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The resilient power of CSR: Sustained risk reduction despite widespread ESG adoption

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ABSTRACT

This paper explores the role of CSR in risk mitigation within an increasingly ESG-focused environment. Using monthly data from 2016 to 2023, we employ several risk measures representing systematic, idiosyncratic and downside risks. Through comprehensive panel regression analysis, we reveal robust risk reduction effects across model specifications, contrasting with the mixed profitability outcomes reported in the literature. Notably, the risk mitigation effect is broad-based and intensifies as ESG adoption becomes widespread, challenging prevailing assumptions of diminishing impact. These results have significant implications for firm valuation and investor decision making.

1. Introduction

Corporate Social Responsibility (CSR) has been a focus of academic research for decades (Viviers and Eccles, 2012). Initially approached from ethics, CSR has evolved towards stakeholder theory (Kumar and Srivastava, 2022) and analyses of corporate decision making (Harjoto and Laksmana, 2018). However, its intersection with finance remains relatively underexplored (Hong et al., 2020). This study positions itself within this area, where most research has followed industry trends by focusing on responsible investing (Dumrose et al., 2022).

While environmental, social and governance (ESG) investing is widely recognized to have an impact on firm value and is often associated with better financial performance, the direction of the effect of CSR remains inconclusive (Atz et al., 2023; Rupp and Limpaphayom, 2024). In contrast, research linking CSR to risk presents more consistent findings. The growing evidence supporting the role of CSR in risk mitigation requires further investigation to validate the robustness of this relationship (Sassen et al., 2016; Leifhelm et al., 2025) and to gain deeper insight into the mechanisms through which CSR influences risk (Gillan et al., 2021).

Our study addresses both questions and contributes to the literature by strengthening the understanding of the CSR-risk link. First, we build on earlier work, which often relied on partial data, such as specific risk concerns (Hoepner et al., 2023; Jo and Na, 2012), by employing more comprehensive ESG scores over an extended period. Second, we examine alternative risk metrics to provide new insights into the unresolved channels connecting CSR and risk. A recent approach demonstrates the hedging properties of responsible stocks in portfolios (Prol and Kim, 2022; Sun et al., 2024). Some studies argue that CSR shields firms from adverse events, focusing on downside risk (Hoepner et al., 2023; Jung and Song, 2023; Shafer and Szado, 2020), while others highlight its role in reducing firms' cost of capital (Albuquerque et al., 2019; Chollet and Sandwidi, 2018; Dorfleitner and Grebler, 2022; Görgen et al., 2020; Shakil et al., 2025) or its impact on firm-specific (idiosyncratic) risk (Fauser and Utz, 2021; Lee and Faff, 2009; Liu et al., 2023; Sassen et al., 2016).

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Improved CSR influences firm value in two stages (Breuer et al., 2024; Görgen et al., 2020): it mitigates corporate risk by reducing the weight of unfavorable outcomes (Albuquerque et al., 2019) and lowers the cost of capital (Pástor et al., 2022), resulting in lower expected returns. The firm's value increases when investor preferences shift, altering underlying assumptions (Ma et al., 2023). In this framework, the prevailing model suggests diminishing returns from CSR as ESG investing becomes widespread (Pástor et al., 2021). Our analysis demonstrates that, when measured through risk, CSR's impact has not diminished but intensified. Furthermore, we aim to bridge the research streams on risk and performance by analyzing more comprehensive and recent data from a period of widespread ESG adoption, which is crucial for achieving theoretical consistency.

The next section outlines the theoretical background and our hypotheses. Section 3 describes the sample, the construction of proxy variables, and the design of the tests. Section 4 presents and discusses the results, and Section 5 concludes.

2. Theoretical background and hypotheses development

2.1. The need for robust proof of the link between CSR and firm risk

Early studies found higher costs of capital in industries such as tobacco, alcohol, weapons, or heavily polluting activities (Hong and Kacperczyk, 2009; Jo and Na, 2012). This effect was attributed to the moral concerns of investors who avoid these sectors. Subsequent work extended this analysis, showing that firms with a stronger balance of CSR strengths over concerns benefit from lower costs of capital (El Ghoul et al., 2011; Nguyen and Nguyen, 2015).

The former binary CSR metrics (strengths and concerns) transitioned to ESG scores, becoming more comprehensive by integrating diverse environmental, social, and governance factors. Not only do ESG scores align better with the broader concept of CSR, but they also correspond with investor behavior, which increasingly relies on such metrics for decision-making rather than excluding certain sectors (Krueger et al., 2020).

