Finance Research Letters 55 (2023) 103875

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Integrating ESG risks into value-at-risk

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ARTICLE INFO

JEL classification:
G01
G21
G28
L10

Keywords:
ESG risk
Financial portfolio
Market risk
Value-at-risk
Volatility

ABSTRACT

This study addresses the regulatory request for sustainability-related risk integration into traditional financial risk measures. We propose a new risk metric that combines a traditional market risk measure expressed in terms of Value-at-Risk (VaR) and environmental, social, and governance (ESG) factors. The new metric, $VaR_{ESG,}$ considers the orthogonality of the ESG criteria with fundamental variables, applying a perturbative approach and an entropy function of ESG factors. The pilot empirical application relies on a financial portfolio comprising approximately 3000 equities. The results show the predictive power of VaR_{ESG} to reduce unexpected losses (i.e., out-of-VaR). The results were confirmed especially under stress conditions, when the values of losses were higher (in terms of magnitude). To the best of our knowledge, this is the first attempt in the financial literature to effectively integrate ESG risks into the VaR measure to predict the expected losses of an equity portfolio. The measure of VaR_{ESG} can be useful to asset managers and institutional investors to reduce unexpected losses, and to supervisors interested in increasing the level of accuracy of VaR estimations.

1. Introduction

In recent years, European financial authorities have called for enhancing the incorporation of environmental, social, and governance (ESG) risks into investment firms' governance and risk management frameworks (EBA, 2019; EBA, 2021; ECB, 2020). Thus, ESG risks must be considered as an additional category of material risks to be integrated into traditional financial measures.

Relying on the well-granted calculation of Value at Risk (VaR) for investment portfolios, this study proposes a methodological contribution for effectively integrating ESG components in market risk measures, therefore defining a new metric called $VaR_{ESG.}$

The calculation of VaR_{ESG} assumes that ESG scores assigned to issuers have the potential to unlock a significant amount of information about firms' resilience when pursuing long-term value creation. The computation of VaR_{ESG} relies on an entropy function of ESG scores, which allows it to move from the simple ESG features of equity portfolios to an effective calculation of portfolios' ESG risks. The concept of entropy verifies the "disorder" of a financial portfolio associated with the ESG characteristics of its constituents. Entropy, as studied by Shannon (1948), has been used in fuzzy portfolio selection theories to measure the uncertainty of portfolio returns (Huang, 2008), as well as in portfolio diversification models, where it is widely accepted as a measure of portfolio diversification (Bera and Park, 2008; Meucci, 2009). Research finds that entropy captures the overall linear and nonlinear dispersion patterns observed in data series; the entropic approach can thus be used as an alternative way of estimating stock market volatility (Sheraz et al., 2015). Our

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https://doi.org/10.1016/j.frl.2023.103875
Received 8 February 2023; Received in revised form 5 April 2023; Accepted 7 April 2023
Available online 11 April 2023

results show that VaR_{ESG} improves the estimates regarding expected losses for investment portfolios.

A growing strand of literature confirms the materiality of ESG factors affecting portfolio volatility. Some studies have shown that the level of market risk is lower for portfolios constituted by firms with higher responsible performance, which prove a lower volatility (Albuquerque et al., 2018; He et al., 2022; López Prol and Kim, 2022). Becchetti et al. (2018) introduce a corporate social responsibility risk factor to capture an additional systematic risk component, rather than an idiosyncratic risk component (differently from Chen et al., 2018, Luo and Balvers, 2017). Irresponsible corporate behavior can increase analysts' earnings forecast errors in absolute value, which represents an additional source of uncertainty (Ajinkya et al., 2005; Becchetti et al., 2013; Chaney et al., 2011). Studies have investigated the role of E, S, and G separately and identified individual impacts on portfolio volatility (D'Hondt et al., 2022). A study by the Principles for Responsible Investments (PRI), focusing on the case of Quotient Investors' U.S. Large Cap Sustainable Alpha fund, shows that the E, S, and G factors explain 2.4%, 1.6%, and 2.7% of positive excess returns, respectively. By performing a sensitivity analysis, the study demonstrates that when ESG factor returns increase by 1%, the fund's returns increase by 0.42%, which is significantly more than for other traditional risk factors such as size and value (PRI, 2016). Focusing on specific issues such as the case of initial public offerings (IPOs), recent research provides evidence that ESG ratings offer value-relevant information around new stock issues, demonstrating that higher ESG ratings are associated with lower IPO underpricing (Baker et al., 2021). Finally, Capelli et al. (2021) prove that ESG risks improve ex-ante volatility estimations of traditional VaR for single securities.

