Can Corporate Social Performance Mitigate The Risk of Extreme Stock Returns?

Abstract

It is commonly believed that there exists a strong negative association between corporate social performance (CSP) and firm risk. To investigate the structure of this relationship, we decompose the dynamics of large U.S. company stock returns into two components: Gaussian and non-Gaussian innovations. Our findings indicate that CSP has positive association with firm's risk through the non-Gaussian risk channel. In particular, it significantly reduces the frequency and the magnitude of extreme returns. However, when examining the effect of CSP on standard Gaussian volatility risk, we find that it is not statistically significant.

Keywords: Corporate social performance, ESG; Boom/Crash risk; Volatility;

JEL: E31, E58, G12, G13

1. Introduction

The COVID 19 outbreak as well as the recent Ukraine-Russia war has reminded investors of the recurrence of market crashes. Conventional wisdom supports the idea that investing into firms with strong corporate social performance (CSP) helps navigate through market turbulences by delivering better performance than less socially performing firms as supported by Lins et al. (2017). In the same spirit, Mishra and Modi (2013) show that positive corporate social responsibility (CSR) reduces firms' idiosyncratic risk while negative CSR increases it. This negative association between CSR and idiosyncratic risk tends to dissipate for highly leveraged firms. Andreou et al. (2012) find that firms with strong governance display less idiosyncratic stock price crash risk and that this effect is even more prevailing for firms operating in less competitive industries and subject to more return uncertainty. The rational for trying to relate CSP to crash risk can be justified by two concurrent effects: for undervalued firms, managers are less inclined to report inflated earning and more willing to allocate their CSR resources prudently as in Sawicki and Shrestha (2014), while overvalued firms tend to increase their CSR effort to dissimulate their tendency to hide bad news as in Chi and Gupta (2009). Conversely, Wang et al. (2021) find that banks who exhibit strong social activity tend to increase their stock prices crash risk. This effect can be explained by their desire to divert shareholders' attention from managers' misbehaviour. Nofsinger and Varma (2014) show that socially responsible mutual funds tend to outperform conventional ones during times of market turbulences and under-perform under normal conditions. Hence, socially responsible investments seem to provide a natural hedge against downside risk. Shiu and Yang (2017) show that CSR activities provide some insurance firm's stock and bond prices benefit from CSR activities through insurance-like effects while Jia et al. (2020) find that stock price risk pushes managers to intensify their CSR effort as a risk mitigation device. Kim et al. (2014) demonstrate the mitigating effect of CSR performance on crash risk and that this effect is more pronounced for firms with a low level of corporate governance and institutional ownership. Dumitrescu and Zakriya (2021) analyze what components of CSR affects the most stock price crash risk and find that mostly the social component of CSR mitigates crash risks while the governance and environmental only have marginal effects. The impact of CSR performance on stock price crash risk can also be analyzed through the lens of ESG sentiment as in Yu et al. (2023) who establish a negative relationship between ESG (Environmental, Social and Governance) news sentiment and crash risk. This effect is even more prominent for firms with low analyst coverage.

