-0.0049	-0.0985	-0.1273	-0.0706	0.0077	0.1467
Omega ratio	1.2882	0.9036	0.9354	0.6197	0.9739	0.7664	0.8388	0.7642	1.1102	0.9865	0.7589	0.6978	0.8222	1.0217	1.4738
Sortino ratio	0.1170	-0.0461	-0.0306	-0.2147	-0.0129	-0.1167	-0.0788	-0.1162	0.0503	-0.0060	-0.1277	-0.1538	-0.0877	0.0104	0.2147
Sharpe/VaR99	0.0387	-0.0159	-0.0102	-0.0750	-0.0043	-0.0403	-0.0269	-0.0412	0.0165	-0.0021	-0.0423	-0.0547	-0.0303	0.0033	0.0630
VaR 95% norm.	0.0785	0.1114	0.1408	0.2094	0.1095	0.1422	0.1551	0.1298	0.0917	0.0975	0.1701	0.1812	0.1296	0.1138	0.0678
VaR 99% norm.	0.1110	0.1576	0.1992	0.2961	0.1549	0.2012	0.2194	0.1836	0.1297	0.1380	0.2406	0.2562	0.1833	0.1609	0.0959
VaR 95% histor	0.0673	0.1164	0.1447	0.1920	0.1110	0.1388	0.1405	0.1367	0.0831	0.0972	0.1646	0.1820	0.1333	0.1049	0.0738
VaR 99% histor	0.1118	0.1702	0.2152	0.3353	0.1877	0.2181	0.2392	0.2048	0.1348	0.1526	0.2888	0.2806	0.1943	0.1539	0.1024
Max.Drawdown	0.4008	0.6381	0.7136	0.9475	0.6920	0.8056	0.7389	0.6776	0.5197	0.5414	0.8914	0.8485	0.7254	0.6687	0.3390

Note: Q1 represents the first quartile for each strategy, showing the returns of the top-ranked portfolios of stocks ranked by PTV, ESG, or both (PTV-ESG) among all ESG-rated global energy companies by OWL ESG Analytics. ESG-PTV portfolios are presented in the Appendix B. All quartile portfolios are constructed at the beginning of each month and returns are calculated through the end of the month (October 2009 - March 2022). The MSCI World Energy Index and the MSCI World Index are benchmarks for the global energy industry and the global equity market, respectively. The 1-month US Treasury Bill return is used as a proxy for both the risk-free return and the threshold return for the downside measures.

Table 8. Performance and downside risk analysis. Second part of the sample period (from March 2017 to March 2022)

