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Corporate social performance as a market force: Analysing its impact on stocks' tail risk and upside potential in the Spanish equity market

El desempeño social corporativo como fuerza de mercado: Análisis de su impacto sobre el riesgo de cola y el potencial alcista en el mercado continuo español

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ABSTRACT

This study examines the impact of corporate social performance (CSP) and its subdimensions (workforce, human rights, community, and product responsibility) on firms' tail risk and upside potential in the Spanish stock market. Focusing on the period from 2014 to 2021, annual corporate financial performance (CFP) metrics were computed through filtered historical simulation (FHS), a semiparametric approach based on Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models and bootstrapping. This approach allows the main stylized facts of stock returns (i.e., autocorrelation, volatility clusters, and heavy tails) to be accounted for and, at the same time, firms' financial performance to be computed from the simulated distribution. The main findings reveal a complex time-dependent connection between CSP and its subdimensions and firms' tail risk and upside potential. In fact, while CSP reduces tail risk in the short term, it increases maximum loss in the long term. Interestingly, the results do not provide any evidence of the existence of a risk–return trade-off effect. Finally, the study highlights the need to monitor specific CSP subdimensions such as human rights and community, since they entail higher tail risk and lower upside potential.

Keywords: Corporate social performance, Tail risk, Upside potential, Filtered historical simulation.

RESUMEN

Este estudio analiza el impacto del desempeño social corporativo (DSP) y sus subdimensiones (empleo, derechos humanos, comunidades locales, responsabilidad sobre productos) sobre el riesgo de cola y el potencial alcista en el mercado continuo español, durante el periodo 2014-2021. Las métricas de desempeño financiero han sido estimadas mediante simulación historical filtrada, un método semi paramétrico que combina modelos de heterocedasticidad condicional y remuestreo aleatorio con repetición. Esté método permite estimar la distribución empírica de las rentabilidades, considerando sus características principales (i.e., autocorrelación, clústeres de volatilidad y colas pesadas). Los resultados revelan una compleja dependencia temporal entre el DSP y sus subdimensiones y el desempeño financiero, medido por el riesgo de cola y el potencial alcista. Mientras que el DSP reduciría el riesgo de cola a corto plazo, generaría un aumento de la perdida máxima a largo plazo. Asimismo, los resultados no muestran evidencia empírica respecto a una compensación entre la rentabilidad y el riesgo. Finalmente, este estudio subraya la relevancia de analizar el efecto específico de subdimensiones como los derechos humanos o las comunidades locales, dado que parecen conllevar un mayor riesgo de cola y un menor potencial alcista.

Palabras clave: Desempeño social corporativo, Riesgo bajista, Potencial alcista, Simulación histórica filtrada.

1. INTRODUCTION

Socially responsible investment (SRI) plays a relevant role in the transition towards sustainable development, given its potential to influence the behaviour of companies (Widyawati, 2020). SRI strategies have evolved from more basic approaches, such as negative screening, to more sophisticated ones, like impact investing (Folqué *et al.*, 2021). In this context, attention to environmental, social and governance (ESG) factors affects the various stages of the investment process, starting with asset allocation (De Giuli *et al.*, 2024). Therefore, it appears highly relevant that different stakeholders, namely investors (both institutional and retail), policymakers and academics, fully comprehend the effect of ESG factors on the financial performance (FP) of investments (Cunha *et al.*, 2020).

The effect of ESG performance on the FP of stocks has mainly been analysed by considering the risk–return paradigm (Widyawati, 2020). However, the impact of firms' ESG performance on the risk of their stocks has recently gained attention in the scholarly literature. In this research area, empirical evidence often shows contradictory and mixed results (Bruna & Lahouel, 2022; Pistolesi & Teti, 2024; Rouine *et al.*, 2022). Papers refer to different theoretical frameworks to motivate their working hypotheses and when discussing their results. In summary, stakeholder theory and signalling theory appear to support an inverse relationship between ESG performance and risk (Diemont *et al.*, 2016; Wu & Hu, 2019). Nevertheless, according to agency theory, if high ESG performance is not perceived as genuine it may lead to higher risk (Landi *et al.*, 2022). Other authors go beyond the linear paradigm and propose a quadratic relationship (Korinth & Lueg, 2022; Pistolesi & Teti, 2024).

Most studies focus on classical risk metrics (i.e., overall, systematic, and idiosyncratic risk), and only a few analyse the effect of ESG performance on tail risk (Bax *et al.*, 2023; Diemont *et al.*, 2016; Lööf *et al.*, 2022; Viviani *et al.*, 2019; Zhang *et al.*, 2023). Tail risk reflects the maximum expected loss over a period, associated with a given probability. According to Diemont *et al.* (2016), "even minor variations in the VaR [Value at Risk] in terms of percentages can have great impact on the monetary value" (p. 228). Therefore, understanding the effect of ESG performance on tail risk may be relevant. The available empirical evidence highlights some aspects that may enable a proper understanding of this relationship. First, it appears to be highly relevant to analyse the effect of ESG performance at the disaggregated level. The findings of Diemont *et al.* (2016) reveal that the effect of corporate social responsibility (CSR) on tail risk varies with the different subdimensions. Secondly, ESG performance may affect tail risk in both the short and the long term (Lööf *et al.*, 2022). Finally, the nature of this relationship appears to depend on the ESG-awareness level (Zhang *et al.*, 2023), the expectations of investors (Diemont *et al.*, 2016), and the regulatory environment (Brooks & Oikonomou, 2018). The empirical analysis of a concrete market may provide valuable insights.

It may also be relevant to assess whether the risk–return trade-off holds in the case of ESG. Some authors argue that, in a market in equilibrium, stocks with high ESG performance may yield lower returns because the risk is perceived to be lower (Luo, 2022). Conversely, other scholars consider that, under the weak version of the efficient market hypothesis, taking ESG reporting into account may lead to higher returns (Ni & Sun, 2023). The integration of these two opposite views is proposed in the literature, by considering the existence of a transition period in which increasing ESG concerns and investor preferences provide superior returns on stocks with high ESG performance (Cornell, 2021; Pástor *et al.*, 2022).

This study focuses on the effect of corporate social performance (CSP) and its subdimensions (workforce, human rights, community, and product responsibility) on stocks' tail risk and upside potential. The focus is placed on the social dimension of ESG performance since most of the subdimensions of CSP are targeted at primary stakeholders (Dumitrescu & Zakriya, 2021). An empirical analysis is conducted in the Spanish stock market for the period 2014-2021. Tail risk and upside potential metrics are estimated through the filtered historical simulation (FHS) method. Likewise, the correlated random effects (CRE) approach is used to analyse the effects of CSP on tail risk and upside potential. This paper contributes to the literature in three ways. First, FP metrics that consider features of stock returns are employed. The estimated tail risk (upside potential) metrics account for series dependence, volatility clustering and heavy-tailed distribution. Second, the relationship between CSP and tail risk (upside potential) is analysed at the disaggregated level. The relationship appears to vary between the specific subdimensions. While some subdimensions may have a significant effect (either negative or positive), others may lack statistical significance. Moreover, some specific effects may not be reflected in the overall score because of compensatory effects. However, most of the previous scholarly literature appears to assess the effect of overall ESG performance (including the three pillars together). Third, this study focuses on a particular market. As has been previously discussed in other works, the effect of sustainability performance on tail risk (upside potential) appears to depend on the region under study. The relevance of SRI in Spain has grown significantly in the last decade. Assets managed in a way that considers ESG factors have increased from 125,239 million euros in 2013 to 236,894 million euros in 2023 (Spainsif, 2024).

The rest of this paper is structured as follows. First, the literature on the relationship between ESG performance and FP is reviewed, and hypotheses are developed. Secondly, the methods used in this study are explained in section 3. The sample is described in section 4. After this, empirical evidence is presented and discussed. Finally, implications and limitations are developed in the conclusions section.

