# ESG as Protection Against Downside Risk

Roman Kräussl[1,2], Tobi Oladiran[1], and Denitsa Stefanova[1]

[1]University of Luxembourg

[2]Hoover Institution at Stanford University

January 2023

**Abstract**

We examine whether the uncertainty related to environmental, social, and governance (ESG) regulation developments is reflected in asset prices. We proxy the sensitivity of firms to ESG regulation uncertainty by the disparity across the components of their ESG ratings. Firms with high ESG disparity have a higher option-implied cost of protection against downside tail risk. The impact of the misalignment across the different dimensions of the ESG score is distinct from that of ESG score level itself. Aggregate downside risk bears a negative price for firms with low ESG disparity.

JEL Classification: G12, G18, G32

Keywords: ESG, rating, downside risk, options, regulation, risk premium

# 1 Introduction

There has been an increasing number of environmental, social, and governance (ESG)-related regulatory developments around the world.[1] Nowadays both firms and investors face dealing with uncertainty from the new, updated, and proposed ESG-related regulations. In this paper, we explore the ESG uncertainty emanating from the development of ESG regulations and the firm's ability to manage this regulatory development. We proxy the latter by the observed disparity across the firm's environmental, social, and governance performance which we term "ESG disparity". We investigate whether ESG policy uncertainty is priced in the options market. Specifically, we explore whether the cost of option protection against downside tail risk is higher for firms that are more exposed to ESG regulatory uncertainty. We further study the pricing of the uncertainty related to a firm's ESG performance to determine whether investors pay a premium to hedge against this risk.

First, we examine whether the uncertainty related to ESG regulation developments is reflected in the options market. (Ilhan et al. (2021) and Cao et al. (2022)) consider firms' ESG ratings to proxy for the sensitivity of firms to ESG regulation. Arguably, firms with high ESG performance are less sensitive to ESG regulatory developments compared to firms with low ESG performance. The combined ESG score of a firm, however, hides any potential disparity between its environmental, social, or governance performance. High disparity across the different dimensions that constitute the sustainability footprint of a firm would reflect an increased operational or regulatory uncertainty the firm faces. Thus, we consider ESG disparity across firms' environmental, social, and governance performance to proxy for their sensitivity to ESG regulation. We interpret ESG disparity as a signal of the management's ability

[1] At the global level, there exist the International Sustainability Standards Board (ISSB), the Carbon Disclosure Project (CDP), the Climate Disclosure Standard Board (CDSB), the Global Reporting Initiative (GRI), Task Force on Climate-related Financial Disclosures, Value Reporting Foundation, among others. In Europe, there is the Corporate Sustainability Reporting Directive (CSRD), Sustainable Finance Disclosure Regulations (SFDR), Green/EU taxonomy, among others. In Mainland China, there are EU-China Common Ground Taxonomy (CGT), China Securities Regulatory Commission (CSRC) ESG risk disclosure rules. In the US, we have the following ESG-related proposed regulations: SEC climate-related disclosure rules, Climate Risk Disclosure Act, and ESG Disclosure Simplification Act. For example, the European Commission has delayed several times the implementation of the SFDR, contributing to the uncertainty with respect to the final regulation. Once in place as of January 2023, the SFDR outlines a set of 14 core indicators comprising Level 2's mandatory reporting template with a focus on adverse environmental and social impacts. However, the implementation of the Level 2 requirements has raised confusion among investors, leading the European Supervisory Authorities to call for the European Commission to clarify what defines a sustainable investment. https://www.esginvestor.net/sfdr-level-2-uncertainty-unnerves-managers/

to manage its ESG regulatory development. Firms might struggle with identifying ESG regulatory standards to follow and with aligning their reports to various ESG-related reporting frameworks, resulting in disparity across their reported environmental, social, and governance performance.[2] We proxy for the firm's ability to manage the ESG regulatory development by the disparity across its environmental, social, and governance scores. Firms with high (low) ESG disparity signal a low (high) ability to manage the ESG regulatory environment or development.

We focus on the options market to investigate whether investors account for the ESG uncertainty reflected in the disparity across the different components of a firm's ESG rating and whether investors are ready to pay in order to hedge it. Options are a natural asset class to study pricing and hedging of downside tail risk, as their prices reflect the forward expectations of investors and do not require a realization of the state. Considering that investors may care more about downside losses than upside gains (Roy, 1952; Kahneman and Tversky, 2013; Gul, 1991), we focus here on downside risk. We estimate the cost of protection against downside risk for each US firm following Ilhan et al. (2021) and Kelly et al. (2016).

Firms with high ESG performance have a lower option-implied cost of protection against downside risk compared to firms with low ESG scores. This evidence is in line with Ilhan et al. (2021)'s findings on carbon-intense firms. Interestingly, while all three components of the ESG score contribute significantly to the price of downside risk, the implications of the governance score have the opposite sign. Firms that score highly on governance also have a higher option protection against downside tail risk. Regardless of their level of ESG performance, however, firms with high ESG disparity – or as we conjecture, with a low ability to manage ESG regulatory developments – have a consistently higher cost of option protection against downside risk.

Second, we investigate the effect of ESG treatment (or labeling) on the cost of option protection against downside tail risk. We find that the cost is lower for firms that receive ESG scores in a given year relative to firms without a score and with

[2] For instance, Coca-Cola claims to align its 2021's ESG report to the following reporting framework and standards: Global Reporting Initiative (GRI), Task Force on Climate-related Financial Disclosures, The Sustainability Accounting Standards Board (SASB), The United Nations Global Compact (UNGC), UN Guiding Principles Reporting Framework (UNGPRF), and The United Nations Sustainable Development Goals (SDGs). Pepsico, on the other hand, claims to align its 2021's ESG report to the Global Reporting Initiative (GRI), the Sustainability Accounting Standards Board (SASB), the Task Force on Climate-related Financial Disclosures (TCFD), and Carbon Disclosure Project (CDP). Of course, while there are some similarities in their reporting framework and standards, any difference therein could impact their environmental, social, and governance performance assigned by third-party ESG raters like Thomson Reuters or MSCI.

similar fundamental characteristics. As the uncertainty relative to the ability of a firm to manage ESG regulation is reduced for investors with the publication of an ESG rating, the cost of protection against tail risk reflected in the options market is reduced.

Third, we examine the pricing of aggregate downside risk conditioned on the two aspects of firms' ESG performance: the level of a firm's overall ESG score and the disparity across its components. We extract both the firm-specific and aggregate downside risk measures from the option market which captures the forward expectation of all future events including rare events. We estimate each US firm's downside risk (FDR) following Gao et al. (2018) and extract an aggregate downside risk measure through principal component analysis (PCA) based on the correlation of the monthly estimates of firm downside risk measures (Siriwardane, 2015). We find that there is a one-factor structure driving the time series variation in FDR across all firms. This single factor represents the aggregate downside risk (ADR) measure in our study. Given this aggregate option-implied measure of tail risk, we investigate whether downside risk is priced in the cross-section of stock returns conditional on the level of the ESG score of firms or on the disparity across the different components of the score. We find that aggregate downside risk bears a negative price of risk for firms with either high or low levels of ESG performance. When we condition on the disparity across the E, S, and G dimension of sustainability scores, we find that the cross-sectional relationship between expected stock returns and downside risk betas is significant in the cross-section of firms with low ESG disparity.

