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ESG PERFORMANCE AND RISK-RETURN CORRESPONDENCE FOR THE LARGE ENERGY COMPANIES DURING THE COVID-19 PANDEMIC

This paper investigates the relationship between Environmental, Social, and Governance (ESG) performance and the risk-return characteristics of publicly traded energy companies from 2019 to 2023. Using a sample of 39 companies across different energy subsectors, including oil & gas, utilities, and renewable energy, this study offers a two-part analysis. First, correlation analysis shows no statistically significant linear relationships between aggregate ESG scores and both annual returns and risk. These results are consistent with previous empirical findings that highlight the long-term nature of ESG signals. Second, K-means cluster analysis reveals three distinct company profiles based on ESG, return, and volatility, thereby uncovering hidden patterns that traditional regression models often fail to capture. The clusters include: (1) high-return/high-risk extractive companies with low ESG scores; (2) infrastructure firms with moderate ESG ratings and variable performance; and (3) ESG leaders, mainly in renewable energy, with low risk and moderate returns. The results indicate that ESG may not serve as a short-term predictor of stock performance but rather as an indicator of strategic resilience. This paper contributes to ESG literature by proposing clustering as a viable approach for creating typologies in sector-specific ESG research. Limitations and future research directions are discussed, highlighting the need to develop dynamic, nonlinear models, apply machine learning techniques, and conduct sensitivity analyses under various economic conditions.

Keywords: ESG performance, energy sector, stock returns, risk, cluster analysis, sustainable finance, finance performance.

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ВЗАЄМОЗВ'ЯЗОК МІЖ ПОКАЗНИКАМИ ESG ТА ПРИБУТКОВІСТЮ Й РИЗИКОМ ВЕЛИКИХ ЕНЕРГЕТИЧНИХ КОМПАНІЙ ПІД ЧАС ПАНДЕМІЇ COVID-19

У статті досліджено взаємозв'язок між екологічними, соціальними та управлінськими (ESG) показниками та характеристиками дохідності й ризику акцій публічних енергетичних компаній у 2019–2023 роках. На основі вибірки з 39 компаній, що представляють різні підсектори енергетики (нафта й газ, комунальні послуги, відновлювана енергетика), виконано двоетапний аналіз. На першому етапі кореляційний аналіз не виявив статистично значущого лінійного зв'язку між агрегованими ESG-оцінками та показниками річної дохідності й ризику. Такі результати узгоджуються з попередніми емпіричними дослідженнями, які підкреслюють довгостроковий характер ESG-сигналів. На другому етапі кластерний аналіз методом K-середніх дозволив виокремити три типові профілі компаній за критеріями ESG, дохідності та волатильності, виявивши приховані закономірності, які традиційні регресійні моделі не фіксують. Кластери охоплюють: (1) видобувні компанії з високою дохідністю і ризиком та низькими ESG-оцінками; (2) інфраструктурні фірми з помірними ESG-показниками і змінною результативністю; (3) лідери ESG, здебільшого з відновлюваної енергетики, із низьким ризиком і помірною дохідністю. Результати вказують на те, що ESG-показники не є короткостроковими предикторами фондової ефективності, але можуть слугувати індикаторами стратегічної стійкості. Стаття робить внесок у літературу з ESG, запропонувавши кластеризацію як ефективний інструмент для типологізації в галузевих ESG-дослідженнях. Обговорюються обмеження дослідження та напрями подальших робіт, зокрема необхідність розробки динамічних нелінійних моделей, використання методів машинного навчання та проведення аналізу чутливості в різних економічних умовах.

Ключові слова: ESG-показники, енергетичний сектор, прибутковість акцій, ризик, кластерний аналіз, сталий розвиток, фінансова ефективність.

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INTRODUCTION

Over the past few decades, the concept of sustainable development has become a key part of the global agenda, influencing both economic policy and corporate governance practices. Its intellectual roots can be traced back to the influential report The Limits to Growth by the Club of Rome [1] with a more systemic formulation presented in Our Common Future [2], which defined sustainable development as that which "meets the needs of the present without compromising the ability of future generations to meet their own needs". Since the 1990s, there has been a gradual shift away from conventional models of corporate assessment that primarily focused on only financial outcomes, toward a multidimensional framework that incorporates environmental (E), social (S), and governance (G) considerations. This transformation laid the foundation for the ESG (Environmental, Social, and Governance) paradigm, which has since evolved into a global benchmark for evaluating non-financial performance.

Further milestones in the public discourse were marked by the adoption of the Paris Agreement in 2015 and the launch of the European Green Deal in 2019, both of which reinforced the urgency of integrating sustainability into economic decision-making and corporate accountability mechanisms.