However, discrepancies among raters still raise concerns about the reliability of these measures (Berg et al., 2022). Gradual convergence could be achieved on the basis of common standards, mainly promoted by the EU Taxonomy (Breuer et al., 2024). While such convergence takes root, we conduct our analysis employing two alternative sets of ESG ratings to test:

Hypothesis 1. CSR reduces risk robustly across model configurations, measures, industries, and periods

2.2. The channels that conduct the effect

The prevailing theoretical framework integrates two key effects of CSR: the minimization of the probability of negative outcomes (i.e., cashflow scenarios weighted by investors) and the reduction of the cost of capital (Breuer et al., 2024). However, existing models often focus on only one of the effects—either reduced cashflow uncertainty (Hsu et al., 2023) or lower cost of capital (Pástor et al., 2021). Concurrently, many studies concentrate on downside or idiosyncratic risks as proxies for cashflow uncertainty (Hoepner et al., 2023; Lee and Faff, 2009), or systematic risk for the cost of capital (Albuquerque et al., 2019; Görgen et al., 2020).

To address the broad impact versus the prevalence of one of the effects, we test two hypotheses comparing the intensity of opposing risk measures:

Hypothesis 2.1 Better CSR relates to reduced systematic and firm-specific risks

Hypothesis 2.2 Better CSR relates to reduced bilateral and downside risks

2.3. The persisting effect as maturation arrives

Sustained superior financial performance in firms with better CSR, measured ex-post, is inconsistent with the lower cost of capital associated with safer firms. Instead, this may well be a temporary outcome driven by shifts in investor preferences as ESG standards gain traction. This effect on performance should diminish as ESG principles become widely adopted (Pástor et al., 2022). However, the risk mitigation effect may not dissipate after the revaluation of firms.

The recent reversal of previously positive flows into ESG funds in the US market (Morningstar, 2024) provides the scenario to test the persistence of CSR's risk-reducing effect:

Hypothesis 3. The risk reduction effect of CSR persists after ESG investment reaches maturity

3. Data and methods

We obtained data from Bloomberg and MSCI for an average of 1,847 firms over 82 months, resulting in 151,498 firm-month observations from September 2016 to June 2023. The MSCI database initially included 1,411 firms, expanding to 2,434 by the end of the period. This time frame was chosen to minimize fluctuations in firm coverage and avoid methodological changes in MSCI's database, most prevalent between 2012 and 2015. We conducted an additional reassessment using S&P Robeco's scores.

As summarized in Table 1, we measure total risk using two approaches: 30-day realized volatility ($SIGMA_S$) and the implied volatility of "at-the-money" call options ($IVATMC$). The latter reflects investors' risk expectations and is broadly available for US firms (Hoepner et al., 2023).

Table 1
Descriptive statistics.

	Mean	Std. Dev.	Min	25%	50%	75%	Max.	n
Risk Variables								
IVATMC	0.511	0.374	0.000	0.297	0.421	0.612	21.642	172,871
SIGMA_S	0.486	0.527	0.000	0.257	0.380	0.572	21.420	203,308
BETA	1.045	0.732	−23.966	0.653	1.009	1.394	21.374	206,547
SIGMA_I	0.436	0.522	0.001	0.217	0.332	0.514	21.389	201,931
IVOTMP	0.550	0.390	0.000	0.324	0.456	0.658	21.642	172,871
SMIRK	0.039	0.112	−4.396	0.010	0.026	0.045	2.525	172,871
SORT	0.320	0.317	0.000	0.162	0.251	0.388	10.583	201,815
MXDD	0.210	0.151	0.000	0.099	0.171	0.282	1.000	193,252
ESG Variables								
ESG	4.827	2.014	0.000	3.300	4.800	6.300	10.000	151,498
ENVIRONMENTAL_PILLAR	4.768	2.089	0.000	3.200	4.600	6.200	10.000	151,498
SOCIAL_PILLAR	4.564	1.483	0.000	3.600	4.500	5.500	10.000	151,477
GOVERNANCE_PILLAR	5.300	1.325	0.000	4.500	5.400	6.200	10.000	151,477
Control Variables								
BS_TOT_ASSET	10 171.782	40 122.064	0.000	470.569	1616.926	6007.178	1772124.000	209,094
MTB	3.206	2.511	0.001	1.425	2.426	4.237	17.163	175,096
OPERATING_ROA	0.054	0.093	−0.221	0.009	0.059	0.108	0.302	170,281
CAPASSETS	0.008	0.007	−0.001	0.003	0.006	0.012	0.031	183,908
RMOM	217.101	3757.176	−97.366	−16.401	−1.704	14.651	162 229.154	205,698
DEBT_TO_ASSET	0.272	0.212	0.000	0.077	0.260	0.415	0.941	205,746
DVD_PAYOUT_RATIO	0.157	0.242	−0.221	0.000	0.000	0.269	1.261	156,841
EQY_INST_PCT	0.770	0.341	0.000	0.542	0.858	1.024	1.745	202,914

Note: Risk variables and ESG variables are defined in the main text. Control variables include total balance sheet assets (BS_TOT_ASSET) to represent firm size, market-to-book (MTB), return on assets ($OPERATING\_ROA$) to capture profitability, capital expenditures on assets ($CAPASSETS$) for investment intensity, relative market momentum ($RMOM$), leverage ($DEBT\_TO\_ASSET$), dividend payout ratio (DVD_PAYOUT_RATIO) and institutional ownership (EQY_INST_PCT). n is the number of observations.