2. LITERATURE REVIEW, THEORETICAL NOTES, AND DEVELOPMENT OF HYPOTHESES

The effect of ESG performance on risk is gaining increasing attention in the scholarly literature. In this research area, empirical evidence shows diverse results. Some studies find that high ESG performance lowers risk (Liu *et al.*, 2023; Shakil, 2021). This inverse relationship is explained in the literature by reference to two different theories, namely stakeholder theory and signalling theory. According to stakeholder theory, companies, through active engagement with their stakeholders, reduce the probability of negative social events having an impact on their operations (Diemont *et al.*, 2016; Shakil, 2021; Viviani *et al.*, 2019). Companies with poor CSP may be exposed to several social risks such as consumer protests and labour strikes (Gao *et al.* 2025). Risks derived from adverse social events appear to be of concern to a wide range of stakeholders (including institutional investors), despite the difficulty of measuring them (Boiral *et al.*, 2020). Therefore, high performance in terms of material social issues may lower the risk perceived by investors.

Signalling theory also suggests an inverse relationship between CSP and risk. According to Wu and Hu (2019), negative news about a firm may lead to massive stock sell orders, given the information asymmetries between the company and investors. These authors suggest that financial markets might perceive CSR as a positive signal, reducing information asymmetries. Lower information asymmetries appear to contribute to a decrease in perceived risk. Therefore, if investors understand CSP as a positive signal, high CSP may reduce risk.

Conversely, a direct relationship between CSP and risk may be explained by agency theory. Managers may engage in social activities to enhance their reputation, raising the agency costs (Korinth & Lueg, 2022). Landi *et al.* (2022) argue that:

> This generates a non-negligible agency risk and leads to penalizing these companies in the stock market. In addition, the investments made toward sustainability by a company could be considered a sacrifice of profit for an unnecessary social or environmental cause, rather than an entrepreneurial opportunity that is preserved over time through an economic added value. (p. 1104)

Therefore, non-genuine social engagement appears to increase the risk perceived by investors, because of an inefficient allocation of resources. Moreover, high CSP may lead to higher risk in regions where the overall CSP of firms is already high. According to Diemont *et al.* (2016), in regions where the CSR commitment of companies and the expectations of investors are high, additional investment may not yield a benefit, and may thus increase the perceived risk.

Some authors have recently proposed the existence of a quadratic relationship between ESG performance and risk. Pistolesi and Teti (2024), for the U.S. stock market, document an inverted U-shaped relationship between ESG performance and systematic risk. This relationship appears to hold for the three pillars (i.e., environmental, social, and governance) individually. According to these authors, initial ESG investment requires a considerable amount of resources and yields relatively low benefits. This leads to higher perceived risk. Once a certain investment threshold is overcome, the benefits of ESG investment are realized and the risk perceived by investors is decreased. By contrast, Korinth and Lueg (2022) find a U-shaped relationship between ESG performance and risk in the German stock market. Results are consistent across environmental and social pillars. These authors explain that investors initially value the benefits of investing in ESG activities, reducing perceived risk. However, investors may consider that exceeding a certain threshold entails an inefficient allocation of resources, leading to a higher perceived risk.

Considering the diversity in empirical evidence, the employment of risk measures that properly account for the key features of stock returns may contribute to enhancing the robustness of the results. After analysing the performance of several Dow Jones sustainability indices (Global, Asia-Pacific, Emerging Markets, Europe, and US), Cunha *et al.* (2020) highlight the relevance of using financial performance metrics that consider the non-normality of stock returns. Likewise, some scholars have recently emphasized the relevance of assessing the impact of CSP on risk metrics that adequately consider the asymmetric preferences of investors regarding negative and positive deviations from expected returns (Gao *et al.*, 2025; Hoepner *et al.*, 2024). Tail risk reflects the maximum expected loss over a period associated with a given probability. This risk measure has been widely employed in internal market risk management frameworks, since it uses one number to summarize a complex reality (Marimoutou *et al.*, 2009). Moreover, the estimation of tail risk appears to play a relevant role in the regulatory capital requirements set by Basel III (Ruiz & Nieto, 2023). The accurate estimation of tail risk demands the consideration of certain stock return features, namely series dependence, volatility clustering and heavy-tailed distribution (Wang *et al.*, 2011).

Diemont *et al.* (2016) conducted one of the first studies on the relationship between sustainability performance and tail risk. These authors highlight various conclusions from their empirical study of the effect of CSR on the tail risk of a global equity sample (2003-2011). First, the effect appears to vary between the different CSR dimensions. The period under study may play a relevant role too, with the statistical significance of the relationship increasing under highly volatile market conditions. Finally, the relationship appears to depend on the region under study. Lööf *et al.* (2022) analyse the effect of ESG scores on the tail risk of an international sample of stocks. The empirical study is divided into two periods: 2018-2019 and 2020. The authors consider both the short-term and the long-term effect of ESG scores on firms' tail risk. The results indicate that better ESG scores lead to lower tail risk. In 2018-2019, the effect is only significant in the long term, but during the pandemic ESG scores also reduced tail risk in the short term. The environmental pillar appears to drive the long-term effect. Viviani *et al.* (2019) also study the effect of CSR on tail risk, analysing a global sample. Their findings document an inverted relationship between tail risk and CSR. At the disaggregated level, high performance in the following subdimensions appears to entail lower tail risk: human resources, environment, business behaviour, community involvement and human rights. Shafer and Szado (2020) show an inverse relationship between ESG performance and tail risk, over the period 2009-2015. Results are consistent across the three pillars. Abdelaziz *et al.* (2024) assess the impact of ESG performance on stock's extreme returns in the U.S. stock market, over the period 2016-2023. According to their findings higher ESG performance appears to reduce the magnitude of extreme returns. However, the effect over the probability of suffering extreme stock returns appears not to be clear. The environmental and social pillars display a similar pattern to that of the overall score. Gao *et al.* (2025) analyse the effect of ESG performance on the tail risk and upside potential of U.S. financial institutions, over the period 2016-2019. They find that financial institutions with higher ESG performance appear to have lower tail risk exposure and higher upside potential. Finally, Zhang *et al.* (2023)

analyse the relationship between ESG performance and tail risk at the fund level in China, during the period 2018-2021. These authors consider that the effect of ESG performance on fund tail risk depends on three different channels. Two of these, the firm and flow channels, are expected to lower tail risk. Conversely, under modern portfolio theory, the diversification channel is expected to increase tail risk. Zhang *et al.* (2023) argue that the final effect depends on which of the channels dominates.

Applying the previous reasoning and working on the basis that investors perceive the social engagement of firms in the Spanish stock market to be genuine, the following hypothesis is proposed:

H1: An increase in CSP lowers tail risk.

Additionally, it may also be relevant to analyse the effect of CSP on upside potential to assess whether the risk–return trade-off holds. Furthermore, investors appear to react heterogeneously to negative and positive deviations from expected returns (Gao *et al.*, 2025). The existence of a positive relationship between stock returns and CSP is supported by some studies. Based on the resource-based view, Inoue and Lee (2011) argue that high CSP may contribute to the creation of various intangible assets (e.g., employee commitment, customer loyalty, and corporate reputation). According to these authors, these intangible resources may positively influence investors' expectations for the future financial performance of the firm. However, it is also argued that CSP would only provide investors with superior returns if this information is not fully priced in (Mănescu, 2011; Ni & Sun, 2023). Furthermore, the existence of investors who obtain non-financial utility from investing in stocks with high CSP may also explain a positive effect on stock returns (Mănescu, 2011).

On the other hand, the empirical evidence provided by other studies points to a negative effect of CSP on stock returns. Several authors argue that, in a market in equilibrium, investors may perceive that companies with low CSP bear higher levels of risk, and so demand a premium (Ni & Sun, 2023). The empirical evidence provided by Luo (2022) points to the existence of an ESG premium in the UK stock market from 2003 to 2020. The results of Díaz *et al.* (2021) also show that an ESG factor significantly explains stock returns in the U.S. financial market during Covid-19. Lööf *et al.* (2022) show that the risk–return trade-off holds, through the assessment of the effect of ESG scores on both the tail risk and the upside potential of stocks. Likewise, investors may consider that the potential economic benefits associated with CSP do not exceed its costs, and hence may lower their expectations for the future financial performance of the firm. If CSP is not fully priced in, a negative effect on stock returns would be expected (Mănescu, 2011).