Today, ESG disclosure is widely regarded as an essential component of sound corporate governance, reputation management, and financial resilience assessment. In many jurisdictions, ESG reporting has been elevated to a legal obligation. Within the European Union, for example, three key regulatory instruments have been adopted:

- The Corporate Sustainability Reporting Directive (CSRD) mandates large companies to report on non-financial matters by unified European Sustainability Reporting Standards (ESRS) starting in 2024.
- The Sustainable Finance Disclosure Regulation (SFDR), which imposes ESG-related disclosure requirements on financial market participants.
- The EU Taxonomy for Sustainable Activities provides criteria for defining environmentally sustainable economic activities.

In contrast, jurisdictions such as the United States maintain a predominantly voluntary approach to ESG disclosure. Nevertheless, the Securities and Exchange Commission (SEC) has proposed several rules regarding the disclosure of climate-related risks. Despite the absence of mandatory requirements, many corporations in the U.S. and Canada voluntarily publish sustainability reports aligned with leading frameworks such as GRI, SASB, and TCFD, recognizing that institutional investors, creditors, and rating agencies increasingly incorporate ESG indicators into their decision-making processes.

The theoretical rationale linking a company's ESG profile to its market valuation is grounded in the financial principle that stock prices reflect investor expectations regarding future cash flows and risk exposure. When ESG indicators signal a lower probability of reputational, regulatory, or operational shocks, they reduce the required risk premium and, in turn, increase the company's capitalization while decreasing its cost of equity. During periods of exogenous shocks such as the COVID-19 pandemic, energy crises, or geopolitical disruptions, firms with stronger ESG profiles tend to exhibit lower volatility and better stock performance, as they are perceived to be more adaptive, resilient, and accountable [3, 4].

In Ukraine, the implementation of ESG practices is still in its early stages of development. On the one hand, domestic companies face growing obligations to align their reporting systems with EU standards as part of broader integration into the European economic and energy space. On the other hand, ESG adoption has the potential to facilitate access to international capital markets, enhance corporate valuation, and improve funding opportunities during the post-war recovery period.

Within the energy sector, ESG performance plays a particularly critical role due to the industry's systemic impact on the environment, economy, and society. First, the energy sector is among the most significant contributors to global greenhouse gas emissions, placing it at the forefront of climate policy and regulation. The environmental (E) dimension thus serves not only as an indicator of compliance with sustainability standards but also as a proxy for long-term ecological risks that directly influence both the cost of capital and access to finance. Second, the social (S) dimension carries substantial weight in the energy industry due to workplace safety risks, impacts on local communities, the need for a just transition in fossil fuel-dependent regions, and the importance of transparent stakeholder communication. A high social rating signals adherence to non-discriminatory policies, labor rights, and human rights standards that are critical for both institutional investors and reputational positioning. Moreover, energy companies typically operate on a large scale, involve capital-intensive investments, and exhibit complex organizational structures. These factors underscore the importance of the governance (G) pillar, which encompasses corporate governance efficiency, transparency in decision-making, and ethical compliance. Governance quality directly determines a company's capacity to adapt to market, regulatory, and technological changes, and consequently affects its long-term valuation and resilience in times of transformation.

Therefore, the energy sector is susceptible to ESG factors, which influence not only firms' ability to navigate environmental, social, and governance challenges but also their market capitalization, cost of capital, and overall investment appeal. Against the backdrop of tightening sustainability requirements, a comprehensive understanding of the relationship between ESG performance and financial outcomes in energy companies becomes increasingly valuable. This necessitates a structured review of existing theoretical frameworks and empirical research, followed by an evidence-based analysis of the relationship between stock returns, risk, and ESG scores.

LITERATURE REVIEW

The widespread adoption of ESG practices in corporate management, driven by both regulatory mandates and mounting pressure from investors and civil society, has led to a substantial increase in academic research examining the impact of non-financial factors on firms' financial performance. Meta-analyses, such as the systematic review by [6, 7], confirm an exponential increase in ESG-related publications following 2015.

A prominent strand of this research focuses on testing the explanatory and predictive power of ESG indicators about key financial metrics, including profitability, volatility, cost of capital, Tobin's Q, and stock returns. Beyond performance metrics, several key questions recur across the literature:

- Does ESG disclosure reduce information asymmetry between managers and shareholders?

- Does a high ESG rating indicate greater corporate resilience to external shocks (e.g., the COVID-19 pandemic)?
- How do ESG-related factors shape investor behavior in both the short and long term?

In terms of perspective, the literature can be broadly classified into:

1. Investment-focused studies, where dependent variables include return, risk premium, or volatility;
2. Corporate performance studies, which examine the effect of ESG on accounting-based indicators such as ROA, ROE, or firm valuation;
3. Thematic studies exploring climate risks, regulatory frameworks, and institutional contexts [8].

An important distinction is made between ESG disclosure and ESG integration. In some instances, the publication of sustainability reports serves primarily a signaling function, rather than reflecting a genuine transformation of governance practices. This creates room for *greenwashing*, where ESG branding is used superficially without substantive backing in operational behavior. Notable cases of regulatory enforcement illustrate this issue [9].

