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The Impact of ESG Scores on Risk Market Performance

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Abstract: Over the last two decades, there has been an increased attention to and awareness of corporate environmental, social, and governance (ESG) responsibilities. The asset allocation process has changed accordingly to consider these ESG responsibilities, and it has largely been recognized that private and institutional investors are sensitive to ESG factors when deciding on firms in which to invest. In addition to ESG factors, other key stock-related factors to which investors generally pay attention are risk-adjusted indicators, such as the Sharpe ratio (SR) and the Sortino index (SI), as well as tail risk measures, such as the Value-at-Risk (VaR) and the Expected Shortfall (ES). Overall, the SR, SI, VaR, and ES can provide a guide for investors concerning the risk market performance of a stock under investigation. In this context, the research question that arises is the following: are firms' performances sensitive to ESG rates? The present contribution aims to answer this question. In particular, the SR, SI, VaR, and ES measures of a set of listed firms are calculated and evaluated. Among these, there are firms with low ESG grades and some with high ESG grades according to two ESG rate providers. The list of stocks under consideration consists of the first 25 constituents (by weight) of the S&P500 index in the period from 2020 and 2022. The empirical findings indicate that risk market performance does not properly depend on high or low ESG rates.

Keywords: ESG rating; investments; stock returns; Value-at-Risk; Expected Shortfall

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1. Introduction

Empirical research concerning the impact of environmental, social, and governance (ESG) factors on firms' performance has largely been assessed in the business and economic literature [1–3] because it helps institutional investors to identify, measure, and manage investment risks and opportunities arising from significant ESG issues [4]. Investors and policymakers involved in socially responsible investment have drastically increased in recent years [5], thus raising the attention given to ESG issues and their influence on the profitability [6] and financial viability of firms. Corporate managers and policymakers have traditionally relied on two sets of information: fundamental corporate information and technical information provided by the stock market. Indeed, ESG information represents an extra set of data that can also provide insight into future performance and can support investors in making sound investment decisions [4]. An expanding body of research has focused on the investigation of ESG measures and ranking methodologies [7], as well as the evaluation of the impacts of ESG factors on financial performance and risk management [8,9]. Many studies have tried to summarize the different results [10] and others have analyzed the impact of ESG factors on the performance of information technology [11]. Usually, the objective of scientific studies is to use ESG tools to achieve financial results in portfolio management. The findings from over 1000 research reports were that the correlation between ESG features and financial performance was not conclusive. Indeed, the related literature shows positive, negative, and nonsignificant links, even though most of the studies present a significant positive correlation [4]. The lack of clear evidence in favor of ESG-related funds' performance can be due to both the outperformance and underperformance of ESG investing [12]. For this reason, there is still room for the question of how and to what extent ESG criteria impact risk market performance. A general tool for assessing the risk market performance of a stock is looking at its risk-adjusted indicators and the occurrences of unfortunate events when the stock returns are extremely low. These events have a low probability of happening, but when they occur, the consequences are generally severe. From the risk management perspective, the interest is, therefore, in the capital that a market participant should hold as a buffer against unexpected future losses. The Basel–I, Basel–II, and Basel–III agreements [13] set these minimum capital requirements. Two of the most popular tail risk measures suggested by the Basel agreements are the Value-at-Risk (VaR) and Expected Shortfall (ES). Nowadays, verifying the adequacy of such risk measures is crucial not only for meeting the challenges of the Basel agreements, but also for providing popular benchmarks for managing financial risk. The VaR, which was introduced by J.P. Morgan in their RiskMetrics publication [14], is defined as the maximum loss that is likely to occur at a fixed confidence interval and over a specified period. More importantly, the VaR represents one of the most widespread risk measures. The ES is defined as the expected loss that occurs when the returns are beyond the VaR. Unlike the VaR measure, the ES has some desirable properties, such as coherence [15,16]. The VaR and ES provide the most popular benchmarks from the perspective of risk management [17,18]. In this framework, an issue that has remained unexplored in the literature is the relationship between ESG rates and risk market performance. Therefore, our research question is the following: Is the listed firms' performance—in terms of risk-adjusted indicators and the adequacy of the VaR and ES—sensitive to ESG rates? In other words, do listed firms with high ESG rates perform better in terms of risk market performance than firms with low ESG rates? The present paper aims to answer this question.

This paper is organized as follows. Section 2 reviews the main literature concerning ESG responsibilities. Section 3 introduces the theoretical research questions; it describes the method and the data used for the empirical investigation. Section 4 presents the results that were reached, and they are further discussed in Section 5, which also highlights the weaknesses of the analysis and suggests insights for further research.

2. Literature Overview

Many countries have developed a common framework for using ESG metrics for sustainable finance [19]. There are various studies that have explored the effects of ESG factors on the portfolio selection process for the achievement of high sustainability. Van Duuren et al. (2016) [20] examined the integration of ESG in the investment process. Their results showed significant differences between American and European fund managers. Sassen et al. (2016) [21] analyzed the impact of ESG factors on firm risk at the European level. However, an important link between ESG disclosure and company performance was identified in the literature [22]. As has been broadly discussed [23–25], the debate concerning the nexus of ESG ratings and financial performance is still open. Fried et al. (2015) [26] analyzed ESG investing relative to more than 2000 empirical works to show a positive correlation between ESG and a company's financial performance over time (see also the works of [27,28] on the same topic). Many studies have confirmed this important result [29–31]. In addition, Zhao et al. (2018) [32] found that high ESG scores in Chinese firms could improve financial performance. Brogi and Lagasio (2019) [33] showed the positive impact of ESG on American firms' profitability. From the same perspective, Ortas et al. (2015) [34] obtained the same finding for Spain, France, and Japan. Aureli et al. (2020) [35] identified the importance of ESG disclosure for a firm's market, while Giese et al. (2019) [5] explored how reduced capital costs, higher valuations, high profitability, and a lower exposure to tail risk could be opportune channels for positively affecting firms' valuation and their financial performance. However, a conclusion about ESG ratings and financial performance has not been attained. There is still room for other findings. Indeed, some works did not observe a clear statistical impact [36], while some other contributions highlighted very weak effects [37]. Because of the different methodologies adopted in these investigations relative to the different countries in which they were performed, it is hard to perform a robust interpretation of the findings. Regarding the performance of ESG portfolios, empirical studies have confirmed that investing in ESG-firm-based portfolios can generate good performance [38–40]. Yen et al. (2019) [41] demonstrated that socially responsible investment portfolios achieved a high performance in Japan, thus confirming the results of other studies [42]. Further studies analyzed the interaction between ESG and green innovation to assess the final impact on a company's value and documented that green innovation and ESG could generate positive value [43]. Finally, the impact of ESG elements on credit rankings has been evaluated in the literature. Attig et al. (2013) [44] showed that companies with a high social performance could benefit from good ratings. In the same direction, Devalle et al. (2017) [45] and Weber et al. (2010) [46] confirmed that companies with a relevant performance in terms of the environment and sustainability could benefit from credit rates. Bhattacharya and Sharma (2019) [47] found a positive effect on credit rankings but only for small and middle-level firms. Table 1 summarizes the contents of the literature review discussion.

The previous discussion about the different strands in the literature leads to the conclusion that it is difficult to confirm ESG responsibilities' relevance. Thus, there is a necessity for further empirical research to investigate opportune actions when coping with ESG issues and sustainable finance.

Table 1. Literature Overview.

Title	Authors
Estimation risk in financial risk management.	Christoffersen and Goncalves (2005) [18]
The environmental, social, governance, and financial performance effects on companies that adopt the United Nations Global Compact.	Ortas et al. (2015) [34]
Impact of ESG factors on firm risk in Europe.	Sassen et al. (2016) [21]
Does ESG performance have an impact on financial performance? Evidence from Germany.	Velte (2017) [28]
Foundations of ESG investing: How ESG affects equity valuation, risk and performance.	Giese et al. (2019) [5]
The impact of environmental, social, and governance performance on stock prices: Evidence from the banking industry.	Miralles et al. (2019) [37]
The Interaction Effect between ESG and Green Innovation and Its Impact on Firm Value from the Perspective of Information Disclosure.	Zhang et al. (2020) [43]
ESG screening strategies and portfolio performance: How do they fare in periods of financial distress?	Torricelli and Bertelli (2022) [9]
Impact of ESG performance on firm value and profitability.	Aydoğmuş et al. (2022) [6]
A Systematic Literature Review on ESG during the COVID-19 Pandemic.	Savio et al. (2023) [48]

3. Risk-Adjusted Indicators and Tail Risk Measures

To explore the implications for risk performance related to the incorporation of ESG information into investment strategies, an analysis based on different risk-adjusted indicators and tail risk measures was carried out.