	PTV-Q1	PTV-Q2	PTV-Q3	PTV-Q4	ESG-Q1	ESG-Q2	ESG-Q3	ESG-Q4	PTV-ESG-Q1	PTV-ESG-Q2	PTV-ESG-Q3	PTV-ESG-Q4	ESG Energy Ind.	World Energy Ind.	World Ind.
Beta (ESG-En.)	0.5616	0.8219	1.0772	1.5390	0.6642	1.0529	1.2341	1.0492	0.6477	0.7348	1.2001	1.4211	1	0.8961	0.3858
Beta (Wld En.)	0.5315	0.7831	1.0228	1.4636	0.6095	1.0077	1.1810	1.0026	0.6007	0.7148	1.1290	1.3595	0.9501	1	0.3691
Beta (World)	0.9953	1.3295	1.6502	2.2599	1.1024	1.6799	1.8097	1.6459	1.0717	1.2532	1.8747	2.0420	1.5593	1.4073	1
Alpha (ESGEn)	0.0055	0.0034	0.0045	-0.0113	0.0066	0.0001	-0.0023	-0.0019	0.0053	0.0037	0.0020	-0.0087	0	0.0059	0.0096
Alpha (Wld En)	0.0021	-0.0016	-0.0020	-0.0206	0.0025	-0.0063	-0.0098	-0.0083	0.0014	-0.0008	-0.0053	-0.0173	-0.0064	0	0.0072
Alpha (World)	-0.0036	-0.0092	-0.0114	-0.0335	-0.0038	-0.0160	-0.0201	-0.0177	-0.0047	-0.0080	-0.0160	-0.0289	-0.0170	-0.0094	0
Treynor ratio	0.0043	-0.0014	-0.0014	-0.0129	0.0043	-0.0055	-0.0075	-0.0074	0.0027	-0.0005	-0.0039	-0.0117	-0.0050	0.0016	0.0200
Sharpe ratio	0.0430	-0.0153	-0.0153	-0.1401	0.0457	-0.0616	-0.0835	-0.0811	0.0282	-0.0056	-0.0427	-0.1291	-0.0565	0.0173	0.1764
Omega ratio	1.1448	0.9558	0.9531	0.6683	1.1379	0.8208	0.7769	0.7812	1.0876	0.9829	0.8733	0.6811	0.8398	1.0518	1.6045
Sortino ratio	0.0517	-0.0185	-0.0195	-0.1821	0.0619	-0.0761	-0.1035	-0.0973	0.0353	-0.0066	-0.0602	-0.1559	-0.0697	0.0232	0.2541
Sharpe/VaR99	0.0185	-0.0066	-0.0066	-0.0602	0.0196	-0.0265	-0.0359	-0.0348	0.0121	-0.0024	-0.0183	-0.0555	-0.0243	0.0074	0.0758
VaR 95% norm.	0.0917	0.1228	0.1582	0.2328	0.1034	0.1548	0.1812	0.1566	0.1016	0.1120	0.1812	0.2112	0.1446	0.1404	0.0719
VaR 99% norm.	0.1296	0.1737	0.2238	0.3292	0.1462	0.2189	0.2563	0.2215	0.1436	0.1584	0.2563	0.2987	0.2045	0.1986	0.1017
VaR 95% histor	0.0770	0.1155	0.1060	0.1829	0.0814	0.1141	0.1383	0.1470	0.0816	0.1158	0.1331	0.1788	0.1202	0.1062	0.0744
VaR 99% histor	0.1843	0.2262	0.2790	0.3666	0.1727	0.2779	0.3152	0.3001	0.1819	0.2176	0.2759	0.3909	0.2552	0.2317	0.1105
Max.Drawdown	0.5151	0.6708	0.7050	0.9085	0.5603	0.7592	0.8152	0.7664	0.5670	0.6284	0.7934	0.8702	0.7312	0.5105	0.2394

Note: Q1 represents the first quartile for each strategy, showing the returns of the top-ranked portfolios of stocks ranked by PTV, ESG, or both (PTV-ESG) among all ESG-rated global energy companies by OWL ESG Analytics. ESG-PTV portfolios are presented in the Appendix B. All quartile portfolios are constructed at the beginning of each month and returns are calculated through the end of the month (March 2017 - March 2022). The MSCI World Energy Index and the MSCI World Index are benchmarks for the global energy industry and the global equity market, respectively. The 1-month US Treasury Bill return is used as a proxy for both the risk-free return and the threshold return for the downside measures.

Table 8 and the right panel of Table B.2 show the performance measures for the second part of the sample period, starting in March 2017. In this last period, all three benchmark indices performed better, especially the WI. As a result of the sharp stock market decline in this sector in February and especially in March 2020, the 99% VaR of the benchmarks related to the energy sector increased significantly. Energy sector raw returns are particularly affected by the pandemic and lockdowns in March 2020, with the WEI falling 34.6% and the ESG energy portfolio declining 43.0%. The global market portfolio (WI) is down 14.8%.

PTV-Q1, the portfolio with the best performance over the entire sample period, shows deteriorating performance metrics. A decrease in the Sortino ratio values and an increase in the historical 99% VaR and MDD stand out. The PTV-ESG-Q1 and ESG-PTV-Q1 portfolios also show a deterioration in performance measures, but to a lesser extent. It is noteworthy that the ESG-Q1 portfolio improves on all measures in this second period compared to the full sample. Sorting ratio and MDD show the largest improvement.

The ESG-Q1 results are now quite similar to the PTV-Q1 results, reflecting a broad improvement in the behavior of the ESG-Q1 strategy and a deterioration in the PTV-Q1 strategy during this second subperiod. As a result, the first quartile of PTV- and ESG-based strategies significantly outperforms both the equal-weighted portfolio with the universe of ESG-labeled energy companies and the value-weighted index with all energy companies (WEI). In this second part of the sample, the ESG strategy becomes more consistent across quartiles.

