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Forecasting volatility by integrating financial risk with environmental, social, and governance risk

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[Correction added on 17 September 2021, after first online publication: The author byline have been corrected to alphabetical order.]

Abstract

The study aims to verify whether the consideration of a risk measure based on environmental, social, and governance (ESG) factors can reduce the difference between the ex-ante financial risk and ex-post volatility of financial assets. The statistical models are run on 17,996 firm-year observations (3332 active firms from 55 countries and 10 industries, listed on the ECPI Global Ethical Equity index) in 2007–2015. According to our main results, the forecasting effectiveness of traditional financial risk measures can be improved by integrating financial risk with an ESG risk measure that considers the ESG entropy. We found that the dispersion of ESG scores within a country, sector and year is a risk factor that would be helpful in predicting the volatility of financial assets. Other similar long-run risk measures, such as issuers' credit ratings, do not reveal the same forecasting power. By reducing unexpected volatility, especially in the medium term, the ESG risk measure provides investors and fund managers with a useful metric for decision making.

KEYWORDS
credit rating, ESG risk, risk management, socially responsible investing, value-at-risk, volatility

1 | INTRODUCTION

The application of asset pricing models shows that a proportion of excess stock returns is not captured by the most commonly used risk factor components, which suggests there is a need for additional research (Carhart, 1997; Fama & French, 1993). Financial research has therefore focused on how to reduce the difference between ex-ante financial risk measures and ex-post volatility of financial assets (Engle, 2004; Fama & French, 2017; Prokopczuk & Simen, 2014). Value-at-Risk (VaR), and its different specifications, have been adopted as standard tools to measure the ex-ante financial risk of assets (BCBS, 1996). VaR is directly related to risk factors: if a factor is deemed relevant for pricing, it should be included in the VaR model (Bloomberg, 2015). However, given the limits of VaR in delivering accurate forecasts, research interest has increasingly focused on methodologies and assumptions able to produce the best overall volatility estimations (Bams et al., 2017; Berkowitz & O'Brien, 2002; Engle, 2004; Giot & Laurent, 2004; Louzis et al., 2014; Nieto & Ruiz, 2016; Prokopczuk & Simen, 2014).

Environmental, social, and governance (ESG) factors are increasingly integrated into the financial investment analysis process in this context (Kotsantonis et al., 2016). Today, socially responsible investing (SRI) strategies tend to formally combine financial analysis with ESG analysis in the evaluation of securities' issuers (Eurosif, 2018; GSIA, 2016). Empirical and theoretical studies on SRI show that ESG issues have real and quantifiable financial impacts in the long term, affecting stock market returns and price volatility (Boutin-Dufresne & Savaria, 2004; Brogi & Lagasio, 2019; Friede et al., 2015; Khan & Bradbury, 2016; Kotsantonis et al., 2016; Lo & Kwan, 2017; Russo, Mariani, & Perrini, 2016). ESG risk factors are considered to be the most severe in terms of their likelihood and potential impact on the economy and society at large, as well as on firms and individuals (World Economic Forum, 2021). Moreover, ESG risk factors can

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affect other types of business risks, exposing firms to serious reputational and operational risks (González Sánchez & Morales de Vega, 2018; Humphrey & Lee, 2012; Xie et al., 2019; Young & Thyil, 2014).

Considering the above theoretical and empirical context, this study aims at verifying whether considering a measure of ESG risk can reduce the difference between the ex-ante financial risk and the ex-post volatility of financial assets. In other words, we tested whether a measure of ESG risk, able to statistically capture the contribution of an asset to the "disorder" of a portfolio in terms of ESG characteristics of its components, might be useful for estimating the asset financial volatility. We also deepen the analysis of the role of issuers' credit ratings by testing whether they improve the forecasting effectiveness of traditional financial risk measures.

To test our hypotheses, we use an unbalanced longitudinal dataset comprising 17,996 firm-year observations, referring to 3332 listed, active firms from 55 countries and 10 industries with a yearly ESG score in 2007–2015. In particular, we propose a rigorous framework for measuring ESG risk exposure, considering the ESG scores of financial assets and applying the concept of entropy, as studied by Shannon (1948). Entropy is historically associated with the concept of disorder and has been used in finance as a measure of risk in portfolio selection and diversification (Bera & Park, 2008; Huang, 2008; Meucci, 2009; Zhou et al., 2013). In investigating stock market volatility, entropy can be adopted as an alternative approach to ex-post volatility (Sheraz et al., 2015). In this study, entropy is applied to measuring ESG risk, starting from the ESG scores assigned to each financial asset.

Our main results show that the forecasting effectiveness of traditional financial risk measures applied to financial assets can be improved by integrating measures of financial risk with a measure of ESG risk which takes into account entropy of the ESG scores. The ESG risk measure makes it possible to better estimate volatility, so as to reduce the ex-post differences compared to expectations. It provides investors and fund managers with a useful metric for decision making which reduces unexpected volatility, especially in the medium term. Other similar long-run risk measures, such as issuers' credit ratings, do not reveal the same forecasting power and are thus not as effective in improving risk analysis.

In the remainder of this paper, we proceed as follows. We begin in Section 2 by analyzing the relevant literature and introducing our main hypotheses. In Section 3, we present the measure of ESG risk as well as the sample and methodologies applied to test our hypotheses. In Section 4, we discuss our main results. In Section 5, we conclude with the practical implications of our approach and suggestions for future research.

2 | LITERATURE REVIEW AND HYPOTHESES

In the definition given by Jorion (2001), VaR is the worst loss expected from a financial asset, over a target horizon, and within a determined confidence level. Since the RiskMetrics model specifying VaR was published in 1996 (Morgan & Reuters, 1996), and the use of risk-adjusted measures of capital adequacy based on VaR was introduced by the Basel Committee on Banking Supervision (BCBS, 1996), this metric has been widely used in risk management.

The estimation of volatility is a key input for calculating VaR: it directly depends on the expected volatility, time horizon, and confidence interval for the continuous returns under analysis. Although VaR is an indicator of the tail losses, VaR modeling is also a natural application of volatility estimates for forecasting ex-post volatility. Several studies have tested the performance of VaR in volatility forecasts and tested its limits against ex-post benchmarks (Bams et al., 2017; Engle, 2004; Giot & Laurent, 2004; Louzis et al., 2014; Nieto & Ruiz, 2016; Prokopczuk & Simen, 2014). VaR usually underestimates ex-post volatility. Brooks and Persand (2003) find that simpler volatility specifications produce better VaR forecasts. Bams et al. (2005) argue that simpler VaR models often produce an underestimation of the VaR. As an example, the popular VaR methodology based on a normality assumption on the conditional distribution of returns often leads to underestimation of financial losses, as fat tails are not accounted for.

Investors and financial institutions can face unexpected losses as a deviation of actual returns compared with the VaR forecast. This has led to the search for model specifications to capture volatility dynamics of asset returns, and for the assumptions which produce the overall best volatility forecasts, by backtesting procedures (Andersen & Bollerslev, 1998; Angelidis & Degiannakis, 2008; Degiannakis et al., 2013; Koopman et al., 2005). In this literature, the parameters estimated for the distribution of asset returns, the model for the tail behavior of conditional volatility distribution, and the different approaches based on daily or intradaily data are key specifications impacting the capacity of the measure to deliver accurate forecasts.

The literature briefly reviewed above shows that there is no clear consensus on the possibility of reliable predictive (ex-ante) estimates of the (ex-post) volatility of financial assets. Based on the well-known aphorism generally attributed to the statistician George Box, "All models are wrong, but some are useful," we rely on the literature testing the VaR method for ex-ante volatility estimate, compared to the ex-post realized volatility. Our first hypothesis is thus as follows:

> **H1.** *A positive relationship exists between ex-ante financial risk and ex-post volatility of financial assets*.

On the basis of this relationship, we aim to verify whether the forecasting power of VaR increases if it is combined with another measure of risk based on non-financial factors (Poon & Granger, 2003). Based on findings in previous literature, we argue that financial factors included in VaR parameters for predicting the risk of loss from a financial asset cannot completely explain ex-post volatility, and consider ESG factors as one of the missing components when financial risk is measured using VaR (Paul, 2017; PRI, 2016).

During the last decade, SRI has become more common on international financial markets, which suggests there is a need for the integration of ESG analysis into the evaluation of securities' issuers (Jayne & Skerratt, 2003).