When it comes to measuring crash risk, Kim et al. (2014) uses two measures, namely the negative conditional skewness of the previous fiscal year and the down-to-up volatility ratio. Dumitrescu and Zakriya (2021) measure crashes through two other different measures that are both related to the number of times returns falls 3.09 standard deviations below their means. Our approach differs in two aspects as we do not consider only downside risk but rather take into account extreme returns both on the upside and the downside. Indeed, while it is clear that investors are known for being crash-averse as pointed out by Weigert (2016), Chabi-Yo et al. (2018) and Ouzan (2020) risk averse investors do not only dislike crashes in particular but also dislike uncertainty in general. Hence, rational investors will aim at building portfolios that reduce their exposure to volatility during normal market conditions and to extreme movements during very volatile markets. Practical intuition to explain these investors' preferences can be found in Martin (2013) who show that risk-averse agents typically like odd order cumulants such as mean and skewness and dislike even order cumulants such as volatility and kurtosis. Hence, stock return risk cannot be reduced to volatility and should capture higher order moments. Our analysis focuses on the impact of CSP on stock extreme movements as well as standard Gaussian volatility. To this aim we use a parametric structural model to capture the dynamics of stock returns while accounting for both the frequency and magnitude of extreme returns, namely booms and crashes. Secondly, we are able to separate risk into a pure volatility component, through Gaussian innovations which capture moderate aspects of stock risk and a non-Gaussian component that measures the risk of extreme returns, accounting for both booms and crash manifestations of stock returns. Our measure of tail risk borrows from the extent asset pricing literature. Indeed, Kelly and Jiang (2014), Barro and Jin (2011) and Gabaix (2009), to pick a few, use the power law distribution to model the left tail of asset returns. By contrast, we use this type of distribution to model both the crash and boom aspects of stock return dynamics. Hence, in our model, stock price risk stems from two sources: Gaussian risk and jump risk. By applying our risk decomposition to SP 500 firms, we cast a new perspective on the nexus between CSP and firm risk. Firstly, we find that CSP mainly affects stock price risk by decreasing the likelihood and magnitude of extreme returns, both booms and crashes. Surprisingly, we find no statistically significant relation between CSP and standard Gaussian volatility. Furthermore, we generalize the strand of literature that focuses on the impact of CSP on crash risk and show that CSP not only reduces the risk of stock price crashes but also diminishes the likelihood of extreme upside moves.

The next section specifies our parametric approach used to model stock return dynamics. Section 3 describes the moment matching procedure being used to estimate the parameters of our fat-tailed model for stock returns. Section 4 analyzes the impact of CSR on our various measures of firm's risk. The last section concludes.

2. Stock return dynamics

To model the tail behavior of stock returns we assume that the latter are driven by both Gaussian and non-Gaussian innovations as follows:

$$r_{i,t+1} = \mu + u_{t+1} + v_{t+1} \tag{1}$$

$$u_{t+1} \sim \mathcal{N}(0,\, \sigma^2)$$

$$v_{t+1} = \begin{cases} 0 & \text{with probability } 1 - p_d - p_u \\ -v_{d,t+1} & \text{with probability } p_d \\ v_{u,t+1} & \text{with probability } p_u \end{cases}$$

where r_{t+1} represents the daily log return for a given stock and both processes v_d, v_u are respectively crash and boom processes that are distributed exponentially:

$$v_{d,t+1} \sim exp(\alpha_d)$$

$$v_{u,t+1} \sim exp(\alpha_u)$$

Effectively, stock return r_{t+1} is a combination of a constant growth rate μ, a Gaussian innovation u_{t+1} and a non-Gaussian jump process v_{t+1} that can be positive with probability p_u or negative with probability p_d. This jump process is idle most of the time with a probability $1 - p_d - p_u$. When this process becomes active, the magnitude of the non-Gaussian process is exponentially distributed with tail exponent α_d if a crash occurs and α_u otherwise. When both these exponents are $+\infty$ or when the probability of crash/boom occurrence are 0 the jump process becomes idle and the stock return turns out to be Gaussian.

Conversely, the lower the tail exponents α_u, α_d the more severe the boom (respectively the crash) may be, should it occur. These dynamics are akin to the model used Abdelaziz and Chibane (2023) for general assets and in Chibane and Kuhanathan (2023) for inflation break-evens. Note that the non-Gaussian innovation v does not distinguish between a systemic and an idiosyncratic shock. Indeed, here we are not concerned with the correlation of extreme movement between various assets but how CSR intensity impacts stock return tail distribution on a company per company basis.

3. Data and estimation

3.1. Fat-tailed model estimation methodology

We define the set of model parameters we wish to estimate as:

$$\theta = (\mu, \sigma, p_u, p_d, \alpha_u, \alpha_d) \tag{2}$$

which leaves 6 parameters to determine.