With the aim of moving from the simple analysis of the role of an equity portfolio's ESG features to the effective calculation of its ESG risk, to the best of our knowledge, this study is the first attempt to combine an ESG risk measure with a traditional market risk measure to obtain an integrated metric, i.e., VaR_{ESG}. VaR_{ESG} is able to prudentially capture both financial and sustainability-related characteristics of equity portfolios.

2. Methodology

If VaR is generally expressed as $VaR = k\sqrt{x'\Sigma x}$, with x weights vector and Σvariance-covariance matrix, we define an integrated $VaR_{ESG} = \sqrt{x' \cdot \Sigma_{fin+ESG} \cdot x}$, where $\Sigma_{fin+ESG}$ also includes ESG variables. Integrating ESG factors into the traditional VaR requires the following steps.

For each linearizable function, a Taylor expansion has been used, and $VaR(P)$, where P is an asset portfolio, can be decomposed in first order in terms of VaRdelta (first derivative) (Garman, 1997): $VaR(P) = VaR(P_0) + VaRdelta(P_0) \cdot \varepsilon + o(P^2)$, where $P = P_0 + \varepsilon$, P_0 is the initial portfolio and ε is small.

To compute a measure of ESG risk, we started from issuers' ESG scores, then considered their securities (p) frequency distribution in eight ranges or classes (i), where scores go from >0 to 10, labelled from A (i.e., lower class) to H (higher class) (Capelli, 2016; Capelli et al., 2021). Ranges have been built as follows[1]: [8;10], [7;8), [6;7), [5;6), [4;5), [3;4), [1;3), [0;1). We then used the concept of entropy (Shannon, 1948) reported in formula (1), where it represents disorder owing to the different portfolio configurations in these eight classes:

$$S_{ESG} = -\sum_{i=1}^{8} p_i \log(p_i) \tag{1}$$

Recent research shows that high ESG portfolios have lower volatility and even lower returns, resulting in lower Sharpe ratios (López Prol and Kim, 2022). This corroborates the assumption that an effective measure of ESG risk (R_{ESG}) increases if a portfolio invests primarily in classes with lower ESG scores and decreases when higher ranges are more populated. Therefore, a corrective factor (i.e., the minimum j of each range) can improve the effectiveness of R_{ESG}, as reported in Eq. (2):

$$R_{ESG} = -\sum_{i=1}^{8} \left(p_i \log(p_i) \cdot \frac{1}{\min j \in i(p_j) i} \right). \tag{2}$$

R_{ESG} is decomposable via Taylor expansion as well. Therefore, it is linearized in the first order in terms of R_{ESG} delta (first derivative), as $R_{ESG}(P) = R_{ESG}(P_0) + R_{ESG}delta(P) \cdot \varepsilon + o(P^2)$.

As shown in the literature, ESG factors are complementary to fundamental ones (Capelli et al., 2021; PRI, 2016). VaR and R_{ESG} are then orthogonal, as well as their derivatives (i.e., their tangents). If $VaRdelta \equiv \nabla$ and $R_{ESG}delta \equiv \partial$, it makes sense to define a risk coefficient C via Pythagoras theorem such as the hypotenuse of a right triangle $C_i = \sqrt{\nabla_i^2 + \partial_i^2}$.

VaR, expressed by the formula $VaR = k\sqrt{x'\Sigma x}$, is decomposable[2] in terms of Component VaR (CVaR), where each $CVaR = x_i \cdot \nabla_i$:

$$VaR = \sqrt{x'\Sigma x} = \sum_{i=1}^{n} x_i \nabla_i$$

By analogy, we define this as follows:

[1] Many classes might bring to a deeper granularity to better estimate the portfolio entropy. However, 8 classes represent a reliable representation of the risk nature of equity mutual funds.