A growing interest in SRI can be seen in the number of asset managers globally who have signed the United Nations-backed Principles for Responsible Investment (PRI) and in the increase in assets under management in SRI portfolios (Eurosif, 2018; Morningstar, 2016b; PRI, 2016).

In this context, risk management is just one of the main drivers of the development of SRI strategies in Europe, especially among mutual funds (Eurosif, 2018; GSIA, 2016; Ielasi, Limberti, Rossolini, 2018; KPMG, 2016; PRI, 2016). A growing body of academic and professional research indicates the materiality of ESG factors for obtaining long-term value by investors. In particular, to verify the impact of ESG integration on asset returns, recent research evaluates ESG variables as risk factors in performance attribution analysis. Investigating the case of Quotient Investors' U.S. Large Cap Sustainable Alpha fund, a study by the PRI shows that ESG factors explain 2.4, 1.6, and 2.7% of positive excess returns, respectively. Performing a sensitivity analysis, the research demonstrates that when ESG factor returns increase by 1%, the fund's returns increase by 0.42%, significantly more than for other traditional risk factors, such as size and value (PRI, 2016). To the best of our knowledge, this study is the first attempt to measure the role of ESG factors in explaining a portion of return variation for mutual funds.

The relationship between the market risks of a financial portfolio and its ESG characteristics can be confirmed by analyzing the volatility of mutual funds according to their ESG score (Morningstar, 2016b). This score applied to a mutual fund is an asset-weighted average measure that reflects companies' management systems, practices, policies, and other indicators related to ESG issues. It evaluates all potential and forward-looking risks of an ESG-related controversy in which a firm might be involved (Morningstar, 2016a). A negative relationship is found between the volatility of mutual funds and its ESG score (i.e., the number of Morningstar globes). Other studies find a strong negative association between firm stock return volatility and sustainable behaviors, and a strong positive relationship between stock volatility and irresponsible practices (Bae et al., 2018).

The association between ESG practices and stock volatility is consistent with findings of a strand of literature on the relationship between corporate behaviors on ESG issues and different types of business risks. This literature finds that environmental and social "irresponsibility", as well as bad governance practices, expose firms to serious reputational and operational risks and affect their level of disclosure (Humphrey & Lee, 2012; Lagasio & Cucari, 2019; McCormick, 2010; Waddock & Graves, 1997; Xie et al., 2019; Young & Thyil, 2014). "Irresponsible" firms also face a higher probability of conflict with stakeholders, which can lead to boycotts by potential investors and consumers, active engagement in social and environmental concerns, as well as class actions (Becchetti et al., 2018; de Haan et al., 2012; Dimson et al., 2015; Engle, 2007; Freeman, 1984; Humphrey & Lee, 2012; Luo & Balvers, 2017). ESG factors can also act as shock-absorbing elements. In particular, environmental and social responsibility, as well as good governance practices, can serve as a buffer during market turmoil and economic downturns. On the other hand, failing to take account of ESG variables in stock selection makes the performance more vulnerable especially during times of economic turbulence, which increases volatility (Lins et al., 2017; Nofsinger & Varma, 2014). ESG factors can also have a mitigating effect on crash risk and the conditional skewness of the return distribution, as well as a moderating effect on the asymmetry in risk (Kim et al., 2014; Verheyden et al., 2016). The lower level of risk for companies with high ESG strengths and low ESG concerns is confirmed by their lower cost of equity (Chava, 2014; El Ghoul et al., 2011; El Ghoul et al., 2018) and lower cost of debt (Goss & Roberts, 2011; Jiraporn et al., 2014; Oikonomou et al., 2014). Lastly, the literature explains stock pricing anomalies by considering the role of investors; responsible investors are shown to be more loyal and less reactive to market shocks, which reduces the volatility of SRI investments (Bollen, 2007; Flammer, 2013; Renneboog et al., 2008).

Since according to the above literature, ESG factors affect corporate risks, we measure statistically the ESG risk applying the concept of entropy.

Entropy is historically associated with the concept of disorder, randomness, chaos, or even uncertainty, in fields other than finance. In many systems, phases with more structural order (crystalline) exhibit less entropy than less structural phases (fluid) under the same thermodynamic conditions (Michaelides, 2008). The association of entropy with randomness or disorder stems from the molecular description of matter, which is essentially a question of statistical mechanics or thermodynamics. In probability theory, the entropy of a random variable measures uncertainty, whilst in the field of information, entropy represents the loss of information of a physical system observed by an outsider (Brillouin, 1953). The application of entropy in finance can be regarded as the extension of the information entropy and the probability entropy (Zhou et al., 2013). Following Shannon (1948), entropy in finance has been used in fuzzy portfolio selection theories for measuring the uncertainty of the portfolio returns (Huang, 2008), and in portfolio diversification models, where it is widely accepted as a measure of the degree of portfolio diversification (Bera & Park, 2008; Meucci, 2009). With specific reference to stock markets, the literature finds that entropy captures the overall linear and nonlinear dispersion patterns observed in the data series; the entropic approach can thus be used as an alternative way of estimating stock market volatility (Sheraz et al., 2015).

We apply the concept of entropy to verify the contribution of an asset to the "disorder" of a financial portfolio relating to the ESG characteristic of its components to obtain a better understanding of its level of risk. Note that the ESG scores of each asset provided by consulting companies and rating agencies are not true risk measures, as they lack theoretical assumptions about underlying distribution and a probabilistic framework, and they have no predictive power (Scalet & Kelly, 2010). They assess the ESG quality (i.e., ESG strengths and concerns) of companies, projects, sectors, or countries, without any estimation of statistical parameters. Investors following an SRI approach use them to screen out unethical firms from the investment universe (Trinks & Scholtens, 2017), or to identify the best-in-class securities for investment purposes (Avetisyan & Hockerts, 2017; Chatterji et al., 2009; Scalet & Kelly, 2010). In the same way, ESG controversy indicators or reputational indices evaluate criticisms pertaining for example to human rights abuses, corruption, child and forced labor, frauds, tax evasion, environmental degradation, local pollution, poor governance practices, and can impact an organization's reputation, its potential controversies with stakeholders, or its compliance issues.

They identify the media and stakeholder exposure of a company, project, sector, or country, the potential for stakeholder sanctions, and level of criticism concerning ESG issues. They provide information about a firm's ESG practices, but they are not calculated for financial risk purposes. Therefore, we base our calculations on an ESG evaluation for each asset, by considering the contribution to the randomness and the disorder of these evaluations across the sample, other than the ESG scoring classes in which the scores are more concentrated. The result is a real measure of risk related to non-financial characteristics of assets.

Based on findings in the literature that suggest the relevance of moderating factors to well-known relationships (Zelner, 2009), we expect the inclusion of the ESG risk measure will improve our understanding of the relationship between the ex-ante financial risk and the ex-post volatility of financial assets. In particular, we expect that ESG risk factors contribute to moderating this positive relationship. Our second hypothesis is as follows:

> **H2.** *ESG risk negatively moderates the relationship between ex-ante financial risk and ex-post volatility of financial assets.*

Other than ESG risk, we aim to verify whether issuers' credit ratings, a risk measure incorporating both financial and non-financial characteristics of firms, is able to mitigate the relation between VaR and ex-post volatility. Credit ratings at a corporate level are a risk measure that indicates a company's probability of default. Academic literature analyzing credit ratings revealed statistically significant positive relationships between credit quality and ESG factors (Attig et al., 2013; Jiraporn et al., 2014; Oikonomou et al., 2014). In particular, negative news and events regarding ESG issues increase a firm's credit risk (Kölbel et al., 2017). Jiraporn et al. (2014) confirm that concerns about ESG practices, able to produce disastrous financial consequences, are significantly negatively associated with credit ratings, while potential strengths in ESG are not significantly related to ratings. The literature finds that including ESG factors improves the explanatory power of credit rating, and enhances the predictive power of bankruptcy/default forecasting models (Schröder, 2014). ESG considerations can thus be an important element in the forward-looking rating framework (PRI, 2017).