As a robustness analysis and to conclude this section, we perform a recalculation of the PTV using a two-year rolling window approach spanning 504 days. This method deviates from our primary approach, which utilizes a one-year rolling window of 252 daily returns. The purpose of employing this alternative window length is to evaluate the consistency and robustness of the PTV strategies across different time horizons. The results of this analysis are presented in Table C, which can be found in Appendix C.

The comparison of performance and downside risk measures between the PTV calculated over a two-year sample period (Table C) and the one-year sample (Tables 7 and 8) reveals a clear consistency in the results. Desired trends in portfolio behavior are consistently observed across all measures. As portfolios move from the top quartile to the bottom quartile, all performance measures deteriorate, while downside risk measures exhibit the opposite pattern. Notably, PTV-Q1 represents the lowest risk portfolio, while PTV-Q4 represents the highest risk portfolio. The numerical values exhibit only minor variations, with performance measures (downside risk) showing slightly lower (higher) values in the full sample, and the reverse trend observed in the latter part of the sample period. These findings demonstrate a comprehensive assessment of the PTV strategies' performance and stability across different estimation sample sizes, thereby enhancing the reliability and robustness of our conclusions.

4. Conclusions

The purpose of this paper is to evaluate the effectiveness of simple and cost-efficient investment strategies based on two risk factors commonly used in the financial industry. Both factors are based on the principles of behavioral finance and assume that investors are not strictly rational in the sense of modern financial theory. The PTV, which is calculated according to the cumulative prospect theory, is considered together with the ESG score, which is provided monthly by OWL Analytics. Our analysis covers all ESG-labeled energy companies from October 2009 to March 2022.

We construct quartile portfolios each month based on both PTV and ESG factors, as well as a combination of the two. The ex-post performance analysis includes the evaluation of various aspects. This assessment encompasses raw returns, risk-adjusted returns using an AR(1)-GARCH(1,1) model to capture daily conditional volatility, excess returns beyond the expected returns based on the systematic risk factors derived from the Fama-French (1993) and Carhart (1997) four-factor model, as well as the examination of several traditional and downside risk performance measures. We use the equal-weighted ESG energy universe and the value-weighted MSCI World Energy and MSCI World indices as benchmarks for comparison.

Among all the strategies examined, the PTV-Q1 strategy consistently and significantly outperforms both the ESG energy universe and the WEI benchmark. Notably, despite being an equally weighted portfolio, the performance of PTV-Q1 is not significantly different from that of the broader stock market index. While the PTV-ESG-Q1, ESG-PTV-Q1, and ESG-Q1 strategies do not perform as well as the PTV-Q1 strategy, they still outperform the ESG energy universe.

In portfolio formation, when PTV is the main factor, as observed in the PTV and PTV-ESG strategies, there is a notable consistency in performance across quartiles. As we move from the top quartile to the lower quartiles, a clear trend of performance deterioration becomes apparent. Notwithstanding, when the main factor is based on ESG scores, particularly in the case of ESG-PTV strategies, we report on a different pattern. Portfolios in Q1 and Q3 outperform portfolios in Q2 and Q4, respectively. These findings suggest that the PTV criterion dominates the ESG criterion in terms of performance.

In the examination of the most recent five years within the sample timeframe, both the PTV and ESG factors demonstrate parallel outcomes. Notably, the ESG criterion emerges as an exceptionally robust investment approach throughout this specific period. These strategies clearly outperform the ESG energy universe and the WEI in this subsample, and even the WI after April 2020. Moreover, not all ESG-labeled energy companies perform equally, but the ESG-Q1 strategy clearly outperforms all other quartiles.

The results of our study contribute to the growing literature on behavioral finance and factor investing. We have consistently found that simple quartile strategies based on behavioral factors are profitable in the energy sector over a period of more than a decade. As a factor-based allocation strategy, PTV outperforms diversified portfolios of energy stocks and broad stock market indices. In recent years, strategies based solely on ESG scores have even outperformed the global energy sector. Moreover, we confirm that a simple equal-weighted strategy can outperform more diversified portfolios such as value-weighted markets (Asness, 2016; Asness et al., 2017; Dichtl et al., 2021). Investors and portfolio managers can benefit from our findings on a simple and cost-efficient quartile approach. Finally, our results suggest that self-funding portfolios can earn excellent returns by holding long positions in Q1 and short positions in Q4.