To separate idiosyncratic risk from systematic risk, most studies calculate idiosyncratic risk as the residual after modeling expected returns with a model of choice (Chollet and Sandwidi, 2018). We follow the assumptions of the CAPM model (Lintner, 1965; Sharpe, 1964):

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

where $r_{i,t}$ represents the return of stock i at time t, α_i is the stock's alpha, β_i is its beta, $r_{m,t}$ is the market return, and $\varepsilon_{i,t}$ is the idiosyncratic component. Assuming expected returns follow a normal distribution with mean μ and volatility σ, $\varepsilon_{i,t}$ is $N(0,1)$-distributed:

$$r_{i,t} = \mu_i + \sigma_i \varepsilon_{i,t} \tag{2}$$

Substituting the market return in Eq. (1) with its own generating process (Eq. (2)), we obtain:

$$r_{i,t} = \alpha_i + \beta_i \mu_{m,t} + \beta_i \sigma_{m,t} \varepsilon_{m,t} + \varepsilon_{i,t} \tag{3}$$

Taking the variance of both sides, where α_i, β_i, μ_m, and σ_m are constants for any t, results in:

$$\mathrm{Var}(r_{i,t}) = \mathrm{Var}(\beta_i \sigma_{m,t} \varepsilon_{m,t}) + \mathrm{Var}(\varepsilon_{i,t}) \tag{4}$$

This simplifies to:

$$\sigma^2_{Ti} = \beta_i^2 \sigma^2_{Mt} + \sigma^2_{Ii} \tag{5}$$

where σ^2_{Ti} represents the total risk of a stock, decomposed into systematic risk ($\beta_i^2 \sigma^2_{Mt}$) plus idiosyncratic risk (σ^2_{Ii}). Solving for σ_{Ii} yields:

$$\sigma_{Ii} = \sqrt{\sigma^2_{Ti} - \beta_i^2 \sigma^2_{Mt}} \tag{6}$$

As an implicit measure of downside risk, we employ the implied volatility of out-of-the-money puts ($IVOTMP$) (Kräussl et al., 2023), along with the lower end of the volatility smile ($SMIRK$) (Ilhan et al., 2021; Kräussl et al., 2023; Shafer and Szado, 2020). $SMIRK$, a term introduced by Shafer (Shafer and Szado, 2020) for its resemblance to half of a traditional volatility smile, is calculated as the difference between the volatility of out-of-the-money puts ($IVOTMP$) and at-the-money calls ($IVATMC$). This metric captures the skew in the volatility structure, offering a valuable tool for assessing market expectations of downside risk.

For a historical measure of downside risk, we introduce the second lower partial moment, which quantifies the standard deviation of returns falling below a specified threshold. We set this threshold at zero to minimize external bias, focusing on the standard deviation of negative returns. Developed in the late 1970s (Bawa and Lindenberg, 1977; Price et al., 1982), this measure has seen

Table 2
Segment analysis of eight risk measures.

Quintile		ESG	IVATMC	SIGMA_S	BETA	SIGMA_I	IVOTMP	SMIRK	SORT	MXDD
(L)	1	2.103	0.543	0.476	1.201	0.418	0.583	0.040	0.323	0.222
	2	3.748	0.504	0.445	1.152	0.388	0.547	0.043	0.302	0.209
	3	4.882	0.467	0.412	1.083	0.357	0.507	0.040	0.280	0.193
	4	6.008	0.436	0.396	1.058	0.341	0.474	0.039	0.270	0.187
(H)	5	7.638	0.379	0.356	0.974	0.304	0.415	0.036	0.242	0.167
H-L		5.525	−0.155	−0.114	−0.223	−0.108	−0.158	−0.003	−0.076	−0.052
t		1172.287	−75.179	−44.814	−109.422	−58.838	−68.844	−11.528	−36.177	−39.769

Note: This table represents the average value for each of the variables for each quintile in which the sample has been divided according to its ESG level. $IVATMC$ and $SIGMA_S$ proxy total risk, $BETA$, systematic risk, $SIGMA_I$, idiosyncratic risk, $IVOTMP$, $SORT$ and $MXDD$, downside risk, and $SMIRK$, the downside risk premium. $H-L$ represents the average value of quintile five (high) minus the average value of quintile one (low). t is Students t, calculated with Newey West errors. $H-L$ values are all significant to the 0.01 level.

limited application in our field (Hoepner et al., 2023). We designate it as $SORT$, as this second partial moment also forms the denominator of the Sortino ratio (Sortino and Meer, 1991), a widely used portfolio management metric emphasizing downside risk.