Given our set of historical data for the stock returns denoted by $(r_{t+1})_{1 \leq i \leq N, 0 \leq t \leq T}$, we first compute its empirical moment generating function (MGF) defined by:

$$\widehat{MGF}_k = \frac{1}{T} \sum_{t=0}^{T} e^{k r_{t+1}}$$

Furthermore, we show in Appendix A that within the fat-tailed model, the stock return's MGF is obtained analytically as a function of model parameters:

$$MGF_k = e^{k\mu + \frac{1}{2}k^2\sigma^2} \left(1 - p_d - p_u + p_d \frac{\alpha_d}{\alpha_d + k} + p_u \frac{\alpha_u}{\alpha_u - k}\right)$$

The estimation procedure consists, for a given set of historical returns, in trying to match moment orders as high as possible so as to reach maximum precision (in practice we go up to order 6). Consequently, using this historical return data, our estimation procedure solves the following minimization program:

$$\begin{aligned}
&\widehat{\theta} = \arg\min_{\theta} J(\theta) \\
&s.t \\
&0 \leq p_d, p_u \leq 1 \\
&\alpha_u, \alpha_d > 0
\end{aligned}$$

where:

$$J(\theta) = \sum_{k=1}^{6} \left(\widehat{MGF}_k - MGF_k(\theta) \right)^2$$

We perform our estimation on the constituents of the S&P 500 stock prices for which we extract daily data. We execute this estimation procedure for each stock on a rolling basis, using an estimation window of 2 years where the first set of daily returns spans the period [01-01-2015,30-12-2016]. Hence, the first model estimation is performed as of 02-01-2017. We then move the estimation window by one day and repeat the same procedure for each stock until the end of the sample. We therefore obtained the model parameters $\mu, \sigma, p_u, p_d, \alpha_u, \alpha_d$ for 1597 consecutive business days. To get some intuition about the cross-sectional distribution of the fat-tailed parameters $p_u, p_d, \alpha_u, \alpha_d$ we display in Table 1 the summary statistics of these parameters' cross-sectional distribution for four different dates corresponding to the first estimation date (January 2017), the pre-COVID 19 period (end of December 2019), the post-COVID 19 period (end December 2020) and the end of the full sample (February 2023). We observe that over the pre-COVID 19 period, parameters are rather stable with returns boom probability close to 3.9%, a crash probability close to 2.9%, both showing low standard deviation of less than 0.6% among all stocks. However, after the outbreak of the COVID 19, the average of the boom probability across all stocks seem to increase substantially to 4.4% while the standard deviation decreases. Interestingly this effect dissipates a little bit at the end of the sample with a boom probability decreasing slightly to 4.2% and a standard deviation of 0.5%. Surprisingly, the advent of the Ukraine-Russia was does not seem to affect the boom probability significantly. Turning our attention to the crash probability, there seems to be no effect coming from neither the COVID-19 outbreak nor Ukraine-Russia tensions since p_d stays around 2.9% on all observation dates. We now set our attention to the boom and crash intensities. We observe that parameters α_u, α_d are fairly stable on the pre-COVID 19 periods and that booms are less pronounced than crashes with respective mean intensity parameters of 31.1 and 22.5 over the pre-COVID 19 with period with respective standard deviations of 6 and 5.5 approximately. However, post-COVID 19 the two parameters drop substantially to 22.6 and 15 respectively, indicating a higher propensity for extreme returns in the post-COVID period. This phenomenon dissipates a little bit towards the end of the sample with α_u, α_d increasing respectively to 19.5 and 27.5 in February 2023. To better understand how the fat-tailed model parameters change across the different segments of companies considered we plotted in Figure 1 the cross-sectional probability density function of crash and boom parameters. We can see that while the crash probability is largely unchanged along the cross-section, the pattern is rather different for the boom probability. Indeed, for stocks which exhibit a low boom probability p_u in 2017, this probability becomes even lower after the outbreak of the COVID-19 outbreak while those who had a high boom probability see this probability increase after the crisis. Looking at the intensity parameters α_u, α_d we find they both behave similarly: stocks exhibiting low parameter are more frequent and those exhibiting a higher intensity parameter are less frequent, thus indicating that if rare extreme returns occur, they are likely to be more substantial than prior to the COVID 19 outbreak.