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Appendix A

Table A. Estimated conditional volatility model for daily returns

Portfolio	Panel A: mean equation		Panel B: variance equation											
	ϕ		ω		α		β		ξ		ν		LM (1)	
PTV_Q1	0.071	(3.93)***	0.000	(0.85)	0.119	(3.46)***	0.864	(24.58)***	0.875	(36.24)***	6.846	(6.11)***	2.519	(0.11)
PTV_Q2	0.051	(2.85)***	0.000	(0.79)	0.087	(2.91)***	0.902	(27.71)***	0.890	(45.98)***	8.923	(12.74)***	0.158	(0.69)
PTV_Q3	0.044	(2.30)**	0.000	(0.20)	0.072	(0.75)	0.919	(8.64)***	0.930	(23.85)***	8.786	(2.45)**	0.165	(0.68)
PTV_Q4	0.066	(3.68)***	0.000	(2.20)**	0.074	(7.06)***	0.916	(79.44)***	0.963	(41.54)***	9.602	(6.93)***	8.458	(0.00)***
ESG_Q1	0.068	(3.96)***	0.000	(1.53)	0.068	(8.61)***	0.928	(118.14)***	0.907	(41.65)***	7.052	(9.18)***	0.505	(0.48)
ESG_Q2	0.058	(3.22)***	0.000	(0.77)	0.086	(3.10)***	0.906	(31.19)***	0.934	(37.92)***	8.196	(6.20)***	0.506	(0.48)
ESG_Q3	0.033	(1.87)*	0.000	(1.50)	0.071	(4.94)***	0.918	(55.21)***	0.937	(40.31)***	9.404	(6.58)***	0.406	(0.52)
ESG_Q4	0.063	(3.50)***	0.000	(2.04)**	0.083	(6.59)***	0.901	(61.22)***	0.917	(40.73)***	8.171	(7.67)***	0.915	(0.34)
PTV_ESG_Q1	0.067	(3.79)***	0.000	(1.12)	0.097	(5.20)***	0.895	(48.50)***	0.903	(42.98)***	7.039	(10.86)***	0.598	(0.44)
PTV_ESG_Q2	0.049	(2.72)***	0.000	(1.94)*	0.092	(6.18)***	0.885	(49.72)***	0.880	(38.04)***	8.562	(6.88)***	1.535	(0.22)
PTV_ESG_Q3	0.060	(3.47)***	0.000	(0.52)	0.068	(1.97)**	0.926	(24.93)***	0.951	(50.22)***	8.393	(22.10)***	0.272	(0.60)
PTV_ESG_Q4	0.053	(2.98)***	0.000	(1.98)**	0.077	(6.63)***	0.913	(70.65)***	0.954	(41.90)***	9.057	(7.14)***	0.825	(0.36)
ESG Energy market	0.062	(3.42)***	0.000	(0.68)	0.079	(2.38)**	0.910	(24.72)***	0.917	(35.89)***	9.072	(5.23)***	0.228	(0.63)
World Energy Index	0.049	(2.80)***	0.000	(1.38)	0.075	(5.95)***	0.919	(71.32)***	0.943	(42.91)***	7.074	(9.19)***	0.275	(0.60)
World Index	0.110	(6.26)***	0.000	(0.69)	0.129	(3.32)***	0.862	(24.82)***	0.899	(49.85)***	5.731	(14.00)***	81.291	(0.00)***

Note: This table provides information on the estimation of the univariate AR(1)-GARCH (1,1) models to represent the daily volatility of the different portfolios over the entire period. We assume a skewed student-t distribution in the estimation process. The parameters related to the univariate mean processes are reported in Panel A, while those describing the persistence and skewness of the different portfolios are reported in Panel B. Lagrange Multiplier (LM) statistics computed under different lags are reported to assess the persistence in second orders. t-values are reported in parentheses for the case of GARCH coefficients, while p-values are reported to assess the LM test. The significance levels for *, **, and *** are 10%, 5%, and 1%, respectively.