We start by presenting two risk-adjusted indicators: the widely used Sharpe ratio (SR), which was developed by [49], and the Sortino ratio [50]. The SR index compares the return of an investment with its risk and is calculated as the ratio of the total return differential versus a benchmark, such as the risk-free rate of return, and its standard deviation:

$$SR = \frac{R_p - R_f}{\sigma_p} \tag{1}$$

where

- R_p is the expected return of the investment under consideration;
- R_f is the risk-free rate of return;
- σ_p is the standard deviation of returns of the investment under consideration.

A higher value of the SR indicates that the security has superior performance.

The Sortino index (SI) is a modification of the SR and measures the risk-adjusted return of an asset by using the target rate of return. The SI uses the downside deviation rather than the standard deviation in the denominator, and it is calculated by dividing the difference between an asset's return and risk-free rate by the standard deviation of negative returns (returns falling below a user-specified target).

$$SI = \frac{R_p - R_f}{\sigma_D} \tag{2}$$

where

- R_p is the expected return;
- R_f is the risk-free rate of return;
- σ_D is the standard deviation of the downside.

Ideally, a high SI is preferred, as this indicates that an investor will earn a higher return for each unit of downside risk. Analysts commonly prefer to use the SR index to evaluate low-volatility investment portfolios and the SI to evaluate high-volatility portfolios.

The $VaR_{t,\tau}$ at time t and at level τ is defined as the worst return to be expected at a probability of $1 - \tau$ over a specific horizon [51]. Formally,

$$Pr(r_t < VaR_{t,\tau} | \mathcal{F}_{t-1}) = \tau,$$

where r_t is the one-period return from time $t-1$ to time t, $\tau \in (0,1)$ is the quantile level, and $\mathcal{F}_t$ is the information set at time t.

Despite its widespread use, the VaR measure has the limitation that it gives no information regarding any possible loss beyond the given threshold value.

The ES is defined as the conditional expectation of returns when the VaR is violated (exceedance beyond the VaR) [52,53], that is,

$$ES_{t,\tau} = E[r_t | r_t < VaR_{t,\tau}, \mathcal{F}_{t-1}].$$

In this work, the VaR was estimated according to two different approaches: the parametric and semiparametric approaches. In the parametric approach, the GARCH [54] model was used to estimate the one-step-ahead conditional standard deviation σ_t. Then, the VaR was obtained by multiplying the one-step-ahead conditional standard deviation σ_t by the quantile of the hypothesized error distribution. In this work, we assumed a Gaussian distribution. Formally,

$$VaR_{t,\tau} = \sigma_t \Phi^{-1}(\tau),$$

where Φ^{-1} is the inverse cumulative density function of the standard Gaussian distribution.

The other model used here to calculate the VaR was the CAViaR model of Engle and Manganelli (2004) [55], which belongs to the class of semiparametric methods because it does not assume a specific parametric distribution of the returns, but it assumes an updating formula for the VaR. The CAViaR model directly specifies the τth conditional quantile of r_t by using the following autoregressive process:

$$VaR_{t,\tau} = \beta_0(\tau) + \sum_{i=1}^{p} \beta_i(\tau) VaR_{t-i,\tau} + \sum_{j=1}^{q} \alpha_j(\tau) \ell(\boldsymbol{x}_{t-j}),$$

where $\ell(\cdot)$ is the news impact curve.

Different choices of $\ell(\boldsymbol{x}_{t-j})$ are available. In this work, we referred to the CAViaR–asymmetric slope (CAViaR-AS):

$$\begin{aligned} VaR_{t,\tau} = \beta_0 + \beta_1 VaR_{t-1,\tau} + \\ (\beta_2 I(r_{t-1} > 0) + \beta_3 I(r_{t-1} < 0)) \mid r_{t-1} \mid, \end{aligned}$$

where $I(\cdot)$ is an indicator function.

The ES obtained from the parametric models with a Gaussian error distribution is:

$$ES_t(\tau) = -\sigma_t \frac{\phi(\Phi^{-1}(\tau))}{\tau}, \tag{3}$$

where $\phi(\cdot)$ is the probability density function (PDF) of the standard Gaussian distribution.

Following [56], in the case of semiparametric models, the ES can be computed jointly with the VaR by maximizing the following asymmetric Laplace density, that is,

$$f(r_t \mid VaR_t(\tau), \tau) = \frac{\tau - 1}{ES_t(\tau)} \exp\left(\frac{(r_t - VaR_t(\tau))\left(\tau - \mathbb{1}_{(r_t \le VaR_t(\tau))}\right)}{\tau ES_t(\tau)} \right), \tag{4}$$

where the ES in (4) is calculated as:

$$ES_t(\tau) = (1 + \exp(\gamma_{\mathrm{ES}})) VaR_t(\tau). \tag{5}$$

Assessing the quality of the tail risk forecasts is the aim of the backtesting procedures (see the reviews on this topic of [57,58], among others). In this work, next to the actual over expected (AE) exceedance ratio as a common measure of goodness of fit, we employed four different backtesting procedures to evaluate the tail risk forecasts:

- The unconditional coverage test (UC, Kupiec, 1995 [59]).
- The conditional coverage test (CC, Christoffersen, 1998 [60]).
- The dynamic quantile test (DQ, Engle and Manganelli, 2004 [55]) .
- The CC test of McNeil and Frey (2000) [61] for the ES (ES-CC).

The AE exceedance ratio is the number of times that the VaR has been violated over the expected VaR violations. The closer this ratio is to one, the better the model producing the VaR measures is. Moreover, if the AE is larger than one, the model has produced many VaR violations (over those expected). Therefore, it underestimates the risk.

The UC test is a likelihood-ratio-based test, where the null hypothesis assesses whether the actual frequency of VaR violations is equal to the chosen τ level. The CC test verifies not only whether the observed frequency of violations is in line with the prefixed τ, but also if these VaR violations are independently distributed over time. The DQ test always verifies the independence of the VaR violations jointly with the correctness of the number of violations—as in the CC test—but it was shown [62] to have more power over it. In particular, the DQ test consists of running a linear regression in which the dependent variable is the sequence of VaR violations and the covariates are the past violations and possibly any other explanatory variables.

Similarly to the VaR violation tests, the ES-CC test of McNeil and Frey (2000) [61] is based on the size of the discrepancy between the actual return and the estimated ES when a VaR violation occurs. The null hypothesis of this test is that the mean of the standardized exceedance residuals is i.i.d. and has zero mean, against the alternative hypothesis that the ES is systematically underestimated.

4. Empirical Analysis

This analysis aims to investigate whether and how much the positive/negative ESG screening of a firm is correctly recognized by the stock market in terms of risk-adjusted indicators and the adequacy of tail risk measures. The analysis was performed on the daily data of the first 25 constituents (by weight) of the S&P500 index at the time of writing this text. The sample period went from 2020 to 2022.

Table 2 summarizes the last available ESG scores for each selected asset according to the Eikon and Sustainalytics providers. The higher the Eikon score is, the lower the ESG risk is, while the smaller the Sustainalytics score is, the lower the ESG score is. In particular, the ESG grade by Eikon ranges between 0 (a poor score indicates a high ESG risk) and 100 (a good score indicates a low ESG risk). According to Eikon, the companies are ranked from D− to A+. However, the ESG grade from Sustainalytics always ranges between 0 and 100, but this time, 100 indicates a high level of risk and 0 indicates the absence of risk. According to Sustainalytics, the companies are ranked in five categories: negligible (with a score of 0–10), low (with a score of 11–20), medium (with a score of 21–30), high (with a score of 31–40), and severe (with a score larger than 40). It is worth noting that there is no strong consensus about the ESG grades between the two providers used in this work. To illustrate this point, we colored the cells of Table 2 to highlight the grade of agreement/disagreement between Eikon and Sustainalytics. Therefore, green cells in Table 2 indicate the homogeneity of high and medium scores (Apple, Mastercard, Microsoft, NVIDIA, PepsiCo, Bank of America, Costco Wholesale, Eli Lilly, P&G, and Tesla), meaning that the ESG scores provided by Eikon and Sustainalytics entirely or almost wholly agree on the ESG grades. On the other side, orange and red cells in Table 2 indicate small and large degrees of heterogeneity between Eikon and Sustainalytics.