Panel A. Boom probability cross-sectional summary statistics

	Mean (%)	Std (%)	Skewness	Kurtosis
January 2017	3.877	0.571	0.215	1.851
December 2019	3.970	0.586	−0.096	1.988
December 2020	4.360	0.407	−0.370	2.393
February 2023	4.189	0.495	−0.489	2.649

Panel B. Crash probability cross-sectional summary statistics

	Mean (%)	Std (%)	Skewness	Kurtosis
January 2017	2.817	0.550	0.596	2.447
December 2019	2.930	0.604	0.272	2.350
December 2020	2.932	0.802	0.644	1.921
February 2023	2.918	0.682	0.333	1.723

Panel C. Boom intensity cross-sectional summary statistics

	Mean (%)	Std (%)	Skewness	Kurtosis
January 2017	31.185	6.075	−0.398	2.987
December 2019	31.114	5.720	−0.258	3.152
December 2020	22.228	4.194	−0.178	3.104
February 2023	27.488	5.350	−0.148	2.421

Panel D. Crash intensity cross-sectional summary statistics

	Mean (%)	Std (%)	Skewness	Kurtosis
January 2017	22.609	5.542	−0.977	3.166
December 2019	22.546	5.341	−0.938	3.209
December 2020	15.021	5.304	0.227	1.923
February 2023	19.457	5.837	−0.442	1.918

