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Measuring ESG risks in multi-asset portfolios: Decomposing $\mathrm{VaR}_{\mathrm{ESG}}$ into $\mathrm{CVaR}_{\mathrm{ESG}}$

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ABSTRACT

This study investigates the contribution of different asset classes to investment portfolio risk by integrating environmental, social, and governance (ESG) factors into traditional financial risk measures. We propose a new methodology for decomposing $\mathrm{VaR}_{\mathrm{ESG}}$ by measuring the Component $\mathrm{VaR}_{\mathrm{ESG}}$ ($\mathrm{CVaR}_{\mathrm{ESG}}$) of a multi-asset financial portfolio. A pilot empirical application's results provide evidence of the reliability of $\mathrm{CVaR}_{\mathrm{ESG}}$ to define the maximum contribution of the risk accepted for securities or parts of the financial portfolio. This study contributes to the debate on how ESG factors can have quantifiable long-term financial impacts and clarifies the risk contribution of each security included in a financial portfolio.

1. Introduction

The inclusion of environmental, social, and governance (ESG) factors in a financial portfolio's selection and management affects its risk profile (Becchetti et al., 2018; Bolton and Kacperczyk, 2021; He et al., 2022). Studies have shown that ESG considerations are useful for predicting the level of risk of both a security and a portfolio (Ilhan et al., 2021; Lo and Kwan, 2017). Studies on this matter are usually based on equities and equity portfolios (López Prol and Kim, 2022) or specific types of bonds (Höck et al., 2023), while the case of multi-asset investments still requires additional investigation. This study investigates the contribution of different asset classes to investment portfolio risk by integrating ESG factors into traditional financial risk measures. Starting with the concept of value-at-risk (VaR) corrected by the level of portfolio ESG risk ($\mathrm{VaR}_{\mathrm{ESG}}$), this study proposes a new methodology for decomposing $\mathrm{VaR}_{\mathrm{ESG}}$ by measuring the Component $\mathrm{VaR}_{\mathrm{ESG}}$ ($\mathrm{CVaR}_{\mathrm{ESG}}$) of a multi-asset financial portfolio.

According to the CVaR concept[1] under the assumption of normality in the return distribution, asset managers can verify the contribution of each security included in a portfolio to the entire risk and define the maximum contribution of risk accepted for parts of the financial portfolio (Garman, 1997). Following a bottom-up approach, CVaR allows setting specific limits in terms of risk-taking based on, for example, the type of asset, geographical area, or economic sector to which the issuer belongs. Moreover, applying the

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[1] We refer to the original Component VaR notation introduced by Garman (1997), i.e., CVaR also called Marginal VaR contribution. Currently, this notation is also used to point to Conditional VaR (or Expected Shortfall). However, the Expected Shortfall is out-of-scope for this study.

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CVaR to a financial portfolio makes it possible to compute simulations to verify the potential effects of a change in the percentage of assets on portfolio risk. Consequently, CVaR is particularly useful for risk and asset managers to help manipulate a portfolio to produce the desired change in its risk/return profile. The relevant literature corroborates using the CVaR technique when dealing with portfolios of linear instruments and monitoring their volatility (Mausser and Rosen, 1998; Pearson, 2002).[2]

To our knowledge (EBA, 2023), this study is the first attempt to decompose a measure of VaR that integrates ESG risks, $\mathrm{VaR_{ESG}}$ (Capelli et al., 2023), to obtain the correspondent $\mathrm{CVaR_{ESG}}$. Theoretical implications emerge, highlighting how ESG factors can have quantifiable long-term financial impacts (Albuquerque et al., 2018; Cheema-Fox et al., 2021; Harjoto et al., 2021; Wong and Zhang, 2022). This study contributes to the research stream that verifies the effects of integrating ESG factors into financial risk metrics to improve volatility forecasts (Bax et al., 2023; Morelli and D'Ecclesia, 2021; Olofsson et al., 2021; Viviani et al., 2019). This study presents a bottom-up methodology to identify the risk contribution of each security included in a financial portfolio, with a specific focus on the differences among types of assets (i.e., equities, corporate bonds, and government bonds) whose components typically differ in terms of the risk/return ratio, as well as the distinctive characteristics affecting their exposure to ESG risks.

In light of the above considerations, relying on previous definitions of $\mathrm{VaR_{ESG}}$ (Capelli et al., 2023), we carried out an in-depth methodological improvement of the model, to make it both a theoretical tool and an operational tool for portfolio managers. Indeed, the study results are relevant for portfolio managers who intend to implement effective risk management practices compliant with sustainable finance legislation (BCBS, 2021; EBA, 2023; European Parliament, 2019, 2020), which calls for the integration of ESG risks in financial products' management.

