Review of Finance, 2024, **28**, 483–510
https://doi.org/10.1093/rof/rfad034
Advance access publication 3 October 2023
Article

ESG shareholder engagement and downside risk

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Abstract

We show that engagement on environmental, social, and governance issues can benefit shareholders by reducing firms' downside risks. We find that the risk reductions (measured using value at risk [VaR] and lower partial moments) vary across engagement types and success rates. Engagement is most effective in lowering downside risk when addressing environmental topics (primarily climate change). Further, targets with large downside risk reductions exhibit a decrease in environmental incidents after the engagement. We estimate that the VaR of engagement targets decreases by 9 percent of the standard deviation after successful engagements, relative to control firms.

Keywords: ESG, shareholder engagement, downside risk.
JEL classifications: G34, G11, G23.

1. Introduction

Institutional investor engagement on environmental, social, and governance (ESG) issues has become increasingly prevalent in financial markets. A primary goal of these engagements is to engender higher standards of corporate ESG practices that serve as an insurance mechanism against harmful, risk-inducing events as well as mitigating the likelihood of regulatory, legislative, or consumer actions against the firm. Several factors contribute to this trend, including the increased public interest in ESG issues, the growing size and importance of institutional shareholdings, and the still relatively low passing rates for shareholder proxy proposals on many of the ESG issues of importance to institutional investors.[1]

In this article, we examine the relationship between investor engagement of a portfolio firm and the firm's subsequent downside risk. Downside risks can be particularly important for a number of investors. For example, pension funds face large liabilities toward their beneficiaries and the failure of their assets to meet those liabilities carries significant penalties

[1] See Gillan and Starks (2000, 2007) or Grewal, Serafeim, and Yoon (2016).

Received: December 27, 2021. **Accepted:** September 29, 2023
Editor: Alex Edmans

(Ang, Chen, and Sundaresan 2013). Thus, such investors face downside risk constraints. The importance of downside risk for banks and insurance companies is reflected in the fact that regulatory capital requirements include calculations based on downside risk measures, usually value-at-risk (VaR) measures. Evidence also suggests that mutual fund managers and their shareholders consider downside risk in their investment decisions (Artavanis, Eksi, and Kadlec 2019; Bodnaruk, Chokaev, and Simonov 2019). Finally, while standard mean–variance investors would be more focused on volatility than downside risks, key assumptions in this framework are violated in practice. For example, although the mean–variance framework relies on the assumption that asset returns are jointly normally distributed, empirical evidence shows that returns are typically skewed, suggesting downside risk as an additional consideration.[2]

To examine whether shareholder engagements on ESG issues can result in downside risk reductions, we employ proprietary engagement data provided by a large institutional investor based in the UK. This investor is considered to be one of the most influential activists when it comes to promoting the development of higher ESG standards at portfolio firms. The investor not only has the weight of its own holdings, but also speaks on behalf of other large institutional investors for whom it conducts engagement activities. The institution's assets under advisement exceed \$1 trillion by the end of 2020. The investor primarily employs a private, nonpublic, approach to engage the portfolio firms, consistent with the more general evidence on institutional investor engagement in McCahery, Sautner, and Starks (2016).

Our data include 1,443 engagements across 485 targeted firms worldwide which the investor initiated during the 2005–2018 sample period. The investor provided us with full access to the engagement database, including shareholdings, engagement activities, action reports, and the investor's measures of engagement success. The measure of engagement success consists of four milestones (M): (i) the investor raises a concern with a target (M1); (ii) the target acknowledges the concern that was raised (M2); (iii) the target takes actions to address the concern (M3); and (iv) the investor successfully completes the engagement (M4). Out of all engagements in our sample, 33 percent successfully achieve all four milestones by the end of the sample period, 19 percent achieve M3, and 30 percent reach M2.

The investor most commonly engages firms regarding governance issues, which account for 51 percent of the sample engagements and frequently center on executive pay and board structure. The next most common engagement type (26 percent) consists of those that relate to environmental issues with a primary focus on climate risk, which has become an important engagement topic among institutional investors (Krueger, Sautner, and Starks 2020; Ilhan et al. 2023). The third most common engagement type covers social issues (23 percent), with three primary concerns: health and safety, supply chain, and illegal acts (e.g., bribery and corruption).

While engagements on environmental and social issues could be expected to reduce downside risk due to lower probabilities of harmful risk-inducing events, it is less obvious why engagements on governance issues should result in decreased downside risks. In fact, one may argue the opposite: such engagements could be intended to *increase* risk-taking if undiversified managers take too little risk compared with what is optimal for diversified shareholders.[3] In our setting, however, some governance engagements can reduce downside

[2] See Harlow and Rao (1989), Harvey and Siddique (2000), or Ang, Chen, and Xing (2006). Even Markowitz (1959) considered investors to be mean–semi-variance rather than mean–variance optimizing. Referring to semi-variance, a downside risk measure, as "S" and to variance as "V" Markowitz (1959: 193–194) explains that "analyses based on S tend to produce better portfolios than those based on V. Variance considers extremely high and extremely low returns equally undesirable. An analysis based on V seeks to eliminate both extremes. An analysis based on S, on the other hand, concentrates on reducing losses."

[3] For example, Gormley and Matsa (2016) show that poor governance (the adoption of antitakeover laws in their setting) causes managers to inefficiently reduce stock volatility and the risk of distress.

risks that originate from illegal activities or fraud, and risk reductions from such engagements are in the interest of shareholders. To illustrate, the investor's engagements to increase the independence of the audit or risk committee have the potential to reduce downside risks related to accounting fraud. Likewise, engagements to increase the holding period of equity-based pay should lower incentives to manipulate short-term earnings. However, not all governance engagements would be expected to reduce downside risk. For example, the investor's governance engagements that address issues related to increasing the CEO's pay-for-performance sensitivity do not have a clear expectation of affecting downside risks.[4]

To examine whether the investor's ESG engagement activities reduce the portfolio firms' downside risks, we employ two measures that reflect the potential wealth-protection motives of ESG engagements: (1) the target firm's VaR (Duffie and Pan 1997)[5] and (2) the lower partial moment (LPM) of the second order (Bawa 1975; Fishburn 1977), which captures *negative* return fluctuations. Using these measures, we employ the Gormley and Matsa (2011) stacked regression approach to estimate the changes in firms' downside risks from before to after the engagements, relative to a control group of matched firms, where matches are based on the country of the headquarters location, industry, and size. We employ the stacked regression approach, rather than staggered difference-in-differences (DiD) regressions, to avoid potential bias because of heterogeneous treatment effects or variation in treatment timing. Such bias could originate from previously targeted firms acting (implicitly) as control firms for firms that are targeted at later points in time (see Baker, Larcker, and Wang 2022).[6]

Using monthly data for the downside risk measures over 2-year windows surrounding the investor's initial engagement, we find the investor's engagements to be associated with subsequent reductions in the target firms' downside risk. These effects are driven by the engagements classified as successful, that is, at least M2 is achieved. We find the VaR declines by 0.205 from before to after the engagement, which is economically significant (9 percent relative to the standard deviation). The magnitude of the risk reduction effect increases if we impose a stricter definition of engagement success and consider only engagements where at least M3 has been achieved (i.e., the target management has started to take actions). Notably, we do not detect a risk reduction effect of engagement for those targets where M2 is not achieved (the target does not acknowledge the existence of an issue), which is consistent with our hypothesis that the engagement has causal effects.

Next, we consider *which* engagement types are most effective in reducing downside risks by examining how the effects vary across the investor's ESG themes. Considering M2 and M3 as the success threshold, engagements over environmental topics—primarily over climate change—deliver the highest benefits in terms of risk reductions. This is consistent with the survey evidence in Krueger, Sautner, and Starks (2020) and Ilhan et al. (2023) that engagement over climate risk and climate risk disclosure is an important channel through which institutions try to tackle climate risks—our results suggest that such engagements can deliver substantial benefits for investors, by lowering the downside risk exposures. The environmental risk reductions we detect echo broader evidence that environmental risks have become salient and highly costly when they materialize. A recent example illustrating the

4 This difference in the investor's risk goals for governance engagements may explain why in the subsequent analyses we find that governance engagements, on average, do not reduce downside risks.

5 The VaR measure should capture ESG risk because firms with better ESG performance become less vulnerable to firm-specific negative events (Krueger 2015). Ilhan, Sautner, and Vilkov (2021) use options-implied measures of tail risks to measure downside risk. We cannot take this approach because our international sample contains few firms for which liquid out-of-the-money puts are available.

6 We create, for each treatment event, an event-specific "cohort" dataset, whereby a cohort is defined by the firms (first) engaged in a given month (plus the corresponding matched firms). These datasets are then "stacked" together and a DiD regression is estimated using the stacked dataset, with cohort-specific fixed effects being added to the fixed effects structure.

tail risk character of environmental incidents is PG&E's climate-related bankruptcy in 2019.[7]

A central problem with measuring downside risk reductions in response to shareholder engagements is that its main effect might be to reduce the probability of a rare disaster. In this case, it could be difficult to measure any effect during our sample period because the potential disaster would then not occur. However, the implication of this issue is that the downside risk reductions we measure would be a lower bound on the total downside risk reductions. Further, our evidence on the environmental risk reductions that we do capture is consistent with related evidence in the climate finance literature as detailed by the Giglio, Kelly, and Stroebel (2021) review. For example, Ilhan, Sautner, and Vilkov (2021) document the pricing of carbon-related tail risks between 2009 and 2016. Similarly, Barnett (2020) finds his climate policy event index to be more discriminating between firms with varying degrees of climate risk for the "climate policy-focused" period from 1996 to 2017 than for his entire sample period (1973–2017). More recently, Sautner et al. (2023) show that discussions about climate risks in earnings conference calls have increased sharply since 2011.