Indeed, leading financial institutions which issue internal ratings of the creditworthiness of companies consider ESG issues as risk variables (Bae et al., 2018). Credit rating agencies themselves are increasingly granulating ESG factors in their credit rating process, in order to improve the discriminating quality of quantitative rating models for credit assessments (Moody's, 2015; S&P, 2016, 2017). In their holistic credit risk assessments, ESG factors are clearly linked to the creditworthiness of issuers: they can cause reputational damage to a business, affect its ability to raise funding, and negatively impact its financial performance, thus increasing the relative probability of default (Ashbaugh-Skaife et al., 2006; Oikonomou et al., 2014). Reviewing its global corporate rating actions since November 2013, S&P (2015) showed 299 cases in which environmental and climate risks have either resulted in (or contributed to) a corporate rating revision, or were significant factors in its rating analysis. In their assessment, rating agencies more precisely reflect the riskiness of a "wrongdoer," than the potential opportunities of a "do-gooder" company (Bae et al., 2018).

As well as measuring the creditworthiness of a company, credit ratings also affect the standard deviation of stock returns (Bae et al., 2018). This finding is consistent with the literature that investigates the reaction of financial market volatilities to rating announcements (Filipe et al., 2016; Hull et al., 2004; Norden & Weber, 2004).

Since issuer ratings are a forward-looking risk measure that incorporates long-run information on companies, this paper aims to investigate whether they produce a moderating effect on the relationship between ex-ante financial risk and ex-post volatility. Our approach follows the methodology introduced by the Basel Committee on Banking Supervision in the document "Basel III: Finalizing Post-Crisis Reform" for the standardized and the internal model approach for market risks (BCBS III, 2017). Indeed, following the "Fundamental Review of the Trading Book," a Default Risk Charge was added to obtain a comprehensive measure of market risks. We thus test the following hypothesis:

> **H3.** *Credit ratings negatively moderate the relationship between ex-ante financial risk and ex-post volatility of financial assets.*

3 | METHODOLOGY

3.1 | Empirical setting and sample

A key issue in the empirical design of our study was the selection of an appropriate research setting. We needed an empirical context able to satisfy the following requirements simultaneously: (a) Companies had to be ranked in at least one ESG index; (b) Companies had to be ranked in the same ESG index for at least two subsequent years; and (c) Companies had to be active throughout the period of analysis. These characteristics were necessary to compute a relevant and significant measure of ESG risk, which represents the focal point of this analysis.

To build a sample of companies meeting the above requirements, worldwide public companies active in 2007–2015 were selected from the Datastream Thomson Reuters Asset4 database. The initial sample comprised 22,643 firm-year observations (12 industries and 73 segments based on the Bloomberg industry classification). We excluded firms for which no information was available, in terms of both financial and non-financial (i.e., ESG) data. Our final sample was an unbalanced longitudinal dataset comprising 17,996 firm-year observations, referring to 3332 listed, active firms from 55 countries and 10 industries with yearly ESG scores in 2007–2015. The use of time-varying data on the same set of firms enabled us to control for unobserved sources of stocks' differences in terms of risk analysis and volatility. Moreover, unlike other studies (Becchetti et al., 2015; Eccles et al., 2014), we did not focus on small caps, but considered medium and large capitalization companies, the issuers of the main assets in open-ended mutual funds. Large capitalization firms tend to be more sensitive to reputational risk given the potentially higher negative impact on their stock returns and volatility compared with small cap firms (Minor & Morgan, 2011; Mollet & Ziegler, 2014; Udayasankar, 2008). Consequently, large capitalization companies should be more motivated to apply ESG principles to receive a higher sustainability rating (Avetisyan & Hockerts, 2017; Morningstar, 2016a; Paul, 2017).

Given the nature of our study, data were collected from different sources. We obtained financial data from Datastream Thomson Reuters and Bloomberg databases. Datastream Thomson Reuters was used to collect data referring to the control variables in the analyses, and the Bloomberg database provided financial data, such as VaR and volatility, as well as credit ratings referring to each firm in the sample. On the other hand, ESG data, that is, a yearly ESG score for each firm in the sample, were collected from the ECPI Global Ethical Equity index (Romolini et al., 2014). ECPI evaluates ESG sustainability using a regulated approach that includes about 80 key performance indicators; it relies only on public information from issuers, specific data providers, and media sources. The evaluation assigns a maximum score of 120 points to ESG performance (up to 60 points for environmental performance and 60 points for social and governance performance). Each of these two macro-categories contains further areas on

TABLE 1 Sample description

ESG rating	2008	2009	2010	2011	2012	2013	2014	2015	Total by rating	CAGR
EEE	229	278	369	570	688	635	774	759	4302	16%
EEE-	189	255	291	280	314	279	337	332	2277	7%
EEE–	230	284	413	570	668	609	716	725	4215	15%
EE	254	270	284	336	328	317	368	368	2525	5%
EE-	211	240	268	406	502	464	536	529	3156	12%
EE–	142	134	128	113	101	105	110	118	951	−2%
E	12	14	7	8	11	8	10	11	81	−1%
F	47	46	48	62	68	62	76	80	489	7%
Region	2008	2009	2010	2011	2012	2013	2014	2015	Total by region	CAGR
Europe	521	542	582	671	708	637	737	738	5136	4%
North America	427	441	445	456	531	506	574	577	3957	4%
Asia	288	431	654	1007	1227	1153	1404	1402	7566	22%
Other Countries	78	107	127	211	214	183	212	205	1337	13%
Developing Countries	96	235	465	706	747	681	814	813	4557	31%
Developing Countries (%)	*7%*	*15%*	*26%*	*30%*	*28%*	*27%*	*28%*	*28%*	*25%*	
Industry	2008	2009	2010	2011	2012	2013	2014	2015	Total by industry	CAGR
Basic Materials	103	137	174	236	271	249	281	288	1739	14%
Communications	107	118	135	162	182	157	211	205	1277	8%
Consumer, Cyclical	180	201	244	323	384	351	453	441	2577	12%
Consumer, Non-cyclical	217	236	273	351	403	375	435	437	2727	9%
Diversified	15	17	26	41	32	35	33	32	231	10%
Energy	84	99	118	140	162	154	178	176	1111	10%
Financial	230	273	332	431	474	437	497	501	3175	10%
Industrial	239	275	325	429	503	473	541	537	3322	11%
Technology	61	68	76	107	125	118	148	151	854	12%
Utilities	78	97	105	125	144	130	150	154	983	9%
Total by year	1314	1521	1808	2345	2680	2479	2927	2922	17,996	11%
Key financials	2008	2009	2010	2011	2012	2013	2014	2015	Average	CAGR
Volatility (Ave.)	27.45	30.52	30.46	30.56	29.30	28.19	27.95	28.05	28.95	0%
Volatility (*SD*)	8.25	9.30	9.41	9.34	9.37	8.95	9.08	9.35	9.25	2%
Beta (Ave.)	1.06	1.12	1.03	1.04	1.04	0.98	0.97	1.01	1.02	−1%
Beta (SD)	0.55	0.67	0.45	0.43	0.55	0.56	0.50	0.65	0.55	2%
Total assets (Ave. USD Bln)	49.57	50.23	42.81	40.33	39.50	40.63	35.84	41.17	41.30	−2%

Note: N = 17,996.
Abbreviations: CAGR, compound annual growth rate.

which companies are judged. Within each area, several indicators are considered. The ESG score therefore ranges from EEE, which is "very good," to F, which is "insufficient." A description of our sample is provided in Table 1.

3.2 | Dependent variable: Volatility

The main aim of this study was to test the explanatory power of an ESG risk measure to predict the volatility of an investment, especially in the medium term. To measure *volatility*, we used the historical volatility of the securities in our sample, which is a statistical measure of the dispersion of returns for a given security or market index over a given period (Bams et al., 2017; Prokopczuk & Simen, 2014). We collected annual data on volatility from Bloomberg, where volatility is calculated by determining the deviation from the average return of a financial instrument and is measured as exponentially weighted daily volatility over a 1-year period.

3.3 | Predictor: Financial risk

In the first stage of the analysis, the direct relationship between the ex-ante financial risk associated with each equity in our sample and the ex-post volatility of the same asset was investigated. The financial risk was computed using VaR (Bali & Cakici, 2004; Berkowitz & O'Brien, 2002). Data were collected from Bloomberg for the equities in the sample, assuming a yearly value of VaR computed through a Monte Carlo simulation with a 99% level of confidence. Relying on Bloomberg computation of VaR, the variance is estimated using exponentially weighted moving averaging (EWMA) on historical factor data. As a robustness check of VaR as an explanatory variable for ex-post volatility, a 95% confidence level was also implemented, and results did not change.