A further methodological challenge lies in the inconsistency of ESG assessment frameworks used by different rating agencies, such as MSCI, LSEG (Refinitiv), or Sustainalytics. The divergence in scoring methodologies undermines cross-study comparability and often complicates empirical inference [10].

While the majority of studies report a positive relationship between ESG performance and financial outcomes, the results are far from uniform. Some authors [11] argue that ESG effects are highly context-dependent, varying by country, industry, investor type, and macroeconomic environment. The paradox of the *"greenium" versus "carbon premium"* illustrates a particularly complex dynamic: firms with high carbon footprints sometimes offer higher returns due to embedded risk premiums, despite lower ESG scores [12].

Another valuable insight is that market-based indicators (e.g., stock prices) tend to react more quickly and strongly to ESG signals than traditional accounting-based financial metrics. This supports the interpretation of ESG as a proxy for market expectations regarding firm stability and governance quality. In this context, ESG ratings play an informational role in environments characterized by information asymmetry, helping to mitigate adverse selection and enhance capital allocation efficiency [13].

Empirical studies on the relationship between ESG performance and financial outcomes employ a broad range of methodologies, including regression analysis, panel data models, structural modeling, structural equation modeling (SEM), logit and probit models, beta coefficient estimations, and variance analysis of stock returns. The choice of methodology is typically contingent upon data availability, industry context, time horizon, the nature of the dependent variable, and the type of ESG indicators used [6, 7].

Despite increasing scholarly focus, there are still several limitations in the existing body of research. Remain frequently cited:

- The absence of a standardized ESG scoring framework;
- The relative scarcity of studies focused on emerging markets;
- insufficient differentiation between ESG disclosure as a market signal and ESG integration as a managerial practice;
- The difficulty of establishing causal inferences due to endogeneity and selection bias;
- limited consideration of sector-specific materiality in ESG factor relevance.

These limitations open up important avenues for future research, particularly in accounting for industry-level differences (as in the case of the energy sector), focusing on transition economies, examining the temporal dynamics of ESG profiles, and exploring the interaction between ESG characteristics and firms' responsiveness to external shocks [14].

Given the strategic role of the energy sector in the global ecological transition, it is crucial to examine how ESG profiles impact the market behavior and financial resilience of energy companies, especially during periods of heightened volatility and uncertainty.

RESEARCH OBJECTIVE

The primary objective of this study is to conduct a quantitative analysis of the dynamics of return and risk indicators for publicly traded energy companies over the period from 2019 to 2023. Specifically, the study aims to assess whether ESG performance, both in aggregate form and across its dimensions (environmental, social, and governance), has a statistically significant impact on stock return and risk.

By decomposing the ESG score into its constituent pillars, the research seeks to identify which specific dimension(s) may serve as relevant explanatory variables for fluctuations in the financial performance of firms operating within the energy sector.

DATA AND METHODOLOGY

To conduct the empirical analysis, a sample of 50 publicly listed energy companies was constructed, comprising firms whose shares are traded on stock exchanges in the United States and Canada. The selection was based on market capitalization as of 2019, enabling the authors to capture the transition of large-scale energy corporations through the market shock caused by the COVID-19 pandemic. The sample includes companies from various subsectors, such as energy extraction, transmission and distribution, and electricity generation. It features both traditional oil and gas giants (e.g., ExxonMobil (XOM), Chevron (CVX), ConocoPhillips (COP)) and firms focused on infrastructure and renewable energy (e.g., NextEra Energy (NEE), Duke Energy (DUK), Kinder Morgan (KMI)).

Financial data were obtained using the yfinance library in Python, an open-source interface that enables automated access to historical stock prices, trading volumes, and other financial metrics from the Yahoo Finance platform [15]. The observation period spans five full calendar years, from January 1, 2019, to December 31, 2023, with a weekly frequency. This approach strikes a balance between statistical robustness and minimization of short-term fluctuations. The verification of data for this period allowed the study to include 39 companies out of 50.

For each firm, weekly stock returns were calculated as the percentage change in the adjusted closing price, which takes into account dividends and stock splits. Annualized return and risk indicators were derived using the following formulas:

$$R_{\text{annual}} = \bar{r}_{\text{weekly}} \cdot 52$$

$$\sigma_{\text{annual}} = \sigma_{\text{weekly}} \cdot \sqrt{52}$$

Where $\bar{r}_{\text{weekly}}$ is the average weekly return over the calendar year, and σ_{weekly} is the standard deviation of weekly returns for the same period.

In addition to financial indicators, auxiliary metadata were collected for each company, including name, country of registration, industry classification according to the Global Industry Classification Standard (GICS), and operational focus. These variables serve as the basis for potential sample stratification and cluster analysis.