Finally, we provide evidence on a channel through which the observed engagement activities reduce downside risk. As the risk reductions we document originate primarily from environmental engagements, we focus on negative outcomes related to environmental incidents, which we measure using news-based data from RepRisk. We exploit within-target variation to identify whether the engagement-induced risk reductions relate to actual changes in environmental incidents. Specifically, we contrast the change in environmental incidents around the investor's engagement between targets with large versus small reductions in downside risk. We find large and highly significant decreases in the number of environmental risk incidents at target firms that exhibit large engagement-induced downside risk reductions. For such targets, the number of incidents declines by 26 percent from before to after the engagement. In contrast, we find no corresponding declines in environmental incidents among engagements where downside risks did not decrease by a large amount.

We contribute to the literature on investor engagement, and specifically ESG engagement in two primary ways. First, we provide evidence to support the hypothesis that intervention over ESG topics reduces downside risk. This finding complements work that focuses primarily on the effects of shareholder engagements on first moments, that is, firm values or returns (Smith 1996; Carleton, Nelson, and Weisbach 1998; Becht et al. 2009; Dimson, Karakaş, and Li 2015; Barko, Cremers, and Renneboog 2022; Becht, Franks, and Wagner 2023). Including risk as an outcome variable, Dimson, Karakaş, and Li (2015) find that stock return volatility decreases after successful ESG engagements. Second, our evidence relates to contemporaneous work by Akey and Appel (2020), Naaraayanan, Sachdeva, and Sharma (2021), and Chu and Zhao (2019), who demonstrate that environmental shareholder activism has real effects through emission reductions. Our results complement their evidence by showing that activism can benefit shareholders through the lowering of downside risks.

2. Engagement data and process

2.1 Engagement data

We obtain the engagement data from a large institutional asset manager in the UK who is considered to be highly influential through an active ownership strategy. The proprietary database contains 1,443 ESG engagements targeting 485 firms worldwide, covering the period between January 2005 and April 2018[8]: We have access to many details of the

[7] See "PG&E: The First Climate-Change Bankruptcy, Probably Not the Last," *Wall Street Journal*, January 18, 2019.

[8] The investor also engages on "strategy" topics, which are not examined in this article as our focus is on ESG engagements.

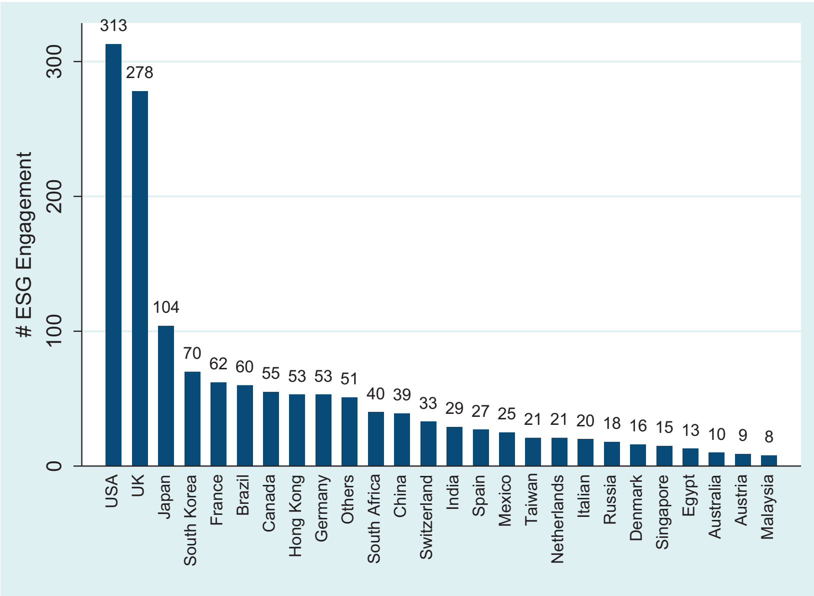

Figure 1. ESG engagements by country. This figure reports engagements by the target firm's country of incorporation. The sample consists of 1,443 engagements across 485 targeted firms over the period January 2005 through April 2018.

investor's engagement database, including the engagement reports, action reports, and success milestones.

Figures 1–3 display the breakout of the engagements by geographic location, industry, and year. Figure 1 shows that the investor engages firms across many countries, with the largest number of engagements targeting firms in the USA (313 or 22 percent of the sample) and the UK (278 or 19 percent). These countries are followed by two large Asian economies (Japan with 104 engagements or 7 percent; South Korea with 70 or 5 percent), two continental European countries (France and Germany, each about 4 percent), and Brazil (4 percent). Figure 2 illustrates that the most prominent engagement sectors are Financials, Basic Materials, Consumer Goods, Oil and Gas, Industrials, and Consumer Services.[9] The sectors less environmentally exposed (Technology and Telecommunications) are less frequently targeted. Figure 3 shows that the investor gradually increased the intensity of engagements from 2005, reaching a peak with 200 engagements in 2010, and then conducting slightly lower numbers of engagements in the remaining years of the sample. Although the number of engagements per year decreases after the peak, the investor remains very active, commencing 170 and 139 engagements in 2016 and 2017, the last two complete sample years.

2.2 ESG engagement process

The investor has a stated goal of engaging firms to incorporate long-term sustainability and risk management into their business operations and corporate policies. The investor believes that firms with informed and involved shareholders are better able to manage risk and minimize the occurrence of tail risk events. The investor further states that the engagement process consists predominantly of a constructive, confidential dialog, which is achieved with a team of more than thirty professionals who engage on behalf of the investor's own assets as well as on behalf of clients.

9 In the figure, industries are classified based on one-digit FTSE Russell Industry Classification Benchmark (ICB) codes.

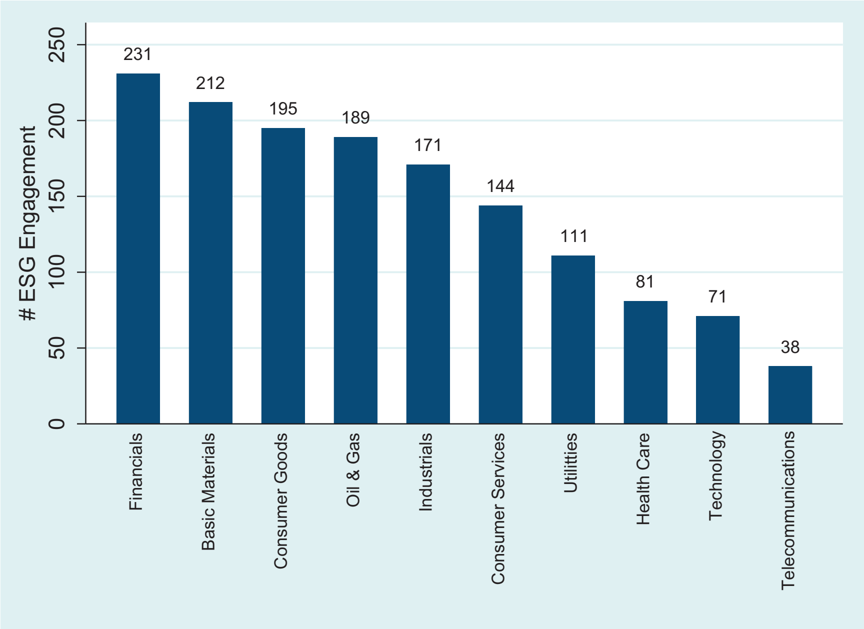

Figure 2. ESG engagements by industry. This figure reports engagements by the target firm's industry. The sample consists of 1,443 engagements across 485 targeted firms over the period January 2005 through April 2018. Industries are classified based on one-digit FTSE Russell Industry Classification Benchmark (ICB) codes.

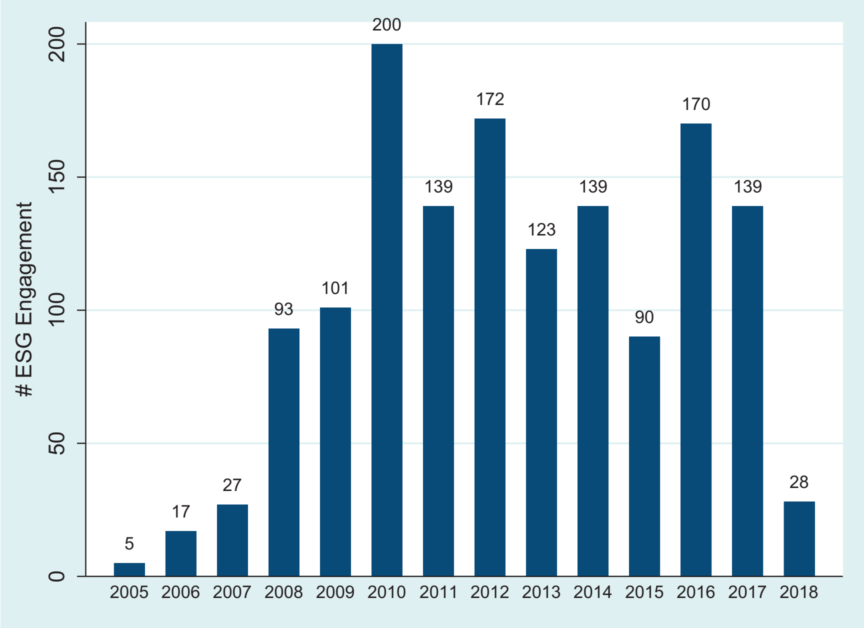

Figure 3. ESG engagements by year. This figure reports engagements by year of the initial engagement. The sample consists of 1,443 engagements across 485 targeted firms over the period January 2005 through April 2018. The 2018 year is partial year; thus, the 2017 year is the last year with complete engagement data in our sample.