The focus on downside risk is particularly relevant, given its central role in the discussion about the nature of the CSR-risk relationship. To this end, we consider maximum draw-down ($MXDD$), a measure that quantifies the largest price decline during a specified period relative to the historical peak as used in the mutual fund industry. Compared to assumption-heavy metrics like cumulative abnormal returns, $MXDD$ is a model-free metric, which only depends on the time window of analysis. We employ 60- and 180-day windows and conduct robustness tests with alternative parameters.

Additionally, it is important to note that we use β as a proxy for systematic risk. As shown in Eq. (5), systematic risk is calculated as $\beta\sigma_M$. Since σ_M remains constant across all firms in any given period, quantifying the percentage impact of systematic risk through the percentage change in β remains valid for the analysis.

Our tests begin by dividing firms into quintiles based on their ESG ratings. We then examine differences in mean risk values, assess their statistical significance, and evaluate the monotonic decrease in risk across segments (Shafer and Szado, 2020). Unlike studies focused on optimal investment strategies, our research considers the impact on firm valuation. Consequently, we assign equal weights to all firms, which helps mitigate biases arising from the concentration of value in a few large stocks.

We perform panel regression analyses using the equation:

$$\text{RISK}_{it} = \beta_0 + \beta_1\,\text{ESG}_{it} + \beta_2\,X_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{7}$$

Here RISK_{it} denotes the risk for entity i at time t, evaluated using eight alternative metrics; β_0 is the intercept, β_1 represents the coefficient for the CSR variable, specified as the aggregate ESG. β_2 is the set of coefficients for the matrix of control variables X_{it}, γ_i accounts for entity fixed effects, capturing unobserved heterogeneity across entities, while δ_t controls for time-specific fixed effects affecting all entities. ε_{it} represents the error term.

To ensure the robustness of our results, we model entity effects alternatively at firm, sub-industry, and industry levels; we test for variations among industries and periods, use an alternative ESG data source (Berg et al., 2022; Chollet and Sandwidi, 2018), and evaluate the stability of our findings by restricting the sample to firms with a minimum number of observations[1].

4. Results and discussion

4.1. CSR reduces risk consistently across model configurations, measures, industries, and periods

Using the 5-segment technique, firms in the high ESG tier exhibit significantly lower risk than those in the low segments (Table 2). With Newey–West standard errors, the differences are statistically significant and consistently negative for all risk metrics. Risk decreases monotonically throughout ESG levels with one exception: only one of the 28 echelon steps is positive, and its value is a fraction of the average of the negative values.

Our regression analysis confirms a significant relationship between CSR and risk across all metrics (Table 3). The coefficients are consistently negative and statistically significant across model specifications and remain stable when entity effects, time effects, and control variables are included. At the industry level, based on the Global Industry Classification Standard (GICS), five of the 21 industries do not exhibit statistically significant results. Among the remaining 16 industries, the negative coefficients are significant at the 0.01 level, highlighting the robustness of the CSR-risk relationship (Table 4).

Our results support our first hypothesis and align with recent studies that show that improved CSR —as captured by comprehensive ESG scores— consistently drives significant risk reduction amidst evolving investor preferences and regulatory advancements (Shafer and Szado, 2020; Kräussl et al., 2023).

From a sectoral perspective, while ESG investing was in its early stages of adoption (Krueger et al., 2020) precursor work found the risk-reduction effect of CSR limited to controversial sectors (Harjoto and Laksmana, 2018) or reported inconsistent results,

1 A representative number of alternative model tests are shown in the tables. The results for all the tests are available upon request.

Table 3
Regression analysis of eight risk measures.