[2] R_{ESG} as well is decomposable in CR_{ESG} (Component R_{ESG}): $R_{ESGi} = x_i \cdot \partial_i$.

$$VaR_{ESG} = \sum_{i=1}^{n} CVaR_{ESG} \equiv \sum_{i=1}^{n} x_i C_i$$

A better definition can be expressed as follows, formula (3):

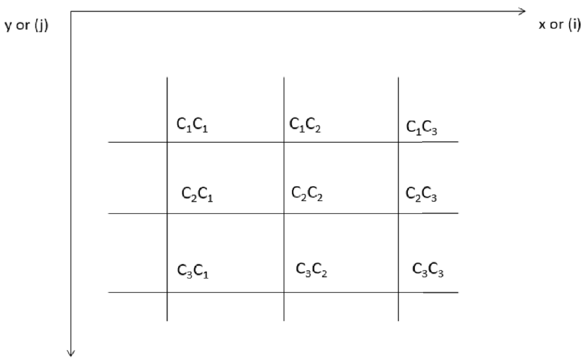
$$VaR_{ESG} = \sum_{i=1}^{n} x_i C_i = \sum_{i=1}^{n} x_i \sqrt{\nabla_i^2 + \partial_i^2} \equiv \sqrt{x' \cdot \Sigma_{fin+ESG} \cdot x} \tag{3}$$

Considering a portfolio including three securities as an example, we assumed $\Sigma_{fin\,+\,ESG} \equiv \Sigma_C$ in the following way:

$$\Sigma_C = \begin{pmatrix} C_1^2 & C_2C_1 & C_3C_1 \\ C_1C_2 & C_2^2 & C_3C_2 \\ C_1C_3 & C_2C_3 & C_3^2 \end{pmatrix}$$

It is possible to generalize this approach to n securities by substituting the standard variance-covariance matrix with the new "C-matrix". To represent the portfolio and its diversification, we considered it as a distribution of securities in a lattice and used the Ising model (Ising, 1925; Landau and Lifshitz, 1958; Yang, 1952), for which the system energy is$H = -J\sum_{ij} s_i s_j$. Then, $\Sigma_{fin\,+\,ESG}$ represents the interaction on the lattice (through the products of C_i coefficients); therefore, there is a superimposition (or dual representation) between the matrix terms and reticular positions, expressed as x and y (or i and j):

$$\begin{pmatrix} C_1C_1 & C_2C_1 & C_3C_1 \\ C_1C_2 & C_2C_2 & C_3C_2 \\ C_1C_3 & C_2C_3 & C_3C_3 \end{pmatrix} \longrightarrow$$



This approach allowed for "calibrating" the VaR_{ESG} value via a coupling (or interaction) factor $J>0$. In Physics, a coupling constant is a number that determines the strength of the force exerted in an interaction; the natural interaction factors for each couple in a lattice are 1 or 1/2. In financial terms, the latter value corresponds to diversification that halves the total risk. Regarding portfolios, one could see more collinearity if all the securities are equities, while this tends to be reduced, increasing the percentage of bonds. It is possible to define $J = \frac{1}{q}$, where J has values ranging from > 0 (i.e., no interaction or zero correlation between securities) to 1 (i.e., the maximum correlation effect among securities). For a pure equity fund, q is assumed equal to 2 in the first simplified model. Using $J = 1/2$ has several advantages. First, it represents both a standard assumption (in the mean average field, that is, the same J value for the whole portfolio[3]) used in the Ising model in the case of electrons; second, it expresses a neutral approach, assuming a correlation of approximately 0.5. Therefore, to increase the usefulness of the measure while managing portfolios, a proper calibration of J is necessary, to reduce unexpected losses and, at the same time, avoid extreme estimates of expected losses.