These clients consist of more than forty asset owners, the vast majority of which are public pension funds, and the assets represented by our investor exceed $1 trillion by the end of 2020.

In Table 1, we report the frequency of engagements across the ESG themes. The investor most commonly engages portfolio firms over governance issues, accounting for 51 percent of all engagements, followed by engagements on environmental (26 percent) and social issues (23 percent). This distribution mirrors the percentages of engagements by a different asset manager studied by Dimson, Karakaş, and Li (2015) who also find for their investor a greater frequency of governance engagements than engagements on environmental and social topics.

Among all environmental topics (Panel A), the investor focuses primarily on issues related to climate change (47 percent). The importance of climate-related topics in our sample is reflected by the fact that the number of such engagements (179) amounts to more than 85 percent of the number of engagements on the most common "traditional" engagement

Table 1. Summary statistics on engagement themes.

This table provides summary statistics across three engagement themes: ESG. The table also breaks down these themes into subthemes and reports the number (percentage) of engagements within each engagement theme. The sample consists of 1,443 engagements across 485 targeted firms over the period January 2005 through April 2018.

Panel A: Environmental engagements		
Sub-themes	**#**	**%**
Climate change	179	47
Environmental policy and strategy	51	13
Supply chain management	44	12
Water	40	11
Pollution and waste management	38	10
Forestry and land use	27	7
Total	379	100
Percent of engagements ($N = 1{,}443$)	26.3	
Panel B: Social engagements		
Sub-themes	**#**	**%**
Human rights	142	42
Labor rights	91	27
Bribery and corruption	47	14
Conduct and culture	39	12
Other social	16	5
Total	335	100
Percent of engagements ($N = 1{,}443$)	23.2	
Panel C: Governance engagements		
Sub-themes	**#**	**%**
Executive remuneration	206	28
Board independence	193	26
Board diversity skills and experience	165	23
Succession planning	84	12
Shareholder protections and rights	81	11
Total	729	100
Percent of engagements ($N = 1{,}443$)	50.5	

topic: executive compensation (206). This observation reflects a wider trend: Climate change has become an important engagement topic for many institutions, apparently caused by their belief that climate risks have the potential to adversely affect the values of the assets they manage (Krueger, Sautner, and Starks 2020). Additionally, many institutions find climate risks difficult to price and hedge, making direct engagement, such as demanding robust climate disclosure or a reduction in emissions, an important risk-management tool. Beyond this financial motivation, climate-related issues may also be addressed for nonfinancial reasons based on the view that institutional investors have a responsibility to protect the planet. IA Table I in the Supplementary Appendix shows that, across the investor's 179 climate engagements, 28 percent target a firm's carbon strategy and risk management, 27 percent aim to improve carbon disclosure, 25 percent strive to reduce a firm's carbon intensity, and 6 percent address stranded asset concerns.

In terms of social themes, as shown in Panel B of Table 1, the investor engages primarily over concerns regarding human rights (42 percent), labor rights (27 percent), and bribery and corruption (14 percent). These themes are similar to the social themes examined in Dimson, Karakaş, and Li (2015). Within the governance area (Panel C), the investor most frequently intervenes because of concerns over executive pay (28 percent), board independence (26 percent), board diversity (23 percent), and succession planning (12 percent). These concerns also reflect concerns of the broader institutional investor community, as shown in industry publications (Wilcox and Sodali 2017) and in surveys (McCahery, Sautner, and Starks 2016; Edmans, Gosling, and Jenter 2022).

Table 2, Panel A, reports the proportions of the engagements that reach each milestone by the end of the sample period. Across all categories of engagements, 30 percent achieve at least M2 (the target acknowledges the concern), 19 percent go one step further and achieve at least M3 (the target takes actions to address the concern), and 33 percent reach M4 (engagement is successfully completed). Thus, according to these milestones, the engagements have been met with varying success rates.

While similar to the success rates in Dimson, Karakaş, and Li (2015), the success rates in our sample are lower than those reported by activist hedge funds, who engage in a different way and generally for different purposes (the hedge fund success rates are 60 percent in Brav et al. [2008] and 60 percent in Klein and Zur [2011]). One reason could be that it is harder to persuade top management and the board to incorporate the requested ESG changes as compared with requested financial changes (capital structure or dividend policy), which traditionally have been the focus of activist hedge funds. Second, hedge funds typically target firms that are in need of the requested financial changes, and they bring other investors on board to lobby firm management for changes (Kedia, Starks, and Wang 2021; Brav, Jiang, and Li 2022).

Table 2, Panel B, shows that it takes on average 2 months to complete M1, then an additional 4 months until a portfolio firm also acknowledges an issue raised by the investor (M2), and 18 additional months until the target has also taken actions or developed a strategy to improve an issue (M3). For those targets for which all milestones are successfully completed, the process takes 35 months, on average.[10] The table also shows variation across the engagement themes in the time it takes to complete the engagement milestones.

In IA Table II, Panel A, in the Supplementary Appendix, we report the "actions" taken by the investor to achieve the engagement goals. Among all actions, about 45 percent take the form of meetings, followed by substantive emails (18 percent) and conference calls (16 percent). M1 and M2 can be completed, on average, with one or two meetings per engagement, while it takes an average of three meetings to achieve M3 and five meetings to achieve M4. Moving from M2 to M3, and especially from M3 to M4, are the more difficult

10 These rates can be compared with Becht et al. (2009) who find that collaborative corporate governance engagements take 16 months, whereas confrontational ones take 43 months. Brav et al. (2008) find that the average duration of an engagement undertaken by a hedge fund is 12 months.

Table 2. Summary statistics on engagement success and duration.

This table displays descriptive statistics on measures of engagement success ("milestones") (in Panel A) and on engagement durations (in months) (in Panel B), reported by milestone (M) and engagement theme. In Panel A, the success percentages are relative to all engagements as well as relative to all engagements of a given theme (E, S, or G). As the average engagement duration equals 35 months and our data end in early 2018, some engagements are still work-in-progress or pending by the end of the sample period, implying that M3 or M4 may not yet have been achieved. The sample consists of 1,443 engagements across 485 targeted firms over the period January 2005 through April 2018.

	Panel A: Engagement success		Panel B: Engagement duration (months)		
	#	% E, S, G, or all engagements	Mean	STD	Max
M1: Concern raised with target					
E engagements	77	20	2	6	43
S engagements	55	16	3	8	57
G engagements	130	18	2	4	24
All engagements	262	18	2	6	57
M2: Issue acknowledged by target					
E engagements	152	40	4	9	62
S engagements	95	28	3	6	31
G engagements	186	26	9	17	109
All engagements	433	30	6	13	109
M3: Actions taken by target					
E engagements	67	18	19	16	65
S engagements	84	25	24	24	101
G engagements	126	17	27	22	98
All engagements	277	19	24	21	101
M4: Engagement successfully completed					
E engagements	83	22	35	27	108
S engagements	101	30	41	26	118
G engagements	287	39	32	25	119
All engagements	471	33	35	25	119
Total engagements	1,443				

steps, requiring a larger number of meetings, emails, calls, and letters. IA Table II, Panel B, in the Supplementary Appendix, shows that the investor has dialogs over social and environmental topics mostly with senior executives, whereas the investor tends to communicate most with the board and the chairperson over governance issues.

3. ESG downside risk reduction

3.1 Downside risk measures

Downside, or left-tail risk, is an important consideration in asset pricing, particularly given that the distribution of stock returns can be characterized by skewness and heavy tails.[11] In this case, risk measures, such as volatility that do not distinguish between positive and negative outcomes, may be uninformative, while downside risk measures better capture

[11] See Bawa (1975), Bawa and Lindenberg (1977), Singleton and Wingender (1986), Harlow and Rao (1989), and more recently, Harvey and Siddique (2000) or Ang, Chen, and Xing (2006).

investors' perceptions of risk (Harlow 1991). Moreover, as argued earlier, many institutional investors have a natural focus on left-tail risk due to their business interests or because of regulation. Thus, if downside risk is an important consideration for ESG engagement outcomes, we would expect a relationship between successful ESG engagements and subsequent changes in measures of firms' downside risks.

We employ two widely used measures to identify downside risk. As a first measure, we calculate a firm's VaR (Duffie and Pan 1997). We measure VaR at the firm-month level by calculating daily return outcomes ranked in the bottom fifth percentile (5 percent-VaR). We use absolute values such that smaller numbers reflect less downside risk.

Our second measure, the second-order LPM, captures the distribution of returns that fall below 0 percent, that is, we consider the negative return part of the distribution. LPM is calculated as the square root of the semi-variance below 0 percent (Bawa 1975; Fishburn 1977):

$$\mathrm{LPM} = \sqrt{\frac{1}{N_1 - 1}\sum_{i=1}^{N_1} (r_{n,i} - \overline{r_{n,i}})^2},$$

where $r_{n,i}$ indicates the negative return of firm i and $\overline{r_{n,i}}$ is the mean value of $r_{n,i}$. N_1 is the number of observed *negative* returns for firm i during the measurement period. We calculate the measure at the firm-month level from daily (log) stock return data.

3.2 Risk reduction effects: empirical tests of ESG engagement

3.2.1 Empirical methodology

In the risk analysis, we exclude fifty-seven targets in the utilities and health sectors from the full sample of 485 firms as they operate in heavily regulated environments where activists have lower chances to affect change over the horizon we consider in this article (some of the engagements may require legislative changes as well). We lose fifty-one firms for which we cannot find a match in the FTSE All-World index and ninety-eight firms for which there are missing data on the control variables. Our final sample for the risk analysis in turn contains 279 target firms matched to the same number of control firms.