3.4 | Interaction terms: Moderating effect of ESG risk and credit ratings on the relationship between VaR and volatility

ESG risk and *credit ratings* are investigated in this study as moderators of the relationship between the ex-ante financial risk and ex-post volatility of financial assets. Academic literature has discussed the specific relationship between ESG and credit rating, and provided evidence of statistically significant positive relationships, in terms of correlation between selected credit ratios and ESG factors (Schröder, 2014). In this study, these variables are thus treated independently as alternative factors able to predict the volatility of financial assets. Following established research (Zelner, 2009), we operationalized the interaction terms as a multiplicative interaction term to assess the effect of a variable x_1, conditional on the level of a second variable x_2; where, x_1 in our study is the ex-ante financial risk, measured through the VaR, and x_2 are the moderating variables, ESG risk, and credit ratings. The above interaction terms are expected to have an impact on the ex-post volatility, which is our dependent variable. Operationalization of both ESG risk and credit rating variables is detailed in the remainder of this section.

3.4.1 | ESG risk

To the best of our knowledge, no rigorous quantitative methodology to calculate ESG risk for financial assets, offering a statistical metric linked to an easy financial interpretation, exists in the literature. Both research and practice in the fields of management and SRI typically refer to ESG scores, which are not truly risk measures, because they are not statistical parameters with predictive power. ESG scores only assess the ESG quality (i.e., performance) of a firm and not its "risk" exposure at a certain time horizon and confidence level. Moreover, ESG scores are generally adjusted to ESG controversies, which are again indicators or reputational indices calculated not for financial risk purposes.

To overcome the above limits, we introduced an ESG risk measure relying on the concept of entropy, as studied by Shannon (1948). Shannon's model can be used to investigate stock market volatility in the entropic approach (Sheraz et al., 2015): entropy reaches the maximum value when all likely events have the same probability of occurrence. In other words, the entropy captures the overall linear and nonlinear dispersion patterns (volatility) observed in the data series.

To compute our measure of ESG risk, therefore, we relied on the concept of entropy (Shannon, 1948) as reported in Equation (1):

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

where p_i represented the distribution of the ESG scores of the firm securities' (p) frequency in a portfolio, and i was the number of classes ranging from 1 to n, where the scores ranged from >0 to 10. Assume the portfolio was represented by all the equities in the eligible universe in the year t (in our analysis, the eligible universe is our whole sample). Within this portfolio, we identified $n = 8$ classes, labeled from EEE (i.e., higher class) to F (lower class), according to the ESG scores assigned to equities in the sample, and the ranges were thus built as follows: [0;1), [1;3), [3;4), [4;5), [5;6), [6;7), [7;8), [8;10]. Consider the following example: a portfolio characterized by a broad dispersion in six classes (i.e., [3;4), [4;5), [5;6), [6;7), [7;8), [8;10]), respectively, 2, 3, 5, 30, 45, and 15%, reveals a measure of entropy (S_{ESGt} in Equation 1) of 1.34. On the other hand, a highly concentrated portfolio (e.g., 30, 50, and 20% in the last 3 classes, [6;7), [7;8), [8;10]) has a measure of entropy of 1.03. Thus, as presented in Equation (1) the entropy represents the disorder and randomness due to the portfolio's configurations in these classes based on the ESG score for the equities in the portfolio. On the one hand, it would be possible to apply deeper granularity and a higher number of classes of frequency, but we use just eight classes in this study for two main reasons: (a) In the distribution of the classes in our sample (Table 1), the last and last but two classes (F and EE−) contain more members than the E class, though E covers a double range compared to other classes; (b) The EEE class considers all the companies with a very high ESG score, so that in terms of true risk it is not relevant to have a more detailed breakdown by halving its range. On the other hand, the ESG score is a weighted average among different sub-scores (namely, ESG). Given the lack of a common and unique framework for defining and measuring ESG sub-scores within a portfolio, we calculate entropy using the ESG score as described above, therefore, increasing the generalizability of our measure.

We also introduced a corrective factor, the minimum j of each range (e.g., 8 for [8;10]), which made it possible to show that ESG risk at time t increases if an asset manager invests primarily in classes with low scores and decreases when higher ranges are more populated, as reported in Equation (2):

$$R_{ESG_t} = -\sum_{i=1}^{8}\left[p_i \log(p_i)\cdot\frac{1}{\min_{j\in i}(p_j)_i}\right] \tag{2}$$

For instance, a portfolio characterized by a strong concentration (e.g., 90%) in [4;5) is significantly riskier than another with the same percentage of securities belonging to [7;8). Compared to the weighted average of ESG scores, starting from single positions, because entropy is a measure of uncertainty, it is a good candidate to assess risk.[1]

Finally, we calculated the weighted average ESG risk associated with a portfolio including equities from a specific country (C) and industry (I) in our sample for each year t, where t ranged from 2007 to 2015, as shown in Equation (3)[2]:

$$R_{ESGt[C,I]} = \frac{\sum_{C=1}^{N}\sum_{I=1}^{N}\sum_{i=1}^{8}\left(p_i \log(p_i)\cdot\frac{1}{\min_{j\in i}(p_j)_i}\right)}{N_{C,I}} \tag{3}$$

Within the initial annual portfolio (t), we thus use a country/industry ESG risk score that measures the ESG risk level for the above portfolio, which we consider a sub-portfolio by country and sector as calculated in Equation 3. $R_{ESGt(C,I)}$ is a first approximation of a component R_{ESG} representing the contribution to the portfolio ESG risk of sub-portfolio C, I. Therefore, we define $R_{ESGt(C,I)}$ as the ESG risk associated with each equity belonging to portfolio C, I at time t. Unlike a traditional financial risk measure (i.e., VaR) depending on the correlations between securities, in the case of ESG risk (i.e., R_{ESG}) the link between securities is given by their contribution to the entropy within the portfolio, which is a non-linear relation. Due to the poor granularity of ESG factors, we can argue that entropy is the best representation of the links between equities in a portfolio.

3.4.2 | Credit ratings

This variable was created by collecting from the Bloomberg database the grade assigned to each firm by the three major rating agencies, Standard & Poor's, Moody's, and Fitch. As confirmed by Kliger and Sarig (2000), ratings contain valuable information and their presence is positively considered by investors (Sufi, 2007). It is worth highlighting how ratings from different agencies convey different information. Standard & Poor's primarily focuses on giving an opinion about the probability of default, whereas Moody's is more concerned with expected loss. In this research, ratings were incorporated to control for the risk of default; furthermore, following Ashbaugh-Skaife et al. (2006) and Oikonomou et al. (2014), the designated letter grades were collapsed into a 7-point scale, where 7 indicates the highest grade possible (AAA for Fitch and S&P, Aaa for Moody's).

3.5 | Control variables

Following the literature, we introduced several controls that might influence the volatility of financial assets. First, *firm size* affects stock market volatility (Cheung & Ng, 1992); we thus controlled for firm size, measured as the log of the total assets of the firm. Similarly, we controlled for the financial *solvency ratio* as a firm's long-term debt/equity ratio (Zarb, 2018). *Return on equity* (ROE) was also included in the analysis as a factor influencing investors' decisions and stock market volatility (Kryzanowski & Mohsni, 2015). We included a dummy variable to control for the organizational structure of firms in the sample (Ezzamel & Watson, 1993); it was coded one for *holding* companies and zero if the firm is an operating firm. We controlled for industry effects using Bloomberg's industry classification (*industry dummy variables*) for 10 industry categories; basic materials, communications, consumer, cyclical, consumer, non-cyclical, diversified, energy, financial, industrial, technology, and utilities; dummy "utilities" were considered to be the base value and were excluded from the regression models. We used a similar approach to control for the country/regional effects considering the geographical location of each firm in the sample (*country dummy variables*). We created four regional dummy variables: Asia, Europe, North America, and Other Countries. We used the other countries group as the base value. Lastly, we accounted for *temporal effects* by including year dummy variables. We collected key data related to the above control variables from different sources such as the Thomson DataStream database and Bloomberg.