Calibrating VaR_{ESG} with J as expressed in formula (3), we finally defined VaR_{ESG} as in formula (4), where $J > 0$:

$$VaR_{ESG} \equiv \sqrt{x' \cdot \Sigma_{C(J)} \cdot x} \tag{4}$$

With$J \neq 1$:

$$VaR_{ESG} = \sqrt{x' \cdot \Sigma_{C(J)} \cdot x} = \sqrt{J} \sum_{i=1}^{n} x_i C_i$$

Recalling the above example of a portfolio with three securities, $\Sigma_{C(J)}$ will be as follows:

[3] To replace all interactions among couples of securities with an average or effective interaction, one reduces a many-body problem into an effective one-body problem.

$$\Sigma_{C(J)} = J \cdot \begin{pmatrix} C_1^2 & C_2C_1 & C_3C_1 \\ C_1C_2 & C_2^2 & C_3C_2 \\ C_1C_3 & C_2C_3 & C_3^2 \end{pmatrix}$$

According to the Ising model (Rispoli et al., 2019), we assume a scenario of a critical regime, that is a strongly declining market value (i.e., in the words of physics, the presence of a strong magnetic field). Under this condition, the pair interaction, that is products C_iC_j, is a proxy of the *entanglement* among securities, which tends to produce resonance, passing among transition states where the total correlation is mitigated by the perturbative subtraction of decorrelation terms.[4] In other words, over time, in the Ising particles model: 1) in a weak thermic regime (random), there are very small correlations among all the *n* particles; 2) in a transitional regime, there are high correlations, which involve groups of particles and not all of them; 3) in a critical regime, there are very high correlations among all the particles, that is, resonance. Translated in financial terms, under stressed conditions, the correlation among securities increases. As a consequence, for an accurate application of the model to real portfolios, a suitable calibration of J needs to consider the sector breakdown of the portfolio and the securities' behavior under market-stressed conditions.

3. A pilot empirical test

For a pilot empirical test on a real portfolio, we applied the model to the Exchange Traded Fund (ETF) of the MSCI World Index (ACWI FP Bloomberg ticker), often used as a benchmark for the global equity market, with roughly 3000 constituents, throughout the period 2016–2020. First, we downloaded the constituents on the last day of each year over the analyzed period and "backwarded" this portfolio throughout the year. Second, we calculated a Gaussian VaR using a variance-covariance simple method at a 99% confidence level[5] for each month of every year, varying the return data on 260 days (e.g., at the end of February, we estimated the loss in terms of VaR expected in March using the 260 days before). For every year, we then calculated R_{ESG} using the "backward" weights and Datastream ESG scores at the end of the previous year. Finally, we calculated VaR_{ESG} for every month.

The idea was to test how much VaR_{ESG} is more prudential than the Gaussian VaR to avoid the daily out-of-VaR. Table 1 shows the value of R_{ESG} for each year in the period under analysis, as well as the monthly VaR and VaR_{ESG} by applying $J = 1/2$.

With the Gaussian measure, the results show the following out-of-VaR: 2 in February 2016; 0 in 2017; 20 in 2018 (1 in January, 4 in February, 4 in March, 1 in April, 1 in June, 4 in October, and 5 in December); 4 in 2019 (1 in May, 2 in August, and 1 in October); and 13 in 2020 (1 in January, 3 in February, 7 in March, and 2 in April).

By applying VaR_{ESG}, we obtained values that were more aligned to the real market conditions, which require a general more prudential approach to estimate the risk. From 2016 to 2019 no out-of-VaR was recorded. On the other hand, throughout 2020, seven out-of-VaRs also remained using VaR_{ESG} (2 in February and 5 in March), corresponding to the shock due to the widespread pandemic crisis.

To summarize, VaR_{ESG} covers approximately 82% of unexpected losses (i.e., 32 out of 39 out-of-VaRs). In 2020, the most volatile year throughout the period of analysis and therefore the most useful year to test our approach, approximately 46% of unexpected losses according to the financial model (i.e., standard VaR) are now forecasted by the integrated metric (i.e., VaR_{ESG}). In 2020, the value-added of ESG variables (using R_{ESG}) is still relevant despite their impact decreasing owing to the jump in traditional VaR.

We also performed a sensitivity analysis of VaR_{ESG} by applying $J = 1$. Table 2 shows the comparison between VaR and VaR_{ESG}. In the year 2020, 3 Out-of-VaR_{ESG} remain during March. As highlighted, the measure of VaR_{ESG} increased when J increased. By increasing J, it was possible to calculate a more prudential integrated VaR, which could entail out-of-VaR_{ESG} in the year of highest volatility.