Tables 3–8 are the key tables of our work. These tables report the risk-adjusted indicators (SI and SR) and the adequacy of the tail risk measures (AE and the p-values of the four backtesting tests, that is, UC, CC, DQ, and ES-CC) according to the two models presented above (GARCH and AS-CAViaR), the sample period, and the ESG score provider. In these tables, the shades of gray denote that the backtesting procedure in a column did not pass at a significance level of $\alpha = 0.05$. In Table 3, the tail risk measures were obtained with the AS-CAViaR model, the sample period went from 2020 to November 2022, and the assets were reported from the highest ESG risk (top of the table) to the lowest ESG risk (bottom of the table) on the basis of the 2020 Eikon data. Surprisingly, both the SI and SR, as well as the backtesting results, did not significantly change among the low- and high-rated ESG firms. For instance, the firm with the highest ESG risk, Berkshire Hathaway, had the same SI and SR indexes as the two top-rated (in terms of ESG risk) firms, PepsiCo and Microsoft. More interestingly, all three of these firms largely passed the backtesting procedures. To confirm our thesis that the stock market performance in terms of risk-adjusted indicators and the tail risk measures' adequacy was not affected by the ESG rates of the firms under investigation, we repeated the analysis reported in Table 3 with the GARCH model instead of AS-CAViaR. The results are illustrated in Table 4. Though the SI and SR indexes did not change from Tables 3 and 4, in the latter table, we noted that many firms did not pass the backtesting procedures. However, in line with Table 3, the bad performance of these firms was uniformly distributed across low and high ESG scores. Thus, we can conclude that the GARCH model was mainly responsible for the failure of the backtesting procedures. These results were confirmed even when we excluded the beginning of the COVID-19 pandemic from the analysis. In Tables 5 and 6, we report, respectively, the analysis of the risk-adjusted indicators and the tail risk measures' adequacy for AS-CAViaR and GARCH for the period from 2021 to November 2022 while using Eikon as the ESG score provider. Both Tables 5 and 6 corroborate our thesis that the ESG scores did not affect the stock market performance analyzed here. For instance, the SI and SR indexes of the Meta Platform, a firm with a high ESG risk, were both negative. However, Amazon, a firm with a low ESG risk according to Eikon, reported negative SI and SR indexes for the same period. In terms of the tail risk measures' adequacy, we again noted that the AS-CAViaR model almost always allowed all of the firms—independently of the ESG scores—to pass all of the backtesting procedures. As for the period from 2020 to November 2022, the GARCH model did not always produce accurate tail risk measures, but the failures were once more uniformly distributed among all of the firms (those with both low and high ESG rates). Finally, similar results were achieved when the firms under investigation were ranked according to the data from Sustainalytics. As illustrated in Tables 7 and 8, the good and bad performance in terms of risk-adjusted indicators and the tail risk measures' adequacy did not depend on the ESG rates.

To summarize, we could not identify superior financial performance according to higher ESG scores (in the cases of both the Eikon and Sustainalytics providers), and vice versa. Therefore, the stock market performance regarding risk-adjusted indicators and the adequacy of tail risk measures did not positively react to high ESG rankings. At the same time, the stock market performance did not negatively respond to low ESG scores. This is in line with results in the literature claiming that firms may react very differently to being rated [63]. Indeed, corporate responses may also depend on managers' beliefs regarding the material benefits of adjusting to and scoring well on ESG ratings and their alignment with corporate strategies [63].

Table 2. Assets and ESG ratings.

Name	Tick	ESG—Eikon	ESG—Eikon: Grade	ESG—Sustainalytics	ESG—Sustainalytics: Grade
AbbVie	ABBV	82.4	A−	29.7	Medium
Alphabet INC	GOOG	81.87	A−	24.6	Medium
Amazon	AMZN	86.75	A	30.3	High
Apple	AAPL	79.49	A−	16.7	Low
Bank of America	BAC	73.76	B+	26.8	Medium
Berkshire Hathaway	BRK-A	28.87	C−	40.1	Severe
Chevron	CVX	86.55	A	38.8	High
Coca-Cola	KO	78.58	A−	37.7	High
Costco Wholesale	COST	72.61	B+	24.2	Medium
Eli Lilly	LLY	66.21	B	24.5	Medium
Exxon Mobil	XOM	66.33	B	36.5	High
Home Depot	HD	71.1	B+	12.5	Low
J&J	JNJ	88.35	A	24.4	Medium
JP Morgan Chase	JPM	82.49	A−	29.3	Medium
Mastercard	MA	75.65	A−	15.6	Low
Merck & Co	MRK	82.1	A−	21.6	Medium
Meta Platform	META	65.53	B	34.5	High
Microsoft	MSFT	92.49	A	15.2	Low
NVIDIA	NVDA	79.15	A−	13.6	Low
P&G	PG	73.1	B+	26.7	Medium
PepsiCo	PEP	86.95	A	16.3	Low
Pfizer	PFE	80.73	A−	25.2	Medium
Tesla	TSLA	65.01	B	28.7	Medium
United Health	UNH	73.75	B+	17.4	Low
Visa Inc.	V	54.37	B−	15.6	Low

Notes: This table reports the latest available ESG scores according to the Eikon and Sustainalytics providers. The higher the Eikon score is, the lower the ESG risk is. The smaller the Sustainalytics score is, the lower the ESG risk is. Green cells indicate scores' homogeneity. Orange and red cells indicate small and large scores' heterogeneity.

Table 3. Results for the period January 2020–November 2022; ESG data: 2020; provider: Eikon; model: AS-CAViaR; $\tau = 0.05$.

Name	Tick	ESG—Eikon	ESG—Score: Grade	*SI*	*SR*	AE	UC	CC	DQ	*ES*-CC
Berkshire Hathaway	BRK-A	27.77	C−	0.04	0.03	0.98	0.91	0.98	0.97	0.84
Visa Inc.	V	54.37	B−	0.01	0.01	0.98	0.91	0.8	0.64	0.6
Meta Platform	META	62.72	B	−0.04	−0.03	0.98	0.91	0.8	0.6	0.34
Tesla	TSLA	63.10	B	0.08	0.06	0.98	0.91	0.15	0.03	0.74
Exxon Mobil	XOM	66.33	B	0.05	0.03	1.01	0.96	0.77	0.5	0.81
Eli Lilly	LLY	69.33	B	0.11	0.07	1.01	0.96	0.72	0.75	0.75
Costco Wholesale	COST	72.61	B+	0.07	0.05	0.98	0.91	0.67	0.7	0.67
Mastercard	MA	72.67	B+	0.01	0.01	1.01	0.96	0.77	0.78	0.79
Home Depot	HD	72.98	B+	0.04	0.03	0.98	0.91	0.8	0.99	0.42
P&G	PG	73.10	B+	0.03	0.02	0.98	0.91	0.8	0.82	0.66
United Health	UNH	73.75	B+	0.06	0.04	1.12	0.47	0.07	0.00	0.8
Apple	AAPL	76.74	A−	0.05	0.04	1.01	0.96	0.14	0.42	0.93
Alphabet INC	GOOG	77.78	A−	0.03	0.02	0.98	0.91	0.8	0.98	0.66
Coca-Cola	KO	77.94	A−	0.02	0.02	0.98	0.91	0.8	0.77	0.58
NVIDIA	NVDA	79.11	A−	0.05	0.04	0.98	0.91	0.8	0.93	0.86
Pfizer	PFE	80.73	A−	0.04	0.03	0.98	0.91	0.1	0.25	0.79
AbbVie	ABBV	81.40	A−	0.08	0.06	1.01	0.96	0.14	0.25	0.69
Bank of America	BAC	81.53	A−	0.01	0.01	0.98	0.91	0.67	0.77	0.41
Merck & Co	MRK	82.10	A−	0.04	0.03	1.01	0.96	0.77	0.9	0.52
Chevron	CVX	83.90	A	0.04	0.03	0.98	0.91	0.8	0.73	0.31
JP Morgan Chase	JPM	84.49	A	0.00	0.00	0.98	0.91	0.98	0.48	0.31
J&J	JNJ	86.11	A	0.04	0.03	0.98	0.91	0.8	0.67	0.71
Amazon	AMZN	86.75	A	−0.00	−0.00	0.98	0.91	0.8	0.93	0.46
PepsiCo	PEP	89.71	A	0.04	0.03	1.01	0.96	0.77	0.78	0.68
Microsoft	MSFT	93.52	A+	0.04	0.03	1.01	0.96	0.14	0.48	0.73