3.6 | Estimation procedure

Because our study includes firm-year observations from 2007 to 2015, we ran population-averaged regression models and used generalized least squares (GLS) to control for firm heterogeneity. GLS is a technique for estimating the unknown parameters in a linear regression model when a certain degree of correlation exists between the residuals in a regression model. Our dependent variable is a continuous variable taking only non-negative values in a specific range. Given the structure of our dependent variable, GLS methodology offers better treatment for over-dispersion and serial correlation (Liang & Zeger, 1986), especially for a limited-range dependent variable. Moreover, in light of the issues typically associated with the use of an unbalanced panel of time series and cross-section, as an additional test we adopted an instrumental variable approach, performing a two-stage least squares estimation to predict our main independent variable (i.e., VaR) as a function of firm size, solvency ratio, ROE, holding structure, industry effect, country effect, and temporal effect at time *t*. Consistent with the continuous structure of the first-stage dependent variable, we performed a maximum likelihood estimation, while accounting for the panel structure of the data and correcting for autocorrelation using a first-order autoregressive process. Furthermore, we accounted for unobserved heterogeneity by including fixed-effects parameters and controlling for year dummies. To take serial correlation under control due to the use of a fixed-effect model, a bias-corrected Born and Breitung (2016) test was also performed to check if some serial correlation there might over the first order. In more detail, we settled at a second-order level the test for serial correlation, which reflected a 2-year possible serial correlation in the covariance matrix. Results of the test reported that data might be free of second-order serial correlation.

The results from this procedure showed that neither the regression coefficients nor the significance changed significantly compared with the results of the GLS estimation procedure. Therefore, we decided to report only the latter results. Here, we used population averaging to control for cross-sectional heterogeneity, because it allowed us to consider the nature of our dependent variable explicitly.

A hierarchical regression was used to build the regression models and test our hypotheses. Control variables were introduced in the first step, and predictor, moderators, and interaction terms in subsequent steps. The main equation testing the direct effect of our predictor (i.e., VaR) on the dependent variable (i.e., volatility) is presented in Equation (4).

$$\begin{aligned} \textit{volatility}_{t+n} = {} & a + b\cdot \textit{VaR}_t + c\cdot \textit{firm size}_t + d\cdot \textit{holding}_t + e\cdot \textit{solvency ratio}_t \\ & + f\cdot \textit{ROE}_t + g\cdot \textit{dummy year}_t + h\cdot \textit{dunmmy country}_t + i \\ & \cdot \textit{dummy industry}_t + \varepsilon \end{aligned} \tag{4}$$

The same equation is integrated with moderators and interaction terms to test the moderating effect of ESG risk and credit ratings on the above direct relationship. Equations are respectively presented in (5) and (6).

$$\begin{aligned} \text{volatility}_{t+n} = {} & a + b\cdot \text{VaR}_t + c\cdot \text{ESG risk}_t + d\cdot \text{Var}_t \times \text{ESG risk}_t + e \\ & \cdot \text{firm size}_t + f\cdot \text{holding}_t + g\cdot \text{solvency ratio}_t + h\cdot \text{ROE}_t + i \\ & \cdot \text{dummy year}_t + l\cdot \text{dunmmy country}_t + m \\ & \cdot \text{dummy industry}_t + \varepsilon \end{aligned} \tag{5}$$

$$\begin{aligned} \text{volatility}_{t+n} = {} & a + b\cdot \text{VaR}_t + c\cdot \text{credit rating}_t + d\cdot \text{Var}_t \times \text{credit rating}_t + e \\ & \cdot \text{firm size}_t + f\cdot \text{holding}_t + g\cdot \text{solvency ratio}_t + h\cdot \text{ROE}_t + i \\ & \cdot \text{dummy year}_t + l\cdot \text{dunmmy country}_t + m \\ & \cdot \text{dummy industry}_t + \varepsilon \end{aligned} \tag{6}$$

We were mindful of the potential for endogeneity in predicting the accuracy of volatility because of several factors such as expectations based on firm resources, performance, and industry conditions. To account for potential simultaneity bias, we paid significant attention to the appropriate lags between our independent and dependent variables. Given that it is simple to implement, lagging suspected variables is the most common approach to deal with potential endogeneity (Wooldridge, 2001). Therefore, we conducted a twofold analysis for the dependent variable, that is lagged by 1 year ($t + 1$) and by 3 years ($t + 3$) over the predictors and control variables. This analysis also allowed us to investigate the short- and medium-term impact of our predictors on the dependent variable.

We checked for potential multicollinearity in our independent variables in two ways. First, we assessed the variance inflation factors (VIF) by running ordinary least squares regressions; we found that none of the values exceeded the accepted maximum of 10 (Chatterjee & Price, 1991). Second, in running our models, we systematically deleted one independent variable at a time, checking whether this changed the sign or significance level of any of the key independent variables. Neither were affected, supporting our conclusion that multicollinearity had little impact on our analyses.

4 | RESULTS

Table 2 shows the descriptive statistics and correlations for our variables.

Tables 3 shows the results of the regression analyses. Following the hierarchical regression approach described above, we introduced the control variables on the ex-post volatility at $t + 1$ and $t + 3$, in Model 1 and Model 2, respectively. The predictors were then included in the analysis (see Models 3–8 in Table 3).

In the first part of the analysis, we tested the direct forecasting power of VaR on the ex-post volatility. According to Hypothesis 1, financial assets with a higher ex-ante financial risk of losses reveal higher ex-post volatility. The results show a positive strongly significant ($p < 0.001$) relationship, confirming Hypothesis 1, in both the short- (Model 3, at $t + 1$) and medium-term (Model 4, at $t + 3$).

In the second part of the analysis, the moderating effects of ESG risk and credit ratings were introduced into the above direct relationship between ex-ante financial risk and ex-post volatility of financial assets. In more detail, Hypothesis 2 predicted the negative moderating effect of ESG risk, improving the forecasting power of ex-ante financial risk on the ex-post volatility. Results offer empirical evidence of the predicted relationship in the medium-term ($t + 3$), where a negative and statistically significant ($p < 0.05$) relationship was found (Model 6). Hypothesis 2 finds support in the medium-term but is not confirmed in the short-term. Next, shifting to the predicted negative moderating effect of credit ratings on the ex-ante/ex-post relationship between financial risk and volatility, H3 does not find support in either the short- (Model 7) or medium-term (Model 8). Although the interaction term between VaR and credit ratings is statistically significant over both terms ($p < 0.05$ for the short term and $p < 0.001$ for the medium term), the coefficient is positive, thereby contradicting the predicted effect.

TABLE 2 Descriptive statistics and correlations

	Variable	Mean	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Firm size	15.73	1.78																				
2	Solvency ratio	125.82	1.876.90	0.04**																			
3	ROE	10.36	150.65	0.01	−0.04**																		
4	Holding	0.07	0.25	0	0	0																	
5	Europe	0.29	0.45	0.05**	0.02**	−0.02*	−0.07**																
6	North America	0.22	0.41	0.11**	−0.01	0.03**	−0.1**	−0.34**															
7	Asia	0.42	0.49	−0.14**	−0.01	0	0.13**	−0.54**	−0.45**														
8	Other regions	0.07	0.26	0.02*	0	0	0.02*	−0.18**	−0.15**	−0.24**													
9	Basic Materials	0.10	0.30	−0.06**	−0.01	−0.01	−0.02**	−0.05**	−0.05**	0.04**	0.09**												
10	Communication	0.07	0.26	−0.04**	0	0.01	−0.01	0.06**	−0.01	−0.06**	0.01	−0.09**											
11	Consumer, cyclical	0.14	0.35	−0.08**	−0.02*	0	0.04**	−0.03**	−0.01	0.06**	−0.04**	−0.13**	−0.11**										
12	Consumer, non-cyclical	0.15	0.36	−0.13**	−0.01	0.04**	0.01	0.02**	0.04**	−0.05**	−0.01	−0.14**	−0.12**	−0.17**									
13	Other industries	0.06	0.24	−0.09**	0	0	0	−0.05**	0.05**	0.02*	−0.03**	−0.08**	−0.07**	−0.1**	−0.11**								
14	Energy	0.06	0.24	0.04**	0	−0.01	−0.04**	0.01	0.06**	−0.05**	−0.02*	−0.08**	−0.07**	−0.1**	−0.11**	−0.07**							
15	Financial	0.18	0.38	0.4**	0.02**	−0.02*	0.07**	0.03**	−0.03**	−0.02**	0.04**	−0.15**	−0.13**	−0.19**	−0.2**	−0.12**	−0.12**						
16	Industrial	0.18	0.39	−0.12**	0.01	−0.01	−0.04**	−0.01	−0.02**	0.06**	−0.07**	−0.16**	−0.13**	−0.19**	−0.2**	−0.12**	−0.12**	−0.22**					
17	Utilities	0.05	0.23	0.05**	0.01	0	−0.03**	0.03**	0	−0.05**	0.04**	−0.08**	−0.07**	−0.1**	−0.1**	−0.06**	−0.06**	−0.11**	−0.11**				
18	VaR	2.13	0.66	0.05**	−0.01	0.01	−0.02**	0.06**	0.06**	−0.09**	−0.02*	−0.01	0.01	−0.01	0.01	0	0	0	0	0.01			
19	ESG risk	30.93	11.85	−0.1**	−0.01	0.01	−0.02**	−0.36**	0.25**	0.19**	−0.15**	−0.06**	−0.09**	0.01	0.1**	0.02**	−0.02**	−0.03**	0.08**	−0.09**	−0.1**		
20	Credit rating	4.27	0.99	0.42**	0	0.06**	−0.02*	−0.03*	0	0.09**	−0.09**	−0.09**	−0.04**	−0.13**	0.04**	0.04**	−0.02	0.16**	−0.03**	0.02	0.09**	0.04**	
21	Volatility	28.52	9.06	−0.31**	0	−0.08**	0	−0.1**	−0.14**	0.22**	−0.03**	0.16**	−0.04**	0.06**	−0.19**	0.05**	0.07**	0	0.06**	−0.17**	0	0.04**	−0.53**