ESG-related data were obtained from the LSEG ESG database (formerly Refinitiv), which provides standardized scores based on publicly available disclosures, corporate policies, and independent sources. ESG scores are reported on a 0–100 scale, with higher values indicating more substantial alignment with sustainable development principles. This study utilizes both the aggregate ESG score and its components: Environmental (E), Social (S), and Governance (G).

Before the analysis, the dataset was cleaned to remove incomplete or missing observations and exclude companies that lacked consistent time-series coverage over the five years. The resulting dataset comprises a balanced panel, forming the empirical foundation for the quantitative analysis presented in the following sections.

Table 1.

Descriptive Statistics of Key Variables (n = 195)

Variable	Count	Mean	SD	Min	Q1	Median	Q3	Max	Coef Var	IQR
Annual Return	195	0,182	0,331	-1,119	-0,014	0,134	0,346	1,440	1,818	0,360
Annual Risk	195	0,357	0,202	0,100	0,210	0,305	0,447	1,257	0,567	0,237
ESG Score	195	63,574	13,688	24	56	66	73	88	0,215	17
E	195	63,149	16,019	18	52	65	74,5	97	0,254	22,5
S	195	63,174	16,194	13	53	66	75	91	0,256	22
G	195	65,354	20,949	4	54,5	71	82	97	0,321	27,5

Note. Q1 first quartile; Q3 third quartile; IQR interquartile range; CV coefficient of variation (SD / Mean).
Source: Calculated by the authors based on the compiled dataset.

Table 1 presents descriptive statistics for the key variables employed in this study, including annual return, annual risk, and the ESG rating (along with its environmental (E), social (S), and governance (G) components). The analysis reveals substantial heterogeneity in the data, particularly in terms of stock returns, with a mean annual return of 18.2%. In comparison, the standard deviation exceeds 33%, yielding a coefficient of variation (CV) of over 180%. Such volatility is likely attributable to external shocks, notably the COVID-19 pandemic, fluctuations in global oil prices, and overall instability in energy markets during the observation period.

In contrast, annual risk exhibits a lower degree of variability (CV = 0.57), indicating a relatively stable level of market fluctuations in the energy sector even under crisis conditions.

The ESG indicators exhibit moderate dispersion, with an average ESG Score of 63.6 and an interquartile range of 17 points. All three pillars (environmental, social, and governance) show comparable average values but with considerable variation, indicating the potential for heterogeneous effects of individual ESG dimensions on companies' financial performance.

Table 2A and Table 2B present the mean values and standard deviation of key indicators across the years 2019–2023, illustrating structural shifts and asymmetries in the dynamics of the energy sector. Specifically, the year 2020 was marked by a sharp decline in average annual returns and a peak in risk levels (approximately 62%), reflecting the impact of the exogenous shock caused by the COVID-19 pandemic. In 2021, the data show a record increase in average returns (40.3%) accompanied by a decline in risk, which corresponds to the phase of post-crisis recovery. By 2023, average returns had dropped again to 3.8%, accompanied by further risk reduction, which may be interpreted as a market cooling following a period of heightened volatility.

Table 2A.

Annual Means (2019-2023)

Year	Annual Return	Annual Risk	ESG Score	E	S	G
2019	0,130	0,240	61,231	60,949	59,974	64,051
2020	0,076	0,623	64,103	63,795	63,410	66,410
2021	0,403	0,311	64,564	64,436	64,744	64,769
2022	0,262	0,356	64,641	64,231	64,205	66,385
2023	0,038	0,255	63,333	62,333	63,538	65,154

Source: Calculated by the authors based on the compiled dataset.

Table 2B.

Standard Deviations (2019-2023)

Year	Annual Return	Annual Risk	ESG Score	E	S	G
2019	0,097	0,022	253,814	353,366	390,657	435,103
2020	0,135	0,052	218,147	285,483	302,406	412,196
2021	0,114	0,020	161,252	218,042	204,511	492,077
2022	0,099	0,012	164,710	220,709	210,115	471,296
2023	0,021	0,005	150,386	223,439	216,781	425,502

Source: Calculated by the authors based on the compiled dataset.

The ESG profile of the companies remained relatively stable over the observed period. The highest average ESG Score was recorded in 2022 (64.6 points), followed by a slight decrease in 2023. Among the ESG components, the environmental (E) and social (S) dimensions exhibited the least year-to-year variability. In contrast, the governance (G) component, despite the formal consistency of corporate policies, proved to be the most volatile, as indicated by the standard deviations. This pattern suggests that ESG metrics are sensitive to changes in the regulatory environment, corporate disclosure practices, and investor expectations, particularly during times of crisis.

Table 3.

Correlation Matrix of Key Variables

Variable	Annual Return	Annual Risk	ESG Score	E	S	G
Annual Return	1	0,073	-0,010	-0,077	0,028	0,024
Annual Risk	0,073	1	-0,098	-0,173	-0,075	0,021
ESG Score	-0,010	-0,098	1	0,794	0,878	0,634
E	-0,077	-0,173	0,794	1	0,628	0,178
S	0,028	-0,075	0,878	0,628	1	0,366
G	0,024	0,021	0,634	0,178	0,366	1

Source: Calculated by the authors based on the compiled dataset.