Dep. Variable	IVATMC (1)	SIGMA_S (2)	BETA (3)	SIGMA_I (4)	IVOTMP (5)	SMIRK (6)	SORT (7)	MXDD (8)
Intercept	0.6667***	0.5130***	1.0537***	0.4713***	0.6963***	0.0296***	0.3462***	0.2433***
	(135.49)	(127.37)	(128.19)	(115.60)	(140.92)	(15.803)	(109.32)	(132.87)
ESG	−0.0120***	−0.0083***	−0.0190***	−0.0077***	−0.0125***	−0.0005***	−0.0058***	−0.0034***
	(−36.788)	(−27.310)	(−24.934)	(−24.870)	(−35.200)	(−3.7272)	(−24.753)	(−19.501)
BS_TOT_ASSET	−4.319e−07***	−2.647e−07***	−8.236e−08***	−2.836e−07***	−4.656e−07***	−3.378e−08***	−1.886e−07***	−1.277e−07***
	(−17.469)	(−12.720)	(−3.0027)	(−13.077)	(−17.045)	(−9.1538)	(−12.951)	(−11.371)
MTB	−0.0034***	0.0001	0.0177***	−0.0013***	−0.0044***	−0.0010***	−0.0022***	−0.0038***
	(−8.9147)	(0.3240)	(22.586)	(−3.6782)	(−11.140)	(−8.3170)	(−9.9350)	(−22.633)
OPERATING_ROA	−0.7062***	−0.6288***	−1.2255***	−0.5816***	−0.7322***	−0.0260***	−0.4175***	−0.3142***
	(−59.977)	(−54.558)	(−48.023)	(−49.746)	(−58.966)	(−5.5416)	(−51.480)	(−53.484)
CAPASSETS	0.0192	0.5109***	1.5112***	0.4539***	0.1609	0.1416***	0.5426***	0.5291***
	(0.1615)	(5.1389)	(5.7695)	(4.5040)	(1.2818)	(3.2289)	(6.6432)	(9.3489)
RMOM	4.639e−07**	−8.6e−09	−1.457e−06***	2.232e−07	4.35e−07*	−2.895e−08	−2.885e−07	−2.867e−07*
	(2.1149)	(−0.0268)	(−3.5992)	(0.6635)	(1.9297)	(−0.1347)	(−1.4068)	(−1.9390)
DEBT_TO_ASSET	0.0616***	0.0608***	0.1471***	0.0511***	0.0558***	−0.0059***	0.0483***	0.0406***
	(11.882)	(14.263)	(15.018)	(11.793)	(10.130)	(−2.8856)	(15.620)	(17.356)
DVD_PAYOUT	−0.1791***	−0.1347***	−0.3020***	−0.1251***	−0.1805***	−0.0014	−0.0811***	−0.0502***
	(−65.631)	(−49.851)	(−47.318)	(−45.499)	(−59.379)	(−1.1217)	(−38.793)	(−33.913)
EQY_INST_PCT	−0.1166***	−0.0461***	0.1253***	−0.0585***	−0.0964***	0.0202***	−0.0252***	−0.0215***
	(−25.759)	(−14.054)	(18.375)	(−17.602)	(−21.331)	(13.484)	(−10.095)	(−13.971)
Effects	Entity	Entity	Entity	Entity	Entity	Entity	Entity	Entity
	Time	Time	Time	Time	Time	Time	Time	Time
n	91 590	95 114	95 114	94 410	91 590	91 590	95 104	92 348
R-squared	0.1791	0.1254	0.0898	0.1118	0.1644	0.0053	0.1011	0.1131
F-statistic	2215.2***	1512.0***	1040.7***	1317.1***	1997.3***	53.8***	1185.5***	1305.5***

Note: Panel regression results of eight risk measures on ESG scores, including the control variables described in Table 1. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 4
Risk regressed on ESG for 21 industry groups.

Industry group	Energy	Materials	Capital Goods	Commercial & Professional Services	Transportation	Automobiles & Components	Consumer Durables & Apparel
GICS code	1010	1510	2010	2020	2030	2510	2520
ESG	−0.0400***	−0.0104***	−0.0126***	−0.0004	−0.0021	−0.0065***	−0.0074***
	(−15.806)	(−12.248)	(−20.181)	(−0.3292)	(−1.5186)	(−2.7611)	(−7.5434)
n	5243	8859	13 855	5184	2346	2154	4602
R-squared	0.2284	0.2276	0.2623	0.3019	0.2382	0.3774	0.2190
F-statistic	169.3***	286.6***	543.5***	244.5***	78.2***	138.8***	140.3***

Industry group	Consumer Services	Consumer Discretionary Dist. and Retail	Consumer Staples Distribution and Retail	Food, Beverage & Tobacco	Household & Personal Products	Health Care Equipment & Services	Pharmaceuticals, Biotechnology & Life Sciences
GICS code	2530	2550	3010	3020	3030	3510	3520
ESG	−0.0111***	−0.0171***	−0.0007	−0.0039***	−0.0025	0.0037***	−0.0122***
	(−6.9346)	(−8.8068)	(−0.5186)	(−2.6361)	(−0.3630)	(3.4225)	(−6.7241)
n	3685	5055	1809	3090	680	6870	4967
R-squared	0.2795	0.2150	0.2587	0.2812	0.2918	0.2873	0.2463
F-statistic	154.8***	150.9***	66.5***	130.2***	27.0***	303.4***	177.0***