2. Measuring the $\mathrm{CVaR_{ESG}}$: A suggested methodology

$$CVaR_i = MVaR_i V_i \tag{1}$$

where $\mathrm{MVaR_i}$ is the Marginal VaR representing the change in VaR caused when an additional 1 Euro of the asset is added to the portfolio, and V_i is the value of the ith asset. Therefore, $\mathrm{MVaR_i}$ can be calculated as the derivative of VaR concerning V_i, as in Eq. (2).

$$MVaR_i = \frac{\partial VaR_p}{\partial V_i} \tag{2}$$

where, given a portfolio of n assets with x weight vector and Σ covariance matrix, the VaR is typically defined as $VaR \equiv \sqrt{x' \cdot \Sigma \cdot x}$. Consequently, the CVaR builds on the VaR metric and adds up to the portfolio's total VaR (Mausser and Rosen, 1998; Pearson, 2002).

Similarly, to calculate the $\mathrm{CVaR_{ESG}}$, it is necessary to refer to $\mathrm{VaR_{ESG}}$, a predictive metric of expected losses that integrates the financial VaR and ESG risk ($\mathrm{R_{ESG}}$), forecasting a more conservative (prudential) and accurate risk measure (Capelli et al., 2023). According to Capelli et al. (2023), the $\mathrm{VaR_{ESG}}$ value must be "calibrated" via an interaction factor J. In particular, J has values ranging from > 0 (no interaction or zero correlation between securities) to 1 (maximum collinearity among securities). Previous studies relied on a unique coupling parameter J for the entire portfolio to calibrate $\mathrm{VaR_{ESG}}$ in the mean average field (Capelli et al., 2023).[3] Therefore, by calibrating $\mathrm{VaR_{ESG}}$ with J, $\mathrm{VaR_{ESG}}$ is defined in Eq. (3), where $J > 0$.

$$VaR_{ESG} \equiv \sqrt{x' \cdot \Sigma_{C(J)} \cdot x} \tag{3}$$

Moreover, with $J \neq 1$ by substituting the standard variance-covariance matrix with the "C-matrix", that is the covariance matrix that includes the ESG contribution as well:

$$VaR_{ESG} = \sqrt{x' \cdot \Sigma_{C(J)} \cdot x} = \sqrt{J} \sum_{i=1}^{n} x_i C_i \tag{4}$$

Where

$$C_i = \sqrt{\nabla_i^2 + \partial_i^2} \tag{5}$$

In Eq. (5), ∇_i and ∂_i indicate, respectively, VaRdelta and $\mathrm{R_{ESG}}$delta of asset i in the portfolio (Capelli et al., 2023).

Applying the same J for all securities independently of their nature (e.g., equity, corporate bonds, and government bonds) provides a limited perspective in the case of a multi-asset portfolio. Therefore, we argue that differentiating the J factor used for calibration, according to the nature of the asset class, is required to measure the proper $\mathrm{CVaR_{ESG}}$, where $\mathrm{CVaR_{ESG}} = x_i \bullet C_i$.

As an example, consider a simple hypothetical case of a security with $\nabla_i = 4$ and $\partial_i = 3$, which leads to $C_i = \sqrt{16+9} = 5$. Assuming $J = 1/2$ and weight $x_i = 1\%$, the analysis provides an erratic result of ($\mathrm{CVaR_{ESG}} = 2.5$) $<$ ($\mathrm{CVaR} = 4$), given that introducing ESG components should conservatively improve VaR estimation (Capelli et al., 2023). Therefore, a revision of C_i (5) is required to adjust the ESG contribution to $\mathrm{VaR_{ESG}}$ without affecting the VaR value, as follows:

[2] Indeed, when dealing with a portfolio of derivatives (i.e., when non-normality is important), adopting other VaR decomposition methodologies can lead to better results (Peterson and Boudt, 2008).

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

$$C_i = \sqrt{\nabla_i^2 + (\widehat{K}_i \cdot \partial_i)^2}$$

where, $\widehat{K}_i$ represents a suitable coefficient impacting only on the ESG contribution. Continuing with the previous example:

$$C_i = \sqrt{16 + \left(\frac{1}{2} \cdot 3\right)^2} = \sqrt{16 + \frac{9}{4}} \cong 4.27$$

Although $5 > 4.27$, $(C_i = 4.27) > (CVaR = 4)$, this preserves the assumption of integrating ESG risk into CVaR_{ESG}.