Note: The table presents Pearson correlation coefficients between annual return, annual risk, and ESG-related variables (aggregate ESG score and its environmental, social, and governance components). All coefficients are based on the panel dataset comprising 195 firm-year observations.

To investigate the potential relationship between companies' financial indicators and their level of ESG integration, a correlation analysis was conducted. The results, presented in Table 3, did not confirm the presence of a significant linear association between ESG performance and either stock return or risk. Specifically, the correlation between Annual Return and ESG Score was –0.01, indicating virtually no dependence. Similarly, Annual Risk exhibited a weak negative correlation with ESG Score (–0.098), which was not statistically significant.

Given the potential influence of market shocks, additional year-by-year correlation analyses were performed. However, these results yielded similar patterns: in most years, the correlation between ESG and return remained within the range of –0.25 to +0.10. In isolated cases, such as in 2020, a moderate negative correlation was observed (–0.25); however, this finding is insufficient to support generalizable conclusions.

In contrast, strong internal correlations were consistently observed among the ESG components. In particular, the environmental (E) and social (S) dimensions demonstrated a high positive correlation (approximately 0.80), whereas their association with the governance (G) dimension was considerably weaker. This suggests that ESG subcomponents may capture different structural aspects of corporate sustainability, warranting their separate consideration in further analyses.

The graph visualizes the empirical analysis of ESG performance and risk-return correspondence for the investigated energy companies from 2019 to 2023. The results demonstrate the impact of the COVID-19 pandemic. Risk and return are sharply affected by the COVID-19 pandemic. There were reactions in different directions regarding risk, return, and ESG score. This partially explains the low correlation between these indicators for research time. The risk sharply increased in 2020 and then returned to its previous level. The return level demonstrated a change in the opposite direction to risk. At the same time, ESG scores grew from 2019 to 2022, but then decreased in 2023. Such things explain to some extent the absence of strong dependency between them in the short-term period

These findings have important implications for the choice of methodological approach. The absence of linear relationships, combined with high variability in returns and relatively stable ESG scores, raises concerns regarding the explanatory power of classical regression models. In particular, low correlation coefficients suggest weak predictive capacity, while the limited variation in ESG metrics increases the risk of multicollinearity when using panel models with fixed effects.

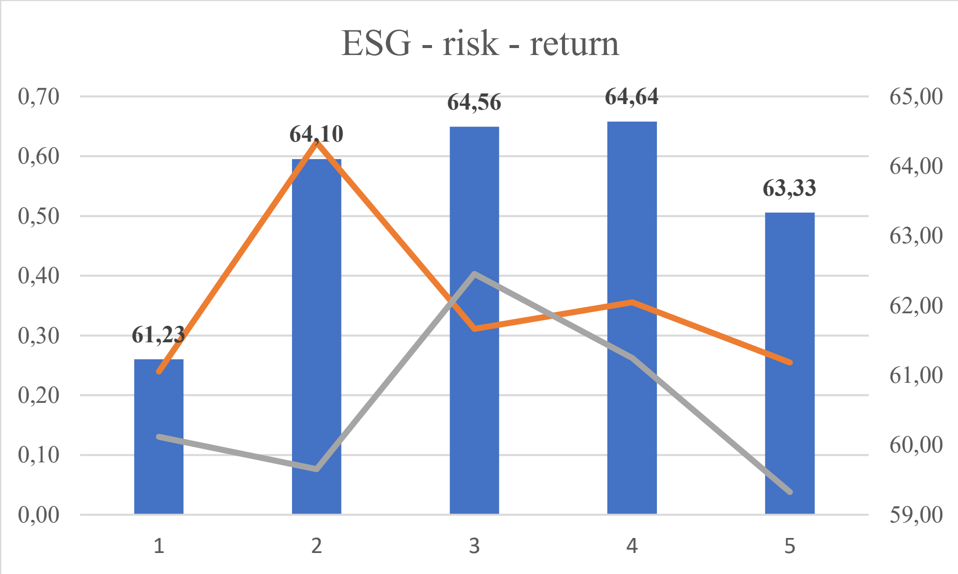

Fig 1. Averages of ESG scores, Annual Return and Annual Risk

Therefore, cluster analysis was chosen as a methodologically justified alternative. Unlike regression models, clustering does not impose a priori assumptions about functional dependence; instead, it identifies latent structures within the data. This enables the exploration of whether companies form stable groups characterized by similar profiles of "return–risk–ESG", which may indicate the presence of strategic behavioral patterns in the market. Identifying such clusters can provide a foundation for future research on the effectiveness of ESG strategies and their market realization in the energy sector.