Notes: Column *SI* denotes the Sortino index based on the average excess return over the downside risk, and *SR* is the Sharpe ratio calculated as the ratio of the asset's mean excess return and its standard deviation. Column AE denotes the actual over expected exceedance ratio. Columns UC and CC report the *p*-values of the unconditional and conditional coverage tests. Column DQ represents the *p*-value of the dynamic quantile test. Column *ES*-CC reports the *p*-value of the McNeil and Frey (2000) *ES* test. Shades of gray denote that the backtesting procedure in the column did not pass at a significance level of $\alpha = 0.05$.

Table 4. Results for the period January 2020–November 2022; ESG data: 2020; provider: Eikon; model: GARCH; $\tau = 0.05$.

Name	Tick	ESG—Eikon	ESG Score Grade	*SI*	*SR*	AE	UC	CC	DQ	*ES*-CC
Berkshire Hathaway	BRK-A	27.77	C−	0.04	0.03	0.98	0.91	0.67	0.55	0.52
Visa Inc.	V	54.37	B−	0.01	0.01	1.01	0.96	0.99	0.29	0.00
Meta Platform	META	62.72	B	−0.04	−0.03	0.82	0.24	0.14	0.75	0.06
Tesla	TSLA	63.10	B	0.08	0.06	0.95	0.77	0.17	0.05	0.09
Exxon Mobil	XOM	66.33	B	0.05	0.03	0.93	0.64	0.85	0.47	0.17
Eli Lilly	LLY	69.33	B	0.11	0.07	0.35	0.00	0.00	0.00	0.05
Costco Wholesale	COST	72.61	B+	0.07	0.05	0.87	0.42	0.33	0.6	0.06
Mastercard	MA	72.67	B+	0.01	0.01	0.87	0.42	0.33	0.68	0.00
Home Depot	HD	72.98	B+	0.04	0.03	0.95	0.77	0.81	0.65	0.00
P&G	PG	73.10	B+	0.03	0.02	0.93	0.64	0.85	0.81	0.00
United Health	UNH	73.75	B+	0.06	0.04	0.87	0.42	0.67	0.61	0.04
Apple	AAPL	76.74	A−	0.05	0.04	0.98	0.91	0.8	0.8	0.07
Alphabet INC	GOOG	77.78	A−	0.03	0.02	0.93	0.64	0.17	0.44	0.01
Coca-Cola	KO	77.94	A−	0.02	0.02	0.84	0.32	0.59	0.66	0.00
NVIDIA	NVDA	79.11	A−	0.05	0.04	0.95	0.77	0.81	0.97	0.11
Pfizer	PFE	80.73	A−	0.04	0.03	0.68	0.04	0.02	0.17	0.05
AbbVie	ABBV	81.40	A−	0.08	0.06	0.76	0.12	0.1	0.08	0.00

Table 4. *Cont.*

Name	Tick	ESG—Eikon	ESG Score Grade	*SI*	*SR*	AE	UC	CC	DQ	*ES*-CC
Bank of America	BAC	81.53	A−	0.01	0.01	0.90	0.52	0.16	0.39	0.28
Merck & Co	MRK	82.10	A−	0.04	0.03	0.82	0.24	0.49	0.59	0.01
Chevron	CVX	83.90	A	0.04	0.03	0.87	0.42	0.67	0.74	0.02
JP Morgan Chase	JPM	84.49	A	0.00	0.00	0.98	0.91	0.8	0.12	0.38
J&J	JNJ	86.11	A	0.04	0.03	1.01	0.96	0.77	0.99	0.01
Amazon	AMZN	86.75	A	−0.00	−0.00	1.04	0.83	0.98	0.68	0.07
PepsiCo	PEP	89.71	A	0.04	0.03	0.95	0.77	0.81	0.85	0.02
Microsoft	MSFT	93.52	A+	0.04	0.03	1.14	0.38	0.65	0.27	0.00

Notes: Column *SI* denotes the Sortino index based on the average excess return over the downside risk, and *SR* is the Sharpe ratio calculated as the ratio of the asset's mean excess return and its standard deviation. Column AE denotes the actual over expected exceedance ratio. Columns UC and CC report the *p*-values of the unconditional and conditional coverage tests. Column DQ represents the *p*-value of the dynamic quantile test. Column *ES*-CC reports the *p*-value of the McNeil and Frey (2000) *ES* test. Shades of gray denote that the backtesting procedure in the column did not pass at a significance level of $\alpha = 0.05$.

Table 5. Results for the period January 2021–November 2022; ESG data: 2021; provider: Eikon; model: AS-CAViaR; $\tau = 0.05$.

Name	Tick	ESG—Eikon	ESG Score Grade	*SI*	*SR*	AE	UC	CC	DQ	*ES*-CC
Berkshire Hathaway	BRK-A	28.87	C−	0.08	0.06	1.00	0.99	0.78	0.98	0.84
Visa Inc.	V	54.37	B−	−0.00	−0.00	1.00	0.99	0.78	0.6	0.51
Tesla	TSLA	65.01	B	−0.02	−0.02	1.00	0.99	0.28	0.17	0.55
Meta Platform	META	65.53	B	−0.07	−0.06	1.00	0.99	0.98	0.6	0.28
Eli Lilly	LLY	66.21	B	0.15	0.09	0.96	0.82	0.97	0.83	0.69
Exxon Mobil	XOM	66.33	B	0.16	0.11	1.00	0.99	0.33	0.12	0.83
Home Depot	HD	71.10	B+	0.04	0.03	1.16	0.42	0.69	0.27	0.89
Costco Wholesale	COST	72.61	B+	0.06	0.04	1.00	0.99	0.98	1.00	0.48
P&G	PG	73.10	B+	0.02	0.02	1.00	0.99	0.98	0.93	0.53
United Health	UNH	73.75	B+	0.10	0.07	1.00	0.99	0.98	0.93	0.74
Bank of America	BAC	73.76	B+	0.04	0.03	1.00	0.99	0.98	0.85	0.73
Mastercard	MA	75.65	A−	−0.00	−0.00	1.04	0.84	0.94	0.99	0.9
Coca-Cola	KO	78.58	A−	0.06	0.04	1.04	0.84	0.94	0.95	0.62
NVIDIA	NVDA	79.15	A−	0.02	0.01	1.04	0.84	0.25	0.71	0.86
Apple	AAPL	79.49	A−	0.02	0.01	1.04	0.84	0.94	0.3	0.77
Pfizer	PFE	80.73	A−	0.07	0.05	0.91	0.66	0.21	0.51	0.91
Alphabet INC	GOOG	81.87	A−	0.01	0.01	1.04	0.84	0.82	0.52	0.54
Merck & Co	MRK	82.10	A−	0.09	0.06	1.29	0.16	0.27	0.00	0.92
AbbVie	ABBV	82.40	A−	0.10	0.07	0.96	0.82	0.97	0.63	0.55
JP Morgan Chase	JPM	82.49	A−	0.03	0.02	1.00	0.99	0.78	0.96	0.79
Chevron	CVX	86.55	A	0.14	0.10	1.00	0.99	0.98	0.48	0.81
Amazon	AMZN	86.75	A	−0.06	−0.05	0.96	0.82	0.31	0.88	0.41
PepsiCo	PEP	86.95	A	0.08	0.05	1.00	0.99	0.98	0.6	0.61
J&J	JNJ	88.35	A	0.05	0.03	0.96	0.82	0.7	0.47	0.61
Microsoft	MSFT	92.49	A	0.02	0.01	0.96	0.82	0.31	0.98	0.48

Notes: Column *SI* denotes the Sortino index based on the average excess return over the downside risk, and *SR* is the Sharpe ratio calculated as the ratio of the asset's mean excess return and its standard deviation. Column AE denotes the actual over expected exceedance ratio. Columns UC and CC report the *p*-values of the unconditional and conditional coverage tests. Column DQ represents the *p*-value of the dynamic quantile test. Column *ES*-CC reports the *p*-value of the McNeil and Frey (2000) *ES* test. Shades of gray denote that the backtesting procedure in the column did not pass at a significance level of $\alpha = 0.05$.