Therefore, it is first necessary to consider the nature of each asset class and second to adjust J to consider the proper contribution of ESG to VaR_{ESG} for each security. Generally, the ESG contribution of government bonds is smaller than that of equities, as the ESG score of countries is tendentially higher than that of equities. For example, consider eight countries (France, Germany, Ireland, Italy, The Netherlands, Portugal, Spain, and Sweden) in the Eurozone, which reported an average Beyond Ratings ESG Global Score[4] of 84.5 in 2020 (increased to 85.0 in 2021). Moreover, corporate bonds have a different correlation with equity and government bonds than with the correlation between assets of the same typology (i.e., equity).

Based on the above considerations and modifications, to achieve a correct decomposition of VaR_{ESG} in $\text{CVaR}_{\text{ESG},}$ we relied on the Floquet anisotropic lattice model (Kyriienko and Sørensen, 2018) using three axes ($x \equiv$ *equity*, $y \equiv$ *corporatebond*, and$z \equiv$ *governmentbond*) to define a new model (called C Model), as in Eq. (6):

$$VaR_{ESG} = \sqrt{x'\Sigma_{c(J)}x} = \sum_x \sqrt{\nabla_i^2 + (\widehat{K}_x \cdot \partial_i)^2} \cdot x_i + \sum_y \sqrt{\nabla_i^2 + (\widehat{K}_y \cdot \partial_i)^2} \cdot x_i + \sum_z \sqrt{\nabla_i^2 + (\widehat{K}_z \cdot \partial_i)^2} \cdot x_i \tag{6}$$

where $\widehat{K}_w = \widehat{J}_w$ with $w = x,y,z$, and $\widehat{J}_w = \widehat{J}_x, \widehat{J}_y, \widehat{J}_z$ are the coupling factors for different asset types (equities, corporate bonds, and government bonds).

Given that $J = 1/2$ represents a standard assumption in the hypothetical case of a full equity portfolio (Capelli et al., 2023),[5] based on Eq. (4), we suggest differentiating the J factor used for calibration according to the nature of the asset class to measure the proper CVaR_{ESG}, which maintains the theoretical properties of CVaR, in particular the property of additivity. We can assume $\widetilde{J}$ is the differentiated J for different asset typologies by considering the different exposures to ESG risks. In this pilot test, based on the security composition of our portfolio and inspired by the approach explored in Kyriienko and Sørensen (2018),[6] we assume the following calibrated values:

$\widehat{J}_x = \widetilde{J}$ if security i is an equity;

$\widehat{J}_y = \frac{1}{3}\widetilde{J}$ if security i is a corporate bond;

$\widehat{J}_z = \frac{1}{4}\widetilde{J}$ if security i is a government bond.

As an example, under the standard assumption of $J = 1/2$ for equity securities, then $\widehat{J}_x = \widetilde{J} = 0.70$, i.e. $\widetilde{J} \equiv \sqrt{J} = \sqrt{\frac{1}{2}} \cong 0.70$; $\widehat{J}_y \cong 0.23$; and $\widehat{J}_z \cong 0.18$.

From a theoretical standpoint, instead of a security distribution in a bi-dimensional lattice, as in the case of a mono-asset financial portfolio, the C Model would be perfectly represented by considering securities distributed on a manifold, that is, a 4-D lattice (x, y, z, w), where the three dimensions are equities (x), corporate bonds (y), and government bonds (z), and the fourth identifies the ESG scores. Each security would be placed in ascending order on the x, y, and z axes based on its portfolio weight, whereas its ESG score would be placed in ascending order on the fourth axis (w).

In the absence of a 4-D graph, Fig. 1 represents the analogous bi-dimensional lattice with a point for each security (belonging to a specific asset class, e.g., equities) that represents its weight in the portfolio as well as its ESG score (the y-axis indicates, for every security, the ESG score range belonging, and the x-axis its weight).[7]

[4] Beyond Ratings ESG Global Score is provided by Refinitiv. It is based on the concept of Sustainable GDP, which is defined as the theoretical part of GDP that is consistent with the level of E, S, or G performance achieved by a country. Therefore, assumed to be at the same or similar level of economic wealth, sustainability differs according to the levels of development achieved (across E, S, and G).

[5] $J = ½$ is a standard value in Physics for the Ising (1925) model (i.e., in the case of electrons), already adopted and corroborated in financial studies (Capelli et al., 2023; EBA, 2023). Therefore, it also seems a reliable value for a VaR_{ESG} model, expressing a neutral approach and assuming a holistic (i.e., financial and ESG) asset correlation of approximately 0.5.