To gain deeper insights into the structural heterogeneity of the sample and identify typical combinations of the "return–risk–ESG" triad, we applied a cluster analysis using the K-means algorithm [17, 18]. The model included the following standardized variables: average annual return (Annual Return), annualized risk (Annual Risk), as well as the aggregated ESG Score and its components (E, S, G).

The algorithm was implemented across various cluster numbers, with the final selection based on empirical interpretability and stability. A three-cluster solution emerged as the most robust. The analysis confirmed that firms indeed group into three relatively stable clusters, each reflecting a distinct configuration of risk, return, and ESG profile. A graphical representation using principal component analysis (PCA) – specifically PC1 and PC2 – supported the presence of clear differentiation between groups with minimal overlap, indicating structural consistency and the meaningfulness of the identified clusters.

Table 4.

Results of Cluster Analysis

Ticker	Industry	Annual Return	Annual Risk	ESG Score	E	S	G	Cluster
AEP	Utilities - Regulated Electric	0,0829	0,2152	70,6	71,6	74,8	63,6	3
AM	Oil & Gas Midstream	0,2547	0,4847	59	71,8	66	34	2
AQN	Utilities - Diversified	0,0117	0,3163	61,6	62,4	54,6	70,8	3
AR	Oil & Gas E&P	0,4343	0,7081	51,8	51,6	46,4	61,8	2
BEP	Utilities - Renewable	0,2210	0,3324	63,2	66,2	56,8	67,2	3
COP	Oil & Gas E&P	0,2476	0,3997	65,2	64,6	77,2	44,6	2
CQP	Oil & Gas Midstream	0,1900	0,3432	70,8	78,4	60,4	76,8	3
CTRA	Oil & Gas E&P	0,1390	0,3883	34,2	32,4	22,8	56,8	1
CVX	Oil & Gas Integrated	0,1583	0,3105	74	66,4	75,2	83,8	3
CWEN	Utilities - Renewable	0,1989	0,3300	39,6	49,8	36,6	26,2	1
D	Utilities - Regulated Electric	-0,0051	0,2546	79,8	80,4	75,4	83,4	3
DUK	Utilities - Regulated Electric	0,0995	0,2278	69	72,8	72,4	58,2	3
DVN	Oil & Gas E&P	0,3543	0,5533	55,2	47,8	66,4	45,8	2
ENB	Oil & Gas Midstream	0,1105	0,2397	77,4	93,2	77,4	58,4	3
EOG	Oil & Gas E&P	0,2076	0,4469	53,8	44,2	47	80,4	2
EPD	Oil & Gas Midstream	0,1187	0,2642	36,8	58,2	38,6	9,8	1
ET	Oil & Gas Midstream	0,1802	0,3883	28,2	33	34	14	1
ETR	Utilities - Regulated Electric	0,0928	0,2474	53,8	47,8	58	58,2	3
EXC	Utilities - Regulated Electric	0,0961	0,2538	58,4	53,6	56	70	3

FANG	Oil & Gas E&P	0,3079	0,5309	58	43,6	54,6	85,6	2
FE	Utilities - Regulated Electric	0,0790	0,2565	65,4	63,8	74,4	56,2	3
HES	Oil & Gas E&P	0,3550	0,4554	75,2	63,4	86,8	72,8	2
KMI	Oil & Gas Midstream	0,1213	0,2797	85,4	89,8	89,6	74	3
MPC	Oil & Gas Refining & Marketing	0,3309	0,4382	72,6	67,4	81,6	63,2	2
NEE	Utilities - Regulated Electric	0,1438	0,3038	75,6	76,8	74,6	75	3
OKE	Oil & Gas Midstream	0,2286	0,3963	67,2	72,4	67,8	60,4	3
ORA	Utilities - Renewable	0,1415	0,3425	58,8	53	53,6	76,6	3
OXY	Oil & Gas E&P	0,2458	0,5729	76,6	63,4	84,4	82,4	2
PBA	Oil & Gas Midstream	0,1437	0,3067	72	65,6	68,2	84,2	3
PEG	Utilities - Regulated Electric	0,0997	0,2320	64,8	62,2	60,8	75,2	3
PPL	Utilities - Regulated Electric	0,0806	0,2694	58,4	39,2	66,6	81	3
PSX	Oil & Gas Refining & Marketing	0,2024	0,3864	69,2	80,8	63,6	61,6	3
RRC	Oil & Gas E&P	0,4296	0,6538	62,6	51,2	55,2	92	2
SO	Utilities - Regulated Electric	0,1674	0,2352	64,6	58,2	60,2	80,8	3
TRP	Oil & Gas Midstream	0,0964	0,2710	56	69,2	49,4	49,8	3
VLO	Oil & Gas Refining & Marketing	0,2630	0,4486	64,6	59,8	62,4	74,2	2
WMB	Oil & Gas Midstream	0,1859	0,2900	73,2	78	60	85,4	3
XEL	Utilities - Regulated Electric	0,1053	0,2249	81,6	84	76,4	83,6	3
XOM	Oil & Gas Integrated	0,1752	0,3161	75,2	74,8	77,6	71	3

Source: Calculated by the authors based on the compiled dataset.