To the best of our knowledge, this is the first paper to examine the ESG uncertainty as captured by the disparity across the different components of the ESG profile of a firm and to relate it to downside risk in the options market. Focusing on a specific ESG aspect - that of carbon emission performance - Ilhan et al. (2021) find that climate policy uncertainty is priced in the options market. More carbon-intense firms are associated with a higher cost of protection against downside risk. Our results corroborate these findings, documenting that firms with high emission reduction scores have lower downside tail risk. Cao et al. (2022) is the closest to our setup. Their paper examines whether firms' ESG scores are related to the expensiveness of their options, as captured by implied volatility. Our paper is in line with their baseline result in that firms' ESG performance is reflected in options prices. However, we focus on the disparity across the different components of firms' ESG performance and find that it is reflected in firms' downside tail risk.

Other studies have attempted to study the relationship between ESG-related performance and risk in other markets other than the options market. Glossner (2017) examines the relationship between ESG risks and long-run stock returns. He finds that the portfolio of firms with high ESG risk generates a negative alpha and attributes the negative alpha to unexpected costly ESG incidents and negative earnings surprises. He et al. (2021) examines the implications of shareholder votes in environmental and social (ES) proposals and finds that higher support in failed ES proposals predicts subsequent ES incidents. They also document a negative relation between ES incidents and risk-adjusted performance. Hoepner et al. (2018) find that ESG engagement reduces a firm's exposure to downside risk.

Our paper is related to the literature on ESG ratings disagreement. Previous literature examines the divergence in ESG ratings across different ESG raters, the cause of the divergence across raters (Christensen et al., 2022; Berg et. al., 2020; Gibson et al., 2021b; Eccles et al., 2019), and whether rating divergence is priced in the cross-section of stock returns ((Gibson et al., 2021b)). Christensen et al. (2022) document that greater ESG disclosure leads to greater disagreement across ESG rating agencies. They observe that rating disagreement is greater when firms have either relatively high or low average ESG ratings. They also find that the environmental and social pillars of ESG, rather than governance, drive more of the positive relationship between ESG disclosures and ESG disagreement. Berg et. al. (2020) investigate the sources of divergence in environmental, social, and governance (ESG) ratings. Gibson et al. (2021b) analyze the level and nature of disagreement about a firm's ESG rating and study the impact of ESG rating disagreement on stock returns. They find a positive relationship between environmental rating disagreement and stock returns, and a negative one for social and governance rating disagreement.

We contribute to that literature by considering a different dimension of disagreement: the uncertainty in the ESG performance of a firm as captured by the divergence across its different environmental, social and governance scores. We find that the uncertainty in ESG performance linked to such disagreement is priced in the options market. While there is literature on the pricing of aggregate downside risk, little is understood about the pricing of downside risk in relation to the ESG performance or profile of the firm. Ang et al. (2006) show that the cross-section of stock return reflects a risk premium for bearing downside risk. Huang et al. (2012) estimate the firm-specific extreme downside risk and document that there is a positive premium on firm-specific extreme downside risk. They find that high extreme downside risk stocks outperform low extreme downside risk stocks. Siriwardane (2015) also find that downside risk obtained from the option market is priced in the cross-section of equity returns. Kelly and Jiang (2014) show that tail risk has strong predictive power for aggregate market returns. We contribute to this stream of literature by relating the pricing of the aggregate downside risk to the firms' ESG performance.

The remaining part of the paper is organized as follows: Section 2 describes the data and the different option-implied risk measures. Section 3 presents the empirical analyses of the relationship between ESG uncertainty and the cost of protection against downside risk. Section 4 examines ESG uncertainty and aggregate downside risk. Section 5 concludes.

# 2 Data and Variables

## 2.1 Firm ESG Performance

We obtain ESG ratings for the sample of US firms covered by Thomson Reuters for the period from December 2002 (the earliest year in the database) to December 2021. Sustainability scores are provided on an annual frequency and reported at year-end. The ESG scores of individual firms incorporate ratings along three dimensions: environmental, social, and governance, and also include each firm's controversy score. Thomson Reuters provides a second level of disaggregation of the sustainability scores: Resource Use, Emissions, and Innovation scores for the environmental dimension; Workforce, Human Rights, Community, and Product responsibility for the social dimension; Management, Shareholders, and Corporate Social Responsibility (CSR) strategy for the governance dimension.

Over the years, the number of US firms' ESG scores in our sample has grown significantly from 59 firms with ESG scores in 2002 to 3,113 US firms. The average ESG performance has also increased over the years. From 2002 to 2013, the ESG combined score increased from 26.21 in 2002 to 40.42 in 2013. Thereafter, the average ESG performance declined slightly. A similar pattern is observed for the environmental, social, and governance scores, where the environmental ratings have increased almost three-fold over the period. Overall, the governance pillar has the highest average performance over time.

We obtain monthly returns for the firms and the S&P 500 index, as well as firm characteristics from Thomson Reuters covering the period from 2002 to 2021. Specifically, we obtain total assets, total debt, normalized EBIT, net income after taxes, gross dividends on common stocks, CapEx, company market capitalization, book value per share, and the total common shares outstanding. monthly return for the firms and S&P 500. We use the data on the firm characteristics to compute the main control variables. We compute the 12-month rolling window CAPM beta and firm return volatility.

## 2.2 Option-Implied Downside Risk Measures

We extract the daily options data on US individual stocks from OptionMetrics covering the period from January 2001 to December 2021. Specifically, we obtain the volatility surface data for standardized options with an expiration of 30 calendar days, the zero coupon yield curve, and the forward and spot rates. We use the filtered options data to compute different measures of downside risk.

The measure of downside risk that we use for our baseline analyses follows Kelly et al. (2016) and Ilhan et al. (2021). We estimate the Implied Volatility Slope (IVS) which relates the left-tail implied volatility to the moneyness measured by the Black Scholes delta of out-of-the-money (OTM) standardized put options with a 30-day maturity. We also process the surface data to make them less discrete in moneyness and interpolate the observed implied volatilities as a function of moneyness.[3] We regress the implied volatility of OTM standardized put options on the corresponding delta (ranging between -0.5 and -0.1) and a constant to extract the IVS for each US individual stock or firm in our sample. This slope captures the cost of protection against downside risk (Kelly et al., 2016; Ilhan et al., 2021).

For robustness, we also estimate an array of different measures of option-implied downside risk offered in literature. The descriptions of these measures can be found in the appendix.