To test whether ESG engagements are related to subsequent downside risk reduction, we compare the downside risk of engagement targets before and after the engagement, relative to a matched control group. We estimate changes in downside risk at the firm-month level over the two-sided 24-months window around the date in which a target is first engaged by the investor. We match each targeted firm to one control firm based on the headquarters country, industry, and size. We match one-to-one, instead of one-to-*N*, to avoid bias originating from risk diversification benefits of a portfolio of *N* control firms. Targeted firms do not act as matched control firms for firms that are later targeted. To identify control firms, we use the initial engagement date and search for a control firm in the FTSE All-World index (the index covers about 95 percent of the world's investable market capitalization and includes more than 4,000 firms from nearly fifty countries). Matching by country is important because ESG regulations and ESG performance vary across countries. (We replace country by region in sixteen cases where a firm is unique in its industry and size bracket within its country.) We match by industry, using two-digit FTSE Russell ICB codes, as downside risk itself may vary across industries and an engagement may be more successful in industries with recent ESG scandals.[12] Finally, we match on size as ESG incidents may have more adverse reputational effects for larger firms—they tend to be more salient to investors or customers—and as large firms respond more positively to shareholder activists

[12] Consistent with this conjecture, Dimson, Karakaş, and Li (2021) find that the success rate in their sample varies across industries.

(Dimson, Karakaş, and Li 2015). As discussed in detail below, our matching implicitly assumes that the targeted firms and their matched counterparts would follow similar trends in downside risk in the absence of engagement.

Baker, Larcker, and Wang (2022) show that when, as in our case, treatment is rolled out in a staggered way, estimates from DiD regressions can be biased because of heterogeneous treatment effects and variation in treatment timing. The specific concern in our setting is that previously targeted firms may act as (implicit) control firms for firms that are later targeted. Staggered DiD estimates would therefore build on both “good” comparisons between treated and not-yet-treated firms as well as “bad” comparisons between treated and already-treated firms. This can lead to a violation of the parallel trends assumption. One way to address bias originating from such “bad” comparisons is to use a stacked regression approach as in Gormley and Matsa (2011). The idea behind this approach is to create, for each treatment event, an event-specific “cohort” dataset, whereby a cohort is defined by the firms (first) engaged in a given month plus the corresponding matched firms (these matched firms are never engaged). These datasets are then “stacked” together and the DiD regression is estimated using the stacked dataset, with cohort-specific fixed effects being added to the fixed effects structure. Using the two-sided 24-month window around the engagement date, the stacked regression estimates for firm i of cohort c and month t result in the following regression:

$$\text{Downside risk}_{c,i,t} = \alpha + \beta_1 \text{Target}_{c,i} \times \text{Post}_{c,t} + \beta_2 \mathbf{X}_{c,i,t-12} + \text{Fixed effects} + \varepsilon_{c,i,t}, \quad (1)$$

where Downside risk represents one of the two measures of downside risk (VaR or LPM); Target equals 1 for all firm-month observations if firm i is a target in cohort c, and 0 if it is a matched firm; and Post equals 1 for all firm-month observations in cohort c after firm i has been targeted in month t, and 0 before.[13] The vector **X** contains control variables that may affect downside risks beyond shareholder engagement, measured with a lag of 1 year (not all variables are available for all firm-months). Following Gormley and Matsa (2011) and the advice in Baker, Larcker, and Wang (2022), we also estimate a variant of the stacked regression model that excludes the control variables. We include industry-by-year fixed effects and country fixed effects, which we interact with cohort fixed effects. We account for cohort-specific treatment and time effects by interacting Post and Target with the cohort fixed effects (individual effects for Post and Target are absorbed by these fixed effects). Industries are again classified at the two-digit FTSE Russell ICB codes level. Summary statistics of the variables used in the regression analysis are reported in Table 3.

The identifying assumptions underlying the estimation as well as identification threats are discussed in Section 3.3.

3.2.2 Overall effects of ESG engagement on downside risk

In Table 4, we report the estimates of Equation (1) to understand the effects of shareholder engagement on downside risk. Columns 1–4 display results for VaR and Columns 5–8 report results for LPM. We present in Columns 1 and 5 estimates of the overall effects of ESG engagement on VaR and LPM, and in the remaining columns the results are separated by engagement success. We consider two definitions of engagement success. The first definition in Columns 2 and 6 classifies as successful those cases where, at the minimum, the target acknowledges an issue of concern raised by the investor (i.e., at least M2 has been achieved). The second definition, applied in Columns 3 and 7, is stricter and requires that the target not only acknowledges the issue but takes actions to address it (at least M3 is

[13] The post-engagement window was reduced from 24 to 21 months for two firms, a target firm and its matched control firm, because the target’s shares were suspended from trading because of an event unrelated to the specific engagement (a delayed disclosure of the audited financial statement).

Table 3. Summary statistics.

This table reports summary statistics at the firm-month level of the variables used in the stacked regressions. The sample in this analysis includes 279 targeted firms and 279 matched control firms. Variable definitions are provided in Appendix A.

Variable	Mean	STD	25%	Median	75%	Obs.
VaR	3.28	2.24	1.80	2.71	4.08	26,082
LPM	1.58	1.06	0.88	1.30	1.95	26,082
Target	0.50					26,082
Post	0.50					26,082
Log(Market value)	9.07	1.32	8.16	9.01	9.99	26,082
Market-to-book ratio	2.98	3.05	1.24	1.94	3.34	26,082
Leverage (in percent)	34.09	21.08	19.17	32.37	47.88	26,082
Investment (in percent)	11.17	15.86	2.84	5.57	12.63	26,082
Profit margin (in percent)	15.60	13.27	6.37	12.60	20.71	26,082
Freefloat (in percent)	71.89	25.87	50.00	80.00	94.00	26,082

reached).[14] As we estimate regressions at the firm-month level—rather than the firm-engagement-month level, we need to create a measure of engagement success in the case of multiple overlapping engagements. In such cases, we calculate the average engagement success rate across the engagements and require the *average* milestone to exceed 2 or 3, respectively.[15]

Columns 1 and 5 demonstrate that on average across all engagements, whether successful or not, downside risk decreases at targeted firms from before to after the engagement, relative to the control group. Importantly, the magnitude of the effects sharply increases if we condition on engagement success in Columns 2, 3, 6, and 7. Specifically, Columns 2 and 6 show that ESG engagements significantly reduce downside risk among those engagements where at least M2 is achieved, that is, among targets that acknowledged the existence of an ESG issue or responded with actions to the investor's demands. The estimate in Column 2 for VaR implies that the downside risk of targets decreases by 0.205 after the engagement, relative to the control firms; these risk reductions correspond to about 9 percent of the variable's standard deviation. As shown in Column 6, we obtain similar results with LPM as the measure of downside risk, both in terms of statistical and economic significance (the effect equals 8 percent of the standard deviation).

In Columns 3 and 7, we impose a stricter definition of success and only consider as successful those engagements where at least M3 has been achieved. In these estimations, the economic significance of the risk effects increases further, by a factor between 3 and 4, depending on the risk measure. The larger effects make sense as they capture the engagements where we know that the target started to take actions to address the investor's ESG concerns. In Column 3, VaR decreases by 0.993 from before to after the engagement, relative to control firms. We find positive and significant effects also for LPM in Column 7.

On the other hand, Columns 4 and 8 show no evidence of significant downside risk reductions among those targets where engagement has not achieved M2. As we discuss in more detail below, these results are notable and reduce potential concerns about

14 The classification of success implies a reduction in the sample size used for the estimation, especially when we consider M3 (which has the benefit of allowing us to cleanly identify effects of successful engagements).

15 We calculate this average success rate as the sum of the milestones achieved, coding as 1 if M1 has been achieved, 2 for M2, etc., and divide the sum of these milestones by the number of engagements. For example, in case the investor reached at one target firm M2 for one engagement and M3 for another engagement with the respective firm, the average success rate would be (M) 2.5. This procedure is in line with the approach taken by Dimson, Karakaş, and Li (2015), who use a different investor's data in their analysis.

Table 4. Effects of ESG engagement on downside risk: Baseline results.