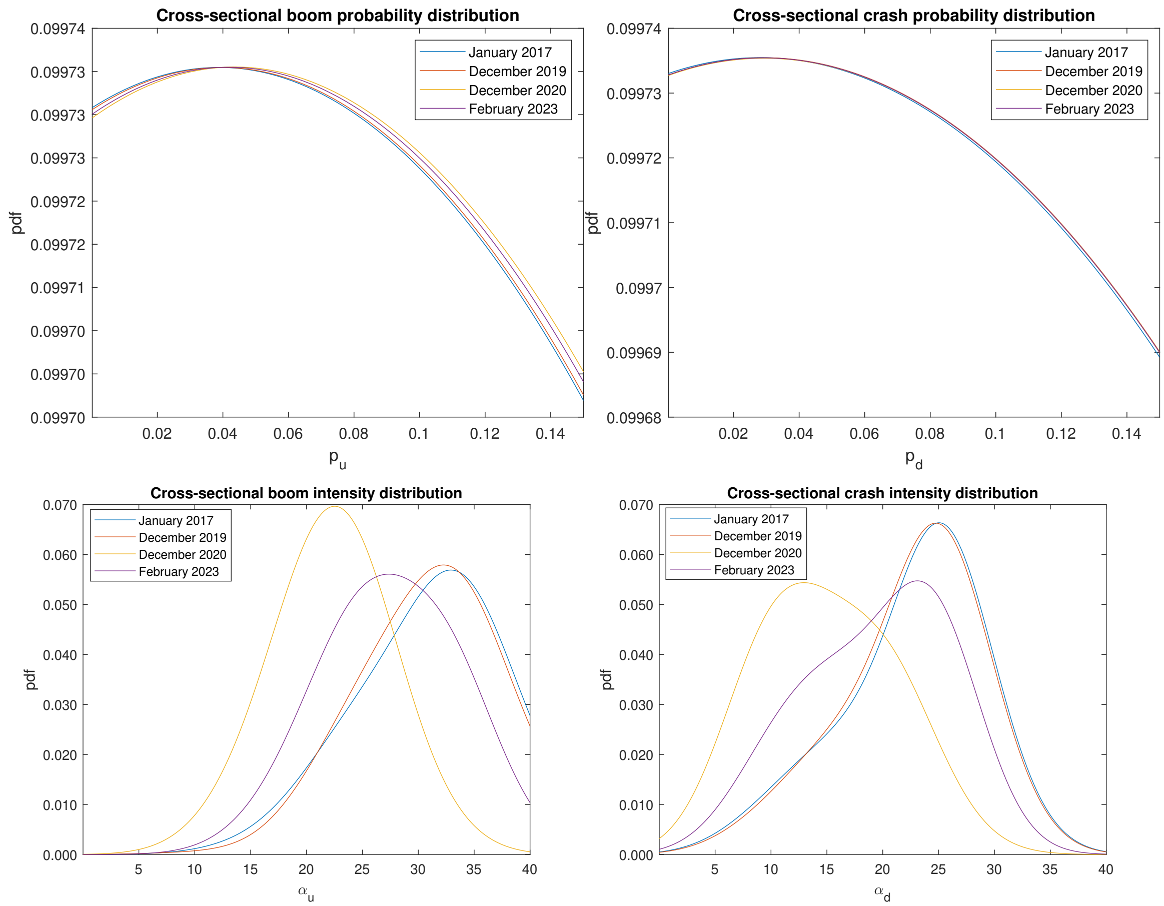

Figure 1: **Fat-tailed model parameter distribution**

These graphs show the cross sectional probability density function of the fat-tailed model parameters obtained by kernel smoothing for different dates, respectively the beginning of January 2019, the end of December 2019 (Pre-COVID 19) and December 2020 (Post-COVID 19), as well as the last sample date.

4. Relation between corporate social performance and extreme stock returns for the S&P500

4.1. Empirical model

To investigate the impact of CSP on the probability of crash and boom of S&P 500 stocks, we proxy CSP for each firm by their ESG ratings. ESG ratings are numerical scores ranging from 0 to 100. We then perform the following regressions:

$$
\begin{aligned}
X_t = \beta_0 + \beta_1 ESG_t + \beta_2 Return_t, + \beta_3 SigmaRV_t + \beta_4 Size_t \\
+ \beta_5 Leverage_t + \beta_6 PtB_t + \beta_7 RoA_t \\
+ Firm + Year + \epsilon_t
\end{aligned} \tag{3}
$$

where variable X_t represents the value at time t of one the fat-tailed model parameters $\mu, \sigma, p_u, p_d, \alpha_u, \alpha_d$. The regressions are done independently for each of the dependent variables.

All of our variables are extracted from Bloomberg. Our main variable ESG_t is the ESG rating from S&P. The scores are based on about 1000 data points for each firm and on over 130 question-level scores. The earliest ratings were issued in September 2016 and our daily data set ranges from September 2016 to February 2023. Here t, is the date at which the ESG rating is released or updated by S&P. Our control variables in Equation 3 are consistent with existing literature (Chen et al. (2001), Kim et al. (2011)). $Return_t$ is the mean of firm-specific weekly returns for the year preceding the ESG rating, $SigmaRV_t$ is the mean of firm-specific standard deviation of weekly returns for the year preceding the ESG rating (i.e. realized volatility). $Size_t$ is the natural logarithm of market capitalisation at the time of the rating, $Leverage_t$ is the debt-to-asset ratio, PtB_t is the price-to-book ratio at the time of the rating and RoA_t is the net profit divided by total assets as known at the time of the ESG rating. Furthermore, we control for firm and year effects.

4.2. Data & Baseline regressions

Table 2 offers a detailed statistical analysis of our main variables. The dataset comprises 2324 distinct observations of firm-ratings. Unsurprisingly, the ESG ratings, a key variable in our analysis, exhibits a mean value close to the mid-range score of 50, specifically at 52.17 for our sample. The relatively high standard deviation of 27 points in this measure, also points to notable disparities in the CSP across the sample. This substantial variation suggests that the firms in our sample exhibit a wide spectrum of approaches towards ESG issues, with some firms demonstrating superior commitment and efficacy in addressing these critical concerns. In the following sections, we will examine the potential relationships between stock extreme event risk and CSP.