Panel A of Table 1 presents the descriptive statistics on the measures of option-implied (downside) risk we consider estimated over the period from 2002 to 2021. The IVS estimates we report represent firm's average cost of protection against downside risk. As expected and highlighted by Ilhan et al. (2021), the IVS is typically positive which indicates that deeper OTM puts are more expensive. The average cost of protection against downside risk across firms is 0.44 and our estimates range between a minimum of -2.11 and a maximum level of 4.31.

In Panel B of Table 1, we report descriptives of the ESG scores of the firms in our sample, as well as the various components of the aggregate score. The average

[3]See Kelly et al. (2016) and Ilhan et al. (2021) for more information on the computation procedures.

ESG score across firms is 42. The governance component generally attains higher levels relative to E and S, with a G score of 53.4 for the average firm. It is also the least volatile component of the three.

Panel C of Table 1reports descriptives of the control variables that we use in our analysis. The CAPM beta and volatility are obtained from a 12-month rolling regression of the firm's monthly returns on the return of the S&P 500 index. Firm size is prixied by the logassets variable which is computed as the natural logarithm of the firm assets. divnetinc is the ratio of the firm's gross dividend to net income. ebitassets is the ratio of the firm's earnings before interest and tax (ebit) to assets. capexassets is the ratio of the firm's capital expenditure (capex) to assets. booktomar is the ratio of the firm's equity book value to its market value.

# 3 ESG Uncertainty and the Cost of Protection Against Downside Tail Risk

In this section, we examine the relationship between firms' sustainability performance and the cost of protection against downside risk. We examine whether ESG uncertainty is priced in the options market. We first consider the level of firms' sustainability performance and its various components. We then incorporate our measure of ESG uncertainty – the disparity across firms' environmental, social, and governance performance – to evaluate the expensiveness of protection against left-tail events for firms with high or low levels of ESG uncertainty. Thus, we investigate whether investors pay a premium to hedge against uncertainty in the ESG performance of firms.

## 3.1 ESG Level and Firm's Downside Risk

The baseline regression equation is as follows:

$$IVS_{i,m,t+1} = \alpha_0 + \beta_1 Sustain_{i,t} + \boldsymbol{\delta X_{i,t}} + \epsilon_{i,m,t+1} \tag{1}$$

where $IVS_{i,m,t+1}$ denotes the implied volatility slope of firm $i$ at month $m$ in year $t+1$ and $Sustain_{i,t}$ is the $ESG_{i,t}$, $E_{i,t}$, $S_{i,t}$, $G_{i,t}$ of firm $i$ sustainability score in year $t$. $X_{i,t}$ is a vector of controls for firm i at time t. We average on a monthly basis the daily implied volatility slope for each firm. We match the firm's IVS at year $t+1$ to the firm's sustainability score at year $t$ because Thomson Reuters mainly updates its sustainability score when they receive the firm's annual report, therefore, resulting in a delay in ESG score update. We include beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar as controls and also control for fixed year effect. Beta, volatility, and return are measured at a monthly level while the sustainability scores, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar are measured at yearly level.

Table 2 presents the result of the firm-month level regression of the Implied Volatility Slope (IVS) – which represents the cost of protection against downside risk – on firms' aggregate ESG score as well as the first-level ESG disaggregate score across firms' Environmental (E), Social (S), and Governance (G) performance. The result shows that there is a negative relationship between the cost of protection against downside risk and the aggregate ESG, E, and S performance of the firms. This implies that firms with higher aggregate ESG performance, environmental performance, and social performance have lower cost of protection against downside risk. The higher the firm's ESG, E, and S performance, the lower the cost of protection against downside risk. However, governance performance exhibits a negative relationship with the cost of protection against downside risk. It implies that firms with higher governance performance have a higher cost of protection against downside risk. All the results on the sustainability performance are statistically significant. For the control variables, we find the expected relationship with the cost of protection against downside risk. For instance, the higher the CAPM beta, the higher the cost of protection against the downside risk. Larger, more profitable, high capital expenditure, and lower financial leverage firms have lower cost of protection against downside risk.

We also consider the second level of ESG disaggregation along the following dimensions: Resource Use, Emissions, and Innovation scores for the environmental dimension; Workforce, Human Rights, Community, and Product responsibility for the social dimension; Management, Shareholders, and CSR strategy for the governance dimension. The positive and significant relationship between the firms' governance score and the cost of protection against downside risk motivates us to examine the second level of disaggregation to understand what might be driving the positive relationship. Table 3 reports the firm-month level regression to examine the relationship between the second level of disaggregation and the cost of protection against downside risks.

For the environmental and social dimensions, all underlying components have a negative and significant relationship with the cost of protection against downside risks. Firms with better efficient use of resources, lower emissions, and better innovation toward reducing environmental costs and burdens have lower cost of protection against downside risks. As well, firms with a better workforce, human rights, community, and product responsibility score have lower cost of protection against downside risks. The pattern is more nuanced along the governance components. There, higher shareholder and CSR strategy scores are associated with lower cost of option protection. Higher management scores, however, imply the opposite. Firms with better board structure, compensation policy, and board functions have a higher cost of protection against downside risks. Given that the weighting methodology of Thomson Reuters attributes substantially higher weight to management in their governance score, the positive association with firm's downside risk is also reflected in the governance dimension of the firm's score.

## 3.2 ESG Disparity and Firm's Downside Risk

Here, we examine the relationship between the disparity across the firm's sustainability profile (i.e Environmental, Social, and Governance performance) and firm's cost of option protection against downside risk. We conjecture that the observed disparity across the components of the firm's sustainability metric proxy for its ability to manage ESG regulatory developments. A firm with high ESG disparity signals a low ability to manage ESG regulatory requirements.

For each firm in our sample with an ESG rating, we compute the disparity across its E, S, and G scores as the mean absolute deviation (MAD) across the different components. We sort firms in deciles according to the MAD metric. Next, we estimate the baseline regression in Equation (1) for firms within each MAD decile. Table 4 presents the $\beta_1$ estimates for firms in the 90th quantile (representing those with the highest disparity) and in the 10th quantile (representing those with the lowest disparity). Both high- and low-disparity firms associate higher cost of downside option protection with poor ESG scores. However, when disparity is low, the individual components of the sustainability score are not significantly associated with the cost of option protection.

Next, we introduce the ESG disparity as an independent continuous variable to the baseline regression. The (augmented) baseline regression equation is as follows:

$$IVS_{i,m,t+1} = \alpha_0 + \beta_1 Sustain_{i,t} + \lambda_1 ESGdisparity_{i,t} + \boldsymbol{\delta X_{i,t}} + \epsilon_{i,m,t+1} \qquad (2)$$

$IVS_{i,m,t+1}$ is the implied volatility slope of firm i at month m in year t+1, and $Sustain_{i,t}$ is the $ESG_{i,t}$, $E_{i,t}$, $S_{i,t}$, $G_{i,t}$ of firm i sustainability score in year t. $X_{i,t}$ is a vector of controls for firm i at time t. The ESG disparity is the firm's mean absolute deviation across its environmental, social, and governance performance which captures the ability of the firm to manage its ESG regulatory development.