Fig. 1 shows the time evolution of VaR and VaR_{ESG}, with $J = 1$ and $J = 1/2$, during the investigation period. The plotted time series confirm that VaR_{ESG} with $J = 1$ provides a more prudential representation of the market conditions, with potentially higher levels of losses. With $J = 1/2$, VaR_{ESG} considers portfolio diversification, which reduces the estimation of the expected losses in a first approximation. Fig. 2 shows the correspondence among the three variables: at each time point (i.e., the end of each month), every point in the 3D graph represents the risk portfolio position $P =$ (VaR, VaR_{ESG} with $J = 1$, and VaR_{ESG} with $J = 1/2$). The colored plateaux reflect the different market conditions over time (e.g., the circled point refers to March 2020).

To test the tail loss out-of-sample in our model, we considered the year 2022 for the same ETF (Table 3). We referred to data related to 2022 because of the yearly market negative performances, which allow express the predictive power of VaR_{ESG}. Running a Gaussian VaR in line with the previous analysis, the ACWI FP ETF reported 21 out-of-VaR. Then, we compared the results with the VaR_{ESG}, which reported 1 out-of-VaR_{ESG} in January 2022. These results confirm the reliability of VaR_{ESG}, which expressed its powerfulness in reducing unpredicted losses, maintaining them under the threshold of overshootings considered as acceptable by the supervisory authorities (BCBS, 1996; CESR, 2010).[6]

[4] Therefore, we interpret the real nature of diversification effect such as expression/effect of perturbative de-correlating interaction among securities (for example, due to different asset types).

[5] As a robustness check, we also tested the case by applying more sophisticated VaR models (e.g., Modified VaR or Cornish-Fisher, and Monte Carlo) to improve the financial risk estimation. However, a Gaussian VaR with a variance-covariance simple method provides a more reliable view of the holistic portfolio risk.

[6] To carry out this robustness analysis, we used a calibration of J = ½, which is aligned to the main analyses and results reported in the manuscript.

Table 1
A comparison between VaR and VaR_{ESG} ($J = 1/2$).

Variable	Month										
Year: 2016	J	F	M	A	M	J	J	A	S	O	N	D
VaR	2.73%	2.86%	2.89%	2.89%	2.85%	2.88%	2.79%	2.48%	2.35%	2.21%	2.22%	2.11%
VaR_{ESG}	4.47%	4.53%	4.54%	4.54%	4.52%	4.55%	4.51%	4.38%	4.33%	4.28%	4.28%	4.24%
R_{ESG}	5.34											
Year: 2017	J	F	M	A	M	J	J	A	S	O	N	D
VaR	1.23%	1.65%	1.58%	1.52%	1.48%	1.38%	1.34%	1.38%	1.33%	1.34%	1.29%	1.23%
VaR_{ESG}	3.70%	3.85%	3.83%	3.81%	3.79%	3.75%	3.73%	3.75%	3.73%	3.73%	3.72%	3.70%
R_{ESG}	4.99											
Year: 2018	J	F	M	A	M	J	J	A	S	O	N	D
VaR	1.16%	1.24%	1.33%	1.34%	1.33%	1.37%	1.35%	1.33%	1.35%	1.53%	1.54%	1.65%
VaR_{ESG}	3.56%	3.58%	3.61%	3.62%	3.61%	3.62%	3.62%	3.62%	3.62%	3.69%	3.69%	3.74%
R_{ESG}	4.80											
Year: 2019	J	F	M	A	M	J	J	A	S	O	N	D
VaR	1.96%	1.86%	1.80%	1.72%	1.77%	1.78%	1.77%	1.93%	1.94%	1.85%	1.78%	1.67%
VaR_{ESG}	3.76%	3.72%	3.70%	3.66%	3.68%	3.69%	3.68%	3.75%	3.75%	3.72%	3.69%	3.64%
R_{ESG}	4.63											
Year: 2020	J	F	M	A	M	J	J	A	S	O	N	D
VaR	1.59%	1.84%	3.74%	3.98%	4.01%	4.12%	4.13%	4.06%	4.11%	4.13%	4.16%	4.16%
VaR_{ESG}	3.48%	3.57%	5.22%	5.38%	5.39%	5.47%	5.47%	5.43%	5.46%	5.47%	5.50%	5.50%
R_{ESG}	4.47											

Table 2
A comparison between VaR and VaR_{ESG} ($J = 1$).