This table reports stacked regressions at the firm-month level to estimate the effects of ESG engagement on downside risk. For each treatment event, we create an event-specific "cohort" dataset, whereby a cohort is defined by the firms (first) engaged in a given month (plus the corresponding matched firms). These datasets are then "stacked" together and a DiD regression is estimated using the stacked dataset, with cohort-specific fixed effects being added to the fixed effects structure. Regressions are estimated for the two-sided 24-month window around the month in which a target is engaged. The dependent variable is measured as VaR or LPM. VaR is the 5 percent value at risk using absolute values such that smaller numbers reflect less downside risk. LPM is the lower partial moment of the second order of the return distribution. Both measures are calculated at the firm-month level from daily return data. Target equals 1 for firm-month observations if a firm is an engagement target, and 0 if it is a control firm. Post equals 1 for firm-month observations after the initial engagement, and 0 before. Engagement success is measured based on whether certain milestones have been achieved. In the case of multiple engagements at a target, an average success rate (in terms of milestones achieved) is calculated across all engagements at the firm. The sample in this analysis includes 279 targeted firms and 279 matched control firms, where control firms are matched with engagement targets using country, industry, and size as matching criteria. Variable definitions are provided in Appendix A. *t*-statistics, calculated based on robust standard errors clustered by firm, are reported in parentheses. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Dependent variable:	**VaR**				**LPM**			
Engagement success:	**All**	**M2 and above**	**M3 and above**	**Below M2**	**All**	**M2 and above**	**M3 and above**	**Below M2**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Target × Post	−0.081*	−0.205**	−0.993***	−0.000	−0.046**	−0.087**	−0.454***	−0.018
	(−1.67)	(−2.45)	(−3.11)	(−0.01)	(−2.02)	(−2.17)	(−2.92)	(−0.75)
Log(Market value)	−0.893***	−1.012***	−2.548***	−1.020***	−0.439***	−0.511***	−1.206***	−0.489***
	(−17.64)	(−10.91)	(−7.36)	(−13.45)	(−17.57)	(−11.12)	(−7.64)	(−13.41)
Market-to-book ratio	−0.070***	−0.093***	−0.090	−0.065***	−0.034***	−0.046***	−0.043*	−0.029***
	(−6.28)	(−5.15)	(−1.62)	(−4.63)	(−6.24)	(−5.40)	(−1.74)	(−4.50)
Leverage	0.005***	0.002	0.002	0.006***	0.003***	0.001	0.002	0.003***
	(2.66)	(0.59)	(0.12)	(3.05)	(2.69)	(0.35)	(0.22)	(2.66)
Investment	0.000	−0.000	0.055**	0.002	−0.000	−0.000	0.028**	0.001
	(0.10)	(−0.04)	(2.13)	(0.90)	(−0.13)	(−0.05)	(2.28)	(0.49)
Profit margin	0.012***	0.007	0.024	0.021***	0.006***	0.003	0.005	0.009***
	(3.36)	(1.02)	(0.75)	(5.56)	(3.07)	(0.85)	(0.32)	(5.06)
Freefloat	0.002	−0.002	−0.006	0.004***	0.002**	−0.000	−0.004	0.002***
	(1.41)	(−0.40)	(−0.58)	(2.82)	(2.03)	(−0.12)	(−0.74)	(3.23)
Model	Stacked	Stacked	Stacked	Stacked	Stacked	Stacked	Stacked	Stacked
Country × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	26,081	10,263	1,852	15,818	26,081	10,263	1,852	15,818
Adj. *R*-squared	0.426	0.457	0.530	0.420	0.454	0.482	0.539	0.456

the results being driven by a confounding mechanism (e.g., the stock-picking ability of the investor).[16]

For robustness, in IA Table IV in the Supplementary Appendix, we re-estimate Equation (1) without control variables (in Panel A) and with alternative (firm and industry-by-month) fixed effects (in Panel B). In both panels, successful engagements are associated with a decline in downside risk. In Panel C, we show that results are unaffected if we use unwinsorized versions of the dependent variables.

3.3 Identification assumptions and threats

The key identifying assumption for our analysis is that—absent treatment—targeted firms would not have trended differentially from the matched control firms in terms of their changes in downside risk. To assess whether the parallel trends assumption holds, we perform several checks.

3.3.1 Absence of pre-trends

The parallel trends assumption suggests that we should not observe differential trends in downside risk between treated and control firms prior to engagement. To evaluate this, figure 4 displays, for the targeted and control firms, the evolution of the downside risk measures (average values) over the 2-year period prior to the investor's engagement. While both the VaR measure (Panel A) and the LPM measure (Panel B) exhibit time-series variations with slight declines leading up to the engagement, the trends for both the targeted and control firms are similar.

Next, we employ the stacked regression framework to check for differential pre-trends as well as the timing of the risk reductions after the treatment. To do so, we replace Target × Post in Equation (1) with seven terms that interact Target with indicator variables for each half-year period before (HY–3 to HY–1) or after (HY1 to HY4) an engagement, with the half-year period HY–4 being the excluded period.

The estimates in Table 5, Panel A, show that all three interaction terms for the pre-engagement period are statistically insignificant, indicating the absence of pre-treatment trends. Most of the overall downside risk reductions occur in the second and third half year after the engagement. Although statistical significance is lower compared with the baseline estimates in which we pool the post-engagement periods, the magnitudes of the point estimates remain large.

The estimated timelines are intuitive—one would expect it to take time until the investor's engagement successfully reduces stock price-based measures of risk. These results are also consistent with the time frames shown in Table 2, which demonstrate that time is required until the engagement reaches a milestone indicating success. We further observe that the downside risk measures in the fourth half year do not differ significantly between targeted and control firms. This indicates that some of the risk reductions are temporary, which is consistent with the observation that the investor performs repeated engagement in some target firms.

3.3.2 Covariate imbalance

To further evaluate the parallel trends assumption, IA Table V in the Supplementary Appendix evaluates covariate imbalance by comparing the control variables between the target and control firms, calculated over the 24-month pre-engagement period. In terms of leverage, investments, and profitability, the two sets of firms are relatively similar. However, despite matching on size, target firms tend to be larger, have lower average market-to-book ratios, and have a higher free float. A concern with these observed differences is that firms with these characteristics may have trended differentially during the

[16] Financials constitute the most frequently observed industry of the targeted firms (figure 2). As this sector is highly regulated and special in nature, it would be implausible if our results mostly originate from such targets. Indeed, IA Table III in the Supplementary Appendix shows that our results are robust to excluding Financials.

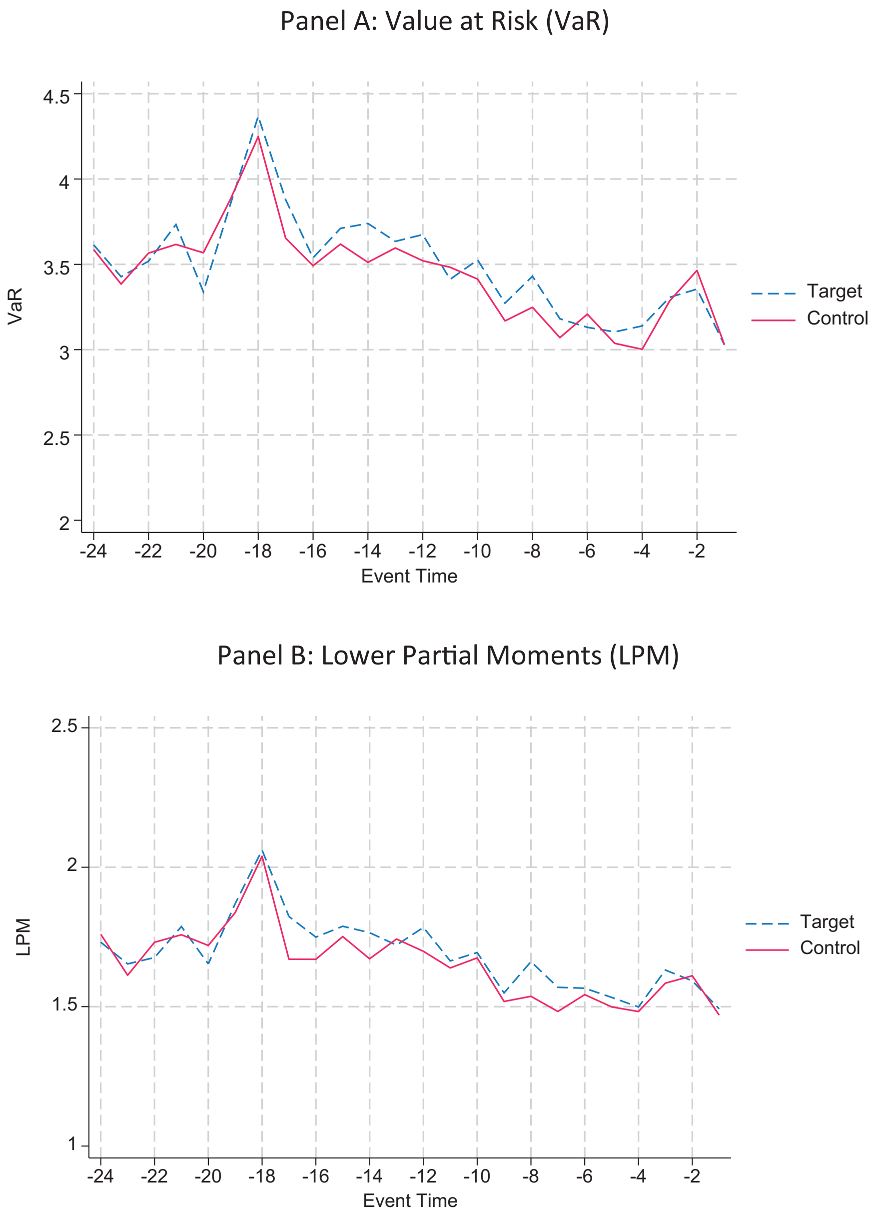

Figure 4. Evidence of parallel trends. This figure reports the time-series evolution of the downside risk measures, VaR in Panel A and LPM in Panel B, over the 24-month period prior to initial engagement. The figure compares target and control firms. The sample in this analysis includes 279 targeted firms and 279 matched control firms, where control firms are matched with engagement targets using country, industry, and size as matching criteria. Variable definitions are provided in Appendix A.

post-engagement period for reasons unrelated to treatment, after controlling for industry, country, and year effects. If this were the case, we would incorrectly attribute any decline in downside risk to the investor's engagement.

We address this concern in different ways. First, according to the investor, target firm selection is motivated primarily by ESG concerns. For example, an ESG issue such as climate

Table 5. Effects of ESG engagement on downside risk: Pre-treatment differences and dynamic treatment effects.