Note: This table shows the correlation matrix between the variables included in the regression models and the dependent variable—volatility—which is measured at a firm level as exponentially weighted daily volatility over a 1-year period. The control variables are included first: the *firm size*, the financial *solvency ratio*, the profitability ratio measured by the return on equity (ROE), the organizational structure of firms in the sample by a dummy variable coded one for holding companies and zero if the firm is an operating firm; the industry effects, the country/regional effects, and the temporal effects are also included in the models through dummy variables. Then, the predictor is included: Value-at-Risk (VaR) estimated at a firm level using exponentially weighted moving averaging (EWMA) on historical factor data. Last, the moderating variables are: the environmental, social, and governance (ESG) risk, based on the measure of entropy presented in this study; the credit rating, based on the three major rating agencies, Standard & Poor's, Moody's, and Fitch, is a 7-point scale, where 7 indicates the highest grade possible (AAA for Fitch and S&P, Aaa for Moody's). Asterisks denote significance at: $^{**}p < 0.01$; $^{*}p < 0.05$.

TABLE 3 Results of the regression analyses: Forecasting volatility

	Model 1 ($t+1$)	Model 2 ($t+3$)	Model 3 ($t+1$)	Model 4 ($t+3$)	Model 5 ($t+1$)	Model 6 ($t+3$)	Model 7 ($t+1$)	Model 8 ($t+3$)
Constant	45.06***	43.19***	46.38***	45.18***	46.01***	42.55***	34.14***	34.41***
Firm size	−1.67***	−1.65***	−1.77***	−1.60***	−1.76***	−1.58***	0.23***	0.43***
Solvency ratio	0.01	0.01	0.01	0.01	0.01	0.01*	0.01	0.01
ROE	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01**
Holding	−1.02**	−1.03**	−1.07***	−1.03***	−1.21***	−1.27***	−0.37	−0.90*
Dummy industry	*Included*							
Dummy country	*Included*							
Dummy year	*Included*							
VaR			1.75***	0.65***	1.57***	1.39***	1.52***	−0.36***
ESG risk					0.01	0.08***		
VaR × ESG risk					0.01	−0.02**		
Credit rating							−5.32***	−5.85***
VaR × Credit rating							0.28**	0.53***
Wald Chi^2	4013.44	3863.42	4002.69	2457.99	3929.37	2473.56	5073.87	3142.24
R^2	0.26	0.24	0.25	0.25	0.26	0.26	0.46	0.45
$p <$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
N	12,116	7454	12,116	7454	11,429	7012	5931	3880

Note: The regressions are population-averaged regression models and Generalized Least Squares (GLS) models are used to control for asset heterogeneity. The table reports results referring to the determinants of ex-post volatility both in the short- ($t+1$) and medium-term ($t+3$), by lagging the dependent variable respectively of 1 and 3 years. Volatility is measured at a firm level as exponentially weighted daily volatility over a 1-year period. The predicting variable is the Value-at-Risk (VaR) estimated at a firm level using exponentially weighted moving averaging (EWMA) on historical factor data. The moderating variables are: the environmental, social, and governance (ESG) risk, based on the measure of entropy presented in this study; the credit rating, based on the three major rating agencies, Standard & Poor's, Moody's, and Fitch, is a 7-point scale, where 7 indicates the highest grade possible (AAA for Fitch and S&P, Aaa for Moody's). The control variables are: the *firm size*, measured as the log of the total assets of the firm; the financial *solvency ratio* measured as a firm's long-term debt/equity ratio; the profitability ratio measured by the return on equity (ROE); the organizational structure of firms in the sample by a dummy variable coded one for holding companies and zero if the firm is an operating firm; the industry effects, the country/regional effects, and the temporal effects are also included in the models through dummy variables. Asterisks denote significance at: ***$p < 0.001$; **$p < 0.05$; *$p < 0.10$.

Finally, some of the control variables included in the analysis show an interesting effect on the dependent variable. ROE and holding variables have a negative impact on ex-post volatility. This suggests that holding companies and companies with a lower level of ROE experience higher volatility, which might have a risky effect on the volatility of stocks issued by firms with such characteristics. On the other hand, firm size reveals a conflicting effect. A negative and significant effect is found on ex-post volatility when the direct effect of VaR, and the moderating effect of ESG risk, are tested. This effect shifts to positive and significant when the moderating effect of credit ratings is tested on ex-post volatility, aligning our results to prior research and suggesting that large capitalization companies should apply ESG principles to receive a higher sustainability rating (Avetisyan & Hockerts, 2017; Morningstar, 2016a; Paul, 2017).

5 | DISCUSSION AND CONCLUSION

This study examined whether the ESG risk of assets improves the forecasting effectiveness of traditional financial measures of volatility. With this aim in mind, we introduced a measure of ESG risk based on the concept of entropy studied by Shannon (1948), assuming that entropy can be used to capture asset volatility (Sheraz et al., 2015). The measure incorporates the dispersion of ESG scores within a country, sector and time period. Empirical results offer evidence of the validity of our new measure of ESG risk. We estimated the relationship between the ex-ante financial risk of assets and the ex-post volatility and found that our ESG risk measure was significant for 3-year forecasts although not for 1 year. ESG risk increased the volatility at this horizon more for low volatility portfolios than high volatility portfolios.

Similarly, we tested the effect of traditional credit ratings on the same relationship between the ex-ante financial risk of assets and the ex-post volatility. Higher credit ratings reduce the volatility at both horizons and the effect is stronger for low volatility portfolios.

Credit ratings are generally considered to be a tool for predicting the ability of an organization to pay back its obligations as well as forecasting the likelihood of its survival. However, as well as measuring the creditworthiness of a company, credit ratings can also be related to a firm's risk in general, which can affect the standard deviation of stock returns. Therefore, we are not surprised to find that credit ratings reduce the volatility of assets. The same logic applies to ESG risk metrics.

The results of this study make an interesting contribution to both theory and practice in the fields of asset management and SRI, and should help investment companies and financial investors navigate the complex landscape of ESG using a measure of ESG risk that affects the volatility of assets in financial portfolios.

The findings of the present study are directly relevant for asset managers of investment funds, such as mutual funds or pension funds, to improve VaR performance.

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ENDNOTES

[1] Strictly speaking, both real entropy, S_{ESG} in Equation (1), and ESG risk, R_{ESG} in Equation (2), are zero if the allocation is 100% concentrated in one class (where $\log(1) = 0$); but this is extremely improbable for a standard fund. A more realistic representation would see 60% in a higher ESG range and 40% in another; if the latter is, for example, [3;4) instead of [6;7), the ESG risk value would be higher.

[2] Technically, to decompose ESG risk into the country and industry contributions, we have to use component R_{ESG} or CR_{ESG}. For each risk class, CR_{ESG0} is given by $CR_{ESG_0} = x_0 \cdot \log(freq) \cdot \frac{1}{s}$, where s is the risk class minimum, x_0 is its weight in the portfolio (given by its capitalization in percentage with respect to total sum of firms' capitalization in the sample), and $\text{freq} = x_0 + \sum_{j=1}^{N-1} x_j$, if there are other N names (with an $N-1$ x_j weight) in the risk class. We can aggregate all the CR_{ESG} values for the country and industry contributions. However, we adopt Equation (3) to provide an early idea of these contributions.