Variable	Month										
Year: 2016	J	F	M	A	M	J	J	A	S	O	N	D
VaR	2.73%	2.86%	2.89%	2.89%	2.85%	2.88%	2.79%	2.48%	2.35%	2.21%	2.22%	2.11%
VaR_{ESG}	6.32%	6.40%	6.42%	6.42%	6.40%	6.43%	6.38%	6.20%	6.12%	6.05%	6.06%	6.00%
R_{ESG}	5.34											
Year: 2017	J	F	M	A	M	J	J	A	S	O	N	D
VaR	1.23%	1.65%	1.58%	1.52%	1.48%	1.38%	1.34%	1.38%	1.33%	1.34%	1.29%	1.23%
VaR_{ESG}	5.23%	5.45%	5.42%	5.38%	5.36%	5.30%	5.28%	5.30%	5.28%	5.28%	5.26%	5.23%
R_{ESG}	4.99											
Year: 2018	J	F	M	A	M	J	J	A	S	O	N	D
VaR	1.16%	1.24%	1.33%	1.34%	1.33%	1.37%	1.35%	1.33%	1.35%	1.53%	1.54%	1.65%
VaR_{ESG}	5.03%	5.07%	5.11%	5.11%	5.11%	5.13%	5.12%	5.11%	5.12%	5.22%	5.23%	5.28%
R_{ESG}	4.80											
Year: 2019	J	F	M	A	M	J	J	A	S	O	N	D
VaR	1.96%	1.86%	1.80%	1.72%	1.77%	1.78%	1.77%	1.93%	1.94%	1.85%	1.78%	1.67%
VaR_{ESG}	5.32%	5.26%	5.23%	5.18%	5.21%	5.21%	5.21%	5.30%	5.31%	5.27%	5.22%	5.15%
R_{ESG}	4.63											
Year: 2020	J	F	M	A	M	J	J	A	S	O	N	D
VaR	1.59%	1.84%	3.74%	3.98%	4.01%	4.12%	4.13%	4.06%	4.11%	4.13%	4.16%	4.16%
VaR_{ESG}	4.92%	5.05%	6.39%	6.58%	6.61%	6.69%	6.70%	6.64%	6.69%	6.70%	6.73%	6.73%
R_{ESG}	4.47											

As a further robustness check, we collected the ESG scores provided by Robeco, to calculate for the same year the R_{ESG} and the integrated measure (Table 3). By using this dataset for computing the $VaR_{ESG,}$ we obtained 2 out-of-VaR_{ESG} in 2022. Although the R_{ESG} with Robeco ESG is less than R_{ESG} obtained with Datastream ESG scores (respectively, 2.96 and 4.80), the number of out-of-VaR is similar (2 versus 1). Obviously, the *J* calibration for different ESG score data providers can reconcile the VaR_{ESG} values.[7]

[7] To verify the benefits of using VaR_{ESG} to manage portfolios, we carried out the test of the integrated measure not only on ETF, but also on actively managed mutual funds. The main findings show that the more prudential management allowed by the use of VaR_{ESG} provides the same performance for the actively managed portfolios as the corresponding benchmarks, and a lower volatility, which translates into higher economic value.