Table 5 presents the estimates of a firm-month level regression of IVS on the sustainability performance and the ESG disparity of firms based on Equation (2). The model is estimated for the aggregate ESG score, as well as its various components. The table reports only the $\beta_1$ and $\lambda_1$ estimates. Throughout all specifications and for all levels of disaggregation of the ESG score, high ESG disparity is consistently and significantly associated with a higher cost of option protection against left tail risk. Investors in firms with poor ESG performance (in the aggregate or along most of the different dimensions of the score) would typically pay a higher cost to protect against extreme left tail events in the option market. However, they would do so consistently when the uncertainty associated with the firm's ability to manage its exposure to ESG regulation is high.

Next, we examine whether the ability of the firms to manage ESG disparity differs across various sectors. We link the firms in our sample to their various sectors based on the Global Industry Classification Standard (GICS). The GICS classifies firms into 12 sectors: Energy, Material, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, and Real Estate. We label firms that we could not match to any sector as "No sector identified". Table A3 presents the results of the regressions of the monthly cost of protection against downside risk (IVS) on the sustainability performance and the ESG disparity based on Equation (2) for each sector. The result shows that there is a heterogenous across sectors on the relationship between the cost of protection against downside risk and both sustainability performance and ESG disparity.

## 3.3 ESG Treatment and Downside Risk

In this section, we examine the impact of ESG treatment on the cost of protection against downside risk. We estimate the causal effect of sustainability score on the cost of protection against downside risk for firms with ESG scores (treated firms) in relation to comparable firms without ESG scores (control firms) based on the common firms' observed characteristics or confounders. We apply the matching technique for panel data developed by Imai et al. (2019) which is a departure from the existing matching methods that assume a cross-sectional set, see Imai et al. (2019), for reference) The method allows for simple diagnostics to check for covariates balance and to estimate the short-term and long-term causal effect or average treatment effect of the sustainability score on the cost of protection against downside risk for the treated firms.

We briefly discuss the matching procedures with reference to Imai et al. (2019). For each treated observation, we find a set of control observations that have identical treatment histories of 12 months period. The 12 months period of identical treatment histories serves as the baseline period since most of our covariates are reported or updated yearly [4]. Next, we adjust the matched set for observed confounding using the Covariates balancing propensity score (CBPS) weighting technique, as a baseline technique, so that the treated and the control observations have similar covariates values. We also consider other several weighting and matching techniques. For matching techniques, we apply up-to-five matching which means that each treated firm can only match to the maximum of five control firms. Then we apply the difference in difference estimator to estimate the causal effect of ESG treatment on the cost of protection against downside risk. The observed confounding variates are quick ratio, size, financial leverage (FL), hard spending, intangible, growth, cash ratio, profitability, and dividend yield.

We plot the variation of the treatment across units (i.e. firms) and time with the aim to compare the treated and control observations. Figure A1 presents the distribution of the treatment across units and time. The red(blue) rectangle represents the treatment(control) firm-year observation. The white area represents the year when a firm is not assigned ESG score. At the beginning of our sample period, most of the firms are not assigned ESG scores or treated but the number of treated or ESG-assigned firms increases over time. Most of the firms that get treated remain stable over the sample period. The treatment distribution of Figure A1 suggests that we can reasonably find control firms to estimate the average treatment effect. We also see that almost all firms do not switch treatment status which also indicates that we could reasonably estimate the long-term causal effects of the treatment.

We present the frequency distribution of the number of matched control units (firms) based on the identical treatment period. Figure A2 presents the frequency distribution of the number of matched control units for up 6, 12, and 24 identical

[4]Specifying the number of treatment histories is a bias-variance trade-off story. Increasing the value improves the credibility of the unconfoundedness assumption but reduces the efficiency of the estimates (Imai et al. (2019).

treatment periods. The bar represents the number of control-matched firms that share the same treatment history as the treated observation prior to the treatment period. The thinner vertical bars at zero represent the number of treated observations that have no matched control units. The main takeaway from the frequency distribution of matched control firms is that irrespective of the identical treatment periods selected, we have a reasonably high number of matched sizes or control units which are clustered around 300 and 600 matched sizes. This implies that we have enough matched control units (based on identical treatment periods) to estimate the average treatment effects and hence make causal inferences.

Next, we refine the matched set of Figure A2 to adjust for confounders. We apply several refinement methods based on the weighting and matching methods. We apply two refinement weighting methods which are the Covariates balance propensity score (CBPS) weighting method and the Propensity score weighting method. We set the baseline matching criterion for the pre-treatment period to 12. The size match represents the maximum number of control units for each treated observation. Figure A3 presents the improved covariates balance of matching over 12 months pre-treatment period based on the weighting method. Figure A3 presents the standardized mean difference between treated observations and the matched control observations. The refinement methods based on the weighting method have a standardized mean difference that is close to zero at each pre-treatment period and reasonably constant over the pre-treatment period. This suggests no imbalance in confounders and that the parallel trend assumption for the difference-in-difference estimator used to estimate the average treatment effect seems reasonable or appropriate.

We estimate the causal effect of ESG treatment on the cost of protection against downside risk. The idea is that for two firms that are the same in their fundamental characteristics but one receives ESG treatment or ESG score and the other does not, what is the impact of the treatment on the cost of protection against the downside risk? We present an estimated average treatment effect based on the matching and weighting methods. Figure 1 shows the estimated average treatment effect of ESG treatment on the cost of protection against downside risk based on the weighting method. For the immediate effect, the average treatment is negative which implies that the cost of protection is lower for firms that receive ESG scores as compared to firms without ESG scores with the same fundamental characteristics. For the long-term or cumulative effect over the next four months, the average treatment effect is also negative. The results are statistically significant at a 95% confidence level. The bootstrap method is used for the standard error calculation. The main takeaway is that ESG treatment lowers the cost of protection against downside risk.

## 3.4 Robustness

In this section, we present further evidence to show that there is a negative relationship between sustainability (particularly the aggregate ESG, E and S) performance and the cost of protection against downside risk.

The first concern is the positive relationship between governance performance and the cost of protection against downside risk as reported in the baseline line regression of Table 2. We investigate whether this relationship differs across different quantiles and could further improve our understanding of what might be driving the positive relationship. We perform quantile regression of the monthly cost of protection against downside risk on the sustainability performance and controls variables based on Equation (1). We also control for year fixed effects. Table A4 reports the quantile results of the regressions of the monthly cost of protection against downside risk (IVS) on sustainability performance based on Equation (1). This table reports only the coefficients on sustainability performance. Column (20) reports the 20th quantile result of the regression. Column 40 (60, 80) reports the 40th (60th, 80th) quantile result of the regression. The standard deviations are reported under the coefficients. For aggregate ESG, Environmental and Social performance, we still observe a negative relationship with cost of protection against downside risk irrespective of the quantile level. For the governance performance, we observe a negative relationship with the cost of protection against downside risk for the 20th and the 40th quantile and observe a positive relationship with cost of protection against downside risk for the 60th and the 80th quantile. This is an indicative of the positive relationship between governance performance and the cost of protection against downside risk driven by the firms that belong in the higher quantile of the cost of protection against downside risk.