[6] Kyriienko and Sørensen (2018) referred to $J = ½ = J_x$, $J_y = \frac{2J_x}{3} = 1/3$, $J_z = \frac{J_x}{3} = 1/6$, which we have also tested as a robustness check of this study. Considering the nature of historical correlation among equity, corporate bonds, and government bonds, as J-coupling provides information on the "connectivity" (expressed in terms of spin glasses in the original Ising model), and due to the structure of our model (i.e., the presence of government bonds, characterized by a low ESG risk level) compared to Floquet one, we have adopted the calibration reported in the text. Indeed, we assessed the average ESG score of three different asset types, where the ESG score of countries is tendentially higher than the others.

[7] To measure ESG risk, the methodology starts from ESG scores and then considers the securities' frequency distribution in classes, where scores go from > 0 to 10, labeled from A (i.e. lower class) to H (higher class) (Capelli, 2016; Capelli et al., 2021). Ranges have been built as follows: [8;10], [7;8), [6;7), [5;6), [4;5), [3;4), [1;3), [0;1).

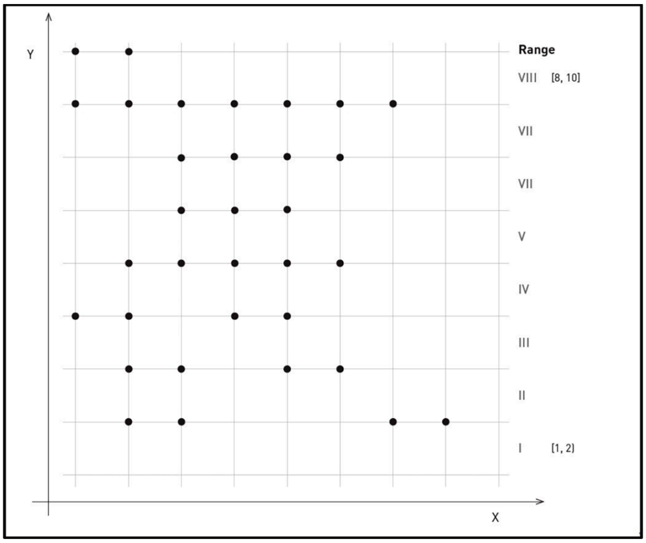

Fig. 1. Bi-dimensional portfolio representation corresponding to a plane of a 4-D lattice.
Source: authors' elaboration representing a hypothetical allocation of a financial portfolio among a specific asset type (i.e., equities). The x-axis represents the portfolio weight of each security. The w-axis represents the ESG score of each security.

3. A pilot empirical test

For a pilot empirical test of a real portfolio, we applied the model to a portfolio comprising 80 equities, 10 corporate bonds, and 10 government bonds randomly selected from the components of the J. P. Morgan GBI EMU Index in 2020. Using MATLAB, we calculated a random weight vector for all assets in the portfolio: to assign random weights to portfolio assets, we calculated 100 random vectors, and we did their average. We maintained fixed weights in 2020. Appendix Table A reports the selected portfolios.

Equity and corporate bond ESG scores at time *t-1* (i.e., 2019) were collected from Refinitiv. Regarding government bonds, in the absence of a robust and well-granted ESG country score, we assigned each country an ESG score from 7 to 10 (Capelli, 2016; Capelli et al., 2021). We used the calculation method applied by Capelli et al. (2021), where a Gaussian VaR using a variance-covariance method[8] at a 99 % confidence level for each month of every year was calculated by varying the return data over 260 days (e.g. at the end of February, we estimated the loss in terms of VaR expected in March using the previous 260 days). Then, we calculated R_{ESG} 2020 using the portfolio's weights and Refinitiv ESG scores at t-1. Finally, we calculated monthly VaR_{ESG}. Table 1 shows the comparison between the monthly VaR and VaR_{ESG}. The VaR measures show the results of the application of the traditional financial risk measure, while the second ones show the measures of VaR integrated with the ESG risk metrics. As reported in Table 1, the VaR_{ESG} is more conservative than the traditional VaR measure, as it considers a risk factor that would otherwise be overlooked. This helps reduce unexpected losses and out-of-VaRs.

In 2020, the portfolio registered 16 out-of-VaR, and six out-of-VaR were missing because of the integration of ESG considerations for calculating the measure of VaR_{ESG}. More in detail, Table 2 compares the out-of-VaR and out-of-VaR_{ESG}, which are presented on a daily-based period to have a clearer representation of the results. The remaining out-of-VaR corresponds to the shock due to the widespread pandemic crisis and confirms the validity of the measure as a predictive risk indicator. In summary, recalling that 2020 was the most volatile year in recent decades and, therefore, the most useful year to test our approach, approximately 38 % of unexpected losses according to the financial model (standard VaR) were forecasted by the integrated metric (VaR_{ESG}); that is, six out of 16 out-of-VaR. This result confirms the PRI's prediction (PRI, 2016) that financial factors included in VaR parameters (for predicting the risk of loss from a financial asset) cannot completely explain ex-post volatility, whereas it can be useful to consider ESG factors as well.