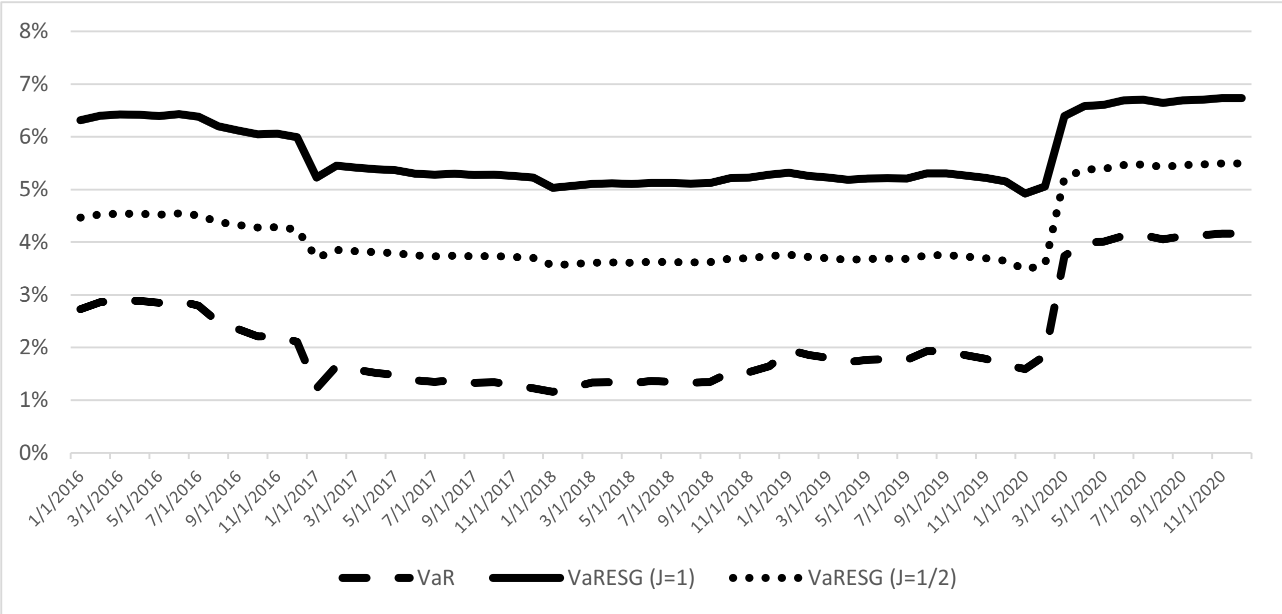


Fig. 1. VaR and VaR_{ESG} evolution.

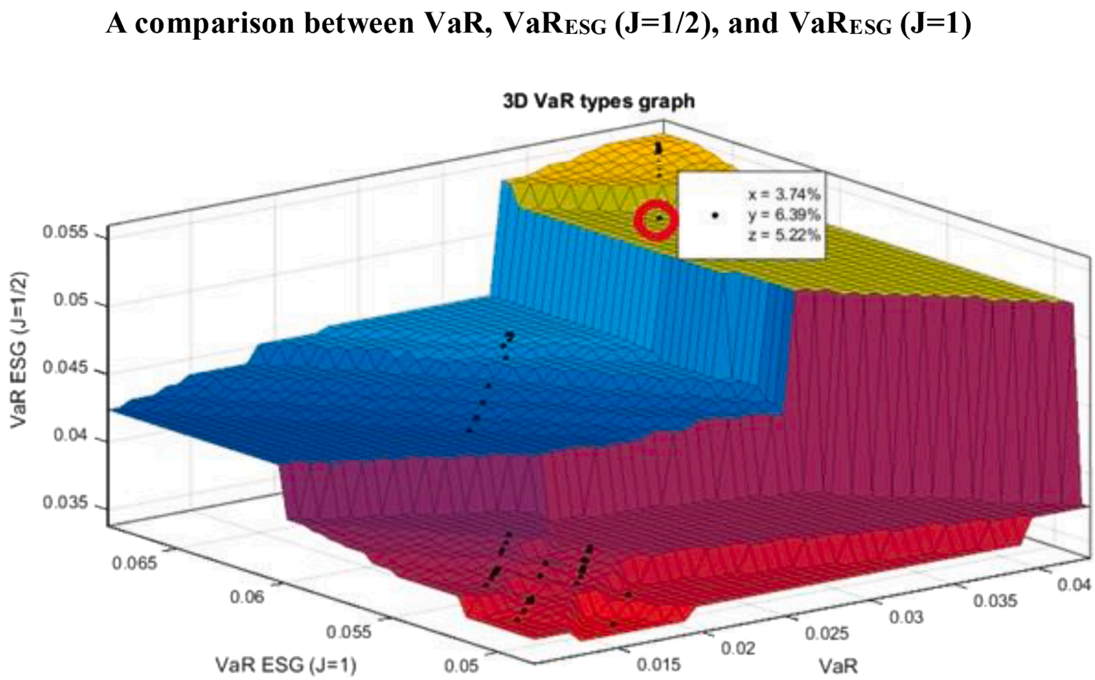


Fig. 2. A comparison between VaR, VaR_{ESG} ($J = 1/2$), and VaR_{ESG} ($J = 1$).