Industry group	Software & Services	Technology Hardware & Equipment	Semiconductors & Semiconductor Equipment	Telecommunic. Services	Media & Entertainment	Utilities	Real Estate
GICS code	4510	4520	4530	5010	5020	5510	6020
ESG	−0.0173***	−0.0119***	−0.0081***	−0.0039	−0.0185***	−0.0154***	−0.0099***
	(−13.204)	(−8.9730)	(−8.5431)	(−0.5912)	(−11.958)	(−12.946)	(−3.8529)
n	4199	5226	3164	1069	3954	4329	1250
R-squared	0.2634	0.2300	0.2766	0.3650	0.2707	0.2280	0.2186
F-statistic	163.1***	170.3***	130.6***	62.4***	159.1***	139.0***	36.0***

Note: This table reports the coefficients from panel regression results of risk measure $IVATMC$ on ESG scores, with control variables detailed in Table 1 (not shown for brevity) for firms in each industry group. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

including conflicting signs for different proxy variables (Nguyen and Nguyen, 2015; Jo and Na, 2012). Subsequent research observed the effect limited to large manufacturing firms (Cai et al., 2016). At a later stage of ESG adoption, we reveal consistent and monotonic risk reduction across sectors.

4.2. CSR relates as closely to systematic as to idiosyncratic risk

As modeled in Eq. (5), total risk is the sum of systematic and idiosyncratic risk. For an average firm, the values are $0.486^2 \approx 1.045^2 \times 0.163^2 + 0.436^2$ (Table 2). Approximately one-seventh of the total risk is attributed to systematic risk (the first term) and six-sevenths to idiosyncratic risk (the second term). The risk reduction from the first echelon to the fifth is −0.114, a reduction of 23% of the total risk, which corresponds to a reduction in systematic risk of −0.223 (a 21% reduction) and firm-specific risk of −0.108 (a 25% reduction). These results prove similar proportion reductions for total, systematic and idiosyncratic risks.

Table 5
Risk regressed on ESG using log-standard values.

Dep. Variable	lnIVATMC (1)	lnSIGMA_S (2)	lnBETA (3)	lnSIGMA_I (4)	lnIVOTMP (5)	lnSMIRK (6)	lnSORT (7)	lnMXDD (8)
ESG	−0.0225***	−0.0199***	−0.0215***	−0.0179***	−0.0205***	−0.0154***	−0.0180***	−0.0138***
	(−13.524)	(−10.220)	(−8.3539)	(−8.0548)	(−11.713)	(−5.4580)	(−8.6611)	(−5.7373)
n	23 526	24 245	22 771	23 928	23 513	20 867	24 138	23 084
R-squared	0.2744	0.1395	0.0631	0.1260	0.2650	0.0581	0.1005	0.0939
F-statistic	979.75***	432.80***	168.90***	379.70***	933.56***	141.47***	296.97***	263.48***

Note: Coefficients from panel regression results of eight log-standardized risk measures on ESG scores, with log-standardized control variables detailed in Table 1 for firms in each industry group. *t*-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

When our regression model is applied to total, systematic, and idiosyncratic risk measures, and the variables are log-standardized to account for differences in magnitudes and variations among metrics, the results reveal significant coefficients for the ESG variables. These coefficients exhibit comparable values for all total risk, systematic risk, and idiosyncratic risk measures, as presented in Table 5.

In summary, we find that the reduction in idiosyncratic risk exceeds that of systematic risk, primarily because idiosyncratic risk is initially larger. When we calculate risk reduction relative to the average firm's risk or standardized across measures, both components contribute similarly to the overall effect.

4.3. The effect on downside risk is driven equally or more by the bilateral component than the downside premium

To analyze the effect of CSR on bilateral and downside risk, we can reverse the definition of $SMIRK$ to derive:

$$RISK_{DOWNSIDE} = RISK_{BILATERAL} + DOWNSIDE\ PREMIUM \tag{8}$$

Or, in terms of our metrics:

$$IVOTMP = IVATMC + SMIRK \tag{9}$$

For the average firm, the values are: $0.550 = 0.511 + 0.039$, and the observed risk reduction is -0.158, which approximates $-0.155+(-0.003)$ (Table 2). This indicates that downside risk (IVOTMP) is reduced by 28.7% of its average value, total risk (IVATMC) is reduced by 30.3%, and the downside premium (SMIRK) is reduced only by 7.7% of its average value. Although the reduction in the downside premium is statistically significant relative to its initial value, the reduction is not quantitatively as relevant as the reduction in bidirectional risk. Therefore, most downside risk reduction can be attributed to its bidirectional component.

When we run our regression model with log-standardized values for the risk variables, we can compare the effect sizes by examining the coefficients. The results in Table 5 show coefficients of similar values: −0.0205 for $IVOTMP$, −0.0225 for $IVATMC$ and −0.0154 for $SMIRK$, indicating comparable effects on downside risk and on its bilateral and premium components. These findings suggest that the effect on the bilateral component of downside risk is at least as significant as its impact on the premium for downside risk.