The mathematical approach for calculating VaR_{ESG} allows decomposing it into $CVaR_{ESG}$. This measure makes it possible to calculate the contribution to the VaR_{ESG} of each security in the financial portfolio, grouped by asset class or according to the specific needs of the asset manager, the economic sector, or other asset characteristics. Tables 3 and 4 show the VaR decomposition results as of March 2020, when the portfolio showed the highest number of out-of-VaR. Table 3 shows the decomposition of $CVaR_{ESG}$ regarding asset classes, and Table 4 considers the investments grouped by economic sector. Given a VaR_{ESG} equal to 3.34 % in March 2020 (Table 1), the main contribution in terms of the asset class is given by equities ($CVaR_{ESG} = 3.21$ % and $CVaR_{ESG}\% = 96.21$ % in Table 3), while in terms of sectorial contribution, the non-cyclical consumer and industrial sectors show a contribution to VaR_{ESG} of approximately 16 % (in Table 4, $CVaR_{ESG} = 0.52$ %, $CVaR_{ESG}\% = 15.69$ %, $CVaR_{ESG} = 0.53$ %, and $CVaR_{ESG}\% = 15.83$ %).

[8] As a robustness check, we also ran more sophisticated VaR models (e.g., Modified VaR or Cornish-Fisher, also with volatility jump) to improve the financial risk estimation. However, the Gaussian VaR with a variance-covariance simple method provides a more reliable view of the holistic portfolio risk.

Table 1
A comparison between VaR and VaR_{ESG}.

	VaR	VaR_{ESG}
Dec-19	1.19 %	2.20 %
Jan-20	1.15 %	2.16 %
Feb-20	1.32 %	2.28 %
Mar-20	2.64 %	3.34 %
Apr-20	2.84 %	3.51 %
May-20	2.91 %	3.58 %
Jun-20	3.04 %	3.69 %
Jul-20	3.06 %	3.71 %
Ago-20	3.04 %	3.69 %
Set-20	3.06 %	3.72 %
Oct-20	3.07 %	3.73 %
Nov-20	3.14 %	3.79 %
Dec-20	3.14 %	3.80 %

Table 2
No. of Out-of-VaR and Out-of-VaR_{ESG}.

	Daily portfolio loss	Out-of-VaR	Out-of-VaR_{ESG}
24/02/2020	−2,41 %	1	1
25/02/2020	−1,57 %	1	0
27/02/2020	−2,64 %	1	1
28/02/2020	−2,29 %	1	1
05/03/2020	−1,44 %	1	0
06/03/2020	−2,65 %	1	1
09/03/2020	−6,28 %	1	1
11/03/2020	−2,02 %	1	0
12/03/2020	−8,34 %	1	1
16/03/2020	−6,12 %	1	1
18/03/2020	−3,63 %	1	1
23/03/2020	−3,52 %	1	1
27/03/2020	−1,62 %	1	0
01/04/2020	−2,96 %	1	0
04/05/2020	−2,95 %	1	0
11/06/2020	−4,04 %	1	1

Table 3
$CVaR_{ESG}$ by asset type contribution in March 2020.

Asset type	$CVaR_{ESG}$	$CVaR_{ESG}$%
Equity	3,21 %	96,21 %
Corporate bond	0,07 %	2,09 %
Government bond	0,06 %	1,70 %
	3,34 %	100,00 %

Table 4
$CVaR_{ESG}$ by sectorial contribution in March 2020.

Sector	$CVaR_{ESG}$	$CVaR_{ESG}$%
Basic Materials	0,28 %	8,24 %
Communications	0,29 %	8,77 %
Consumer, Cyclical	0,24 %	7,05 %
Consumer, non-cyclical	0,52 %	15,69 %
Energy	0,23 %	6,75 %
Financial	0,48 %	14,42 %
Government	0,06 %	1,70 %
Industrial	0,53 %	15,83 %
Technology	0,32 %	9,59 %
Utilities	0,40 %	11,96 %
	3,34 %	100,00 %

As a robustness check, we conducted another pilot empirical test on the same original portfolio with a different asset allocation in the hypothesis of lower exposure to equity (20 %) and higher exposure to bonds, both corporate and government (80 %) (Appendix, Table A).