Other authors try to integrate these two opposing views by considering the idiosyncrasies of the period under study. Cornell (2021) distinguishes two periods: transition and equilibrium. According to this author, in the transition period, concerns regarding ESG issues rise, resulting in a higher demand for stocks with high ESG performance, and, thus, higher returns. When the market reaches an equilibrium, the preference of investors for companies with high ESG performance leads to lower discount rates, lowering the expected return. The evidence provided by the empirical analysis conducted by Pástor *et al.* (2022), in the U.S stock market, supports this hypothesis.

Taking into account the reviewed literature, and assuming that the risk–return trade-off holds for CSP in the Spanish stock market, the following hypothesis is proposed:

H2: An increase in CSP lowers the upside potential.

As has already been mentioned in this section, the effect of CSP on FP may vary over time. The existence of a transition period may explain the time-varying effect of CSP on upside potential (Cornell, 2021; Pástor *et al.*, 2022). Likewise, exceeding a certain threshold may entail changes in the risk that investors perceive to arise from additional investment in CSP (Korinth & Lueg, 2022; Pistolesi & Teti, 2024). Therefore, the following hypotheses are proposed:

H3(a): CSP affects tail risk differently in the short and the long term.

H3(b): CSP affects upside potential differently in the short and long term.

Another relevant aspect to consider is that the effect of CSP on FP may vary within the subdimensions. The studies reviewed in this section show that most of the existing research focuses on analysing the impact of ESG performance on tail risk (upside potential) at the aggregate level. Only a few studies assess the impact of specific stakeholders (Diemont *et al.*, 2016; Viviani *et al.*, 2019). Bouslah *et al.* (2013) suggest that "Two firms with the same aggregate CSP could have different relations with firm risk. Since CSP is a multidimensional construct that embodies several dimensions, the expected impacts on risk predicted by the theories reviewed in the previous section may differ by CSP dimension" (p. 1261). The fact that each subdimension targets a different stakeholder may explain the existence of specific effects at the disaggregated level (Dumitrescu & Zakriya, 2021). Higher performance in subdimensions targeted at primary stakeholders may contribute to the creation of intangible assets that are positively valued by investors (Inoue & Lee, 2011). Furthermore, subdimensions that are easily measurable, have a low degree of ambiguity and are widely accepted by investors are more likely to have an impact on FP (Bouslah *et al.*, 2013). The social dimension of ESG performance targets primary stakeholders (e.g. employees and customers). Likewise, investors appear to be more able to accurately assess the benefits and cost associated with further investments in this dimension, rather than those associated with environmental initiatives (Dumitrescu & Zakriya, 2021). The workforce subdimension is targeted at employees and measures the performance of the firm in the following four areas: diversity and inclusion, career development and training, working conditions, and health and safety. Higher performance in this subdimension may strengthen the commitment of employees, and, hence, have a positive effect on efficiency, productivity, and turnover (Esteban-Sanchez *et al.*, 2017). Product responsibility, a subdimension targeted at customers, assesses the performance of the firm in the following areas: responsible marketing, product quality and data privacy. According to the scholarly literature, high product responsibility may contribute to increased sales through customer loyalty (Inoue & Lee, 2011). Community performance encompasses social issues such as public health, business ethics and being a good citizen. According to Esteban-Sanchez *et al.* (2017), the ultimate effect of this subdimension on FP depends on whether the reputational benefits exceed the cost from philanthropy. Inoue and Lee (2011) point to the degree of dependence between the firm's operations and local communities as a factor that may influence the effect on FP. Finally, human rights assesses the degree to which the firm respects fundamental human rights. Involvement in human rights violation damages the reputation of a firm (Tsai & Wu, 2022).

Accordingly, the following hypotheses are proposed:

H4(a): The effect of CSP on tail risk varies between its different subdimensions (workforce, human rights, community, and product responsibility).

H4(b): The effect of CSP on upside potential varies between its different subdimensions (workforce, human rights, community, and product responsibility).

3. MATERIALS AND METHODS

The analysis of the effect of CSP on the tail risk (upside potential) of stocks encompasses two fundamental challenges. The first challenge is the estimation of annual tail risk (upside potential) metrics. CSP involves long-term organisational change (Bruna & Lahouel, 2022), so it appears more appropriate to assess its impact on long-term tail-risk (upside potential) metrics. Most of the studies use shorter horizon metrics (Abdelaziz *et al.*, 2024; Lööf *et al.*, 2022; Shafer and Szado, 2020). Although daily tail risk (upside potential) metrics can be estimated directly from composite conditional mean and conditional variance models, the proper estimation of multi-period metrics appears to require a more sophisticated approach. The square-root-of-time rule has been popular in the estimation of multi-period risk metrics, but it underestimates the downside risk metrics because it ignores certain distributional features of stock returns (namely autocorrelation, volatility clustering and fat tails) (Wang *et al.*, 2018). Another approach is to employ two-step procedures. According to Ruiz and Nieto (2023), two-step procedures yield more robust estimates by first modelling the conditional variance of stock returns, and then computing the corresponding percentile or conditional expectation. Filtered historical simulation (FHS), an iterated two-step procedure, is the method selected for this study. Given the semiparametric nature of FHS, distributional assumptions regarding future stock returns are not required. Assumed future return distribution plays a significant role in tail risk estimation (Louzis *et al.*, 2014), and simplistic assumptions are often made (Mancini & Trojani, 2011). Furthermore, the employment of conditional variance models enables the consideration of a data generating process that accounts for the main stylized facts of stock returns (Wang *et al.*, 2011). The results of FHS appear to be adapted to the current state of volatility of the market, because of the employment of filtered standardized residuals (Marimoutou *et al.*, 2009). As a result, FHS may enable extreme values that were not included in the original dataset to be forecast (Barone-Adesi & Giannopoulos, 2001). Finally, another advantage often associated with FHS is that it yields a complete distribution of future returns (Mancini & Trojani, 2011). This advantage may enhance the robustness of the analysis since several tail risk (upside potential) measures can be directly computed from the simulated distribution, even at different confidence levels.

Second, the analysis of the effect of CSP on tail risk (upside potential) requires the variability of time series and cross-sectional data to be properly captured. In this study, a panel data analysis is conducted, through the CRE approach proposed by Mundlak (1978).

3.1. Filtered historical simulation (FHS)

The FHS is divided into three phases: risk modelling, filtering of historical returns and estimation of tail risk and upside potential metrics. In the first phase, risk modelling, composite conditional mean and conditional variance models are employed. These econometric time series models consider the following features of stock returns: series dependence, volatility clustering and heavy-tailed distributions (Bollerslev *et al.*, 1992; Engle & Bollerslev, 1986). Three possible conditional mean processes are considered, to account for series dependence: random walk (RW), AR(1), and ARMA(1,1) given by:

$$r_{i,t} = \alpha_i + \varepsilon_{i,t} \tag{1}$$

$$r_{i,t} = \alpha_i + \varphi_1 r_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

$$r_{i,t} = \alpha_i + \varphi_1 r_{i,t-1} + \varphi_2 \varepsilon_{i,t-1} + \varepsilon_{i,t} \tag{3}$$

A symmetric and two asymmetric conditional variance models are considered, to model volatility clusters: GARCH (1,1), GJR (1,1,1) and EGARCH (1,1,1).

$$\sigma_{i,t}^2 = \omega_i + \gamma_1 \sigma_{i,t-1}^2 + \alpha_1 \varepsilon_{i,t-1}^2 \tag{4}$$

$$\sigma_{i,t}^2 = \omega_i + \gamma_1 \sigma_{i,t-1}^2 + \alpha_1 \varepsilon_{i,t-1}^2 + \delta_1 I\left[\varepsilon_{i,t-1} < 0\right] \varepsilon_{i,t-1}^2 \tag{5}$$

$$\log \sigma_{i,t}^2 = \omega_i + \gamma_1 \log \sigma_{i,t-1}^2 + \alpha_1 \left[\frac{\left|\varepsilon_{i,t-1}\right|}{\sigma_{i,t-1}} - E\left(\frac{\left|\varepsilon_{i,t-1}\right|}{\sigma_{i,t-1}} \right) \right] + \delta_1 I \left[\frac{\left|\varepsilon_{i,t-1}\right|}{\sigma_{i,t-1}} \right] \tag{6}$$

Finally, two different distributions of the innovation are considered to account for the potential existence of heavy tails: Gaussian and Student's t.