Fig.2 presents the visualization of cluster analysis. We applied different number of potential clusters and assessed that 3 clusters set is most adequate.

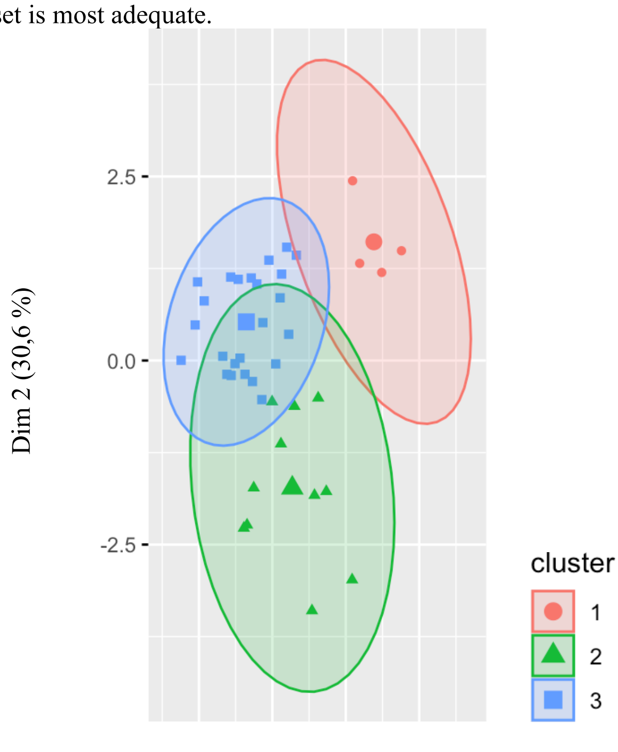

Fig 2. Results of Cluster Analysis (PCA-space)

Cluster 1 comprises companies with high returns and high risk, but relatively low ESG scores, particularly in the Governance (G) dimension. This cluster predominantly includes firms in the Oil & Gas Exploration & Production segment. Such a configuration likely reflects a high-risk business model susceptible to fluctuations in spot energy prices.

Cluster 2 is characterized by moderate returns, elevated risk, and very weak scores in Governance and Social components, which may indicate unstable corporate governance practices or reputational challenges. This group includes infrastructure operators and midstream energy companies.

Cluster 3 represents the most ESG-oriented profile, combining high E, S, and G scores, low market risk, and moderate return levels. It encompasses most firms in the Renewable Energy and Utilities sectors, including companies such as NextEra Energy (NEE) and Brookfield Renewable (BEP). This confirms the hypothesis that strong ESG performance is associated with lower volatility, though not necessarily with superior profitability.

The cluster analysis revealed latent segmentation in the sample that remained invisible to traditional regression-based approaches. The most robust pattern identified was the negative association between ESG scores and risk: companies with higher ESG ratings tend to exhibit lower market volatility. However, return levels showed no clear dependence on ESG performance: both high- and low-ESG firms were present among high-return and low-return observations.

These results support the use of clustering techniques as an effective method to identify typical ESG–financial profiles, providing a basis for further research on the segmentation of ESG behavior and its implications for investment strategies in the energy sector.

DISCUSSION

The obtained results enable us to draw several important conclusions, both theoretically and practically, regarding the role of ESG factors in shaping the market characteristics of companies in the energy sector. First and foremost, the conducted correlation analysis did not reveal any robust statistical relationship between aggregate ESG scores and financial metrics, specifically return and risk. Similar findings have been reported in several empirical studies [7, 19], which highlight that the ESG rating often behaves as a "slow-moving" variable, not always accurately reflecting short-term market fluctuations. Moreover, according to [7], the relationship between ESG indices and financial performance is context-dependent and primarily manifests in the long term.

One of the underlying explanations is that ESG, by its very nature, is designed to serve as an indicator of long-term resilience, corporate responsibility, and governance quality. Therefore, expecting a direct short-term impact of ESG indicators on stock returns, especially under market shocks, is inherently misleading. For instance, in 2020, energy companies experienced an unprecedented collapse in stock prices due to the COVID-19 pandemic and a dramatic oil price crash, factors largely beyond the influence of a company's ESG profile in the short term.

Consequently, in periods of market turbulence, ESG indicators should be viewed not as determinants of lower volatility, but rather as signals of adaptive capacity in the medium to long term. Firms with strong ESG scores may be better positioned to lead the green transition, attract capital at a lower cost, or manage social risks; however, these benefits materialize gradually through the improvement of fundamental indicators.

Given the absence of a clear linear relationship between ESG and financial metrics, the study employed cluster analysis as a methodological alternative to uncover latent patterns within the data. Clustering enabled the grouping of companies based on their similarity in return–risk–ESG profiles and revealed several insightful findings.