The robustness check results revealed 10 out-of-VaR in 2020, and 50 % of unexpected losses, according to the standard VaR, were forecasted using the integrated metric VaR_{ESG} (i.e., five out of ten out-of-VaR). Given a VaR_{ESG} equal to 1.42 % in March 2020, the main contribution in terms of asset class was again for equities ($CVaR_{ESG} = 0.69$ % and $CVaR_{ESG}\% = 48.27$ %), while in terms of sectors, the government sector impacted with a $CVaR_{ESG}$ of 28.52 %, confirming the validity of the model. Indeed, considering the ESG variables too (thanks to the integration between VaR and R_{ESG}) allows for a reduction of the unexpected losses, because the portfolio returns were affected also by sustainability risk, which otherwise remains neglected.

4. Conclusions

This study improves a new market risk measure, VaR_{ESG} (Capelli et al., 2023), by decomposing it to measure the contribution of different asset classes to total risk, suggesting how to move from the measure of VaR_{ESG} to the measure of $CVaR_{ESG}$.

We shift from a top-down VaR_{ESG} calculation to a bottom-up approach. Indeed, by decomposing VaR_{ESG} in terms of $CVaR_{ESG}$, we can rebuild the original VaR_{ESG} from its asset components. In other words, we offer an original recipe to integrate VaR and R_{ESG}, which is a helpful method to manage the multi-asset portfolio allocation (not just an equity-based portfolio). Results offer several contributions relevant to researchers and practitioners (EBA, 2023).

First, $CVaR_{ESG}$ has the useful property to add up to the Euro VaR of the total portfolio by helping asset and risk managers from a risk disaggregation perspective. The measure presented herein can be used for defining specific risk limits in terms of individual security, geographical area, economic sector, and asset type, among others. Through the $CVaR_{ESG}$, it is possible to define the maximum contribution of risk accepted for security or part of the financial portfolio, highlighting the potential contribution of different asset classes (divided into equities, corporate bonds, and government bonds), given their differences, not only from a risk/return perspective but also considering their ESG characteristics. An interesting idea for future research could be to test an optimization portfolio model based on $CVaR_{ESG}$, to have a comparison with the results of recent research focused on different metrics (Hosseini-Nodeh et al., 2022) or other return assumptions, such as alpha-stable distributions (Malek et al., 2023).

Second, the *J* indicator, used to calibrate VaR_{ESG}, measures the coupling strength between securities and considers the correlation between portfolio assets and their ESG scores. The *J* indicator differs for each asset category considered in this analysis. For example, government bonds typically present a lower correlation with equities than corporate bonds and a lower ESG contribution. Therefore, setting the *J* index at a lower level than other asset classes is necessary. Considering different ways of calibrating the VaR_{ESG} allows for the proper application of the measure of $CVaR_{ESG}$ to calculate the contribution to risk in a multi-asset portfolio. Government bonds require special attention, given that a well-granted country's ESG score does not exist. This issue offers an interesting avenue for future research.

As data providers are progressively improving the quality of ESG scores for all the issuers (companies and governments), future research could investigate how a dynamically adjusted calibration of the interaction factor *J* can have implications for the predictive power of the model. Moreover, it would be interesting to monitor the contribution of financial and ESG components over time to the holistic VaR_{ESG} metric, varying respectively and separately VaR and R_{ESG}, making a sector breakdown as well.

By definition, as the fundamental input of the VaR_{ESG} model is the ESG score, the methodology here described cannot be applied to the portfolio portion of derivative instruments or non-linear financial products (e.g., structured products), which do not have an ESG score: future research could bridge this gap.

Finally, this study provides evidence that the $CVaR_{ESG}$ reduces unexpected losses, improving the estimates of expected portfolio volatility, especially under stressful conditions, as reported in this study for the year 2020, when the exogenous factor COVID-19′s impact on the predictability of negative returns emerged. This fact can benefit asset managers, given the integration of specific factors that can affect multi-asset portfolios' financial performance.

CRediT authorship contribution statement

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

Declarations of interest

None.

Data availability

Data will be made available on request.

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Appendix

Table A1

Table A1
Structure and characteristics of empirical portfolios.