Table 6. Results for the period January 2021–November 2022; ESG data: 2021; provider: Eikon; model: GARCH; $\tau = 0.05$.

Name	Tick	ESG—Eikon	ESG Score Grade	SI	SR	AE	UC	CC	DQ	ES-CC
Berkshire Hathaway	BRK-A	28.87	C−	0.08	0.06	1.04	0.84	0.39	0.54	0.67
Visa Inc.	V	54.37	B−	−0.00	−0.00	1.21	0.32	0.59	0.86	0.24
Tesla	TSLA	65.01	B	−0.02	−0.02	1.12	0.54	0.17	0.27	0.23
Meta Platform	META	65.53	B	−0.07	−0.06	0.33	0.00	0.00	0.13	0.06
Eli Lilly	LLY	66.21	B	0.15	0.09	0.50	0.01	0.02	0.05	0.12
Exxon Mobil	XOM	66.33	B	0.16	0.11	0.79	0.27	0.53	0.35	0.09
Home Depot	HD	71.10	B+	0.04	0.03	1.04	0.84	0.82	0.98	0.07
Costco Wholesale	COST	72.61	B+	0.06	0.04	0.71	0.12	0.16	0.81	0.07
P&G	PG	73.10	B+	0.02	0.02	0.87	0.51	0.81	0.83	0.03
United Health	UNH	73.75	B+	0.10	0.07	1.04	0.84	0.82	0.73	0.56
Bank of America	BAC	73.76	B+	0.04	0.03	0.96	0.82	0.7	0.64	0.55
Mastercard	MA	75.65	A−	−0.00	−0.00	1.00	0.99	0.78	0.91	0.02
Coca-Cola	KO	78.58	A−	0.06	0.04	1.04	0.84	0.94	0.69	0.04
NVIDIA	NVDA	79.15	A−	0.02	0.01	0.96	0.82	0.97	0.75	0.6
Apple	AAPL	79.49	A−	0.02	0.01	1.00	0.99	0.98	0.56	0.37
Pfizer	PFE	80.73	A−	0.07	0.05	0.71	0.12	0.1	0.57	0.88
Alphabet INC	GOOG	81.87	A−	0.01	0.01	0.96	0.82	0.31	0.67	0.12
Merck & Co	MRK	82.10	A−	0.09	0.06	0.62	0.04	0.1	0.61	0.03
AbbVie	ABBV	82.40	A−	0.10	0.07	0.67	0.07	0.17	0.05	0.00
JP Morgan Chase	JPM	82.49	A−	0.03	0.02	1.04	0.84	0.39	0.31	0.35
Chevron	CVX	86.55	A	0.14	0.10	0.96	0.82	0.7	0.67	0.07
Amazon	AMZN	86.75	A	−0.06	−0.05	0.91	0.66	0.32	0.92	0.04
PepsiCo	PEP	86.95	A	0.08	0.05	1.04	0.84	0.94	0.53	0.11
J&J	JNJ	88.35	A	0.05	0.03	1.00	0.99	0.98	0.98	0.09
Microsoft	MSFT	92.49	A	0.02	0.01	1.21	0.32	0.59	0.93	0.22

Notes: Column SI denotes the Sortino index based on the average excess return over the downside risk, and SR is the Sharpe ratio calculated as the ratio of the asset's mean excess return and its standard deviation. Column AE denotes the actual over expected exceedance ratio. Columns UC and CC report the p-values of the unconditional and conditional coverage tests. Column DQ represents the p-value of the dynamic quantile test. Column ES-CC reports the p-value of the McNeil and Frey (2000) ES test. Shades of gray denote that the backtesting procedure in the column did not pass at a significance level of $\alpha = 0.05$.

Table 7. Results for the period January 2021–November 2022; ESG data: 2021; provider: Sustain.; model: AS-CAViaR; $\tau = 0.05$.

Name	Tick	ESG—Sustain.	ESG Score Grade	SI	SR	AE	UC	CC	DQ	ES-CC
Berkshire Hathaway	BRK-A	40.10	Severe	0.08	0.06	1.00	0.99	0.78	0.94	0.83
Chevron	CVX	38.80	High	0.14	0.10	1.04	0.84	0.94	0.5	0.86
Coca-Cola	KO	37.70	High	0.06	0.04	1.00	0.99	0.98	0.85	0.6
Exxon Mobil	XOM	36.50	High	0.16	0.11	0.96	0.82	0.97	0.66	0.81
Meta Platform	META	34.50	High	−0.07	−0.06	1.08	0.69	0.42	0.38	0.47
Amazon	AMZN	30.30	High	−0.06	−0.05	1.00	0.99	0.33	0.16	0.36
AbbVie	ABBV	29.70	Med.	0.10	0.07	1.00	0.99	0.98	0.05	0.57
JP Morgan Chase	JPM	29.30	Med.	0.03	0.02	1.00	0.99	0.98	0.65	0.73
Tesla	TSLA	28.70	Med.	−0.02	−0.02	1.00	0.99	0.28	0.05	0.53
Bank of America	BAC	26.80	Med.	0.04	0.03	1.00	0.99	0.78	0.87	0.63
P&G	PG	26.70	Med.	0.02	0.02	1.08	0.69	0.00	0.00	0.81
Pfizer	PFE	25.20	Med.	0.07	0.05	0.96	0.82	0.07	0.28	0.95
Alphabet INC	GOOG	24.60	Med.	0.01	0.01	1.00	0.99	0.98	0.73	0.57
Eli Lilly	LLY	24.50	Med.	0.15	0.09	1.00	0.99	0.98	0.75	0.75
J&J	JNJ	24.40	Med.	0.05	0.03	0.96	0.82	0.27	0.19	0.59
Costco Wholesale	COST	24.20	Med.	0.06	0.04	0.96	0.82	0.97	1.00	0.42
Merck & Co	MRK	21.60	Med.	0.09	0.06	0.96	0.82	0.97	0.98	0.62

Table 7. *Cont.*

Name	Tick	ESG—Sustain.	ESG Score Grade	*SI*	*SR*	AE	UC	CC	DQ	*ES*-CC
United Health	UNH	17.40	Low	0.10	0.07	1.00	0.99	0.78	0.98	0.79
Apple	AAPL	16.70	Low	0.02	0.01	1.00	0.99	0.78	0.15	0.61
PepsiCo	PEP	16.30	Low	0.08	0.05	1.00	0.99	0.98	0.68	0.65
Mastercard	MA	15.60	Low	−0.00	−0.00	1.00	0.99	0.28	0.77	0.55
Visa Inc.	V	15.60	Low	−0.00	−0.00	1.00	0.99	0.33	0.18	0.48
Microsoft	MSFT	15.20	Low	0.02	0.01	1.00	0.99	0.28	0.98	0.61
NVIDIA	NVDA	13.60	Low	0.02	0.01	1.00	0.99	0.28	0.56	0.84
Home Depot	HD	12.50	Low	0.04	0.03	0.91	0.66	0.59	0.94	0.52

Notes: Column *SI* denotes the Sortino index based on the average excess return over the downside risk, and *SR* is the Sharpe ratio calculated as the ratio of the asset's mean excess return and its standard deviation. Column AE denotes the actual over expected exceedance ratio. Columns UC and CC report the *p*-values of the unconditional and conditional coverage tests. Column DQ represents the *p*-value of the dynamic quantile test. Column *ES*-CC reports the *p*-value of the McNeil and Frey (2000) *ES* test. Shades of gray denote that the backtesting procedure in the column did not pass at a significance level of $\alpha = 0.05$.