Appendix B. ESG-PTV strategies

Table B.1. Contents of Tables 2, 4 and 6 corresponding to the ESG-PTV strategies

	Monthly raw returns. Corresponds to Table 2				Monthly risk-adjusted returns (AR(1)-GARCH(1,1) volatility). Corr. Table 4				Analysis of the Four-Factor Model. Corresponds to Table 6				
	ESG-PTV-Q1	ESG-PTV-Q2	ESG-PTV-Q3	ESG-PTV-Q4	ESG-PTV-Q1	ESG-PTV-Q2	ESG-PTV-Q3	ESG-PTV-Q4		ESG-PTV-Q1	ESG-PTV-Q2	ESG-PTV-Q3	ESG-PTV-Q4
Panel A. Full sample (October 2009-March 2022)													
Mean	0.0022	-0.0108	0.0005	-0.0143	0.1321	-0.1211	0.0979	-0.1229	Alpha	-0.81***	-2.45***	-0.99***	-2.82***
Std. Deviation	0.0554	0.0990	0.0612	0.1134	1.0335	1.0968	1.0238	1.0182	Mrkt	0.93***	1.33	0.95	1.41
5th Percentile	-0.0822	-0.1668	-0.1015	-0.1933	-1.6483	-1.9430	-1.7820	-1.9139	SMB	0.07	0.74	0.36	1.07
Q1	-0.0259	-0.0595	-0.0303	-0.0646	-0.5729	-0.9280	-0.6646	-0.7696	HML	0.61***	0.49	0.59	0.79
Median	0.0088	-0.0059	0.0093	-0.0080	0.1973	-0.0868	0.2005	-0.1253	Mom	0.03	-0.54***	-0.06***	-0.57***
Q3	0.0325	0.0455	0.0331	0.0489	0.8134	0.6324	0.7783	0.6684	Adj.R^2	0.6574	0.6244	0.6974	0.6577
95th Percentile	0.0771	0.1113	0.0781	0.1465	1.7685	1.6444	1.6261	1.4209					
Ann. Return	0.0263	-0.1300	0.0056	-0.1712									
Cum. Return	0.3284	-1.6253	0.0700	-2.1399									
% month beats ESG Energy	0.6200	0.4267	0.6333	0.3933	0.6800	0.4067	0.6800	0.3400					
Panel B. From March 2017 to March 2022													
Mean	0.0016	-0.0045	0.0008	-0.0180	0.1287	-0.1425	0.1269	-0.1937	Alpha	-0.77*	-1.65***	-0.92***	-3.08***
Std, Deviation	0.0621	0.0977	0.0725	0.1360	1.1699	1.1499	1.1540	1.0970	Mrkt	0.92***	1.25	1.05	1.53
5th Percentile	-0.0799	-0.1223	-0.1103	-0.1984	-1.8512	-1.9508	-2.0339	-1.9659	SMB	0.27	0.94	0.65	1.77
Q1	-0.0195	-0.0548	-0.0110	-0.0933	-0.5967	-1.0187	-0.2490	-1.1197	HML	0.83***	0.71	0.89	1.18
Median	0.0056	-0.0025	0.0115	-0.0225	0.1991	-0.0181	0.2469	-0.2252	Mom	0.36**	0.00***	0.32	0.15
Q3	0.0296	0.0372	0.0407	0.0553	0.8353	0.5302	0.9134	0.4855	Adj.R^2	0.7058	0.7171	0.8315	0.7526
95th Percentile	0.0778	0.1063	0.0812	0.1531	1.9916	1.7486	1.8168	1.6202					
Ann. Return	0.0196	-0.0535	0.0095	-0.2157									
Cum. Return	0.0995	-0.2720	0.0482	-1.0967									
% month beats ESG Energy	0.5806	0.4677	0.6129	0.3226	0.6721	0.5246	0.6721	0.3115					

Table B.2. Performance and downside risk analysis. Contents of Tables 7 and 8 corresponding to the ESG-PTV strategies