Asset Category	Ticker	Sector	Weights in Equity/Bond (80 %/20 %) Portfolio	Weights in Equity/Bond (20 %/80 %) Portfolio	ESG score
Equity	011,780 KS Equity	Basic Materials	0,94 %	0,23 %	39,96 %
Equity	028,260 KS Equity	Industrial	0,97 %	0,24 %	60,46 %
Equity	086,280 KS Equity	Industrial	1,03 %	0,26 %	77,44 %
Equity	1347 HK Equity	Technology	1,05 %	0,26 %	37,69 %
Equity	1901467D AU Equity	Financial	1,12 %	0,28 %	91,41 %
Equity	2314 HK Equity	Industrial	0,97 %	0,24 %	44,33 %
Equity	2371 JP Equity	ICT	0,92 %	0,23 %	32,21 %
Equity	2388 HK Equity	Financial	0,99 %	0,25 %	69,37 %
Equity	2502 JP Equity	Consumer, non-cyclical	1,04 %	0,26 %	80,57 %
Equity	5108 JP Equity	Consumer, Cyclical	0,93 %	0,23 %	82,04 %
Equity	5201 JP Equity	Industrial	0,88 %	0,22 %	80,90 %
Equity	6504 JP Equity	Industrial	0,98 %	0,24 %	75,11 %
Equity	6762 JP Equity	Industrial	1,08 %	0,27 %	76,83 %
Equity	6971 JP Equity	Industrial	1,00 %	0,25 %	73,50 %
Equity	7201 JP Equity	Consumer, Cyclical	0,96 %	0,24 %	74,27 %
Equity	7267 JP Equity	Consumer, Cyclical	1,03 %	0,26 %	88,32 %
Equity	7751 JP Equity	Technology	1,08 %	0,27 %	73,23 %
Equity	8058 JP Equity	Consumer, Cyclical	0,96 %	0,24 %	81,56 %
Equity	9531 JP Equity	Utilities	1,06 %	0,27 %	75,05 %
Equity	AAPL US Equity	Technology	1,05 %	0,26 %	67,23 %
Equity	ABBV US Equity	Consumer, non-cyclical	1,03 %	0,26 %	78,27 %
Equity	ABF LN Equity	Consumer, non-cyclical	0,93 %	0,23 %	75,48 %
Equity	ACO/X CN Equity	Utilities	1,02 %	0,25 %	39,63 %
Equity	ADEN SW Equity	Consumer, non-cyclical	0,95 %	0,24 %	70,01 %
Equity	ADM US Equity	Consumer, non-cyclical	1,09 %	0,27 %	81,16 %
Equity	ADP FP Equity	Industrial	1,03 %	0,26 %	43,65 %
Equity	ADSK US Equity	Technology	0,98 %	0,24 %	82,38 %
Equity	AENA SM Equity	Industrial	1,03 %	0,26 %	72,84 %
Corporate bond	AL320557 Corp	ICT	1,02 %	4,11 %	83,07 %
Corporate bond	AM1338343 Corp	Industrial	1,13 %	4,54 %	69,43 %
Corporate bond	AM5829149 Corp	ICT	0,91 %	3,66 %	84,64 %
Government bond	AM606745 Corp	Government	0,97 %	3,91 %	78,00 %
Corporate bond	AM754648 Corp	ICT	1,01 %	4,06 %	91,47 %
Equity	AMAT US Equity	Technology	1,03 %	0,26 %	76,80 %
Equity	ANTO LN Equity	Basic Materials	0,96 %	0,24 %	70,23 %
Government bond	AP1154040 Govt	Government	0,98 %	3,96 %	82,38 %
Government bond	AP3656380 Govt	Government	0,94 %	3,80 %	90,65 %
Corporate bond	AP838056 Corp	Financial	0,96 %	3,86 %	65,73 %
Corporate bond	AS1464906 Corp	Financial	0,98 %	3,96 %	90,85 %
Corporate bond	AU6543576 Corp	ICT	0,93 %	3,73 %	81,47 %
Government bond	AU9204705 Govt	Government	1,01 %	4,08 %	75,41 %
Corporate bond	AW8755703 Corp	Utilities	0,95 %	3,81 %	78,34 %
Equity	BA US Equity	Industrial	0,92 %	0,23 %	80,27 %
Equity	BAC US Equity	Financial	1,04 %	0,26 %	80,51 %
Equity	BALL US Equity	Industrial	1,02 %	0,26 %	73,18 %
Equity	BIIB US Equity	Consumer, non-cyclical	0,99 %	0,25 %	76,22 %
Equity	BIM FP Equity	Consumer, non-cyclical	0,90 %	0,23 %	70,32 %
Equity	BJC TB Equity	Consumer, non-cyclical	0,92 %	0,23 %	46,87 %
Equity	BOL FP Equity	ICT	1,09 %	0,27 %	54,73 %
Equity	BP/ LN Equity	Energy	1,00 %	0,25 %	88,02 %
Equity	BX US Equity	Financial	1,05 %	0,26 %	33,50 %
Equity	CA FP Equity	Consumer, non-cyclical	1,05 %	0,26 %	79,02 %
Equity	CAG US Equity	Consumer, non-cyclical	1,04 %	0,26 %	70,78 %
Equity	CAP FP Equity	Technology	0,97 %	0,24 %	70,75 %
Equity	CARLB DC Equity	Consumer, non-cyclical	1,02 %	0,26 %	71,88 %