We also run a number of sub-sample regressions. Since we have a small number of firms with ESG scores at the beginning of our sample period, we further restrict our sample to consider only observations from 2010 onward. Second, a number of firms in our sample have zero environmental scores and non-zero aggregate ESG, social and governance scores. We thus exclude firms with zero environmental scores. For both subsamples, we perform our baseline regression based on Equation (1).

Table A5 presents the results of the sub-sample regressions of the monthly cost of protection against downside risk (IVS) on the sustainability performance and the ESG disparity based on Equation (2). This table reports only the coefficients on sustainability performance and on ESG disparity. The control variables from our baseline analysis as well as year fixed effects are included. Panel A reports results for a sample from January 2010 to December 2021. Panel B documents results for a subsample excluding firms with zero environmental scores. We still observe the same result for the relationship between sustainability performance and the cost of protection against downside risk. There is a positive relationship between aggregate ESG, environment and social performance, and the cost of protection against downside risk while there is a negative relationship between governance performance and the cost of protection against downside risk. ESG disparity still has a positive relationship with the cost of protection against downside risk. The level of ESG disparity increases in magnitude when we consider the sample from 2010 onward.

One major concern with the use of ESG data is the low correlation of ESG data among ESG data providers. We consider MSCI ESG data as an alternative source for data on the sustainability performance of the firms. We obtain the data on the firm characteristics from CRSP covering the period from 2002 to 2021 to compute the standard control variables for the baseline regression. We perform the (augmented) baseline regression of Equation (2). To make the result comparable with the Thomson-based ESG regression result, we adjust the aggregate ESG, environmental and social scores for the industry and the governance scores for the country. For the aggregate ESG, environmental and social score, we can calculate the mean for each industry and subtract this from each firm according to their industry. For the governance score, we calculate the mean for the entire US sample and subtract this from each firm. Next, we compute the ESG disparity based on these industry-adjusted and country-adjusted sustainability scores.

Table A6 presents the results of the regressions of the monthly cost of protection against downside risk (IVS) on the MSCI sustainability performance and the ESG disparity based on Equation (2). For brevity, the table reports only the coefficients on sustainability performance and on ESG disparity. The results confirm our baseline result of a negative relationship between aggregate ESG, environmental and social performance and the cost of protection against downside risk while there is a positive relationship between governance performance and the cost of protection against downside risk. We confirm the positive relationship between ESG disparity and the cost of protection against downside risk. All the reported results are statistically significant.

We compute different risk measures other than the main risk measure termed "the cost of protection against downside risk" in this paper. The different risk measures are categorized into two: one under the downside risk measures and the other one under the general risk measures. For the downside risk measures, we compute the simple model-free implied volatility (smfiv) for OTM puts (downside) from Martin (2011, 2017), model-free implied volatility (mfiv) for OTM puts (downside) from Bakshi et al. (2003), and model-free implied volatility (mfiv) for OTM puts (downside) from Britten-Jones and Neuberger (2000). For the general risk measures, we compute the simple model-free implied volatility (smfiv) from Martin (2011, 2017), model-free implied volatility (mfiv) from Bakshi et al. (2003), model-free implied volatility from Britten-Jones and Neuberger (2000), model-free implied skewness (mfis) based on Bakshi et al. (2003), model-free implied kurtosis (mfik) based on Bakshi et al. (2003), corridor volatility index (cvix) from Andersen and Bondarenko (2007), Andersen et al. (2015) measured on the relative deviation of 2 sigmas from the At-the-Money (ATM) moneyness of 1, and rare disaster concern index (rix) from Gao et al. (2018).

Table A7 presents the results of the regressions of the monthly different risk measures on the sustainability performance based on Equation (1). We adjust for control variables and fixed-year effect. Panel A considers closely related downside risk measures to the baseline downside risk measure termed as the "cost of protection against downside risk". Panel B reports the regressions of the monthly different general risk measures on sustainability performance. Based on Panel A's result on the related downside risk, we find clearly that the different downside risk measures have a negative and statistically significant relationship with aggregate ESG, environmental, and social performance. However, the relationship between different downside risk measures and governance performance remains inconclusive and statistically insignificant.

Based on Panel B's result on the general risk, we find that (1) smfiv, mfiv, mfik, cvix, rix risk measures have a negative and statistically significant relationship with aggregate ESG performance except for the mfis which has a positive and statistically insignificant relationship with aggregate ESG performance; (2) smfiv, mfiv, mfik, cvix, rix risk measures have a negative and statistically significant relationship with environmental performance except for the mfis which has a positive and statistically significant relationship with environmental ESG performance; (3) mfiv, mfik, cvix, rix risk measures have a negative and statistically significant relationship with social performance except for the mfis which has a positive and statistically significant relationship with social performance. smfiv is statistically significant for social performance; and (4) smfiv, mfik, and rix show a positive and statistically significant relationship with governance performance. mfiv and civ show a positive but statistically insignificant relationship with governance performance. Only mfis show a negative but statistically insignificant relationship with governance performance. The main takeaway is that we find a strong positive relationship between different downside risk measures and aggregate ESG, environmental and social performance while the relationship between different downside risk measures and governance performance remains inconclusive.

All the risk measures we have considered so far have been computed based on options data. We departed from these option-based risk measures and consider a bond-based measure called the Credit default swap (CDS). Credit Default Swap (CDS) provides insurance protection to the buyer against the company (reference entity)'s risk of default. This CDS contract involves three parties: the reference entity (issuer of the debt security), the protection buyer (also the buyer of the debt security), and the protection seller. The protection seller guarantees to buy the reference bond at its par value if the reference entity default and in exchange, the protection buyer makes periodic payments (insurance premium) to the protection seller until the maturity date of the contract or until the reference entity default. This periodic payment (insurance premium) is termed as the "CDS spread". In summary, the protection buyer is buying insurance from the protection buyer to protect against the default risk of the reference entity. This implies that the higher the default risk of the reference entity, the higher the CDS spread.

We obtain daily CDS spread based on 5-year senior bonds – which are the most liquid CDS contract and are popularly traded in US markets – from S&P Global covering the period from January 2004 to December 2021. We compute the monthly average for the CDS spread. The CDS spreads are quoted in basis points. Then we match firms with CDS data to their Thomson ESG data. We ended up with 205 US firms with both ESG data and CDS spread based on 5-year senior bonds. Table A8 presents the regressions of the monthly credit default swap on the sustainability performance and the ESG disparity based on Equation (2). We adjust for control variables and fixed-year effect.