Table 3
Out-of-sample analysis: a comparison between VaR and VaR_{ESG} ($J = 1/2$).

Variable	Month											
Year: 2022	J	F	M	A	M	J	J	A	S	O	N	D
VaR	1.59%	1.60%	1.66%	1.78%	1.97%	2.16%	2.19%	2.27%	2.31%	2.38%	2.41%	2.39%
VaR_{ESG} (Datastream)	3.76%	3.76%	3.79%	3.85%	3.93%	4.02%	4.04%	4.08%	4.09%	4.13%	4.16%	4.15%
VaR_{ESG} (Robeco)	2.57%	2.58%	2.62%	2.68%	2.78%	2.88%	2.90%	2.95%	2.96%	3.00%	3.03%	3.02%
R_{ESG} (Datastream)	4.80											
R_{ESG} (Robeco)	2.96											

4. Conclusions

According to the regulatory framework applied to financial institutions, a method for measuring exposure to financial risks is considered inaccurate when more than four overshootings per year are documented, compared to the related one-day VaR estimation (BCBS, 1996; CESR, 2010). In the case of excessive overshootings, the financial institution should inform competent supervisory authorities that can apply stricter measures and control. Therefore, reducing VaR violations with a robust financial risk measure is a relevant goal of financial intermediaries.

This study presents a new market risk measure, VaR_{ESG}, that can pursue this objective. VaR_{ESG} is a predictive metric of expected losses, which integrates in a mathematical coherent manner the financial VaR and ESG risk (R_{ESG}), forecasting a more conservative (prudential) and accurate risk measure. To the best of our knowledge, this is the first attempt to integrate ESG risks effectively into the VaR measure.

Based on our empirical test, this measure reduces the cases of unexpected losses, improving the estimates of the expected portfolio volatility. The application of the model to a broad and global financial portfolio shows that the VaR_{ESG} avoids 82% of the losses, otherwise unexpected from the purely financial calculation of VaR. Regarding managerial applications, verifying the level of greater prudence is particularly useful.

VaR_{ESG} is particularly powerful in stressful conditions. In 2020, high losses were reported owing to the pandemic, and VaR_{ESG} revealed a reduction of approximately 46% in the impact of the exogenous factor COVID on the predictability of negative returns, which is potentially very useful for asset managers, given the integration of specific factors that can affect the financial performance of equity portfolios. Our results are consistent with previous research corroborating the substantial resilience of high ESG performing stocks to financial risk during times of market-wide crisis and a corresponding lower relevance of ESG evaluation in normal times. According to Broadstock et al. (2021), higher ESG companies demonstrate lower price volatility during the pandemic. Investors in high-ESG stocks are available to accept lower returns in normal times to benefit of a higher resilience to financial risk in times of crisis (Engle et al., 2020).

In this study, we show the sensitivity of the new measure to the J parameter, demonstrating that an increase in this variable determines more prudential values of VaR_{ESG}. According to the specific asset allocation of financial portfolios and the portfolio manager's risk appetite, it is possible to introduce a suitable calibration method of J able to properly capture the impact of ESG risks while maintaining sensitivity to market shocks. Further research should apply and discuss more sophisticated models for calculating the correct J calibration in different scenarios.

Finally, in light of the nature of VaR_{ESG} to predict stock returns, future research should also focus on the calibration of risk intervals in a monthly model selection strategy (Dai et al., 2021), more related to forecasted extreme events than traditional historical standard deviation.

Ethical approval

Compliance with Ethical Standards

CRediT authorship contribution statement

Paolo Capelli: Conceptualization, Data curation, Formal analysis, Methodology. **Federica Ielasi:** Validation, Data curation, Writing – original draft, Writing – review & editing. **Angeloantonio Russo:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

All authors declare that they have no conflicts of interest.

Data availability

Data will be made available on request.

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