Table 8. Results for the period January 2021–November 2022; ESG data: 2021; provider: Sustain.; model: GARCH; $\tau = 0.05$.

Name	Tick	ESG—Sustain.	ESG Score Grade	*SI*	*SR*	AE	UC	CC	DQ	*ES*-CC
Berkshire Hathaway	BRK-A	40.10	Severe	0.08	0.06	1.04	0.84	0.39	0.54	0.67
Chevron	CVX	38.80	High	0.14	0.10	0.96	0.82	0.7	0.67	0.07
Coca-Cola	KO	37.70	High	0.06	0.04	1.04	0.84	0.94	0.69	0.04
Exxon Mobil	XOM	36.50	High	0.16	0.11	0.79	0.27	0.53	0.35	0.09
Meta Platform	META	34.50	High	−0.07	−0.06	0.33	0.00	0.00	0.13	0.06
Amazon	AMZN	30.30	High	−0.06	−0.05	0.91	0.66	0.32	0.92	0.04
AbbVie	ABBV	29.70	Med.	0.10	0.07	0.67	0.07	0.17	0.05	0.00
JP Morgan Chase	JPM	29.30	Med.	0.03	0.02	1.04	0.84	0.39	0.31	0.35
Tesla	TSLA	28.70	Med.	−0.02	−0.02	1.12	0.54	0.17	0.27	0.23
Bank of America	BAC	26.80	Med.	0.04	0.03	0.96	0.82	0.7	0.64	0.55
P&G	PG	26.70	Med.	0.02	0.02	0.87	0.51	0.81	0.83	0.03
Pfizer	PFE	25.20	Med.	0.07	0.05	0.71	0.12	0.1	0.57	0.88
Alphabet INC	GOOG	24.60	Med.	0.01	0.01	0.96	0.82	0.31	0.67	0.12
Eli Lilly	LLY	24.50	Med.	0.15	0.09	0.50	0.01	0.02	0.05	0.12
J&J	JNJ	24.40	Med.	0.05	0.03	1.00	0.99	0.98	0.98	0.09
Costco Wholesale	COST	24.20	Med.	0.06	0.04	0.71	0.12	0.16	0.81	0.07
Merck & Co	MRK	21.60	Med.	0.09	0.06	0.62	0.04	0.1	0.61	0.03
United Health	UNH	17.40	Low	0.10	0.07	1.04	0.84	0.82	0.73	0.56
Apple	AAPL	16.70	Low	0.02	0.01	1.00	0.99	0.98	0.56	0.37
PepsiCo	PEP	16.30	Low	0.08	0.05	1.04	0.84	0.94	0.53	0.11
Mastercard	MA	15.60	Low	−0.00	−0.00	1.00	0.99	0.78	0.91	0.02
Visa Inc.	V	15.60	Low	−0.00	−0.00	1.21	0.32	0.59	0.86	0.24
Microsoft	MSFT	15.20	Low	0.02	0.01	1.21	0.32	0.59	0.93	0.22
NVIDIA	NVDA	13.60	Low	0.02	0.01	0.96	0.82	0.97	0.75	0.6
Home Depot	HD	12.50	Low	0.04	0.03	1.04	0.84	0.82	0.98	0.07

Notes: Column *SI* denotes the Sortino index based on the average excess return over the downside risk, and *SR* is the Sharpe ratio calculated as the ratio of the asset's mean excess return and its standard deviation. Column AE denotes the actual over expected exceedance ratio. Columns UC and CC report the *p*-values of the unconditional and conditional coverage tests. Column DQ represents the *p*-value of the dynamic quantile test. Column *ES*-CC reports the *p*-value of the McNeil and Frey (2000) *ES* test. Shades of gray denote that the backtesting procedure in the column did not pass at a significance level of $\alpha = 0.05$.

Robustness Check

So far, no evidence of connections between individual high ESG rates and superior financial performance (and vice versa) has been found. To strengthen our analysis, we performed a robustness check analysis devoted to verifying if the previous findings were confirmed when portfolios (instead of individual stocks) were considered. Therefore, we built three portfolios characterized by a low, medium, and high ESG risk. Due to the heterogeneous degree of rates between the two ESG providers used in this work, the three portfolios differed when Eikon and Sustainalytics data were considered. In particular, when Eikon data were used, the low-risk portfolio consisted of assets with A and A- ESG rates (as shown in Table 2), the medium-risk portfolio with B+ and B, and the high-risk portfolio with B- and C. When Sustainalytics data were used, the low-, medium-, and high-risk (which also included the only asset with a "Severe" rate) portfolios were directly obtained. The detailed composition of the portfolios is described in the table-note of Table 9. Once the portfolios had been built, we adopted an equally weighted strategy to weight the importance of each asset. Then, the portfolio returns were used to evaluate the portfolios' financial performance as done previously with the individual assets. The results of the portfolio analysis are reported in Table 9. Unsurprisingly, all the portfolios brilliantly pass the backtesting procedures, independently of their ESG risk, the model (whether AS-CaViar of GARCH), and the data provider. Regarding the SI and SR indexes, there was a slightly better performance of the medium-ESG-risk portfolio with respect to the low- and high-ESG-risk portfolios.

Table 9. Portfolio analysis for the period January 2021–November 2022; $\tau = 0.05$.

ESG Risk	SI	SR	Model	AE	UC	CC	DQ	ES-CC
			Eikon					
Low	0.05	0.04	AS-CAViaR	1.04	0.84	0.38	0.48	0.93
			GARCH	1.33	0.11	0.28	0.19	0.55
Medium	0.05	0.04	AS-CAViaR	1.00	0.99	0.78	0.81	0.60
			GARCH	1.04	0.84	0.25	0.17	0.16
High	0.03	0.02	AS-CAViaR	1.00	0.99	0.98	0.68	0.70
			GARCH	1.25	0.23	0.48	0.55	0.91
			Sustainalytics					
Low	0.03	0.02	AS-CAViaR	1.00	0.99	0.28	0.45	0.65
			GARCH	0.96	0.82	0.97	0.64	0.21
Medium	0.07	0.05	AS-CAViaR	1.04	0.84	0.94	0.33	0.65
			GARCH	1.12	0.54	0.74	0.38	0.39
High	0.04	0.03	AS-CAViaR	1.00	0.99	0.28	0.46	0.56
			GARCH	1.16	0.42	0.69	0.38	0.29

Notes: Eikon data, low-risk portfolio (A and A− grades as shown in Table 2): MSFT, JNJ, PEP, AMZN, CVX, JPM, ABBV, MRK, GOOG, PFE, AAPL, NVDA, KO, MA; Eikon data, medium-risk portfolio (B+ and B grades as shown in Table 2): BAC, UNH, PG, COST, HD, XOM, LLY, META, TSLA; Eikon data, high-risk portfolio (B− and C grades as shown in Table 2): V, BRK-A. Sustainalytics data, low-risk portfolio: HD, NVDA, MSFT, MA, V, PEP, AAPL, UNH; Sustainalytics data, medium-risk portfolio: MRK, COST, JNJ, LLY, GOOG, PFE, PG, BAC, TSLA, JPM, ABBV; Sustainalytics data, high-risk portfolio: AMZN, META, XOM, KO, CVX, BRK-A. Column SI denotes the Sortino index based on the average excess return over the downside risk, and SR is the Sharpe ratio calculated as the ratio of the asset's mean excess return and its standard deviation. Column AE denotes the actual over expected exceedance ratio. Columns UC and CC report the p-values of the unconditional and conditional coverage tests. Column DQ represents the p-value of the dynamic quantile test. Column ES-CC reports the p-value of the McNeil and Frey (2000) ES test. Shades of gray denote that the backtesting procedure in the column did not pass at a significance level of $\alpha = 0.05$.