We find that there is a negative relationship between aggregate ESG, environmental, social, and governance performance and the Credit Default Swap (CDS) spread. However, the results are statistically insignificant for social and governance performance. We consider the second level of disaggregation. Under the environmental dimension, there is also a negative relationship between resource use, emission reduction and innovation performance and the CDS spread. However, the results are statistically insignificant for both resource use and innovation performance. Under the social dimension, workforce, community, and product responsibility performance have a negative relationship with the CDS spread while Human rights performance has a positive relationship with CDS spread. However, the relationship with workforce performance is not statistically significant. Under the governance dimension, Management and CSR strategy performance have a negative relationship with the CDS spread while shareholder performance has a positive relationship with the CDS spread. However, the CDS relationship with management performance is not statistically significant. We find that there is a positive relationship between ESG disparity and the CDS spread. In line with our results for the option-implied downside risk measure, firms with higher ESG disparity command a higher CDS spread.

We consider different variants of the regression model that include fixed effects and clustered standard errors. We considered four different variants of the regression model: (1) with only year fixed effect and no clustered standard errors. (2) with year-sector fixed effect and no clustered standard error. (3) with year-sector fixed effect and year-clustered standard error. (4) with year-sector fixed effect and year-sector clustered standard error. Table A9 presents the results of the different regressions model of the monthly cost of protection against downside risk (IVS) on the sustainability performance and the ESG disparity based on Equation (2). This table reports only the coefficients on sustainability performance and on ESG disparity. Column(1) provides regression results that incorporate year fixed effect but no clustered standard deviation error. Column(2) provides regression results that incorporate year-sector fixed effect but no clustered standard deviation error. Column(3) provides regression results that incorporate year-sector fixed effect and year clustered standard deviation error. Column(4) provides regression results that incorporate year-sector fixed effect and year-sector clustered standard deviation error. The standard deviations are reported under the coefficients. We find that the regression coefficients are not sensitive to the different regression models we considered.

# 4 ESG Uncertainty and Aggregate Downside Risk

In this section, we examine the relationship between ESG performance and the aggregate downside risk in the US economy. We ask whether ESG investment can serve as a hedge against downside risk. We estimate the risk-neutral probability of downside events in the economy which we termed the "Aggregate Downside Risk (ADR)". We can think of ADR measures as the price of insurance against extreme future downside movements of the financial market (similar to the definition of Gao et al. (2018) for the rare disaster index (RIX)). It captures the ex-ante market expectation about future disasters or downside events.

We begin by constructing each firm downside risk (FDR) measure following Gao et al. (2018)'s procedures[5]. We refer you to the appendix for the description of the firm downside risk (FDR). We proceed next to determine or extract the aggregate downside risk following Siriwardane (2015). We use the principal component analysis to extract the aggregate downside risk (ADR) from the firm downside risk (FDR) in line with the Siriwardane (2015)'s procedures:

$$FDR_{it}(\tau) = \Psi_i * ADR_t(\tau) \tag{3}$$

where $\Psi_i$ is the firm-specific constant and $ADR_t(\tau)$ is the Aggregate Downside Risk measures at time t which depends on the time to maturity $\tau$. Again, the $ADR_t(\tau)$ is the risk-neutral probability of downside events from time t to $t+\tau$ and is common to all firms. Based on the rare disaster or downside event model, all cross-sectional variation in $FDR_{it}(\tau)$ is driven by variation in $\Psi_i$ and $ADR_t(\tau)$ is common to all firms. This implies that $FDR_{it}(\tau)$ is governed by a single factor and figure 2 provides empirical support that there is a one-factor structure driving the time series variation in $FDR_{it}(\tau)$ across all firms i.e explaining approximately 49% variation across $FDR_{it}(\tau)$.

We use the daily data on OTM options of US firms from OptionMetrics covering the period from 2001 to 2021 to construct the firm downside risk (FDR) and aggregate downside risk (ADR). The process to obtain each firm downside risk is similar to Gao et al. (2018)'s process for obtaining the market-wide rare disaster index (RIX). We also focus on the option with 30 days to expiration and only the out-of-the-money put options. We interpolate the implied volatilities across a range of observed moneyness levels and fill in the implied volatilities beyond the observed

[5]Gao et al. (2018) develop a rare disaster index (RIX) to quantify the ex-ante market expectations about disaster events in the future.

moneyness bounds with the volatilities on the bounds. We generate 1001 implied volatility data points over the moneyness range from 1/3 to 3. We use the implied volatility curves to compute the Black Scholes (1973) OTM option prices and then apply A5 to obtain daily FDR for each US firm in our sample. We proceed to obtain ADR through principal component analysis. For the computation of the principal component analysis, a firm must have at least 18 daily observations of its FDR in a month to be included. Principal component analysis is conducted on the correlation matrix of the monthly $FDR_i$. The frequency is monthly by averaging within each month. This analysis applies to a set of firms with at least 192 of their monthly observations and we also fill in the missing value as their mean. We ended up with a total of 1191 US firms for the computation of the ADR [6].

## 4.1 Sustainability Scores and Aggregate Downside Risk

Figure 2 shows the first 10 principal components from a principal component analysis (PCA) on the correlation matrix of the firm downside risk measures, $FDR_i$. The first principal component explains about 45% of the variation across the firm downside risk measures, $FDR_i$, while the variation explained by the remaining principal components is very low – ranging from 9% for the second component to 1% for the tenth component. This indicates that a single major factor drives the time series variation in $FDR_i$ across firms. This single major factor represents the Aggregate Downside Risk (ADR) which is common to all firms.

Figure 3 shows the time series of the ADR measure representing the aggregate risk-neutral probability of downside events. The evidence is in line with the results documented in Siriwardane (2015). Consistent with the interpretation of the ADR as the risk-neutral probability of downside events common to all firms, we see that the ADR experienced the highest spike during the Covid crisis for the sample under consideration (period from January 2001 to December 2021) followed by the spike during the global financial crisis.

We then focus our analysis on investigating whether ESG-based investments can serve as a hedge against downside risk or downside events. We verify whether investing in firms with high ESG ratings can protect investors against aggregate downside risk. To address this question, we first determine each firm exposure to aggregate downside risk (ADR) by running the following 12-month rolling regression for each firm at each time $t$:

[6] 4 times larger than the sample size of Siriwardane (2015)

$$R_{i,m,t} = \alpha_{i,m,t} + \beta_{i,m,t} ADR_{m,t} + \epsilon_{i,m,t} \quad (4)$$

where $R_{i,m,t}$ is the monthly return of firm $i$ for year $t$, $ADR_{m,t}$ is the monthly aggregate downside risk for year $t$, and $\beta_{i,m,t}$ is the downside beta for firm $i$ in month $m$ and year $t$. The monthly returns are filtered to exclude penny stocks which are defined as stocks with less than the share price of $5. We also include firms with ESG scores but without individual options data. After obtaining 12-month rolling downside betas for each firm, we group the firms according to their ESG scores in high, medium, and low sustainability performance terciles at time $t-1$ and compute the average beta in each tercile at time $t$. Finally, we aggregate the average downside risk beta across firms in the same tercile at each time $t$ over our sample period.