The findings of Naik *et al.* (2020) show that the Bayesian information criterion (BIC) provides better results than the Akaike information criterion (AIC) when selecting smaller-order conditional variance models. In this study, the model that best fits each financial time series is selected according to the BIC. Daily logarithmic stock returns from 2004-2021 are employed.[1]

[1] The models that best fit each financial times series are not shown for brevity but are available upon request.

In the second phase of the FHS, historical returns are filtered following the methodological approach proposed by Barone-Adesi *et al.* (1999). This approach is conducted in four steps, as follows: 1) composite conditional mean and variance models are fitted, 2) i.i.d. standardized residuals are computed, 3) bootstrapping and, 4) simulation of n-paths of h-horizon daily returns are performed. The model selected, in the risk modelling phase, is fitted to each logarithmic return time series. Historical conditional means, conditional variances, and residuals are inferred. Thereafter, standardized i.i.d. residuals are computed ($z_{i,t}$). In this study, ten years of earlier daily stock returns are used for the estimation of the coefficients of the models.

In the third step, n-paths of h-horizon standardized residuals are generated, through random sampling with replacement (bootstrapping) (Le, 2020). Bootstrapping allows one to make no assumptions regarding the future distribution of the stock returns. The bootstrapped standardized residuals are introduced into the previously estimated composite conditional mean and conditional variance models, simulating the n-paths of h-horizon daily returns (Barone-Adesi *et al.*, 1999). The simulation algorithm works as follows. First, one-day-ahead conditional variance ($\sigma^2_{i,t}$) is forecasted by plugging into the conditional variance equation the last available residual ($\epsilon_{i,t-1}$) and conditional variance ($\sigma^2_{i,t-1}$). Afterwards, the respective standardized residual ($z_{i,t}$) is drawn from the previously generated n-paths of h-horizon sample. This standardized residual ($z_{i,t}$) is multiplied by the conditional standard deviation forecast ($\sigma_{i,t}$), reflecting the current state of volatility of the markets. This operation yields a forecast for the residual ($\epsilon_{i,t}$). Finally, one-day-ahead logarithmic return ($r_{i,t}$) is forecasted by plugging into the conditional mean equation the residual ($\epsilon_{i,t}$). This process is repeated h-times for each of the n-paths. In this study, 100,000 paths of 250 daily standardized residuals are generated for each year.

Simulated daily logarithmic returns can be aggregated as follows to compute h-period returns, given the additive property of logarithmic returns (Le, 2020):

$$r_{t,h} = \sum_{i=1}^{h} r_{t+i} \tag{7}$$

The filtering process is repeated for each of the eight years through a rolling window scheme, always using ten years of earlier daily stock returns.

In the final phase, the tail risk and upside potential metrics are calculated. Once the complete distribution of future stock returns for a given year has been estimated, several tail risk (upside potential) metrics can be directly computed. Tail risk is defined as the maximum expected loss with a probability p over a given period. Value at Risk (VaR) and Expected Shortfall (ES) are commonly employed as tail risk indicators (Le, 2020). Conversely, upside potential is defined as the maximum expected gain with a probability p over a given period. Value of Return (VoR) and conditional Value of Return (cVoR) can be employed as upside potential indicators.

While VaR is estimated as a percentile of a stock return distribution, ES is computed as the conditional expectation of all the losses above a given VaR level (Yamai & Yoshiba, 2005). ES has gained popularity (Ruiz & Nieto 2023), since disregarding losses over a given VaR level may have profound consequences (Yamai & Yoshiba, 2005). The same applies to the upside potential measures.

$$VaR_{i,t,\alpha} = -\inf\left[r_{i,t} \middle| P\left(R_{i,t} \le r_{i,t}\right) > \alpha\right] \tag{8}$$

$$ES_{i,t,\alpha} = E\left[r_{i,t} \middle| r_{i,t} \le VaR_{i,t,\alpha}\left(r_{i,t}\right)\right] \tag{9}$$

$$VoR_{i,t,\alpha} = \left[r_{i,t} \middle| P\left(R_{i,t} \ge r_{i,t}\right) > \alpha\right] \tag{10}$$

$$cVoR_{i,t,\alpha} = E\left[r_{i,t} \middle| r_{i,t} \ge VoR_{i,t,\alpha}\left(r_{i,t}\right)\right] \tag{11}$$

In this study, VaR, ES, VoR and cVoR measures are estimated at three different confidence levels (90%, 95% and 99%), to enhance the robustness of the analysis. Furthermore, it may be relevant for the various stakeholders to understand how the effect of CSP varies when the selected metric reflects a more extreme situation. The analysis may shed light on specific effects. ES/cVoR appears to be a more robust tail risk/upside potential indicator since it displays the conditional expectation of all the losses/gains beyond a given VaR/VoR level. Likewise, the higher the confidence level, the higher the maximum expected loss.

3.2. *Connecting corporate social performance and tail risk/ upside potential*

The effect of CSP and its subdimensions on tail risk (upside potential) is analysed through the CRE regression approach proposed by Mundlak (1978). Panel data models are often used to handle the endogeneity that may arise from unobserved heterogeneity, by capturing the time series and cross-sectional variability of data (Wooldridge, 2010). The CRE approach combines the advantages of both fixed effect and random effects estimators, by considering the potential correlation between the individual random effects and the explanatory variables (Mundlak, 1978).

The CRE regression model proposed in this study considers both the short-term and the long-term effects of CSP and its subdimensions on the tail risk (upside potential). Sixty different models are estimated, considering the four independent variables (VaR, ES, VoR, cVoR) at three different confidence levels (90%, 95%, 99%). CSP and its four subdimensions (workforce, human rights, community, and product responsibility) are included as explanatory variables. In line with the work of Lööf *et al.* (2022), the following control variables are considered: market value (MV), price to earnings ratio (PER), dividend yield (DIVYIELD) and systematic risk (BETA). Time fixed effects haven been considered to control for the effect of atypical events, such as covid (Lahouel *et al.*,2022), on the dependent variable. The following expression shows an example of the estimated models. In this case, equation (12) captures the impact of CSP on the VaR of stocks.

$$\widehat{VaR_{i,t}} = \beta_0 + \mu_i + \beta_\omega CSP_{i,t} + \beta_b \overline{CSP_i} + \sum_{j=1}^{4} \beta_j FC_{i,t} + \lambda_t + \varepsilon_{i,t} \tag{12}$$

where $\widehat{VaR_{i,t}}$ is the VaR of company i in period t, μ_i is the stock-specific effect, which is uncorrelated with the error term $\varepsilon_{i,t}$, β_b and β_b refer to the within and between estimates, λ_t is the time effects, $FC_{i,t}$ refers to the values of the financial controls of stock i in period t, and $\overline{CSP_{i,t}}$ refers to the average CSP score for stock i. The between estimate measures the long-term influence of the variable, while the within estimate shows the short-term impact. The same rationale is applied to the tail risk (upside potential) metrics and the subdimensions of CSP.

4. SAMPLE SELECTION AND DESCRIPTION

Previous studies have pointed out that the relationship between CSP and tail risk (upside potential) may depend on the region under study. First, the nature of this relationship appears to be influenced by ESG awareness level (Zhang *et al.*, 2023), the expectations of investors (Diemont *et al.*, 2016) and the regulatory environment (Brooks & Oikonomou, 2018). Secondly, the reaction to extreme events may be heterogeneous within regions. Therefore, this study focuses on the empirical analysis of one region. Europe is the selected region, given the strong institutional support granted to the sustainability paradigm. In the last decade, the European Union has adopted several sustainability reporting mandates, namely the Non-Financial Reporting Directive (extended by the Corporate Sustainability Reporting Directive), the Taxonomy Regulation, the Sustainable Finance Disclosure Regulation, and Pillar 3 Disclosures on ESG Risks (Hummel & Jobst, 2024). However, EU member nations present divergent macroeconomic fundamentals (fiscal deficit, competitiveness, and solvency), and thus their stock markets may react differently to extreme events. The findings of Alexakis and Pappas (2018) show that European equity markets reacted heterogeneously to both the Global Financial Crisis (GFC) and the European Sovereign Debt Crisis (ESDC) in terms of the timing and magnitude of the financial contagion. Because of this, the focus is only on one European equity market, the Spanish stock market. According to the survey conducted by Spainsif (2024), the value of assets in Spain that are managed to take into account ESG factors has grown from 125,239 million euros in 2013 to 236,894 million euros in 2023. Regarding the evolution of tail risk, according to the findings of Shahzad *et al.* (2016), European stock markets can be classified into two groups. The VaR of the first group decreased to normal levels after the GFC and ESDC, while the VaR of the second group remained vibrant and registered peaks after 2012. The Spanish stock market belongs to the second group.