Firstly, extractive industry firms demonstrated the highest return–highest volatility profile, consistent with their exposure to global commodity price shocks. Their ESG scores remained comparatively low, which may reflect not only actual environmental impact but also methodological bias in ESG ratings, where resource-intensive industries are systematically downgraded.

Secondly, infrastructure-based companies, such as pipeline operators, power grid utilities, and energy suppliers, formed a separate cluster characterized by lower returns, moderate risk, and high ESG variation, depending on the regulatory context and geographical operations. This cluster appears especially vulnerable to policy shifts, tariff reforms, and structural changes in demand.

Thirdly, the renewable energy segment was the most ESG-oriented cluster, demonstrating high scores across all ESG dimensions. This aligns with the nature of their business models and reputational positioning. However, their returns remained moderate, which likely reflects a focus on long-term growth, subsidies, and the capital-intensive nature of the industry.

Thus, the energy sector is demonstrably heterogeneous, with its subsectors showing significant differences in risk, return, and ESG profiles. This highlights the importance of a stratified approach to analyzing ESG impacts: rather than constructing universal models, researchers should evaluate relationships within homogeneous groups, defined by activity type, development stage, or regional affiliation.

The study is subject to several limitations that must be acknowledged. The time horizon (2019–2023) is marked by high global uncertainty, including the pandemic, energy crisis, and geopolitical tensions, complicating the identification of stable patterns. Moreover, cluster analysis is inherently descriptive and does not establish causality. Nonetheless, it offers a promising foundation for further research, particularly in developing cluster profiles based on non-financial variables (e.g., energy type, climate strategies, transparency) or dynamic clustering in temporal dimensions.

Future research may also focus on refining the methodology for assessing ESG effects under conditions of instability, such as through sensitivity analysis of market indicators to ESG inputs during bull vs. bear phases, or through machine learning techniques to detect nonlinear and hidden dependencies. It is also crucial to consider regional differences and market maturity, as ESG implications may vary between developed economies and emerging markets.

Overall, the results confirm the complex and multidimensional nature of the relationship between sustainable practices and business performance. ESG factors should not be viewed as universal predictors of return or risk, but rather as core components of corporate reliability, whose effects unfold over the long term.

CONCLUSIONS

This study provides a quantitative analysis of the relationship between ESG indicators and market characteristics, specifically examining the returns and risks of publicly traded energy companies from 2019 to 2023.

The sample included 39 firms across various subsectors, ranging from oil and gas extraction to electricity generation and distribution, ensuring broad sectoral representation.

The initial stage of the analysis revealed that ESG scores remained relatively stable over time. The average aggregated ESG rating fluctuated between 61 and 65 points, with no clear upward or downward trend. The individual ESG components (Environmental, Social, and Governance) demonstrated strong internal correlations, suggesting a standardized reporting framework and high interdependence among corporate responsibility practices.

In contrast, stock returns exhibited substantial volatility. In 2020, during the COVID-19 crisis, the average return declined to 7.6% (with some firms experiencing losses exceeding –100%), only to rebound sharply in 2021 to 40.3%. These fluctuations highlight the predominance of short-term market factors in influencing equity performance, thereby diminishing the explanatory power of ESG metrics in the short term.

The correlation analysis confirmed the absence of statistically significant relationships between ESG ratings and financial indicators such as return and risk. The overall correlation coefficients were close to zero, and annual matrices also failed to demonstrate consistent dependencies. These findings contradict the common assumption that ESG functions as a protective factor during market downturns, suggesting that investors prioritize other signals such as oil prices, supply chain stability, or geopolitical risks during turbulent periods.

Therefore, we conclude that ESG scores may have limited predictive power for short-term market performance. Instead, their relevance appears to lie in long-term stabilization, achieved through the reduction of operational, reputational, and regulatory risks. From this perspective, ESG should be interpreted not as a tool to boost returns, but rather as a marker of resilience and governance maturity.

To further explore the internal structure of the sample, a cluster analysis was conducted. Based on three parameters (average return, volatility, and ESG score), companies were grouped into clusters with distinct profiles. The analysis confirmed the existence of three differentiated clusters:

1. Firms with high risk and low ESG performance, typically in the extractive segment;
2. Firms with moderate returns and high ESG scores, often from the renewable energy sector;
3. Firms that are infrastructure operators with moderate risk and variable profitability.

These findings confirm that the energy sector is far from homogeneous, and ESG impact assessments must consider subsector-specific characteristics. Notably, ESG ratings may be systematically penalized for traditional producers due to stringent evaluation criteria. At the same time, renewable energy firms may receive favorable scores by default even when they do not deliver strong financial returns.

Future research should consider expanding the time horizon, incorporating alternative ESG data sources, exploring the effects of firm-level policy changes, and applying causal inference tools to understand the dynamics at play better. The use of longitudinal models and non-linear analytical techniques may also help capture the complexity of ESG-performance interactions more accurately.

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