Panel A of Table 6 presents the average downside risk betas for firms with low, medium, and high overall ESG scores. Since downside risk is decreasing in downside beta, the most negative downside risk betas connote the highest downside risk. We observe that irrespective of their ESG performance, firms are negatively exposed to aggregate downside risk on average. However, firms with high ESG scores have lower exposure to aggregate downside risk as compared to firms with low ESG performance. This implies that investing directly in high ESG firms does not provide insurance against downside risk but an investment strategy of longing high ESG firms and shorting low ESG firms might protect investor portfolios against downside risk. The results remain similar in magnitude when we consider the E, S, and G components of firms' sustainability scores. In Panel B of Table 6, we report the average downside risk betas for firms sorted according to ESG disparity. Firms with low disparity across their E, S, and G ratings have the lowest exposure (in absolute terms) to aggregate downside risk.

## 4.2 The Price of Aggregate Downside Risk

In this subsection, we determine the pricing of aggregate downside risk conditioned on the ESG performance of firms. We categorize firms in low, medium, and high ESG performance quantiles at each time $t$. For each sample of firms, we perform Fama and MacBeth (1973) regressions of month $t+1$ excess stock returns on month $t$ firms' downside betas and the risk factor loadings of standard asset pricing models (the Capital Asset Pricing Model (CAPM), the Fama-French 3 factors model, and the Fama-French 5 factors model).

The downside betas of individual firms and the rest of the factor loadings are obtained by running 12-month rolling regressions of monthly $t$ excess stock return on month $t$ ADR and the set of standard risk factors. For each sample of firms belonging to a given ESG quantile $q$, and at each time $t$, we perform the following cross-sectional regression:

$$R_{i,q,t+1} = \alpha_{0,t} + \lambda_{ADR,q,t}\beta_{ADR,i,q,t} + \Omega_{riskfactors,q,t}X_{riskfactors,i,q,t} + \epsilon_{i,q,t} \qquad (5)$$

where $R_{i,q,t+1}$ is the month $t+1$ excess return of stock $i$ belonging to quantile $q$, $\beta_{ADR,i,q,t}$ is the beta of aggregate downside risk at month $t$ of stock $i$ belonging to quantile $q$, and $X_{riskfactors,i,q,t}$ is the vector of standard risk factor betas estimated at time $t$ for firm $i$ pertaining to ESG quantile $q$.

Table 7 reports the time-series average of monthly $\lambda_{ADR}$ estimates from the cross-sectional regression in Eq. 5 for the entire sample. Regardless of the risk specification, aggregate downside risk is priced in the cross-section and commands a significant negative risk premium.

We then perform the cross-sectional regression in Eq. 5 on three samples conditional on the ESG performance of firms. Table 8 presents the results for a model where aggregate downside risk is the only risk factor (Panel A), a model where ADR is augmented by the market factor (Panel B), a model augmented with the 3-factor Fama-French model (Panel C), and a model augmented by the Fama-French 5-factor risk model (Panel D). The expected return – $\beta_{ADR}$ relationship is negative irrespective of the firms' ESG performance. However, it is statistically significant only in the cross-section of firms that belong to either the top or the bottom ESG score terciles. ADR does not appear to be priced in the cross-section of firms with medium ESG scores. That pattern is confirmed across the different risk specifications considered.

We further condition our sample on the observed disparity between the E, S, and G scores of each firm. We consider three samples of firms according to their ESG disparity: high, medium, and low disparity firms. We repeat the cross-sectional regressions for the three samples of firms and report the results in Panel A of Table 9. For the low ESG disparity sample, ADR remains significantly and consistently priced across all risk model specifications. The exposure to aggregate downside risk maintains a strong relation with expected stock returns for firms with mostly aligned E, S, and G metrics. However, when we consider the sample of firms for which the E, S, and G metrics deviate the most (the high ESG disparity sample), $\lambda_{ADR}$ declines in both absolute magnitude and significance. The relationship between expected stock returns and ADR betas is no longer significant for the high ESG disparity sample.

To further understand the relative importance of the level of ESG scores and their disparity in pricing aggregate downside risk, we further condition both terciles of poorly and best performing firms in terms of ESG scores on the degree of disparity between the E, S, and G components of the score. Results from the cross-sectional regression in Eq. 5 are reported in Panel B and C of Table 9 for firms belonging to the bottom tercile of ESG performance and those belonging to the top tercile of ESG performance respectively. Interestingly, for both sets of firms, we confirm the pattern observed in Panel A of Table 9. Aggregate downside risk is priced only in the cross-section of stocks for which the three components of their ESG score are mostly aligned. Regardless of overall ESG scores, it is only for firms with low ESG disparity that we observe a consistent and strong negative relationship between expected returns and ADR exposure.

# 5 Conclusion

With the increasing number of ESG-related regulatory development, firms are faced with ESG uncertainty emanating from the development of ESG regulations and how to manage these regulatory developments. In this paper, we explore three main areas: (1) the ESG uncertainty emanating from the development of ESG regulations, (2) the firm's ability to manage the regulatory development or the firm's disparity across its environmental, social, and governance performance which we termed as "ESG disparity", and (3) the pricing of ESG exposure to aggregate downside risk.

First, we find that uncertainty relating to environmental, social, and governance (ESG) regulation developments is reflected in asset prices. Firms with high ESG performance have a lower cost of protection against downside risk compared to firms with low ESG performance. Firms with high environmental and social standing have a lower cost of protection against downside risk compared to firms with low environmental and social standing while firms with high governance performance have a higher cost of protection against downside risk compared to low governance firms.

Second, a firm's disparity across environmental, social, and governance performance is priced in the financial markets. Firms with high ESG disparity have a higher cost of protection against downside risk. This implies that firms with a low ability to manage ESG regulatory development command a higher cost of protection against downside risk. There is also heterogeneity in ESG disparity across sectors.

Third, we find a negative price of aggregate downside risk for firms with either high or low ESG performance. Firms with high ESG performance command lower negative price of aggregate downside risk. Both high and low ESG firms have negative exposure to downside risk. However, high ESG firms have lower exposure to downside risk compared to low ESG firms. Investing directly in high ESG firms does not provide insurance against downside risk as they have negative exposure to downside risk. But an investment strategy of longing high ESG firms and shorting low ESG firms might provide insurance against downside risk.

# References


Andersen, T. G., & Bondarenko, O. (2007). Construction and interpretation of model-free implied volatility.

Andersen, T. G., Bondarenko, O., & Gonzalez-Perez, M. T. (2015). Exploring return dynamics via corridor implied volatility. *The Review of Financial Studies,* 28(10), 2902-2945.

Ang, A., Chen, J., & Xing, Y. (2006). Downside risk. *The Review of Financial Studies, 19(4),* 1191-1239.

Bakshi, G., Kapadia, N., & Madan, D. (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. *The Review of Financial Studies, 16(1),* 101-143.

Berg, F. and Kölbel, J. and Rigobon, R., Aggregate Confusion: The Divergence of ESG Ratings (May 17, 2020).