This table reports stacked regressions at the firm-month level to estimate the effects of ESG engagement on downside risk. Regressions are estimated for the two-sided 24-month window around the month in which a target is engaged. The dependent variable is measured as VaR or LPM. VaR is the 5 percent value at risk using absolute values such that smaller numbers reflect less downside risk. LPM is the lower partial moment of the second order of the return distribution. Both measures are calculated at the firm-month level from daily return data. Target equals 1 for firm-month observations if a firm is an engagement target, and 0 if it is a control firm. Post equals 1 for firm-month observations after the initial engagement, and 0 before. Pre-HY–1 (Post-HY1) equals 1 for firm-month observations in the first half year before (after) an engagement, and 0 for all other firm-month observations. Pre-HY–2 to Pre-HY–3 (Post-HY1 to Post-HY4) are defined accordingly, but for the second, third (and fourth) half year before (after) an engagement. Engagement success is measured based on whether certain milestones have been achieved. In the case of multiple engagements at a target, an average success rate (in terms of milestones achieved) is calculated across all engagements at the firm. The sample in this analysis includes 279 targeted firms and 279 matched control firms, where control firms are matched with engagement targets using country, industry, and size as matching criteria. Variable definitions are provided in Appendix A. *t*-statistics, calculated based on robust standard errors clustered by firm, are reported in parentheses. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

	Panel A: Dynamic treatment effects		Panel B: Pre-treatment differences	
Dependent variable:	**VaR**	**LPM**	**VaR**	**LPM**
Engagement success:	**M2 and above**	**M2 and above**	**M2 and above**	**M2 and above**
	(1)	(2)	(3)	(4)
Target × Post			–0.215***	–0.097**
			(–2.60)	(–2.59)
Target × Pre-HY–3	0.014	–0.021		
	(0.06)	(–0.21)		
Target × Pre-HY–2	0.109	0.041		
	(0.61)	(0.52)		
Target × Pre-HY–1	–0.031	–0.049		
	(–0.21)	(–0.75)		
Target × Post-HY1	–0.047	–0.025		
	(–0.29)	(–0.34)		
Target × Post-HY2	–0.266*	–0.157**		
	(–1.75)	(–2.19)		
Target × Post-HY3	–0.288*	–0.146*		
	(–1.84)	(–1.94)		
Target × Post-HY4	–0.117	–0.049		
	(–0.62)	(–0.54)		
Controls	Yes	Yes	No	No
Pre-treatment controls	No	No	Yes	Yes
Pre-treatment controls × Post	No	No	Yes	Yes
Pre-HY–3 to Pre-HY–1 dummies	Yes	Yes	No	No
Post-HY1 to Post-HY4 dummies	Yes	Yes	No	No
Model	Stacked	Stacked	Stacked	Stacked
Country × Cohort fixed effects	Yes	Yes	Yes	Yes
Industry × Year × Cohort fixed effects	Yes	Yes	Yes	Yes
Target × Cohort fixed effects	Yes	Yes	Yes	Yes
Post × Cohort fixed effects	Yes	Yes	Yes	Yes
Obs.	10,263	10,263	10,263	10,263
Adj. *R*-squared	0.465	0.488	0.407	0.427

change leads the investor to focus on specific critical industry sectors, which implies no particular differential trend between a targeted firm and the industry-matched peer. This suggests that target selection is not based on firm characteristics that likely correlate with future differential trends in downside risk *independent* of the investor's engagement. Similarly, the investor may conduct an engagement strategy focused on firms in certain countries because of country-specific ESG concerns. Importantly, as we showed above, the risk reductions are driven by those engagements where at least M2 is achieved, that is, by engagement where the investor recorded some form of engagement success. Hence, if it were the case that targets with certain characteristics would have trended differently independent of the treatment, it is unclear why this would be the case only for successful engagements (unless the parallel trends assumption is violated among successful targets only; this cannot be excluded entirely but constitutes a high hurdle).

In addition, to account for possible differential trends in the downside risk measures based on the firm characteristics, we estimate a set of regressions in which we interact the firm characteristics, including those that vary between target and controls, with the post-engagement dummy. For the firm characteristics, we calculate average values for each firm for the period prior to engagement. The corresponding estimates are reported in Table 5, Panel B. The estimates continue to show that successful engagements are associated with reductions in VaR and LPM, with magnitudes similar to those in Table 4.

3.4 Heterogeneous effects of ESG engagement on downside risk

As shown in figure 1, the investor's engagement strategies have a broad regional reach and as shown in Table 1, the 1,443 engagements also vary across ESG subthemes. Consequently, we test whether differences exist in the engagement outcomes according to region or engagement theme.

3.4.1 Downside risk results by region

Due to differences in markets and institutions, the success of an engagement may depend in part on the geographic location of the firm. For example, using a global shareholder engagement sample, Becht et al. (2017) demonstrate that activists are most successful in reaching their engagement objectives for targeted firms located in North America. Moreover, they find the short-run announcement returns around the disclosure of an activist's equity stake in a target to be highest among North American firms, followed by targets in Asia and Europe, suggesting that investors expect different success rates across these regions.[17] Given this evidence for non-ESG-related engagements, we examine whether our investor's risk reduction engagement effects vary across major world regions. To do so, we re-estimate Equation (1) separately for targeted and control firms in North America, Europe, and the Rest of the World.

Table 6 reports the corresponding results by world region for VaR in Panel A and for LPM in Panel B. Columns 1–3 in both panels report results for all engagements by region (i.e., irrespective of engagement success), while Columns 4–6 consider engagements where at least M2 was reached. We find the effects of ESG engagement on both measures of downside risks are strongest for targeted firms in North America that reach M2, while there is virtually no effect of ESG engagement on downside risk in Europe and insignificant effects in the remaining countries. These regional differences are consistent with the Becht et al. (2017) findings for their hedge fund activist to achieve outcome success.

Based on our conversations with the investor, favorable factors contributing to the measured risk reductions in North America include comparably strong investor rights to execute the engagements, coupled with the possibility to follow up at the annual meeting and

[17] The analysis in Becht et al. (2017) does not consider ESG engagements. Note that Dimson, Karakaş, and Li (2015) are unable to explore the cross-country variation of success rates and announcement returns as their sample is restricted to targets from the USA.

Table 6. Effects of ESG engagement on downside risk: World regions.

This table reports stacked regressions at the firm-month level to estimate the effects of ESG engagement on downside risk for targeted firms. Results are reported by world region (North America, Europe, and Rest of World). Panel A reports results for VaR and Panel B for LPM. Regressions are estimated for the two-sided 24-month window around the month in which a target is engaged. The dependent variable is measured as VaR or LPM. VaR is the 5 percent value at risk using absolute values such that smaller numbers reflect less downside risk. LPM is the lower partial moment of the second order of the return distribution. Both measures are calculated at the firm-month level from daily return data. Target equals 1 for firm-month observations if a firm is an engagement target, and 0 if it is a control firm. Post equals 1 for firm-month observations after the initial engagement, and 0 before. Engagement success is measured based on whether certain milestones have been achieved. In the case of multiple engagements at a target, an average success rate (in terms of milestones achieved) is calculated across all engagements at the firm. The sample in this analysis includes 279 targeted firms and 279 matched control firms, where control firms are matched with engagement targets using country, industry, and size as matching criteria. Variable definitions are provided in Appendix A. *t*-statistics, calculated based on robust standard errors clustered by firm, are reported in parentheses. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A: Effects of ESG engagement on VaR by region and success rate

Dependent variable:	**VaR**			**VaR**		
Engagement success:	**All**			**M2 and above**		
Engagement region:	**North America**	**Europe**	**Rest of world**	**North America**	**Europe**	**Rest of world**
	(1)	(2)	(3)	(4)	(5)	(6)
Target × Post	−0.168**	0.001	−0.095	−0.290**	0.100	−0.246
	(−2.41)	(0.01)	(−1.15)	(−2.49)	(0.66)	(−1.56)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	Stacked	Stacked	Stacked	Stacked	Stacked	Stacked
Country × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Target × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Post × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,032	7,016	12,033	3,608	2,731	3,924
Adj. *R*-squared	0.565	0.480	0.346	0.575	0.547	0.331

Panel B: Effects of ESG engagement on LPM by region and success rate

Dependent variable:	**LPM**			**LPM**		
Engagement success:	**All**			**M2 and above**		
Engagement region:	**North America**	**Europe**	**Rest of world**	**North America**	**Europe**	**Rest of world**
	(1)	(2)	(3)	(4)	(5)	(6)
Target × Post	−0.090**	0.000	−0.052	−0.129**	0.053	−0.098
	(−2.59)	(0.01)	(−1.35)	(−2.20)	(0.69)	(−1.32)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	Stacked	Stacked	Stacked	Stacked	Stacked	Stacked
Country × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

(continued)

Table 6. (continued)

Panel B: Effects of ESG engagement on LPM by region and success rate						
Dependent variable:	**LPM**			**LPM**		
Engagement success:	**All**			**M2 and above**		
Engagement region:	**North America**	**Europe**	**Rest of world**	**North America**	**Europe**	**Rest of world**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Target × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Post × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	7,032	7,016	12,033	3,608	2,731	3,924
Adj. R-squared	0.566	0.502	0.393	0.577	0.572	0.371

ultimately, a possible threat to conduct a proxy fight. A further factor is the relatively higher levels of transparency in the USA about many aspects of the firm and its actions, including transparency regarding additional institutional investors (e.g., based on quarterly public 13f filings) who could assist in pressuring the firm for the requested changes or who could help in a proxy fight if needed (which would be consistent with the results in Kedia, Starks, and Wang [2021] regarding institutional investors aiding hedge fund activists).