	N	mean	sd	min	p25	p50	p75	max
Size	2324	10.401	1.069	5.377	9.596	10.21	10.977	14.784
ESG	2324	52.166	27.005	0.0	30.0	53.0	76.0	100.0
RoA	2324	6.908	7.494	-31.366	2.278	5.631	10.619	52.368
Price-to-Book	2324	16.925	90.339	0.247	2.127	4.006	8.086	1713.086
Leverage	2324	31.459	19.988	0.0	18.801	31.032	42.169	233.654
Return	2324	0.004	0.005	-0.013	0.001	0.004	0.006	0.046
SigmaRV	2324	0.016	0.007	0.003	0.011	0.014	0.019	0.058

Table 2: **Explanatory variables summary statistics**

This table displays the summary statistics for the main regression explanatory variables. N is the number of unique firm-rating observation, mean is the mean of each series, sd is the standard deviation, min, p25, p50, p75 and max are the minimum, the 1st quartile, the 2nd quartile, the 3rd quartile and the maximum, respectively.

Table 3 lays out the primary results derived from Equation 3. These main findings corroborate the significant influence of ESG ratings on p_u, p_d, α_u, and α_d. The coefficients for both p_u and p_d are significant at the 5% threshold and negative. This implies that a reduction in both boom and crash risks is associated with higher ESG scores. However, it is worth noting that the coefficient for p_d is higher, suggesting that an elevated ESG score primarily mitigates the risk of a crash rather more than it reduces the probability of a boom.

Moreover, the coefficients corresponding to ESG ratings for α_u and α_d are both significant (at 5% for α_u and 1% for α_d) and positive. As a larger

α is associated with a less severe jump, our estimate suggests that higher ESG scores are associated with a diminished severity of potential booms or crashes. Let us note that the coefficient for α_u is marginally greater, pointing to a slightly stronger effect on the magnitude of potential booms compared to crashes. However, the difference is less marked than that observed for boom and crash probabilities, meaning that the effect of ESG scores on the severity of jumps is somewhat symmetric.

	p_u	p_d	α_u	α_d	μ	σ
	(a)	(b)	(c)	(d)	(e)	(f)
ESG	-1.94e-05**	-3.216e-05**	0.019*	0.015**	-2.687e-06*	-8.867e-07
	(-2.05)	(-2.342)	(3.01)	(2.03)	(-2.99)	(-0.30)
Return	-0.1741*	-0.116*	-56.25*	0.79	0.059*	0.071*
	(-6.38)	(-2.965)	(-2.97)	(0.03)	(15.93)	(6.19)
SigmaRV	0.1587*	-0.159*	-418.01*	-353.90*	-0.024*	0.405*
	(4.04)	(-3.057)	(-15.07)	(-9.49)	(-5.74)	(23.56)
Size	-0.0003	0.003*	0.543**	0.363	0.001*	-0.001*
	(-0.61)	(5.530)	(2.22)	(1.14)	(10.28)	(-5.40)
Leverage	-3.39e-05***	-2.51e-05	0.019***	0.012	3.629e-06	-3.042e-06
	(-1.93)	(-1.018)	(1.88)	(1.02)	(1.64)	(-0.47)
PtB	1.48e-06	-2.49e-06	-1.78e-05	-0.002	-1.003e-07	1.169e-06*
	(0.79)	(-0.739)	(-0.02)	(-1.51)	(-0.65)	(2.87)
RoA	2.24e-06	-2.92e-05	0.067*	0.015	1.37e-05*	-1.4e-05
	(0.08)	(-0.773)	(3.89)	(0.73)	(4.11)	(-1.52)
Constant	0.043*	0.001	27.68*	20.83*	-0.007*	0.011*
	(9.39)	(0.182)	(10.55)	(6.15)	(-9.01)	(6.33)
R^2	0.05	0.04	0.19	0.09	0.56	0.56
F (robust)	11.1	10.8	43	16.5	121	102
F test (p-value)	0	0	0	0	0	0