(continued on next page)

Table A1 (*continued*)

Asset Category	Ticker	Sector	Weights in Equity/Bond (80 %/20 %) Portfolio	Weights in Equity/Bond (20 %/80 %) Portfolio	ESG score
Equity	CON GR Equity	Consumer, cyclical	0,99 %	0,25 %	81,39 %
Equity	CPB US Equity	Consumer, non-cyclical	1,08 %	0,27 %	85,65 %
Equity	CPG LN Equity	Consumer, cyclical	0,94 %	0,23 %	79,14 %
Equity	CRH ID Equity	Industrial	1,01 %	0,25 %	81,15 %
Equity	CS FP Equity	Financial	0,96 %	0,24 %	82,15 %
Equity	DLFU IN Equity	Financial	1,02 %	0,25 %	56,81 %
Equity	DRE US Equity	Financial	0,95 %	0,24 %	34,59 %
Equity	EDF FP Equity	Utilities	0,93 %	0,23 %	70,53 %
Corporate bond	EJ7233293 Corp	Utilities	0,91 %	3,66 %	74,27 %
Government bond	EK041463 Corp	Government	1,05 %	4,23 %	91,41 %
Corporate bond	EK5085239 Corp	ICT	1,04 %	4,17 %	78,11 %
Government bond	EK6943477 Govt	Government	0,98 %	3,94 %	76,24 %
Government bond	EK6994165 Govt	Government	1,02 %	4,11 %	75,41 %
Equity	ENEL IM Equity	Utilities	1,04 %	0,26 %	88,51 %
Equity	ENI IM Equity	Energy	0,98 %	0,25 %	84,61 %
Equity	EOAN GR Equity	Utilities	0,96 %	0,24 %	76,24 %
Equity	FRVIA FP Equity	Consumer, cyclical	1,05 %	0,26 %	72,22 %
Equity	GOOGL US Equity	ICT	0,96 %	0,24 %	67,74 %
Equity	GSK LN Equity	Consumer, non-cyclical	0,88 %	0,22 %	89,80 %
Equity	HIK LN Equity	Consumer, non-cyclical	1,01 %	0,25 %	67,57 %
Equity	HPQ US Equity	Technology	1,03 %	0,26 %	78,14 %
Government bond	JV9105265 Govt	Government	1,09 %	4,38 %	80,90 %
Equity	KGH PW Equity	Basic Materials	0,96 %	0,24 %	59,02 %
Equity	MF FP Equity	Financial	1,03 %	0,26 %	82,02 %
Equity	NHY NO Equity	Basic Materials	0,95 %	0,24 %	90,65 %
Equity	NICE IT Equity	Consumer, non-cyclical	1,08 %	0,27 %	46,97 %
Equity	NOKIA FH Equity	ICT	1,05 %	0,26 %	91,47 %
Equity	NOVN SW Equity	Consumer, non-cyclical	1,11 %	0,28 %	85,43 %
Equity	O2D GR Equity	ICT	1,01 %	0,25 %	65,99 %
Equity	PFE US Equity	Consumer, non-cyclical	1,05 %	0,26 %	68,09 %
Equity	PGE PW Equity	Utilities	1,03 %	0,26 %	40,91 %
Equity	PTG MK Equity	Energy	0,97 %	0,24 %	46,02 %
Government bond	QZ3864662 Govt	Government	0,97 %	3,91 %	80,00 %
Equity	REP SM Equity	Energy	1,00 %	0,25 %	87,89 %
Equity	RPM US Equity	Basic Materials	1,01 %	0,25 %	40,00 %
Equity	SIE GR Equity	Industrial	0,93 %	0,23 %	86,42 %
Equity	SSE LN Equity	Utilities	0,96 %	0,24 %	60,51 %
Equity	T US Equity	ICT	0,98 %	0,24 %	69,32 %
Equity	UG FP Equity	Consumer, cyclical	1,00 %	0,25 %	81,72 %
Government bond	UV980852 Corp	Government	1,03 %	4,13 %	80,00 %
Equity	VER AV Equity	Utilities	1,08 %	0,27 %	75,41 %
Equity	VST US Equity	Utilities	0,94 %	0,23 %	56,67 %
Equity	VWS DC Equity	Energy	1,03 %	0,26 %	73,29 %
Equity	WFC US Equity	Financial	0,96 %	0,24 %	72,06 %
Equity	XYL US Equity	Industrial	1,11 %	0,28 %	78,00 %

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