REFERENCES

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International economic review*, *39*(4), 885–905.

Angelidis, T., & Degiannakis, S. (2008). Volatility forecasting: Intra-day versus inter-day models. *Journal of International Financial Markets, Institutions and Money*, *18*(5), 449–465.

Ashbaugh-Skaife, H., Collins, D. W., & LaFond, R. (2006). The effects of corporate governance on firms' credit ratings. *Journal of Accounting and Economics*, *42*(1–2), 203–243.

Attig, N., El Ghoul, S., Guedhami, O., & Suh, J. (2013). Corporate social responsibility and credit ratings. *Journal of Business Ethics*, *117*(4), 679–694.

Avetisyan, E., & Hockerts, K. (2017). The consolidation of the ESG rating industry as an enactment of institutional retrogression. *Business Strategy and the Environment*, *26*(3), 316–330.

Bae, S. C., Chang, K., & Yi, H.-C. (2018). Corporate social responsibility, credit rating, and private debt contracting: New evidence from syndicated loan market. *Review of Quantitative Finance and Accounting*, *50*(1), 261–299.

Bali, T. G., & Cakici, N. (2004). Value at risk and expected stock returns. *Financial Analysts Journal*, *60*(2), 57–73. https://doi.org/10.2469/faj.v60.n2.2610

Bams, D., Blanchard, G., & Lehnert, T. (2017). Volatility measures and value-at-risk. *International Journal of Forecasting*, *33*(4), 848–863.

Bams, D., Lehnert, T., & Wolff, C. C. (2005). An evaluation framework for alternative VaR-models. *Journal of International Money and Finance*, *24*(6), 944–958.

BCBS. (1996). *Amendment to the capital accord to incorporate market risks*. https://www.bis.org/publ/bcbs24.htm.

BCBS III. (2017). *Finalizing post-crisis reforms*. https://www.bis.org/bcbs/publ/d424.htm.

Becchetti, L., Ciciretti, R., & Dalò, A. (2018). Fishing the corporate social responsibility risk factors. *Journal of Financial Stability*, *37*, 25–48.

Becchetti, L., Ciciretti, R., & Hasan, I. (2015). Corporate social responsibility, stakeholder risk, and idiosyncratic volatility. *Journal of Corporate Finance*, *35*, 297–309.

Bera, A. K., & Park, S. Y. (2008). Optimal portfolio diversification using the maximum entropy principle. *Econometric Reviews*, *27*(4–6), 484–512.

Berkowitz, J., & O'Brien, J. (2002). How accurate are value-at-risk models at commercial banks? *Journal of Finance*, *57*(3), 1093–1111. https://doi.org/10.1111/1540-6261.00455

Bloomberg. (2015). *Portfolio value-at-risk*

Bollen, N. P. (2007). Mutual fund attributes and investor behavior. *Journal of Financial and Quantitative Analysis*, *42*(3), 683–708.

Born, B., & Breitung, J. (2016). Testing for serial correlation in fixed-effects panel data models. *Econometric Reviews*, *35*(7), 1290–1316. https://doi.org/10.1080/07474938.2014.976524

Boutin-Dufresne, F., & Savaria, P. (2004). Corporate social responsibility and financial risk. *The Journal of Investing*, *13*(1), 57–66.

Brillouin, L. (1953). The negentropy principle of information. *Journal of Applied Physics*, *24*(9), 1152–1163.

Brogi, M., & Lagasio, V. (2019). Environmental, social, and governance and company profitability: Are financial intermediaries different? *Corporate Social Responsibility and Environmental Management*, *26*(3), 576–587.

Brooks, C., & Persand, G. (2003). Volatility forecasting for risk management. *Journal of Forecasting*, *22*(1), 1–22.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82.

Chatterjee, S., & Price, B. (1991). *Regression analysis by example*. Wiley.

Chatterji, A. K., Levine, D. I., & Toffel, M. W. (2009). How well do social ratings actually measure corporate social responsibility? *Journal of Economics & Management Strategy*, *18*(1), 125–169.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, *60*(9), 2223–2247.

Cheung, Y.-W., & Ng, L. K. (1992). Stock price dynamics and firm size: An empirical investigation. *The Journal of Finance*, *47*, 1985–1997. https://doi.org/10.1111/j.1540-6261.1992.tb04693.x

de Haan, M., Dam, L., & Scholtens, B. (2012). The drivers of the relationship between corporate environmental performance and stock market returns. *Journal of Sustainable Finance & Investment*, *2*(3–4), 338–375.

Degiannakis, S., Floros, C., & Dent, P. (2013). Forecasting value-at-risk and expected shortfall using fractionally integrated models of conditional volatility: International evidence. *International Review of Financial Analysis*, *27*, 21–33.

Dimson, E., Karakaş, O., & Li, X. (2015). Active ownership. *The Review of Financial Studies*, *28*(12), 3225–3268.

Eccles, R. G., Ioannou, I., & Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance. *Management Science*, *60*(11), 2835–2857.

El Ghoul, S., Guedhami, O., Kim, H., & Park, K. (2018). Corporate environmental responsibility and the cost of capital: International evidence. *Journal of Business Ethics*, *149*(2), 335–361.

El Ghoul, S., Guedhami, O., Kwok, C. C., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance*, *35*(9), 2388–2406.

Engle, R. F. (2004). Risk and volatility: Econometric models and financial practice. *American Economic Review*, *94*(3), 405–420.

Engle, R. L. (2007). Corporate social responsibility in host countries: A perspective from American managers. *Corporate Social Responsibility and Environmental Management*, *14*(1), 16–27.

Eurosif. (2018). European SRI study

Ezzamel, M., & Watson, R. (1993). Organizational form, ownership structure and corporate performance: A contextual empirical analysis of UK companies. *British Journal of Management*, *4*(3), 161–176. https://doi.org/10.1111/j.1467-8551.1993.tb00056.x

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56.

Fama, E. F., & French, K. R. (2017). International tests of a five-factor asset pricing model. *Journal of Financial Economics*, *123*(3), 441–463.

Filipe, S. F., Grammatikos, T., & Michala, D. (2016). Pricing default risk: The good, the bad, and the anomaly. *Journal of Financial Stability*, *26*, 190–213.

Flammer, C. (2013). Corporate social responsibility and shareholder reaction: The environmental awareness of investors. *Academy of Management Journal*, *56*(3), 758–781.

Freeman, E. R. (1984). *Strategic management: A stakeholder approach*. Pitman.

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, *5*(4), 210–233.

Giot, P., & Laurent, S. (2004). Modelling daily value-at-risk using realized volatility and ARCH type models. *Journal of Empirical Finance*, *11*(3), 379–398.

González Sánchez, M., & Morales de Vega, M. E. (2018). Corporate reputation and firms' performance: Evidence from Spain. *Corporate Social Responsibility & Environmental Management*, *25*(6), 1231–1245. https://doi.org/10.1002/csr.1634

Goss, A., & Roberts, G. S. (2011). The impact of corporate social responsibility on the cost of bank loans. *Journal of Banking & Finance*, *35*(7), 1794–1810.

GSIA. (2016). *Global sustainable investment review*. http://www.gsi-alliance.org/wp-content/uploads/2017/03/GSIR_Review2016.F.pdf.

Huang, X. (2008). Mean-entropy models for fuzzy portfolio selection. *IEEE Transactions on Fuzzy Systems*, *16*(4), 1096–1101.

Hull, J., Predescu, M., & White, A. (2004). The relationship between credit default swap spreads, bond yields, and credit rating announcements. *Journal of Banking & Finance*, *28*(11), 2789–2811.

Humphrey, J. E., & Lee, D. D. (2012). Australian socially responsible funds: Performance, risk and screening intensity. *Journal of Business Ethics*, *102*(1), 519–535.

Jayne, M. R., & Skerratt, G. (2003). Socially responsible investment in the UK—Criteria that are used to evaluate suitability. *Corporate Social Responsibility & Environmental Management*, *10*(1), 1–11. https://doi.org/10.1002/csr.25

Jiraporn, P., Jiraporn, N., Boeprasert, A., & Chang, K. (2014). Does corporate social responsibility (CSR) improve credit ratings? Evidence from geographic identification. *Financial Management*, *43*(3), 505–531.

Jorion, P. (2001). *The new benchmark for managing financial risk: Value at risk*. McGraw Hill.