Table 3: **Regression estimates**

This table displays the coefficients for the main regression. F is the statistical value of the f-test, F test (p-value) is the significance of the observations. Figures in parenthesis are the t-stats for the respective coefficients.***, **, * denotes significance at the 10%, 5% and 1% level respectively

Looking at the regression coefficient for the Gaussian volatility σ, we see that the ESG coefficient is not significant. Such result - associated with our estimates on jump probabilities, would tend to suggest that ESG risk does not have a significant impact on the Gaussian risk associated with a particular stock but rather on the risk of extreme price movements. This casts a new perspective on the relation between CSP on risk through two different aspects. Firstly, we find that their main association is through tail risk (non-Gaussian) rather than through stock volatility (Gaussian). Secondly, increased CSP not only diminishes the probability and severity of extreme negative returns but also diminishes the likelihood and magnitude of extreme positive returns. Lastly, for μ, we observe in equation (e) that the ESG coefficient is significant at the 1% level and that it is negative. This would tend to suggest that higher ESG score reduces returns. This is still an actively debated issue in research as pointed out in Gillan et al. (2021).

The remaining exogenous variables with a significant coefficient are consistent with the literature as well as economic intuition. Leverage decreases the likelihood and magnitude of a boom, with both coefficients being significant at the 10% threshold. We find no statistically significant effect of leverage on the probability and severity of a return crash. Indeed, as higher debt reduces the ability of firms to generate free cash flows to distribute to shareholders, which can limit upside movements for stock prices. Return-on-asset only has positive coefficient in (e) : higher return-on-asset from a corporate would be associated with higher stock return. Price-to-book ratio only has statistically significant (and positive) effect on Gaussian volatility, suggesting that a stock which has a market valuation far above its book value, could be prone to more volatility.

4.3. Robustness tests

In order to confirm our results, we replace the S&P ESG ratings by those provided by Refinitiv for S&P 500 stocks, over the same horizon. The results of this regression are broadly in line with our baseline model. As per Equations (g) and (h), We still find a significant influence of ESG ratings. The coefficients for both p_u and p_d in Equations (i) and (j) are significant and negative, like in our baseline model. However, we note that the coefficient for p_u is slightly higher, unlike in our baseline model, implying that the effect of ESG score could be more symmetric than initially estimated.

The coefficients corresponding to ESG ratings for α_u and α_d are also significant and positive. Both coefficients are similar here, confirming the symmetric impact of ESG scores. We also confirm here that ESG score do not have a significant impact on σ (see Equation (l)), which tends to confirm our initial finding : ESG score have no impact on the Gaussian risk profile of stocks. While in our baseline model, we found a positive relation between ESG score and μ, in (k) the coefficient is not statistically significant. This underlines the very uncertain nature of the nexus between ESG score and stock performance.

	p_u	p_d	α_u	α_d	μ	σ
	(g)	(h)	(i)	(j)	(k)	(l)
$ESG_{Refinitiv}$	-5.622e-05*	-4.742e-05*	0.031*	0.032*	1.252e-06	-3.559e-06
	(-4.39)	(-2.59)	(3.28)	(2.88)	(-1.52)	(-0.94)
Return	-0.128*	-0.022	-79.92*	-29.13	0.002*	0.053*
	(-5.93)	(-0.72)	(-4.94)	(-1.54)	(27.45)	(8.24)
SigmaRV	0.213*	-0.25*	-416.68*	-390.51*	0.003*	0.43*
	(7.43)	(-6.10)	(-19.48)	(-15.61)	(-9.86)	(50.4)
Size	-0.0001	0.001**	0.57**	0.047	3.096e-05*	-0.001*
	(-0.44)	(2.55)	(2.39)	(0.17)	(18.42)	(-8.17)
Leverage	-2.254e-05***	-3.696e-05**	0.02**	0.005	1.251e-06	-1.855e-06
	(-1.76)	(-2.02)	(2.17)	(0.45)	(1.39)	(-0.49)
PtB	1.093e-06	2.166e-07	-0.003***	-0.003***	2.034e-07	1.922e-06*
	(0.53)	(0.07)	(-1.86)	(-1.84)	(-0.95)	(3.12)
RoA	-7.637e-06	-6.758e-06	0.049*	0.0191	1.918e-06*	-3.012e-06
	(-0.39)	(-0.24)	(3.31)	(1.11)	(9.51)	(-0.52)
Constant	0.043*	0.025*	27.34*	24.40*	0.0003*	0.009*
	(12.77)	(5.20)	(10.95)	(8.36)	(-15.95)	(9.33)
R^2	0.05	0.03	0.18	0.11	0.47	0.57
F (robust)	18.6	9.9	79.9	44.3	317.8	470.6
F test (p-value)	0	0	0	0	0	0