We find strong support for hypotheses 2.1 and 2.2: Our results unequivocally demonstrate that CSR lowers investors' perception of the risk of negative outcomes, as shown by the downside and idiosyncratic measures, that proxy cashflow (numerator) effects, both if measured by ex-ante measures (e.g., implicit metrics) and by realized ex-post risks (e.g., downturns and observed volatility). Concurrently, it reduces the cost of capital (denominator effect), as evidenced by the reduction in systematic risk. All of this leads us to propose a reformulation of the risk reduction effect of CSR that is consistent with our results and aligns more closely with prevailing theory (Breuer et al., 2024), emphasizing its broader impact on overall firm risk rather than isolating it into specific components.

4.4. The intensity of the effect of CSR on risk is increasing

The β_1 coefficients for later years (−0.0125 to −0.0140) are significantly larger than those at the beginning of the sample period (−0.0033 to −0.0090). It is worth highlighting that the coefficient for 2020, when the COVID-19 anomaly impacted financial markets, is the largest at −0.0176 (Table 6).

The coefficient for risk reduction nearly doubles for the years after 2020 relative to the earlier years, increasing from −0.0069 to −0.0135. The disruption caused by COVID-19, spanning February 2020 to August 2020, is statistically significant (Chow test: $F = 1,100.8$, $p < .01$) (Table 7). The increased intensity, a multiplying factor of 1.53 to 2.67, is both quantitatively substantial and statistically significant across metrics representing total risk ($IVATMC$, $SIGMA_S$), idiosyncratic risk ($SIGMA_I$) and downside risk ($IVOTMP$, $SORT$, and $MXDD$). Although $BETA$ in the later period is slightly lower (multiplying factor 0.91), accounting for the increase in the market component, the systematic risk reduction $\beta\sigma_M$ is 46% stronger in the later period (see Fig. 1).

While the heightened protection observed during the COVID-19 crisis aligns with prior research suggesting CSR's mitigating role during systemic events (Albuquerque et al., 2020; Sun et al., 2024), the sustained intensification of this effect over time is a novel finding. Unlike the temporary impact of CSR on higher returns, this pattern indicates a persistent impact consistent with a stable

Table 6
Risk regressed on ESG for each of the years.

Year	2016	2017	2018	2019	2020	2021	2022	2023
Dep. Variable	IVATMC	IVATMC	IVATMC	IVATMC	IVATMC	IVATMC	IVATMC	IVATMC
ESG	−0.0033***	−0.0050***	−0.0058***	−0.0090***	−0.0176***	−0.0140***	−0.0125***	−0.0128***
	(−3.3281)	(−9.8786)	(−8.0078)	(−15.994)	(−14.514)	(−16.749)	(−15.079)	(−10.335)
n	3505	11 473	12 284	13 127	14 042	14 983	15 493	6683
R-squared	0.1903	0.1934	0.1222	0.2396	0.1585	0.1998	0.2651	0.2808
F-statistic	87.9***	301.8***	187.7***	454.5***	290.7***	411.7***	615.1***	283.8***

Note: Coefficients from panel regression results of risk measured by $IVATMC$ on ESG scores, with control variables detailed in Table 1. t-statistics are shown in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels.

Table 7
Increased sensitivity of Risk to ESG and breakpoint test.

	IVATMC	SIGMA_S	BETA	SIGMA_I
Before	−0.0069	−0.0057	−0.0176	−0.0055
Conf Interval	[−0.0076, −0.0063]	[−0.0064, −0.0051]	[−0.0198, −0.0154]	[−0.0062, −0.0048]
After	−0.0135	−0.009	−0.016	−0.0084
Conf Interval	[−0.0144, −0.0125]	[−0.0099, −0.0080]	[−0.0182, −0.0138]	[−0.0094, −0.0075]
After/Before	1.96	1.58	0.91	1.53
Chow test (F)	1100.8***	819.6***	1566.7***	623.4***
Dependent variable	IOTMP	SMIRK	SORT	MXDD
Before	−0.0072	−0.0003	−0.004	−0.0027
Conf Interval	[−0.0079, −0.0065]	[−0.0005, −0.0000]	[−0.0046, −0.0035]	[−0.0032, −0.0023]
After	−0.0142	−0.0008	−0.0061	−0.0033
Conf Interval	[−0.0153, −0.0132]	[−0.0012, −0.0003]	[−0.0068, −0.0054]	[−0.0038, −0.0027]
After/Before	1.97	2.67	1.53	1.22
Chow test (F)	926.8***	115.6***	577.0***	640.8***

Note: Coefficients from panel regression results of risk measured by eight risk variables on ESG scores, with control variables detailed in Table 1 during the "Before" period (September 2016 to January 2020) and the "After" period (August 2020 to June 2023). Confidence intervals are displayed at the 95% level. ***, **, and * indicate statistical significance of the Chow test F-statistic at the 1%, 5%, and 10% levels.