3.4.2 Downside risk results by engagement theme

In Table 7, we report the results by the different ESG engagement themes, which allows us to determine whether some engagement topics have greater potential for downside risk reductions. In Panel A, we report results for VaR and in Panel B for LPM, where Columns 1–3 provide results for all engagements (i.e., irrespective of engagement success). In Column 1, the results indicate that firms engaged for environmental issues experience a decline in downside risk. In contrast, in Columns 2 and 3, we do not find statistically significant effects for engagements based on either the social or governance themes. Measuring success based on M2 in Columns 4–6, we continue to find that only engagement on environmental issues results in a statistically significant reduction in downside risk. For engagements over such topics, which, as shown in Table 1, Panel A, primarily have the theme of climate change, VaR at target firms decreases by 0.299 after the engagement, relative to control firms. In Panel B, we consider LPM as the risk measure and find results that are similar, with a significant decline in downside risk for environmental engagements in Column 1. At the same time, the effect for environmental topics reaching M2 in Column 4 is noisier compared with Panel A and marginally insignificant.

This heterogeneity in results across engagement topics shown in Table 7 has several implications. First, the weaker effects for governance topics combined with evidence from prior research suggest that engagements on compensation topics or board independence, the top subthemes within this area, most directly affect the first moments of the return distributions (see Becht et al. 2009; Brav et al. 2008; Dimson, Karakaş, and Li 2015) rather than firm risk.

Second, with regard to the social topics, one reason for the lack of statistical significance in downside risk reduction could be that such themes reflect more subjective concerns. This means that it is rather easy for a target to make some verbal commitment regarding a cultural change or better gender balance, but it would be much harder to then actually define

Table 7. Effects of ESG engagement on downside risk: Engagement themes.

This table reports stacked regressions at the firm-month level to estimate the effects of ESG engagement on downside risk. Results are reported based on the initial engagement theme. Panel A reports results for VaR and Panel B for LPM. Regressions are estimated for the two-sided 24-month window around the month in which a target is engaged. The dependent variable is measured as VaR or LPM. VaR is the 5 percent value at risk using absolute values such that smaller numbers reflect less downside risk. LPM is the lower partial moment of the second order of the return distribution. Both measures are calculated at the firm-month level from daily return data. Target equals 1 for firm-month observations if a firm is an engagement target, and 0 if it is a control firm. Post equals 1 for firm-month observations after the initial engagement, and 0 before. Engagement success is measured based on whether certain milestones have been achieved. In the case of multiple engagements at a target, an average success rate (in terms of milestones achieved) is calculated across all engagements at the firm. The sample in this analysis includes 279 targeted firms and 279 matched control firms, where control firms are matched with engagement targets using country, industry, and size as matching criteria. Variable definitions are provided in Appendix A. *t*-statistics, calculated based on robust standard errors clustered by firm, are reported in parentheses. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A: Effects of ESG engagement on VaR by engagement theme and success rate

Dependent variable:	**VaR**			**VaR**		
Engagement success:	**All**			**M2 and above**		
Engagement topic:	**E**	**S**	**G**	**E**	**S**	**G**
	(1)	(2)	(3)	(4)	(5)	(6)
Target × Post	−0.285***	0.142	0.007	−0.299**	−0.204	−0.038
	(−3.49)	(1.52)	(0.10)	(−2.16)	(−1.22)	(−0.22)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	Stacked	Stacked	Stacked	Stacked	Stacked	Stacked
Country × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Target × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Post × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9,308	5,744	11,029	4,424	2,177	3,662
Adj. R-squared	0.447	0.386	0.455	0.424	0.432	0.574

Panel B: Effects of ESG engagement on LPM by engagement theme and success rate

Dependent variable:	**LPM**			**LPM**		
Engagement success:	**All**			**M2 and above**		
Engagement topic:	**E**	**S**	**G**	**E**	**S**	**G**
	(1)	(2)	(3)	(4)	(5)	(6)
Target × Post	−0.137***	0.037	0.004	−0.106	−0.115	−0.013
	(−3.40)	(1.03)	(0.12)	(−1.52)	(−1.64)	(−0.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	Stacked	Stacked	Stacked	Stacked	Stacked	Stacked
Country × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Target × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Post × Cohort fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9,308	5,744	11,029	4,424	2,177	3,662
Adj. R-squared	0.467	0.422	0.489	0.441	0.473	0.597

tangible actions and even implement them. This explanation is also supported by the time it takes to go from one milestone to the next (Table 2, Panel B): social engagements are quickest when it comes to achieving M2, but they are tied for slowest in M4 achievement. Another potential reason for the weaker risk reduction effects for social engagements might be that investors in a target firm find it difficult to observe, measure, and price improvements related to social topics (to the contrary, environmental improvements related to emission reductions or disclosure are probably easier to objectively measure).

4. Risk reduction channel: empirical results on environmental incidents

4.1 Empirical methodology

One potential economic channel for our results would occur if the downside risk reductions correspond to a decline in observable ESG risk outcomes. Given that the significant risk reduction results in the previous sections originate primarily from environmental engagements, we focus on negative *environmental* risk outcomes. We measure such outcomes using news-based data on environmental risk incidents from RepRisk, a data provider that each day screens more than 100,000 public sources for greater than 200,000 firms globally in twenty-three languages (the languages of all target countries listed in figure 1 are covered). The sources used to identify environmental incidents include print, online, and social media; government bodies, regulators, think tanks, and newsletters; and other online sources. Two benefits of a RepRisk-based measure are helpful in our setting: First, RepRisk provides global coverage and, second, the incidents that it identifies primarily reflect idiosyncratic events (Gantchev, Giannetti, and Li 2022). To identify meaningful reductions in environmental risks, our variable measurement considers the severity of environmental incidents, with more severe incidents receiving higher weights.[18] (We alternatively use a measure reflecting the number of *novel* incidents for robustness.) IA Table VI in the Supplementary Appendix reports the distribution of environmental risk incidents across the sample target firms, showing that the incident distribution is highly skewed.

To document an ESG-incident channel underlying the downside risk reductions, for each firm i in month t that is targeted by an environmental engagement, we estimate the following model:

$$\#\text{ E incidents}_{i,t} = \exp\left(\alpha + \beta_1 \text{Post}_{i,t} + \beta_2 \mathbf{X}_{i,t-12} + \text{Fixed effects} + \varepsilon_{i,t}\right), \qquad (2)$$

where # E incidents is a measure of the number of environmental risk incidents for target i in month t, with the measure accounting for the severity of an incident. The mean of the variable equals 0.88 with a standard deviation of 1.55. Post equals 1 for all firm-month observations after target i has been targeted in month t, and 0 before, and $\mathbf{X}$ contains the same control variables as in Equation (1). We include industry-by-year, and country fixed effects. To identify whether the engagement-induced changes in downside risk relate to actual changes in environmental incidents, we exploit within-target variation and estimate Equation (2) for targets with large versus small reductions in downside risk. For this purpose, we calculate average values for VaR and LPM separately over the

[18] RepRisk determines the severity of an incident as a function of (i) the consequences of the risk incident; (ii) the extent of the impact; and (iii) whether the risk incident was caused by an accident, by negligence, or intent, or even in a systematic way. RepRisk then classifies such incidents using three levels of severity: low, medium, and high severity. Our measure is constructed as the sum of all severe environmental incidents, whereby we weight a severe incident with 1 if it is a low severity incident, with 2 if it is a medium severity incident, and with 3 if it is a high severity incident.

2-year periods before and after the initial engagement, and then classify each target firm based on whether the respective change in VaR or LPM is above ("Large") or below ("Small") the median. Equation (2) is estimated using Poisson regressions, rather than "log1plus" models, to account for the distribution of # E incidents, the count-based outcome variable.[19] In these estimations, we do not apply the stacked regressions. The reason is that Poisson regressions allow us to include our rich set of fixed effects without biasing the estimation, but they base the estimation only on observations with at least one nonzero value for the dependent variable within a fixed effects group (Cohn, Liu, and Wardlaw 2022). This is desirable as it restricts the usable sample to those groups that are informative about the effects of the engagement variable (Post) on # E incidents. The downside of this benefit is that the number of observations would decline by about 30 percent if we were to add cohort fixed effects as required in stacked regressions.[20]

4.2 Downside risk reductions and environmental incidents

Table 8 reports the regression results obtained from estimating Equation (2). In Column 1, which includes all targets independent of the realized change in downside risk, we observe a marginally significant decline in severe environmental incidents after the investor's engagement. More importantly, in Columns 2 and 4, we consider only those target firms for which we observe large declines in VaR or LPM as a result of the investor's engagement over an environmental topic. For these subsets of targets, we find a large and highly significant decrease in the number of environmental risk incidents after the engagement. Column 2 implies that the severity-weighted number of environmental incidents declines by 26 percent from before to after the engagement. In Columns 3 and 5, we find no statistically significant decline in severe environmental incidents among engagements where downside risks did not decrease by a large amount.

IA Table VII in the Supplementary Appendix provides alternative specifications of Equation (2) to address different potential concerns with the analysis. Columns 1–4 consider the subset of targets that exhibit large declines in VaR and LPM. In Columns 1 and 2, results remain negative and significant if we control for a linear time trend, in order to address that RepRisk may have screened more incidents over time. In Columns 3 and 4, we continue to find effects if we only consider those environmental incidents classified as "novel" by RepRisk (i.e., cases where it is the first time that a firm is exposed to a specific environmental issue). This implies that the engagement process reduces the occurrence of new risks, instead of only mitigating the reoccurrence of prior risk issues. Finally, in Columns 5 and 6, we estimate Equation (2) on the full sample of environmental targets and include interaction terms of Post with indicator variables reflecting a large decline in LPM or VaR, respectively. Also, in these specifications, we find larger reductions in environmental incidents for targets experiencing large declines in downside risk.

5. Conclusions

We employ proprietary data from an influential activist investor to examine whether shareholder engagement regarding ESG topics can reduce downside risk. Using two measures of downside risk, VaR and LPM, we demonstrate that ESG shareholder engagements result in risk reductions. Further evidence in support of this hypothesis comes from the fact that the risk-reduction effects are concentrated among the successful engagements. The risk reduction effects vary across ESG engagement themes, being driven primarily by the effects from

[19] Poisson models provide unbiased estimates for dependent variables with a large mass of values at 0 combined with severe skewness (Cohn, Liu, and Wardlaw 2022).