Table 4: **Regression estimates with Refinitiv ESG scores**

This table displays the coefficients for the main regression. F is the statistical value of the f-test, F test (p-value) is the significance of the observations. Figures in parenthesis are the t-stats for the respective coefficients.***, **, * denotes significance at the 10%, 5% and 1% level respectively

5. Conclusion

In this paper, our main objective was to investigate the connection between CSP and extreme events in stock prices. Specifically, we focused on analyzing the probabilities of booms and crashes, their magnitudes while accounting for the Gaussian risk profile of stocks returns as well as financial fundamentals.

Our study identified several key findings: CSP has significant impact on the likelihood of booms and crashes in stock prices. Indeed, companies with higher ESG ratings tend to experience a lower probability of extreme events compared to those with lower ratings. Furthermore, stocks with higher ESG ratings exhibit smaller magnitudes of booms and crashes when such events do occur. This suggests that incorporating ESG considerations into investment decisions can help mitigate the severity of extreme price movements. ESG ratings provide unique insight that goes beyond traditional risk measures and financial performance indicators.

These findings highlight the importance of considering ESG factors in investment decision-making. Incorporating CSP can potentially enhance risk management strategies and contribute to more stable and sustainable investment portfolios. Our study makes a contribution to the literature on the link between CSP and stock performance, by shedding light on the channel by which CSP impacts the overall stock price risk. It does so by lowering jump probabilities and magnitude but does seem to significantly impact the Gaussian risk of a stock. These results should lead to reconsidering ESG ratings in investment decisions and also contribute to the ongoing policy debates on the role of ESG factors in financial markets.

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Appendix A. Derivation of the tail process MGF

The MGF of the fat-tailed process can be obtained analytically as follows:

$$E\left[e^{kv_{t+1}}\right] = (1 - p_d - p_u)\, e^{k\times 0} + p_d E\left[e^{-k\times v_{d,t+1}}\right] + p_u E\left[e^{k\times v_{u,t+1}}\right]$$

For the MGF to be well defined we need:

$$\begin{aligned}
& -k - \alpha_d \leq 0 \\
& k - \alpha_u \leq 0 \\
& \Leftrightarrow \\
& -\alpha_d \leq k \leq \alpha_u
\end{aligned}$$

If this is the case we get:

$$M(k) = E\left[e^{kv_{t+1}}\right] = (1 - p_d - p_u) + p_d \frac{\alpha_d}{\alpha_d + k} + p_u \frac{\alpha_u}{\alpha_u - k}$$

The MGF of the stock return is also given analytically by:

$$
\begin{aligned}
&MGF_k = E\left[e^{kr_{t+1}}\right] \\
&= E\left[e^{k(\mu+u_{t+1}+v_{t+1})}\right] \\
&= e^{k\mu}E\left[e^{ku_{t+1}}\right]E\left[e^{kv_{t+1}}\right] \\
&= e^{k\mu+\frac{1}{2}k^2\sigma^2}M\left(k\right)
\end{aligned}
$$