The relationship between CSP and its subdimensions and tail risk/upside potential, in the Spanish stock market, is analysed for the period 2014-2021. Financial data and CSP scores were obtained from the Thomson Reuters Refinitiv database. The initial dataset comprised the 121 stocks listed on the Spanish stock market. Only those companies showing complete data for scores for CSP and its subdimensions over the period of analysis were included in the final sample. Thus, after checking for the availability of CSP scores in the period under study, 44 stocks were identified. Those that did not have ten years of earlier stock prices were removed, yielding a sample of 34 stocks. Finally, stocks with recurrently extreme tail risk (upside potential) metrics were also excluded. A final sample of 29 stocks with a total of 215 stock-year observations was examined. Nearly 45% of the stocks are from companies that operate in the financial and industrial sectors. Consumer non-cyclicals is the sector with the lowest representation in the sample.

The availability of CSP scores and the length of stock returns time series has restricted the size of the sample, limiting the generalisability of the findings. The popularity of passive investment strategies has lately increased (Laborda *et al.*, 2024). The stocks in the sample represent 83.17% of the IBEX35 market capitalization on 31 December 2023. Thus, this sample could be considered representative of the Spanish stock market, although, the size of the sample limits the generalisability of the findings to a wider context.

Table 1 summarizes the main descriptive statistics of the tail risk and upside potential metrics. Figure 1 displays the boxplots by year of $ES_{0.05}$ and $cVoR_{0.05}$. Figure 1 reveals that 2014 was the year with the lowest maximum expected loss and variability in the Spanish stock market. Likewise, 2021 appears to be the year with the highest maximum expected loss and variability, because of the Covid-19 crisis. However, some stocks appear to have had an especially high upside potential during the pandemic. The year with the highest upside potential in the Spanish stock market was 2015.

Table 1
Descriptive statistics of tail risk and upside potential estimates

Variable	Mean	Median	Std. Dev.	Max	Min
$VaR_{0.1}$	−0.37	−0.37	0.14	−0.07	−0.84
$VaR_{0.05}$	−0.51	−0.52	0.17	−0.14	−1.11
$VaR_{0.01}$	−0.84	−0.84	0.26	−0.29	−1.79
$ES_{0.1}$	−0.58	−0.58	0.19	−0.17	−1.25
$ES_{0.05}$	−0.72	−0.72	0.23	−0.23	−1.54
$ES_{0.01}$	−1.05	−1.06	0.33	−0.37	−2.30
$VoR_{0.1}$	0.36	0.34	0.09	0.75	0.17
$VoR_{0.05}$	0.44	0.43	0.11	0.94	0.24
$VoR_{0.01}$	0.61	0.57	0.16	1.33	0.33
$cVoR_{0.1}$	0.47	0.45	0.12	1.01	0.26
$cVoR_{0.05}$	0.55	0.51	0.14	1.18	0.30
$cVoR_{0.01}$	0.71	0.65	0.20	1.55	0.37

Notes: $VaR_{0.1}$ denotes yearly Value-at-Risk at 90% confidence level. The rest of the variables are interpreted in the same way.

Source: Own elaboration.

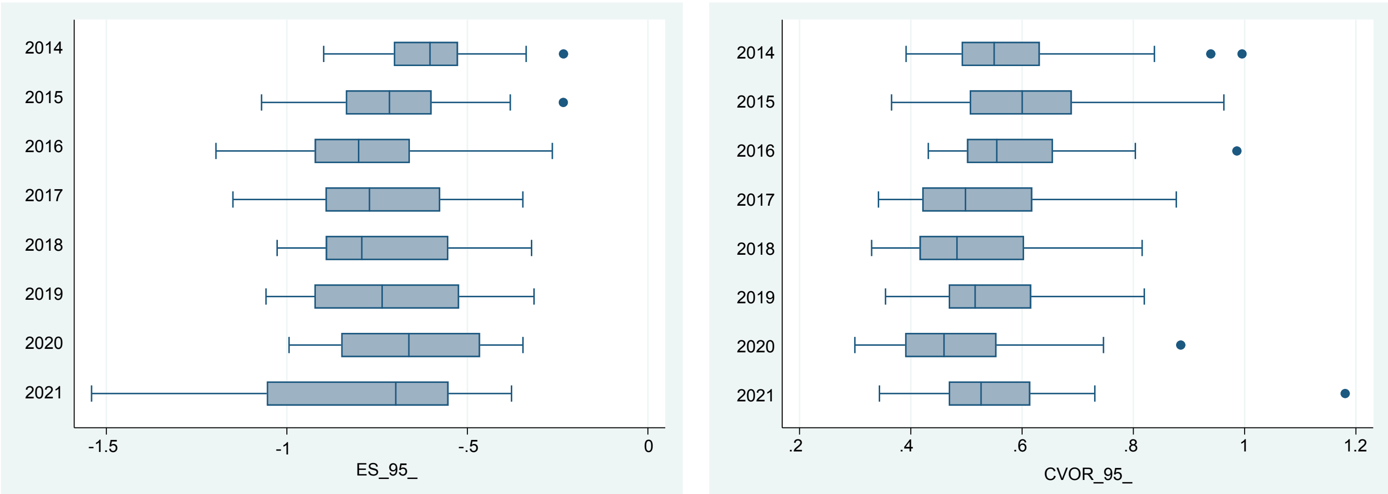

Figure 1
Boxplot of $ES_{0.05}$ and $cVoR_{0.05}$ by year
Source: Own elaboration.

Table 2 shows the main descriptive statistics of CSP scores and their subdimensions. Companies in the sample appear to display high CSP since, in general terms, most of them are in quartiles 1 and 2. These companies appear to perform especially well in terms of workforce. Likewise, the main descriptive statistics of the financial control variables (see Table 2) reveal that the sample contains companies of quite different sizes.

Table 2
Descriptive statistics of CSP scores and control variables

Variables	Mean	Median	Std. Dev.	Max	Min
CSP	79.45	86.29	19.12	98.19	0.90
Workforce	87.17	92.39	17.62	99.80	1.28
Human rights	71.19	80.00	26.54	98.31	0.00
Community	78.08	87.08	25.88	99.86	1.47
Product responsibility	79.71	87.71	23.92	99.70	0.00
MV	18185.94	7740.27	24218.72	105638.90	383.40
PER	22.15	16.35	19.13	135.80	3.20
DivYield	3.92	3.63	2.64	17.69	0.00
Beta	0.92	0.92	0.36	1.94	0.09

Notes: CSP denotes the overall social performance score of a company. The descriptive statistics of the scores of the four subdimensions (workforce, human rights, community and product responsibility) are also summarized in this table. MV denotes de Market Value of the company, PER denotes the Price-to-Earnings ratio of the company, Divyield denotes the dividend yield of a company.

Source: Own elaboration.

5. RESULTS AND DISCUSSION

5.1. *Corporate social performance and tail risk*

Tables 3 and 4 display the results of the panel data regression models that analyse the effect of CSP and its different subdimensions on the tail risk metrics (i.e., VaR and ES) in the Spanish stock market for the period 2014-2021. The results indicate that an increase in overall CSP decreases both VaR and ES, in the short term. However, an increase in overall CSP appears to increase both tail risk metrics in the long term. The empirical evidence supports **H1** only in the short term. Both the proper management of potentially socially adverse events (Diemont *et al.*, 2016; Shakil, 2021) and the reduction of information asymmetries (Wu & Hu, 2019) may have contributed to lowering the maximum loss. The results regarding the short term effect would be in line with previous empirical evidence (Gao *et al.*, 2025; Lööf *et al.*, 2022; Shafer & Szado, 2020; Viviani *et al.*, 2019). In relation to **H3(a)**, CSP appears to affect tail risk differently in the short and long term. This result could imply that investors considered that additional investments were unnecessary in the long term, either because of already high overall CSP (Diemont *et al.*, 2016) or because of agency costs (Landi *et al.*, 2022). The discrepancy between the short and long term effects contradicts the findings of Lööf *et al.* (2022). This could be explained by the fact that our study focuses on the Spanish stock market, while Lööf *et al.* (2022) analyses a global sample. This is in line with the findings of Diemont *et al.* (2016) that show that the relationship between corporate social performance and tail risk may vary within regions. Furthermore, this study employs long term tail risk metrics (i.e., yearly), whereas Lööf *et al.* (2022) use short term tail risk metrics (i.e., monthly).