[20] When we estimate stacked regressions on this smaller sample, we find a large and significant decrease in the number of environmental risk incidents for targets with large declines in the VaR. For the LPM measure, the effect on risk incidents is also large, but it is noisier and eventually insignificant with a *t*-statistic of 1.36.

Table 8. Effects of environmental engagement on subsequent environmental incidents.

This table reports Poisson regressions at the firm-month level to estimate the effects of environmental engagement on subsequent environmental incidents. Regressions are estimated for the two-sided 24-month window around the month in which a target is engaged. We separate the sample based on whether the decrease in downside risk, measured using VaR or LPM, from before to after an environmental engagement is above (Large) or below (Small) the median. The dependent variable is measured as # E incidents, which is a measure of the number of environmental risk incidents in a firm-month, where more severe incidents receive higher weights. Post equals 1 for firm-month observations after the initial engagement, and 0 before. The sample in this analysis includes 99 targeted firms with environmental engagements. Variable definitions are provided in Appendix A. *t*-statistics, calculated based on robust standard errors clustered by firm, are reported in parentheses. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

Dependent variable:	**# E incidents**				
Downside risk measure:		**VaR**		**LPM**	
Δ Downside Risk$_{\text{Pre vs Post}}$:	**All**	**Large**	**Small**	**Large**	**Small**
	(1)	(2)	(3)	(4)	(5)
Post	–0.204*	–0.359***	0.152	–0.356***	–0.011
	(–1.71)	(–2.95)	(1.00)	(–3.00)	(–0.08)
Log(Market value)	0.466***	0.588***	0.240**	0.433***	0.208**
	(5.44)	(4.32)	(2.13)	(4.18)	(1.99)
Market-to-book ratio	–0.065	–0.178*	–0.021	–0.078	–0.151**
	(–1.33)	(–1.93)	(–0.28)	(–1.22)	(–2.52)
Leverage	0.004	0.016	–0.012*	0.008	–0.005
	(0.59)	(1.54)	(–1.67)	(1.04)	(–0.84)
Investment	–0.006	–0.011	–0.014	–0.010	–0.027**
	(–0.84)	(–1.15)	(–1.14)	(–1.26)	(–2.34)
Profit margin	–0.017**	–0.023***	0.024	–0.025***	0.055***
	(–2.49)	(–2.71)	(1.38)	(–3.33)	(3.99)
Freefloat	0.008**	0.011***	0.003	0.014***	–0.017**
	(2.11)	(3.97)	(0.27)	(4.66)	(–1.97)
Model	Poisson	Poisson	Poisson	Poisson	Poisson
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	4,439	2,222	2,217	2,272	2,167
Ps. *R*-squared	0.311	0.430	0.278	0.407	0.314

environmental engagements. The prime issue within this engagement category is climate change. Finally, we provide evidence on a channel through which the engagement activities reduce downside risk. We document a large decline in the number of environmental risk incidents at targeted firms with large engagement-induced downside risk reductions. There is no corresponding decline among targets where downside risks did not decrease by a large amount. Given the increasing engagement by institutional investors on ESG issues, our analysis contributes new insights into understanding the channel through which ESG engagement can create value for investors beyond affecting returns.

Acknowledgments

This article is dedicated to our dear friend and colleague Ioannis Oikonomou who was taken from us far too young on October 25, 2020, after a long illness. Like him, we are inspired by those “who are truthful, passionate and will not give up in the face of adversity.” We are grateful to our data contributing investor for providing us with access to the data and to Alex Edmans (the Editor), an anonymous referee, two associate editors, as well as Rui Albuquerque, Marco Becht, Tobias Berg, Alon Brav, Michael Brennan, John Cotter, Craig Doidge, Alexander Dyck, Andrey Golubov, Michael Halling, Emir Ilhan, Guy Kaplanski, Oğuzhan Karakaş, Tomislav Ladika, Karl Lins, John McConnell, Adair Morse, Cal Muckley, Ser-Huang Poon, Daniel Streitz, and participants at the AFA 2018 Meetings, EFA 2019 Meetings, MFS Conference at Stockholm School of Economics, European Commission, European Science Hub, IAF 2018, Q-Group, SOAS, University College Dublin, PRI Academic Conference 2019, and the 2019 Conference on New Research on Executive Compensation and on Sustainability in Tel Aviv for comments. In addition, we thank the scientific committee of the United Nations-supported Principles for Responsible (PRI) Academic Conference 2019 for awarding an earlier version of this article the Best Quantitative Paper Award. Diego Perez Guisande provided excellent research assistance. The investor studied in this article did not influence the article’s results in any way and we did not have to ask for approval by the investor before submitting the article for publication. We did not receive compensation from the investor for the project and the article is neither commissioned research nor related to paid consulting work. The investor covered the travel expenses for one of the authors when presenting the article at conferences organized by the investor for its clients. A.G.F.H. is on the Academic Advisory Board of RepRisk. Z.S. is a member of the Sustainability Council of Lampe Asset Management (since November 2022) and a Regular Research Visitor at the ECB (since October 2021).

Supplementary material

Supplementary material is available at *Review of Finance* online.

Funding

None declared.

Conflicts of interest: None declared.

Data availability

The shareholder engagement data underlying this article cannot be shared publicly due to the private nature of the data and a non-disclosure agreement. We merge these engagement data with financial data from Datastream and data on ESG incidents from RepRisk.

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Appendix A: Variable definitions

Variable	Definition	Data source
Target	Dummy variable that equals 1 for firm-month observations if a firm is an engagement target, and 0 if it is a control firm. Control firms are matched with engagement targets using country, industry, and size as matching criteria. Control firms are never targeted during the sample period.	Self-constructed
Post	Dummy variable that equals 1 for firm-month observations after an engagement, and 0 for firm-month observations before an engagement.	Self-constructed
Pre-HY-1	Dummy variable that equals 1 for firm-month observations in the first half year before an engagement, and 0 for other firm-month observations. Pre-HY–2 to Pre-HY–3 are defined accordingly, but for the second and third half year before an engagement.	Self-constructed
Post-HY1	Dummy variable that equals 1 for firm-month observations in the first half year after an engagement, and 0 for other firm-month observations. Post-HY2 to Post-HY4 are defined accordingly, but for the second, third, and fourth half year after an engagement.	Self-constructed
VaR	Variable that measures the VaR, calculated at the firm-month level from daily log stock returns. We measure the VaR by taking daily return outcomes ranked at the bottom fifth percentile (5 percent -VaR). This essentially corresponds to the worst daily return during a month. We take the absolute values of the VaR. Winsorized at 1 percent/99 percent.	Datastream
LPM	Variable that measures the LPM of the second order, calculated at the firm-month level from daily log stock returns. It is defined as: $\text{LPM }(0,2) = \sqrt{\frac{1}{\text{N}_1 - 1}\sum_{i=1}^{N_1}(r_{n,i} - \overline{r_{n,i}})^2}$ where $r_{n,i}$ indicates a negative daily return of firm i during a given month and $\overline{r_{n,i}}$ is the mean value of $r_{n,i}$. N_1 is the number of observed negative daily returns for firm i during a given month. Winsorized at 1 percent /99 percent.	Datastream
Market value	Market value of equity, calculated at the firm-month level. Winsorized at 1 percent/99 percent.	
Market-to-book ratio	Market value of equity divided by book value of equity. Market value of equity is calculated at the firm-month level, book value of equity is calculated at the firm-year level. Winsorized at 1 percent /99 percent.	Datastream
Leverage (in percent)	Total debt divided by common equity, calculated at the firm-year level. Total debt is the sum of long-term and short-term debt. Winsorized at 1 percent /99 percent.	Datastream
Investment (in percent)	Capital expenditures over assets, calculated at the firm-year level. Winsorized at 1 percent/99 percent.	Datastream
Profit margin (in percent)	Operating income over total sales, calculated at the firm-year level. Winsorized at 1 percent/99 percent.	Datastream
Freefloat (in percent)	Number of shares available as free float, divided by number of shares issued, calculated at the firm-year level. Winsorized at 1 percent /99 percent.	Datastream

(continued)

(continued)

Variable	Definition	Data source
# E incidents	Measure of the number of environmental risk incidents in a firm-month. In the construction of the measure, more severe incidents receive higher weights. RepRisk determines the severity of an incident as a function of three dimensions: (i) what are the consequences of the risk incident?; (ii) what is the extent of the impact?; and (iii) was the risk incident caused by an accident, by negligence, or intent, or even in a systematic way? RepRisk then classifies such incidents using three levels of severity: low, medium, and high severity. Our measure is constructed as the sum of all severe incidents, whereby we weight a severe incident with 1 if it is a low severity incident, with 2 if it is a medium severity incident, and with 3 if it is a high severity incident. RepRisk identifies environmental risks incidents related to the following topics: Animal mistreatment; climate change, GHG emissions, and global pollution; impacts on landscapes; ecosystems and biodiversity; local pollution; overuse and wasting of resources; and waste issues.	RepRisk
# Novel E incidents	Measure of the number of novel environmental risk incidents in a firm-month. In the construction of the measure, more novel incidents receive higher weights. RepRisk determines the novelty (newness) of an incident based on whether it is the first time a firm is exposed to a specific environmental. RepRisk then classifies such incidents using two levels to measure the magnitude of novelty: 1 or 2. Our measure is constructed as the sum of all novel incidents, whereby we weight each incident with a 1 or 2 depending on the novelty (larger number indicates more novel incidents).	RepRisk