	Panel A. Full sample (October 2009-March 2022)				Panel B. From March 2017 to March 2022			
	ESG-PTV-Q1	ESG-PTV-Q2	ESG-PTV-Q3	ESG-PTV-Q4	ESG-PTV-Q1	ESG-PTV-Q2	ESG-PTV-Q3	ESG-PTV-Q4
Beta (ESG-En.)	0.6585	1.2124	0.7434	1.3917	0.6483	1.0661	0.7907	1.4992
Beta (Wld En.)	0.7086	1.2337	0.7992	1.4603	0.6087	1.0048	0.7575	1.4334
Beta (World)	1.0814	1.7808	1.1677	1.9198	1.0840	1.6932	1.3041	2.1601
Alpha (ESGEn)	0.0058	-0.0041	0.0046	-0.0065	0.0052	0.0015	0.0052	-0.0096
Alpha (Wld En)	0.0018	-0.0115	0.0000	-0.0150	0.0013	-0.0050	0.0004	-0.0187
Alpha (World)	-0.0044	-0.0216	-0.0066	-0.0259	-0.0049	-0.0147	-0.0071	-0.0310
Treynor ratio	0.0033	-0.0089	0.0006	-0.0103	0.0025	-0.0042	0.0010	-0.0120
Sharpe ratio	0.0395	-0.1095	0.0076	-0.1258	0.0263	-0.0457	0.0109	-0.1322
Omega ratio	1.1154	0.7391	1.0215	0.7020	1.0847	0.8692	1.0339	0.6789
Sortino ratio	0.0509	-0.1384	0.0095	-0.1550	0.0319	-0.0622	0.0131	-0.1641
Sharpe/VaR99	0.0170	-0.0470	0.0033	-0.0541	0.0113	-0.0196	0.0047	-0.0568
VaR 95% norm.	0.0912	0.1628	0.1007	0.1865	0.1021	0.1606	0.1192	0.2237
VaR 99% norm.	0.1290	0.2303	0.1424	0.2638	0.1444	0.2272	0.1686	0.3164
VaR 95% histor	0.0822	0.1668	0.1015	0.1933	0.0799	0.1223	0.1103	0.1984
VaR 99% histor	0.1305	0.2899	0.1575	0.2699	0.1955	0.2593	0.2308	0.3871
Max.Drawdown	0.5297	0.9001	0.5303	0.8398	0.5929	0.7595	0.6145	0.8932

Appendix C. Performance of PTV strategies from PTV computed using a two-year rolling window

Table C. Performance and downside risk analysis. Contents of Tables 7 and 8 in which PTV have been recalculated using a two-year rolling window (504 daily returns) instead of the main approach of using a one-year rolling window (252 daily returns)

	Panel A. Full sample (October 2009-March 2022)				Panel B. From March 2017 to March 2022			
	PTV-Q1	PTV-Q2	PTV-Q3	PTV-Q4	PTV-Q1	PTV-Q2	PTV-Q3	PTV-Q4
Beta (ESG-En.)	0.5592	0.8106	1.0405	1.6009	0.5536	0.8013	1.0512	1.6172
Beta (Wld En.)	0.5938	0.8510	1.0938	1.6621	0.5103	0.7358	0.9995	1.5599
Beta (World)	0.9776	1.2915	1.5855	2.2024	1.0033	1.3585	1.6434	2.3007
Alpha (ESGEn)	0.0056	0.0026	0.0025	-0.0126	0.0081	0.0015	0.0021	-0.0067
Alpha (Wld En)	0.0018	-0.0029	-0.0045	-0.0234	0.0044	-0.0039	-0.0050	-0.0176
Alpha (World)	-0.0037	-0.0101	-0.0134	-0.0357	-0.0013	-0.0116	-0.0143	-0.0305
Treynor ratio	0.0036	-0.0032	-0.0040	-0.0143	0.0082	-0.0046	-0.0045	-0.0106
Sharpe ratio	0.0410	-0.0387	-0.0490	-0.1721	0.0844	-0.0499	-0.0502	-0.1153
Omega ratio	1.1202	0.8970	0.8726	0.6342	1.1202	0.8970	0.8726	0.6342
Sortino ratio	0.0533	-0.0477	-0.0618	-0.2131	0.1205	-0.0670	-0.0699	-0.1596
Sharpe/VaR99	0.0176	-0.0166	-0.0211	-0.0740	0.0363	-0.0214	-0.0216	-0.0496
VaR 95% norm.	0.0806	0.1107	0.1397	0.2187	0.0886	0.1208	0.1543	0.2444
VaR 99% norm.	0.1141	0.1566	0.1976	0.3093	0.1253	0.1709	0.2183	0.3456
VaR 95% histor	0.0742	0.1028	0.1439	0.2135	0.0728	0.0966	0.1200	0.2036
VaR 99% histor	0.1107	0.1690	0.2032	0.3438	0.1758	0.2300	0.2769	0.3774
Max.Drawdown	0.6172	0.8011	0.8638	0.9941	0.4794	0.6515	0.7376	0.9101