Concluding, the robustness analysis did not allow us to identify superior financial performance according to higher ESG scores either (meaning that the ESG risk was low) in the cases of both the Eikon and Sustainalytics providers. At the same time, the high-ESG-risk portfolios did not perform differently from the other portfolios. In other words, the stock market performance did not positively (negatively) react to high ESG (low) rankings. This result is in line with what was found in the analysis of individual stocks.

5. Policy Implications and Concluding Remarks

Many companies are organizing their activities to consider the ESG pillars, which are becoming a new paradigm that links self-interest and individual profit. Indeed, the recent literature has confirmed trends in which a firm using strategies to achieve goals based on ESG targets can create greater shareholder value [48]. The present analysis aimed to investigate the risk market performance in terms of risk-adjusted indicators (that is, the Sharpe ratio and the Sortino index) and the adequacy of tail risk measures (namely, the Value-at-Risk (VaR) and Expected Shortfall (ES)) of a set of listed firms with different ESG scores provided by two agencies: Eikon and Sustainalytics. The models used to obtain the VaR and ES measures were the GARCH [54] and asymmetric slope (AS-)CAViaR [55]. The empirical analysis considered the first 25 constituents (by weight) of the S&P500 index in the period from 2020 and 2022. Our findings indicated that the risk market performance did not respond positively to high ESG rates or negatively to low ESG rates, independently of the tail risk models used (whether GARCH or AS-CAViaR) or the ESG data providers. However, there was no evidence to suggest that this would lead to lower performance. The analysis was then completed by a robustness check where three portfolios were built according to a low, medium, and high level of ESG risks. The ESG rates being heterogeneous among the two ESG providers here considered, globally, there were six portfolios. Then, the same analysis performed on individual stocks was carried out on the portfolios. The previous findings were largely confirmed: all the portfolios passed the backtesting procedures, irrespective of their (low, medium, or high) ESG risk, the model used (whether AS-CaViar of GARCH), and the data provider. Thus, both the univariate and multivariate analyses yielded the same conclusions. In more detail, the stock market performance (in terms of risk-adjusted indicators and tail risk measures' adequacy) of both individual stocks and portfolios did not positively (negatively) depend on high (low) ESG rates.

Further research could involve more assets. Moreover, from the multivariate point of view, the analysis could adopt the global minimum variance strategy to find the optimal weights of the portfolios. Furthermore, the set of univariate models could also be enlarged. Moreover, a further analysis is needed to examine the determinants of firms' responses across a larger sample of corporations. It seems reasonable to examine how rating agencies could interact with each other for the data collection and how they could focus their attention on sustainability objectives for investors and firms. In this way, policy actions could be aimed at highlighting the good features of rating agencies and at making the bad ones weak. Another important issue to be noted is that the analysis considered the years 2020 and 2021. This means that the evaluation could have suffered from the influence of the COVID-19 pandemic. Indeed, recent contributions in the literature found that companies could assume different behaviors in terms of ESG in response to the COVID-19 pandemic [48]. In addition, for this reason, further research involving larger sample periods is needed so that the results of this analysis may be compared with those of subsequent years and may thus be considered more robust.

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Abbreviations

The following abbreviations are used in this manuscript:

ESG	Environmental, social, and governance
SI	Sortino index
SR	Sharpe ratio
VaR	Value-at-Risk
ES	Expected Shortfall
UC	Unconditional coverage
CC	Conditional coverage

References

1. Friedman, M. The social responsibility of business is to increase its profits. In *Corporate Ethics and Corporate Governance*; Springer: Berlin/Heidelberg, Germany, 2007; pp. 173–178.
2. Eccles, R.G.; Ioannou, I.; Serafeim, G. The impact of corporate sustainability on organizational processes and performance. *Manag. Sci.* **2014**, *60*, 2835–2857. [CrossRef]
3. Wu, S.; Li, X.; Du, X.; Li, Z. The Impact of ESG Performance on Firm Value: The Moderating Role of Ownership Structure. *Sustainability* **2022**, *14*, 14507. [CrossRef]
4. Alliance, G.S.I. Global Sustainable Investment Review. 2020. Available online: https://www.gsi-alliance.org/wp-content/uploads/2021/08/GSIR-20201.pdf (accessed on 11 February 2023).
5. Giese, G.; Lee, L.E.; Melas, D.; Nagy, Z.; Nishikawa, L. Foundations of ESG investing: How ESG affects equity valuation, risk, and performance. *J. Portf. Manag.* **2019**, *45*, 69–83. [CrossRef]
6. Aydoğmuş, M.; Gülay, G.; Ergun, K. Impact of ESG performance on firm value and profitability. *Borsa Istanb. Rev.* **2022**, *22*, 119–127. [CrossRef]
7. Billio, M.; Costola, M.; Hristova, I.; Latino, C.; Pelizzon, L. Inside the ESG Ratings: (Dis)Agreement and performance. *Corp. Soc. Responsib. Environ. Manag.* **2021**, *28*, 1426–1445. [CrossRef]
8. Verheyden, T.; Eccles, R.G.; Feiner, A. ESG for all? The impact of ESG screening on return, risk, and diversification. *J. Appl. Corp. Financ.* **2016**, *28*, 47–55.
9. Torricelli, C.; Bertelli, B.. ESG screening strategies and portfolio performance: How do they fare in periods of financial distress? *Cefin Work. Pap.* **2022**, *87*.
10. Fulton, M.; Kahn, B.; Sharples, C. Sustainable Investing: Establishing Long-Term Value and Performance. 2012. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2222740 (accessed on 11 February 2023).
11. Egorova, A.; Grishunin, S.; Karminsky, A. The Impact of ESG factors on the performance of Information Technology Companies. *Procedia Comput. Sci.* **2022**, *199*, 339–345. [CrossRef]
12. Hvidkjær, S. ESG investing: A literature review. Report Prepared for Dansif. 2017. Available online: https://dansif.dk/wp-content/uploads/2019/01/Litterature-review-UK-Sep-2017.pdf (accessed on 11 February 2023).
13. Technical Report. Basel Committee on Banking Supervision. Minimum Capital Requirements for Market Risk. 2016. Available online: https://www.bis.org/bcbs/publ/d352.pdf (accessed on 11 February 2023).
14. Morgan, J.P. Riskmetrics—Technical Document. 1996. Available online: https://www.msci.com/documents/10199/5915b101-4206-4ba0-aee2-3449d5c7e95a (accessed on 11 February 2023).
15. Artzner, P.; Delbaen, F.; Eber, J.M.; Heath, D. Coherent measures of risk. *Math. Financ.* **1999**, *9*, 203–228. [CrossRef]
16. Acerbi, C.; Tasche, D. On the coherence of expected shortfall. *J. Bank. Financ.* **2002**, *26*, 1487–1503. [CrossRef]
17. Sarykalin, S.; Serraino, G.; Uryasev, S., Value-at-Risk vs. Conditional Value-at-Risk in Risk Management and Optimization. In *State-of-the-Art Decision-Making Tools in the Information-Intensive Age*; Informs: Catonsville, MD, USA, 2008; Chapter 13, pp. 270–294.
18. Christoffersen, P.; Gonçalves, S. Estimation risk in financial risk management. *J. Risk* **2005**, *7*, 1–28. [CrossRef]
19. Cesarone, F.; Martino, M.L.; Carleo, A. Does ESG Impact Really Enhance Portfolio Profitability? *Sustainability* **2022**, *14*, 2050. [CrossRef]
20. Van Duuren, E.; Plantinga, A.; Scholtens, B. ESG integration and the investment management process: Fundamental investing reinvented. *J. Bus. Ethics* **2016**, *138*, 525–533. [CrossRef]
21. Sassen, R.; Hinze, A.K.; Hardeck, I. Impact of ESG factors on firm risk in Europe. *J. Bus. Econ.* **2016**, *86*, 867–904. [CrossRef]
22. Bermejo Climent, R.; Garrigues, I.F.F.; Paraskevopoulos, I.; Santos, A. ESG disclosure and portfolio performance. *Risks* **2021**, *9*, 172. [CrossRef]