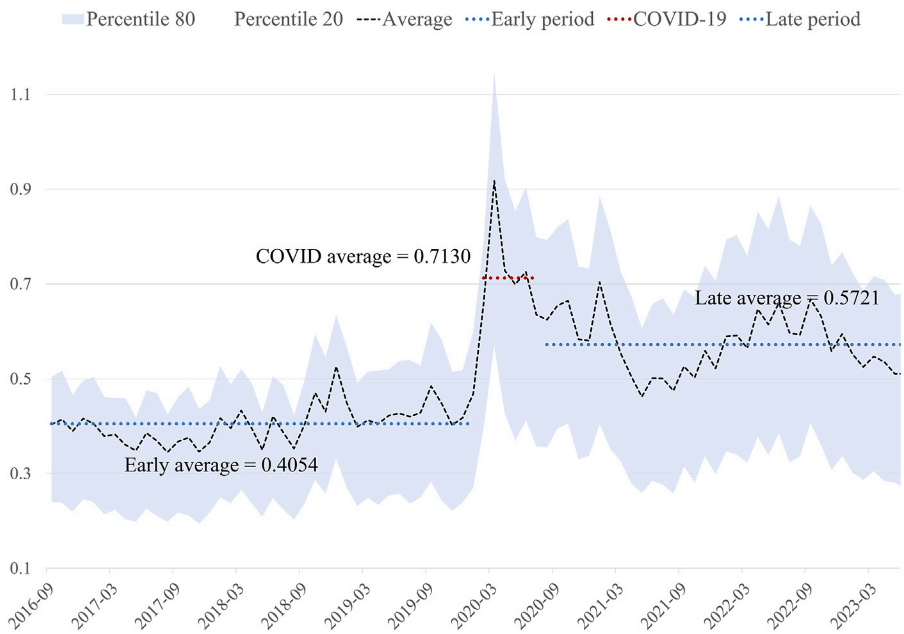

Fig. 1. Time series of risk measured by IVATMC.

shift in risk perception linked to CSR (Pástor et al., 2022). Investor focus on environmental, social, and governance risks may stem from several factors, including improved disclosure practices, the proliferation of ESG scores, ongoing regulatory changes (i.e. EU

Taxonomy), and evolving market norms. Identifying and ranking these factors and their relative contributions presents a valuable opportunity for future research.

5. Conclusion

Our results show that improved CSR reduces all measures of risk. It mitigates risks often categorized in the literature as downside or idiosyncratic, including litigation, stranded assets or technological disruption, as much as it reduces the cost of capital. We demonstrate that broad-spectrum metrics representing total risk provide a more accurate depiction of CSR's impact than metrics focused solely on downside, idiosyncratic risks, or the cost of capital. The broader effect is consistent with investors reassessing the weight of cashflow scenarios (a numerator effect) and firm risks to adjust the required returns (a denominator effect), as found in investor surveys (Krueger et al., 2020) and in our theoretical framework (Breuer et al., 2024; Zhang et al., 2024).

The persistence of the risk reduction effect contrasts with the variability observed in the effect on performance metrics (Ardia et al., 2023; Pástor et al., 2022). Our findings underscore the importance of further research to examine the long-term impact of CSR on risk. If future studies confirm the sustained intensity of the risk reduction effect, better CSR performance would directly support a firm's core objectives through risk mitigation and should be fully integrated into management strategies and asset valuation (Breuer et al., 2024; Shakil et al., 2025).

The period of analysis and the reliability of ESG scores stand out as potential limitations of our study. While our tests remain robust to macroeconomic factors, it is worth noting that risk measures have increased significantly during the period. We cannot exclude the possibility that the benefits of CSR could diminish if market risk decreases. To mitigate the effect of discrepancies in ESG ratings, we have tested our hypotheses with two alternative sources (Berg et al., 2022).

Our choice of US firms relates to the maturity of ESG investment in that market, which has recently shown net negative flows, enabling us to test the endurance of the effects found. Future research could extend the analysis to different sectors and regions to assess the impact of their respective leading and lagging regulatory standards, more fragmented markets, and different degrees of investor protection, which should lead to a deeper understanding and generalizability of the effects of CSR.

The authors used ChatGPT to improve the clarity of the text. After using this tool, the authors edited the content and take full responsibility for the paper.

CRediT authorship contribution statement

Jorge Merladet: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sara Lumbreras:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Andrés Ramos:** Supervision, Methodology, Conceptualization.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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