Table 3

Effect of corporate social performance and its subdimensions on firms' Value at Risk

Indep/Dep	**$VaR_{0.1}$**	**$VaR_{0.05}$**	**$VaR_{0.01}$**	**$VaR_{0.1}$**	**$VaR_{0.05}$**	**$VaR_{0.01}$**	**$VaR_{0.1}$**	**$VaR_{0.05}$**	**$VaR_{0.01}$**	**$VaR_{0.1}$**	**$VaR_{0.05}$**	**$VaR_{0.01}$**	**$VaR_{0.1}$**	**$VaR_{0.05}$**	**$VaR_{0.01}$**
CSP(ω)	0.0012***	0.0014***	0.0017**												
	(0.0005)	(0.0005)	(0.0009)												
CSP(b)	−0.0025**	−0.0031**	−0.0048***												
	(0.0011)	(0.0013)	(0.0018)												
Workforce(ω)				0.0010**	0.0011**	0.0015*									
				(0.0004)	(0.0005)	(0.0008)									
Workforce(b)				−0.0009	−0.0012	−0.0020									
				(0.0008)	(0.0009)	(0.0014)									
Human rights(ω)							0.0006	0.0006	0.0008						
							(0.0004)	(0.0004)	(0.0006)						
Human rights(b)							−0.0020*	−0.0025**	−0.0039**						
							(0.0006)	(0.0013)	(0.0018)						
Community(ω)										0.0003	0.0004	0.0006			
										(0.0003)	(0.0004)	(0.0005)			
Community (b)										−0.0011	−0.0016	−0.0030**			
										(0.0009)	(0.0010)	(0.0015)			
Prod resp(ω)													0.0010**	0.0011*	0.0013
													(0.0005)	(0.0006)	(0.0008)
Prod resp(b)													−0.0016**	−0.0019**	−0.0025**
													(0.0007)	(0.0009)	(0.0013)
MV	2.4e−06***	2.7e−06***	3.3e−06**	2.3e−06***	2.6e−06***	3.1e−06**	2.5e−06***	2.8e−06***	3.5e−06**	2.4e−06***	2.7e−06***	3.3e−06**	2.4e−06***	2.6e−06***	3.4e−06**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PER	0.0003	0.0005*	0.0010**	0.0003	0.0005*	0.0010**	0.0003	0.0005*	0.0010**	0.0002	0.0004	0.0009**	0.0002	0.0004	0.0009**
	(0.0002)	(0.0003)	(0.0005)	(0.0002)	(0.0003)	(0.0005)	(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0005)
DIVYIELD	0.0015	0.0014	0.0007	0.0012	0.0011	0.0002	0.0014	0.0013	0.0006	0.0008	0.0008	0.0000	0.0012	0.0030	0.0001
	(0.0023)	(0.0030)	(0.0051)	(0.0022)	(0.0029)	(0.0049)	(0.0023)	(0.0030)	(0.0051)	(0.0023)	(0.0031)	(0.0052)	(0.0023)	(0.0030)	(0.0050)
BETA	−0.1163***	−0.1446***	−0.2216***	−0.1162***	−0.1443***	−0.2205***	−0.1192***	−0.1482***	−0.2267***	−0.1210***	−0.1501***	−0.2288***	−0.1110***	−0.1390***	−0.2159***
	(0.0424)	(0.0490)	(0.0675)	(0.0438)	(0.0506)	(0.0694)	(0.0435)	(0.0502)	(0.0688)	(0.0457)	(0.0528)	(0.0719)	(0.0463)	(0.0540)	(0.0743)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the main results of CSP (i.e., columns 1, 2, and 3), workforce (i.e., columns 4, 5, and 6), human rights (i.e., columns 7, 8, and 9), community (i.e., columns 10, 11, and 12) and product responsibility (i.e., columns 13, 14, and 15) on Value at Risk (VaR) at three different confidence levels (i.e., 0.90, 0.95, 0.99). Robust standard errors are displayed in parentheses. (ω) and (b) denote the within and between estimates respectively. ***p<0.01, **p<0.05, *0,1.

Source: Own elaboration.

Table 4
Effect of CSP over Expected Shortfall

Indep/Dep	$ES_{0.1}$	$ES_{0.05}$	$ES_{0.01}$	$ES_{0.1}$	$ES_{0.05}$	$ES_{0.01}$	$ES_{0.1}$	$ES_{0.05}$	$ES_{0.01}$	$ES_{0.1}$	$ES_{0.05}$	$ES_{0.01}$	$ES_{0.1}$	$ES_{0.05}$	$ES_{0.01}$
CSP(ω)	0.0014**	0.0015**	0.002												
	(0.0006)	(0.0007)	(0.0012)												
CSP(b)	−0.0034**	−0.0041***	−0.0059**												
	(0.0014)	(0.0016)	(0.0024)												
Workforce(ω)				0.0012**	0.0013*	0.0015									
				(0.0006)	(0.0007)	(0.0011)									
Workforce(b)				−0.0013	−0.0017	−0.0025									
				(0.0010)	(0.0012)	(0.0021)									
Human rights(ω)							0.0007	0.0007	0.0008						
							(0.0005)	(0.0005)	(0.0008)						
Human rights(b)							−0.0028**	−0.0034**	−0.0050**						
							(0.0014)	(0.0016)	(0.0023)						
Community(ω)										0.0004	0.0005	0.0006			
										(0.0004)	(0.0005)	(0.0007)			
Community (b)										−0.0019*	−0.0025*	−0.0040**			
										(0.0011)	(0.0013)	(0.0019)			
Prod resp(ω)													0.0012*	0.0012	0.0013
													(0.0006)	(0.0007)	(0.0011)
Prod resp(b)													−0.0020**	−0.0023**	−0.0030*
													(0.0010)	(0.0011)	(0.0017)
MV	2.8e−06***	3.1e−06**	3.8e−06*	2.7e−06***	2.9e−06**	3.5e−06*	3e−06***	3.3e−06**	4.1e−06**	2.9e−06***	3.2e−06**	3.9e−06*	2.8e−06***	3e−06**	3.7e−06*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PER	0.0006*	0.0008**	0.0015**	0.0006*	0.0008**	0.0015**	0.0006*	0.0008**	0.0015**	0.0005*	0.0007*	0.0013**	0.0005*	0.0007*	0.0014**
	(0.0003)	(0.0004)	(0.0006)	(0.0003)	(0.0004)	(0.0007)	(0.0003)	(0.0004)	(0.0006)	(0.0003)	(0.0004)	(0.0006)	(0.0003)	(0.0004)	(0.0006)
Divyield	0.0013	0.0011	0.0004	0.0009	0.0006	−0.0003	0.0012	0.0010	0.0003	0.0006	0.0004	−0.0003	0.0009	0.0006	−0.0004
	(0.0034)	(0.0043)	(0.0070)	(0.0033)	(0.0042)	(0.0068)	(0.0034)	(0.0043)	(0.0070)	(0.0035)	(0.0044)	(0.0072)	(0.0034)	(0.0043)	(0.0069)
Beta	−0.1618***	−0.1953***	−0.2908***	−0.1613***	−0.1945***	−0.2899***	−0.1657***	−0.1997***	−0.2966***	−0.1676***	−0.2018***	−0.2987***	−0.1563***	−0.1896***	−0.2854***
	(0.0528)	(0.0607)	(0.0830)	(0.0544)	(0.0625)	(0.0852)	(0.0540)	(0.0619)	(0.0840)	(0.0567)	(0.0649)	(0.0871)	(0.0581)	(0.0668)	(0.0904)
TIME FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the main results of CSP (i.e., columns 1, 2, and 3), workforce (i.e., columns 4, 5, and 6), human rights (i.e., columns 7, 8, and 9), community (i.e., columns 10, 11, and 12), and product responsibility (i.e., columns 13, 14, and 15) on Expected Shortfall (ES) at three different confidence levels (i.e., 0.90, 0.95, 0.99). Robust standard errors are displayed in parentheses. (ω) and (b) denote the within and between estimates respectively. ***p<0.01, **p<0.05, *0,1.