23. Brunet, M. A Survey of the Academic Literature on ESG/SRI Performance. 2019. Available online: https://www.advisorperspectives.com/articles/2018/12/10/a-survey-of-the-academic-literature-on-esg-sri-performance (accessed on 11 February 2023).
24. Derwall, J.; Guenster, N.; Bauer, R.; Koedijk, K. The eco-efficiency premium puzzle. *Financ. Anal. J.* **2005**, *61*, 51–63. [CrossRef]
25. Nofsinger, J.; Varma, A. Socially responsible funds and market crises. *J. Bank. Financ.* **2014**, *48*, 180–193. [CrossRef]
26. Friede, G.; Busch, T.; Bassen, A. ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *J. Sustain. Financ. Invest.* **2015**, *5*, 210–233. [CrossRef]
27. Zhou, G.; Liu, L.; Luo, S. Sustainable development, ESG performance and company market value: Mediating effect of financial performance. *Bus. Strategy Environ.* **2022**, *31*, 3371–3387. [CrossRef]
28. Velte, P. Does ESG performance have an impact on financial performance? Evidence from Germany. *J. Glob. Responsib.* **2017**, *8*, 169–178. [CrossRef]
29. Brooks, C.; Oikonomou, I. The effects of environmental, social and governance disclosures and performance on firm value: A review of the literature in accounting and finance. *Br. Account. Rev.* **2018**, *50*, 1–15. [CrossRef]
30. Starks, L.T.; Venkat, P.; Zhu, Q. Corporate ESG Profiles and Investor Horizons. 2017. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3049943 (accessed on 11 February 2023).
31. Giese, G.; Lee, L.E. Weighing the evidence: ESG and equity returns. *MSCI Res. Insight*. **2019**, 1–14.
32. Zhao, C.; Guo, Y.; Yuan, J.; Wu, M.; Li, D.; Zhou, Y.; Kang, J. ESG and corporate financial performance: Empirical evidence from China's listed power generation companies. *Sustainability* **2018**, *10*, 2607. [CrossRef]
33. Brogi, M.; Lagasio, V. Environmental, social, and governance and company profitability: Are financial intermediaries different? *Corp. Soc. Responsib. Environ. Manag.* **2019**, *26*, 576–587. [CrossRef]
34. Ortas, E.; Álvarez, I.; Garayar, A. The environmental, social, governance, and financial performance effects on companies that adopt the United Nations Global Compact. *Sustainability* **2015**, *7*, 1932–1956. [CrossRef]
35. Aureli, S.; Gigli, S.; Medei, R.; Supino, E. The value relevance of environmental, social, and governance disclosure: Evidence from Dow Jones Sustainability World Index listed companies. *Corp. Soc. Responsib. Environ. Manag.* **2020**, *27*, 43–52. [CrossRef]
36. Landi, G.; Sciarelli, M. Towards a more ethical market: The impact of ESG rating on corporate financial performance. *Soc. Responsib. J.* **2018**, *15*, 11–27. [CrossRef]
37. Miralles-Quirós, M.M.; Miralles-Quirós, J.L.; Redondo-Hernández, J. The impact of environmental, social, and governance performance on stock prices: Evidence from the banking industry. *Corp. Soc. Responsib. Environ. Manag.* **2019**, *26*, 1446–1456. [CrossRef]
38. Kempf, A.; Osthoff, P. The effect of socially responsible investing on portfolio performance. *Eur. Financ. Manag.* **2007**, *13*, 908–922. [CrossRef]
39. Statman, M.; Glushkov, D. The wages of social responsibility. *Financ. Anal. J.* **2009**, *65*, 33–46. [CrossRef]
40. Henke, H.M. The effect of social screening on bond mutual fund performance. *J. Bank. Financ.* **2016**, *67*, 69–84. [CrossRef]
41. Yen, M.F.; Shiu, Y.M.; Wang, C.F. Socially responsible investment returns and news: Evidence from Asia. *Corp. Soc. Responsib. Environ. Manag.* **2019**, *26*, 1565–1578. [CrossRef]
42. Auer, B.R.; Schuhmacher, F. Do socially (ir) responsible investments pay? New evidence from international ESG data. *Q. Rev. Econ. Financ.* **2016**, *59*, 51–62. [CrossRef]
43. Zhang, F.; Qin, X.; Liu, L. The Interaction Effect between ESG and Green Innovation and Its Impact on Firm Value from the Perspective of Information Disclosure. *Sustainability* **2020**, *12*, 1866. [CrossRef]
44. Attig, N.; El Ghoul, S.; Guedhami, O.; Suh, J. Corporate social responsibility and credit ratings. *J. Bus. Ethics* **2013**, *117*, 679–694. [CrossRef]
45. Devalle, A.; Fiandrino, S.; Cantino, V. The Linkage between ESG Performance and Credit Ratings: A Firm-Level Perspective Analysis. *Int. J. Bus. Manag.* **2017**, *12*, 53–65. [CrossRef]
46. Weber, O.; Scholz, R.W.; Michalik, G. Incorporating sustainability criteria into credit risk management. *Bus. Strategy Environ.* **2010**, *19*, 39–50. [CrossRef]
47. Bhattacharya, S.; Sharma, D. Do environment, social and governance performance impact credit ratings: A study from India. *Int. J. Ethics Syst.* **2019**, *35*, 466–484. [CrossRef]
48. Savio, R.; D'Andrassi, E.; Ventimiglia, F. A Systematic Literature Review on ESG during the COVID-19 Pandemic. *Sustainability* **2023**, *15*, 2020. [CrossRef]
49. Sharpe, W.F. Mutual fund performance. *J. Bus.* **1966**, *39*, 119–138. [CrossRef]
50. Sortino, F.A.; Van Der Meer, R. Downside risk. *J. Portf. Manag.* **1991**, *17*, 27. [CrossRef]
51. Jorion, P. *Value at Risk*; Irwin: Chicago, IL, USA, 1997.
52. Acerbi, C.; Tasche, D. Expected shortfall: A natural coherent alternative to value at risk. *Econ. Notes* **2002**, *31*, 379–388. [CrossRef]
53. Rockafellar, R.T.; Uryasev, S. Conditional value-at-risk for general loss distributions. *J. Bank. Financ.* **2002**, *26*, 1443–1471. [CrossRef]
54. Bollerslev, T. Generalized Autoregressive Conditional Heteroskedasticity. *J. Econom.* **1986**, *31*, 307–327. [CrossRef]
55. Engle, R.F.; Manganelli, S. CAViaR: Conditional autoregressive value at risk by regression quantiles. *J. Bus. Econ. Stat.* **2004**, *22*, 367–381. [CrossRef]

56. Taylor, J.W. Forecasting value at risk and expected shortfall using a semiparametric approach based on the asymmetric Laplace distribution. *J. Bus. Econ. Stat.* **2019**, *37*, 121–133. [CrossRef]
57. Campbell, S.D. A review of backtesting and backtesting procedures. *J. Risk* **2006**, *9*, 1–17. [CrossRef]
58. Nieto, M.R.; Ruiz, E. Frontiers in VaR forecasting and backtesting. *Int. J. Forecast.* **2016**, *32*, 475–501. [CrossRef]
59. Kupiec, P.H. Techniques for Verifying the Accuracy of Risk Measurement Models. *J. Deriv.* **1995**, *3*, 73–84. [CrossRef]
60. Christoffersen, P.F. Evaluating Interval Forecasts. *Int. Econ. Rev.* **1998**, *39*, 841–862. [CrossRef]
61. McNeil, A.J.; Frey, R. Estimation of tail-related risk measures for heteroscedastic financial time series: An extreme value approach. *J. Empir. Financ.* **2000**, *7*, 271–300. [CrossRef]
62. Berkowitz, J.; Christoffersen, P.; Pelletier, D. Evaluating value-at-risk models with desk-level data. *Manag. Sci.* **2011**, *57*, 2213–2227. [CrossRef]
63. Savio, R.; D'Andrassi, E.; Ventimiglia, F. How Do Companies Respond to Environmental, Social and Governance (ESG) ratings? Evidence from Italy. *J. Bus. Ethics* **2020**, *171*, 379–397.