Khan, S., & Bradbury, M. E. (2016). The volatility of comprehensive income and its association with market risk. *Accounting & Finance*, *56*(3), 727–748.

Kim, Y., Li, H., & Li, S. (2014). Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance*, *43*, 1–13.

Kliger, D., & Sarig, O. (2000). The information value of bond ratings. *The Journal of Finance*, *55*(6), 2879–2902.

Kölbel, J. F., Busch, T., & Jancso, L. M. (2017). How media coverage of corporate social irresponsibility increases financial risk. *Strategic Management Journal*, *38*(11), 2266–2284.

Koopman, S. J., Jungbacker, B., & Hol, E. (2005). Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance*, *12*(3), 445–475.

Kotsantonis, S., Pinney, C., & Serafeim, G. (2016). ESG integration in investment management: Myths and realities. *Journal of Applied Corporate Finance*, *28*(2), 10–16.

KPMG. (2016). European responsible investing fund market

Kryzanowski, L., & Mohsni, S. (2015). Earnings forecasts and idiosyncratic volatilities. *International Review of Financial Analysis*, *41*, 107–123. https://doi.org/10.1016/j.irfa.2015.06.001

Lagasio, V., & Cucari, N. (2019). Corporate governance and environmental social governance disclosure: A meta-analytical review. *Corporate Social Responsibility and Environmental Management*, *26*(4), 701–711.

Liang, K.-Y., & Zeger, S. L. (1986). Longitudinal data analysis using generalized linear models. *Biometrika*, *73*(1), 13–22.

Lins, K. V., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, *72*(4), 1785–1824.

Lo, K. Y., & Kwan, C. L. (2017). The effect of environmental, social, governance and sustainability initiatives on stock value—Examining market response to initiatives undertaken by listed companies. *Corporate Social Responsibility and Environmental Management*, *24*(6), 606–619.

Louzis, D. P., Xanthopoulos-Sisinis, S., & Refenes, A. P. (2014). Realized volatility models and alternative value-at-risk prediction strategies. *Economic Modelling*, *40*, 101–116.

Luo, H. A., & Balvers, R. J. (2017). Social screens and systematic investor boycott risk. *Journal of Financial and Quantitative Analysis*, *52*(1), 365–399.

McCormick, R. (2010). *Legal risk in the financial markets*. Oxford University Press.

Meucci, A. (2009). *Risk and asset allocation*. Springer Science & Business Media.

Michaelides, E. E. (2008). Entropy, order and disorder. *The Open Thermodynamics Journal*, *2*(1), 7–11.

Minor, D., & Morgan, J. (2011). CSR as reputation insurance: Primum non nocere. *California Management Review*, *53*(3), 40–59.

Mollet, J. C., & Ziegler, A. (2014). Socially responsible investing and stock performance: New empirical evidence for the US and European stock markets. *Review of Financial Economics*, *23*(4), 208–216.

Moody's. (2015). *Moody's approach to assessing ESG in credit analysis*. https://www.moodys.com/sites/products/ProductAttachments/ESG-considerations-on-credit-analysis.pdf?WT.z_referringsource=TB~ESGhub~ESGconsiderations.

Morgan, J. P., & Reuters. (1996). *RiskMetricsTM—Technical document*. https://www.msci.com/documents/10199/5915b101-4206-4ba0-aee2-3449d5c7e95a.

Morningstar. (2016a). *Morningstar sustainability rating*. Morningstar. https://www.morningstar.com/content/dam/marketing/shared/research/methodology/744156_Morningstar_Sustainability_Rating_for_Funds_Methodology.pdf

Morningstar. (2016b). *The Morningstar sustainable investing handbook*. Morningstar. https://www.morningstar.com/content/dam/marketing/shared/Company/Trends/Sustainability/Detail/Documents/Morningstar-Sustainable-Investing-Handbook.pdf

Nieto, M. R., & Ruiz, E. (2016). Frontiers in VaR forecasting and backtesting. *International Journal of Forecasting*, *32*(2), 475–501.

Nofsinger, J., & Varma, A. (2014). Socially responsible funds and market crises. *Journal of Banking & Finance*, *48*, 180–193.

Norden, L., & Weber, M. (2004). Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements. *Journal of Banking & Finance*, *28*(11), 2813–2843.

Oikonomou, I., Brooks, C., & Pavelin, S. (2014). The effects of corporate social performance on the cost of corporate debt and credit ratings. *Financial Review*, *49*(1), 49–75.

Paul, K. (2017). The effect of business cycle, market return and momentum on financial performance of socially responsible investing mutual funds. *Social Responsibility Journal*, *13*(3), 513–528.

Poon, S.-H., & Granger, C. W. (2003). Forecasting volatility in financial markets: A review. *Journal of Economic Literature*, *41*(2), 478–539.

PRI. (2016). *PRI practical guide to ESG integration for equity investing*
PRI. (2017). Shifting perceptions: ESG credit risk and ratings wins big at Savvy Investor Awards
Prokopczuk, M., & Simen, C. W. (2014). The importance of the volatility risk premium for volatility forecasting. *Journal of Banking & Finance*, *40*, 303–320.
Renneboog, L., Ter Horst, J., & Zhang, C. (2008). Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of Banking & Finance*, *32*(9), 1723–1742.
Romolini, A., Fissi, S., & Gori, E. (2014). Scoring CSR reporting in listed companies—Evidence from Italian best practices. *Corporate Social Responsibility & Environmental Management*, *21*(2), 65–81. https://doi.org/10.1002/csr.1299
Russo, A., Marriani, M., & Perrini, F. (2016). Cherry picking or depth-oriented strategic investing? evidence from sri activity. *International Journal of Business and Management*, *11*(11), 13–25.
S&P. (2015). *How Environmental and Climate Risks and Opportunities Factor Into Global Corporate Ratings - An Update*
S&P. (2016). *ESG in Credit Ratings*
S&P. (2017). *How S&P Global Ratings would assess European 'Safe' bonds (ESBies)*
Scalet, S., & Kelly, T. F. (2010). CSR rating agencies: What is their global impact? *Journal of Business Ethics*, *94*(1), 69–88.
Schröder, M. (2014). Financial effects of corporate social responsibility: A literature review. *Journal of Sustainable Finance & Investment*, *4*(4), 337–350.
Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, *27*(3), 379–423.
Sheraz, M., Dedu, S., & Preda, V. (2015). Entropy measures for assessing volatile markets. *Procedia Economics and Finance*, *22*, 655–662.
Sufi, A. (2007). The real effects of debt certification: Evidence from the introduction of bank loan ratings. *The Review of Financial Studies*, *22*(4), 1659–1691.
Trinks, P. J., & Scholtens, B. (2017). The opportunity cost of negative screening in socially responsible investing. *Journal of Business Ethics*, *140*(2), 193–208.
Udayasankar, K. (2008). Corporate social responsibility and firm size. *Journal of Business Ethics*, *83*(2), 167–175.
Verheyden, T., Eccles, R. G., & Feiner, A. (2016). ESG for all? The impact of ESG screening on return, risk, and diversification. *Journal of Applied Corporate Finance*, *28*(2), 47–55.
Waddock, S., & Graves, S. B. (1997). The corporate social performance—Financial performance link. *Strategic Management Journal*, *18*(4), 303–319.
Wooldridge, J. M. (2001). *Econometric analysis of cross section and panel data* (5th ed.). MIT Press.
World Economic Forum. (2021). *The Global Risks Report 16th Edition*
Xie, J., Nozawa, W., Yagi, M., Fujii, H., & Managi, S. (2019). Do environmental, social, and governance activities improve corporate financial performance? *Business Strategy and the Environment*, *28*(2), 286–300.
Young, S., & Thyil, V. (2014). Corporate social responsibility and corporate governance: Role of context in international settings. *Journal of Business Ethics*, *122*(1), 1–24.
Zarb, B. J. (2018). Liquidity, solvency, and financial health: Do they have an impact on U.S. Airline Companies' Profit Volatility? *International Journal of Business, Accounting, & Finance*, *12*(1), 42–51.
Zelner, B. A. (2009). Using simulation to interpret results from logit, probit, and other nonlinear models. *Strategic Management Journal*, *30*, 1335–1348. https://doi.org/10.1002/smj.783
Zhou, R., Cai, R., & Tong, G. (2013). Applications of entropy in finance: A review. *Entropy*, *15*(11), 4909–4931.

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