Source: Own elaboration.

The analysis of the relationship between tail risk and each of the four subdimensions individually may enable us to gain a better understanding. The disaggregated analysis may reveal whether the discrepancy between the short- and long-term effects at the aggregate level could really be explained by a threshold effect or, on the contrary, whether it is the combination of specific effects in the subdimensions. The results show that an increase in performance in the workforce subdimension decreases tail risk in the short term. This could indicate that investment in this subdimension may contribute to the creation of intangible assets, such as employee commitment, which reduce tail risk (Esteban-Sanchez *et al.*, 2017; Inoue & Lee, 2011). Better performance in terms of both community and human rights appears to lead to a higher tail risk in the long term. Investors may consider that further expenditure in these subdimensions does not compensate for the potential reputational gain, and thus the maximum loss increases because of an inefficient allocation of resources. Finally, in line with **H3(a)**, product responsibility displays a similar pattern to that of overall CSP. Although investors may grant a positive value to the potential benefits associated with higher performance in this subdimension (i.e., customer loyalty), an investment threshold could be exceeded, leading to an increase in tail risk (Korinth & Lueg, 2022). Therefore, the results support **H4(a)**, highlighting the relevance of analysing specific effects at the disaggregated level, since each subdimension addresses the needs of different stakeholders (Dumitrescu & Zakriya, 2021) and may therefore be subject to different drivers and motivations (Bouslah *et al.*, 2013).

The signs of the coefficients remain robust within both the tail risk metrics and the different confidence intervals. However, the findings show an increase in the confidence level of the estimated tail risk measure that appears to weaken the short-term effect and strengthen the long-term effect of CSP. The short-term effect is not significant when passing from VaR to ES. Unlike the results in other studies (Diemont *et al.*, 2016, Lööf *et al.*, 2022), these results may suggest that the greater the maximum loss, the lower the ability of CSP to reduce tail risk.

5.2. Corporate social performance and upside potential

Tables 5 and 6 display the results of the panel data regression models that analyse the effect of CSP on the upside potential metrics (i.e., VoR and cVoR) in the Spanish stock market for the period 2014-2021. According to the results, the effect of overall CSP on upside potential is not significant. Thus, **H2** and **H3(b)**, that propose a relationship between CSP and upside potential in general and over time, are not supported. Therefore, empirical evidence regarding the risk–return trade-off at the aggregate level is not found in this study. In line with the results of Mănescu (2011), this could indicate either that the effect of CSP on upside potential is irrelevant or that CSP is already priced in. The existence of positive and negative effects that are balanced out at the disaggregated level may also explain the lack of statistical significance.

In relation to **H4(b)**, the effect of each of the four subdimensions is individually analysed. The subdimensions of workforce and product responsibility display a similar pattern to that for the overall CSP. This could imply that the effect on the upside potential of the benefits associated with further investment in these subdimensions (i.e. employee commitment and customer loyalty) have either been already priced in or lack relevance (Mănescu, 2011). Performance in terms of human rights appears to lower the upside potential in the long term. Likewise, an increase in community performance appears to lead to a decrease in upside potential in the short term. This may indicate that the potential economic benefits associated with a further improvement in corporate reputation exceed its cost and, thus, lower upside potential. Therefore, it may be relevant to monitor companies with high human rights and community performance since they appear to have higher extreme losses and lower maximum gains. The results emphasize again the relevance of assessing the effect of CSP at the disaggregated level. In line with the work of Bouslah *et al.* (2013), these results indicate that two stocks with the same overall social score may have different relationships with FP.

The signs of the coefficients are robust within both upside potential metrics. The effect of CSP appears to gain statistical significance when passing from VoR to cVoR. Finally, the relationship between CSP and upside potential appears not to vary with the selected confidence level.

Table 5
Effect of CSP over Value of Return

Indep/Dep	$VoR_{0.1}$	$VoR_{0.05}$	$VoR_{0.01}$	$VoR_{0.1}$	$VoR_{0.05}$	$VoR_{0.01}$	$VoR_{0.1}$	$VoR_{0.05}$	$VoR_{0.01}$	$VoR_{0.1}$	$VoR_{0.05}$	$VoR_{0.01}$	$VoR_{0.1}$	$VoR_{0.05}$	$VoR_{0.01}$
CSP(ω)	−6.76e−06 (0.0003)	−0.0003 (0.0002)	−0.0010* (0.0005)												
CSP(b)	−0.0020 (0.0012)	−0.0024 (0.0016)	−0.0034 (0.0023)												
Workforce(ω)				0.0001 (0.0002)	−0.0001 (0.0002)	−0.0006 (0.0004)									
Workforce(b)				−0.0015 (0.0010)	−0.0019 (0.0012)	−0.0030* (0.0017)									
Human rights(ω)							0.0001 (0.0002)	0.0000 (0.0003)	−0.0002 (0.0004)						
Human rights(b)							−0.0021*** (0.0007)	−0.0026*** (0.0009)	−0.0037*** (0.0013)						
Community(ω)										−0.0003 (0.0002)	−0.0004*** (0.0001)	−0.0009*** (0.0002)			
Community (b)										−0.0010 (0.0009)	−0.0014 (0.0012)	−0.0025 (0.0019)			
Prod resp(ω)													0.0002 (0.0002)	0.0000 (0.0002)	−0.0005 (0.0003)
Prod resp(b)													−0.0008 (0.0007)	−0.0008 (0.0009)	−0.0007 (0.0013)
MV	8.2e−07** (0.0000)	6.7e−07 (0.0000)	4.2e−07 (0.0000)	6.8e−07* (0.0000)	5.10e−07 (0.0000)	1.81e−07 (0.0000)	08.8e−07** (0.0000)	7.1e−07 (0.0000)	3.9e−07 (0.0000)	8.5e−07** (0.0000)	7.1e−07* (0.0000)	4.7e−07 (0.0000)	7.e−07* (0.0000)	5.2e−07 (0.0000)	2e−07 (0.0000)
PER	−0.0003 (0.0003)	−0.0003 (0.0003)	−0.0004 (0.0004)	−0.0003 (0.0003)	−0.0003 (0.0003)	−0.0004 (0.0004)	−0.0003 (0.0003)	−0.0003 (0.0003)	−0.0004 (0.0004)	−0.0003 (0.0003)	−0.0003 (0.0003)	−0.0003 (0.0004)	−0.0003 (0.0003)	−0.0003 (0.0003)	−0.0003 (0.0004)
Divyield	−0.0003 (0.0027)	−0.0004 (0.0030)	−0.0006 (0.0036)	−0.0004 (0.0028)	−0.0005 (0.0031)	−0.0006 (0.0038)	−0.0002 (0.0027)	−0.0003 (0.0030)	−0.0003 (0.0036)	−0.0002 (0.0027)	−0.0002 (0.0030)	0.0000 (0.0036)	−0.0003 (0.0028)	−0.0004 (0.0031)	−0.0006 (0.0039)
Beta	0.0004 (0.0267)	0.0146 (0.0279)	0.0419 (0.0314)	−0.0001 (0.0265)	0.0139 (0.0281)	0.0407 (0.0336)	−0.0004 (0.0264)	0.0144 (0.0278)	0.0427 (0.0332)	−0.0006 (0.0258)	0.0141 (0.0268)	0.0429 (0.0300)	0.0010 (0.0267)	0.0139 (0.0284)	0.0380 (0.0334)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the main results of CSP (i.e., columns 1, 2, and 3), workforce (i.e., columns 4, 5, and 6), human rights (i.e., columns 7, 8, and 9), community (i.e., columns 10, 11, and 12) and product responsibility (i.e., columns 13, 14, and 15) on Value of Return (VoR) at three different confidence levels (i.e., 0.90, 0.95, 0.99). Robust standard errors are displayed in parentheses. (ω) and (b) denote the within and between estimates respectively. ***p<0.01, **p<0.05, *0,1.

Source: Own elaboration.

Table 6

Effect of CSP over conditional Value of Return

Indep/Dep	**$cVoR_{0.1}$**	**$cVoR_{0.05}$**	**$cVoR_{0.01}$**	**$cVoR_{0.1}$**	**$cVoR_{0.05}$**	**$cVoR_{0.01}$**	**$cVoR_{0.1}$**	**$cVoR_{0.05}$**	**$cVoR_{0.01}$**	**$cVoR_{0.1}$**	**$cVoR_{0.05}$**	**$cVoR_{0.01}$**	**$cVoR_{0.1}$**	**$cVoR_{0.05}$**	**$cVoR_{0.01}$**
CSP(ω)	−0.0004	−0.0007**	−0.0015*												
	(0.0003)	(0.0004)	(0.0009)												
CSP(b)	−0.0026	−0.0030	−0.0041												
	(0.0017)	(0.0020)	(0.0028)												
Workforce(ω)				−0.0002	−0.0004	−0.0009									
				(0.0002)	(0.0003)	(0.0008)									
Workforce(b)				−0.0021	−0.0026*	−0.0036*									
				(0.0013)	(0.0015)	(0.0019)									
Human rights(ω)							0.0000	−0.0001	−0.0004						
							(0.0003)	(0.0003)	(0.0005)						
Human rights(b)							−0.0028***	−0.0033***	−0.0045***						
							(0.0010)	(0.0011)	(0.0016)						
Community(ω)										−0.0005***	−0.0007***	−0.0012***			
										(0.0001)	(0.0002)	(0.0004)			
Community (b)										−0.0017	−0.0021	−0.0033			
										(0.0013)	(0.0016)	(0.0024)			
Prod resp(ω)													−0.0001	−0.0003	−0.0008
													(0.0002)	(0.0003)	(0.0006)
Prod resp(b)													−0.0007	−0.0007	−0.0006
													(0.0010)	(0.0011)	(0.0015)
MV	6.4e−07	5.1e−07	2.6e−07	0.00	3e−07	−5.1e−08	6.6e−07	5e−07	1.7e−07	0.00	5.6e−07	3.0e−07	0.00	3.2e−07	−1.5e−08
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
PER	−0.0003	−0.0004	−0.0004	−0.0003	−0.0004	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003	−0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
Divyield	−0.0003	−0.0004	−0.0003	−0.0005	−0.0005	−0.0004	−0.0002	−0.0002	0.0000	−0.0001	0.0000	0.0005	−0.0004	−0.0004	−0.0003
	(0.0031)	(0.0034)	(0.0040)	(0.0032)	(0.0035)	(0.0043)	(0.0031)	(0.0033)	(0.0039)	(0.0031)	(0.0034)	(0.0041)	(0.0032)	(0.0036)	(0.0044)
Beta	0.0193	0.0314	0.0587	0.0185	0.0304	0.0573	0.0193	0.0318	0.0602	0.0191	0.0318	0.0609*	0.0180	0.0287	0.0525
	(0.0280)	(0.0295)	(0.0368)	(0.0285)	(0.0309)	(0.0410)	(0.0281)	(0.0304)	(0.0413)	(0.0267)	(0.0281)	(0.0355)	(0.0288)	(0.0310)	(0.0400)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Notes: This table reports the main results of CSP (i.e., columns 1, 2, and 3), workforce (i.e., columns 4, 5, and 6), human rights (i.e., columns 7, 8, and 9), community (i.e., columns 10, 11, and 12) and product responsibility (i.e., columns 13, 14, and 15) on conditional Value of Return (cVoR) at three different confidence levels (i.e., 0.90, 0.95, 0.99). Robust standard errors are displayed in parentheses. (ω) and (b) denote the within and between estimates respectively. ***p<0.01, **p<0.05, *0,1.

Source: Own elaboration.

6. CONCLUSIONS

The aim of this study was to analyse the effect of corporate social performance (CSP) and its subdimensions (i.e., workforce, human rights, community, and product responsibility) on tail risk and upside potential in the Spanish stock market for the period 2014-2021. The results show that an increase in overall CSP reduces tail risk in the short term but increases it in the long term. At the disaggregated level, product responsibility performance appears to display a similar pattern to that of the overall CSP score. Likewise, an increase in performance in terms of workforce appears to contribute to a lower tail risk in the short term, while an improvement in both community and human rights performance increases it in the long term. The existence of these specific effects highlights the relevance of assessing each subdimension individually. The results may also imply that the greater the maximum expected loss, the lower the ability of CSP to reduce tail risk, in the short term. Empirical evidence regarding the risk–return trade-off was not found. However, it may be relevant to monitor stocks with high human rights and community performance, since these dimensions appear to entail higher tail risk and to have lower upside potential.

The results of this study would entail implications for investors. ESG factors affect all the stages of the investment process from asset allocation to stock selection, given the rising complexity of SRI strategies. In this context, it appears relevant for investors to have updated information on how considering ESG factors affects the FP of their assets. They should be aware that investing on stocks with high CSP appear may lower exposure to tail risk in the short term, but that these assets may suffer greater extreme losses in the long term. The results also have implications for risk managers and policymakers. Tail risk plays a relevant role in the Basel III framework. Risk managers, under the Basel III framework, may be able to ease their capital requirements in the short term by investing in stocks with high CSP. Nevertheless, they should be prepared to bear higher tail risk in the long term. These findings may also help policymakers adapt regulatory frameworks (e.g., Basel III) to current market risk dynamics. Finally, the findings entail implications from a managerial perspective. Companies actively engage with their stakeholders to adapt to current business environment. Our findings suggest that managers should carefully consider additional investments. If social engagement is not perceived as genuine or if CSP is already high, the stocks of the company may be exposed to higher tail risk in the long term. Finally, it is relevant that these implications derive from an analysis at the stock level. At the portfolio level, other effects such as diversification mediate the relationship between CSP and the tail risk (upside potential) of the stocks.

The main limitation of this study would be the size of the sample used in the empirical analysis that restricts the generalisability of the findings to a wider context. The sample covers 83.17% of the IBEX35 market capitalization on 31 December 2023. Therefore, it could be considered as representative of the Spanish stock market, given the rising popularity of passive portfolio management strategies. Likewise, the aim of this paper was to focus on a single European market, as opposed to previous studies that analyse samples either from an international context or from an Anglo-Saxon market. Focusing on a single market restricts the generalisability of the findings to a wider context since, as pointed by previous studies, the effect of sustainability performance on tail risk (upside potential) appears to depend on the region under study. The results also highlight the relevance of design elements that future studies could consider such as the assessment of specific stakeholders and the employment of long-term tail risk (upside potential) metrics. There may also be limitations related to the method used to estimate tail risk and upside potential. In FHS, paths of standardized residuals are generated though random sampling with replacement (bootstrapping). According to Mancini and Trojani (2011), bootstrapping may bias tail risk estimations in the presence of outliers. Unusually high standardized residuals may enter the simulated path several times, leading to an overestimation of the tail risk. To cope with this potential limitation, an initial sample of ten years of earlier daily standardized residuals was employed to generate the bootstrapped paths; furthermore, 100,000 paths were generated.

Future studies may analyse the existence of a nonlinear relationship between tail risk/upside potential and CSP and its subdimensions. The assessment of the effect of environmental and governance pillars at the disaggregate level may also provide valuable insights. Likewise, it may be interesting to consider the effect of variables such as the perceived authenticity of CSP. However, to the best of our knowledge, there are not variables available, in secondary data sources (e.g., Thomson Reuters Refinitiv), that measure stakeholder perceptions. The measurement of stakeholder's perception would demand the generation of primary data through interviews or questionnaires. Finally, the effect of CSP and its subdimensions at the portfolio level could be analysed. As has been previously discussed, at portfolio level, effects such as diversification mediate this relationship.

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Julen Galarza-Maria: Conceptualization, Methodology, Formal Analysis and Investigation, Data curation, Validation, Visualization, Writing Original Draft Preparation; Eduardo Ortas: Methodology, Formal Analysis and Investigation, Data Curation, Validation, Writing- review and editing, Supervision, Project Administration; José M. Moneva: Conceptualization, Writing- review and editing, Resources, Funding Acquisition, Supervision, Project Administration

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