Britten-Jones, M., & Neuberger, A. (2000). Option prices, implied price processes, and stochastic volatility. *The Journal of Finance, 55(2),* 839-866.

Cao, J., Goyal, A., Zhan, X., & Zhang, W. E. (2022). Unlocking ESG premium from options. *Swiss Finance Institute Research Paper,* (21-39).

Christensen D. M., Serafeim G., Sikochi A., 2022, Why is Corporate Virtue in the Eye of The Beholder? The Case of ESG Ratings, *Accounting Review,* 97, Issue 1, p. 147–175.

Eccles, R. G. and Lee, L. and Stroehle, J., 2019, The Social Origins of ESG?: An Analysis of Innovest and KLD.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy,* 81(3), 607-636.

Gao, G. P., Gao, P., & Song, Z. (2018). Do hedge funds exploit rare disaster concerns?. *The Review of Financial Studies,* 31(7), 2650-2692.

Gibson, R. and Krueger, P. and Schmidt, P. S.,2021, ESG Rating Disagreement and Stock Returns. *Financial Analysts Journal,*77:4, 104-127.

Glossner, S. (2017). ESG risks and the cross-section of stock returns. *Paris December 2017 Finance Meeting EUROFIDAI - AFFI.*

Gul, F. (1991). A theory of disappointment aversion. *Econometrica: Journal of the Econometric Society,* 667-686.

He, Y., Kahraman, B., & Lowry, M. (2021). ES risks and shareholder voice.*European Corporate Governance Institute–Finance Working Paper,* (786).

Hoepner, A. G., Oikonomou, I., Sautner, Z., Starks, L. T., & Zhou, X. (2018). ESG shareholder engagement and downside risk.

Huang, W., Liu, Q., Rhee, S. G., & Wu, F. (2012). Extreme downside risk and expected stock returns. *Journal of Banking & Finance,* 36(5), 1492-1502.

Ilhan, E., Sautner Z., & Vilkow, G. (2021): Carbon tail risk, *Review of Financial Studies,* 34, 1540-1571.

Imai, K., Kim, I. S., & Wang, E. H. (2019). Matching Methods for Causal Inference with Time-Series Cross-Sectional Data. *American Journal of Political Science.*

Kahneman, D., & Tversky, A. (2013). Prospect theory: An analysis of decision under risk. *In Handbook of the fundamentals of financial decision making:* Part I (pp. 99-127).

Kelly, B., & Jiang, H. (2014). Tail risk and asset prices. The Review of Financial Studies, 27(10), 2841-2871.

Kelly, B., Pástor, Ľ., & Veronesi, P. (2016). The price of political uncertainty: Theory and evidence from the option market. *The Journal of Finance,* 71(5), 2417-2480.

Martin, I. (2017). What is the Expected Return on the Market?. *The Quarterly Journal of Economics,* 132(1), 367-433.

Martin, I. (2011). Simple variance swaps (No. w16884). *National Bureau of Economic Research*

Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica: Journal of the econometric society,* 431-449.

Siriwardane, E. (2015). The probability of rare disasters: Estimation and implications. *Harvard Business School Finance Working Paper,* (16-061).

Table 1: **Descriptive Statistics**

The table reports descriptive statistics of the variable of interest covering the period from 2002 to 2021. IVS represents the firm's cost of protection against downside risk. It relates the left-tail implied volatility to the moneyness measured by the option's Black Scholes delta for the out-of-the-money (OTM) standardized put options with a 30-day maturity. ESG is the firm's Environmental, Social, and Governance (ESG) combined score which incorporates the ESG controversies. E is the firm's environmental score. S is the firm's social score. G is the firms' governance score. The CAPM beta and volatility are the 12 months rolling regression of the firm's monthly returns. For the CAPM beta, the firms' monthly returns are regressed on the S&P 500 returns and constant. logassets is computed as the natural logarithm of the firm assets which measures the firms'size. divnetinc is the ratio of the firm's gross dividend to net income. ebitassets is the ratio of the firm's earnings before interest and tax (EBIT) to assets. capexassets is the ratio of the firm's capital expenditure (capex) to assets. booktomar is the ratio of the firm's equity book value to the market value. debtassets is the ratio of total debts to total assets

| Statistic | N | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Panel A: Risk Measures** | | | | | |
| IVS | 119,406 | 0.444 | 0.436 | −2.112 | 4.308 |
| smfiv | 119,406 | 0.201 | 0.286 | 0.012 | 8.059 |
| mfiv_bkm | 119,406 | 0.213 | 0.296 | 0.012 | 7.535 |
| mfiv_bjn | 119,406 | 0.204 | 0.273 | 0.012 | 6.779 |
| smfivd | 119,406 | 0.091 | 0.105 | 0.006 | 2.110 |
| mfivd_bkm | 119,406 | 0.137 | 0.211 | 0.007 | 5.651 |
| mfivd_bjn | 119,406 | 0.119 | 0.165 | 0.006 | 4.042 |
| mfis | 119,406 | −0.617 | 0.498 | −3.786 | 4.200 |
| mfik | 119,406 | 5.281 | 2.024 | 1.832 | 29.022 |
| cvix_sigma2 | 119,406 | 0.206 | 0.294 | 0.011 | 7.543 |
| cvix_sigma5 | 119,406 | 0.213 | 0.296 | 0.012 | 7.542 |
| cvix_mnes20 | 119,406 | 0.163 | 0.158 | 0.012 | 2.574 |
| cvix_mnes25 | 119,406 | 0.178 | 0.185 | 0.012 | 3.149 |
| rix | 119,406 | 0.018 | 0.047 | 0.0002 | 1.609 |
| rixnorm | 119,406 | 0.081 | 0.037 | 0.021 | 0.288 |
| **Panel B: Sustainability Measures** | | | | | |
| ESG | 119,406 | 41.979 | 17.873 | 0.869 | 92.516 |
| E | 119,406 | 32.755 | 28.620 | 0.000 | 98.546 |
| S | 119,406 | 45.804 | 21.726 | 0.741 | 97.963 |
| G | 119,406 | 53.417 | 21.722 | 0.292 | 98.599 |
| Resource use | 119,070 | 35.010 | 34.747 | 0.000 | 99.884 |
| Emissions reduction | 119,070 | 33.763 | 33.591 | 0.000 | 99.807 |
| Innovation | 119,070 | 21.267 | 30.017 | 0.000 | 99.367 |
| Workforce | 119,070 | 49.165 | 26.737 | 0.162 | 99.835 |
| Human rights | 119,070 | 21.701 | 30.953 | 0.000 | 99.206 |
| Community | 119,070 | 68.124 | 23.363 | 0.362 | 99.900 |
| Product responsibility | 119,070 | 40.423 | 30.413 | 0.000 | 99.780 |
| Management | 119,070 | 57.773 | 27.436 | 0.052 | 99.983 |
| Shareholders | 119,070 | 55.924 | 27.484 | 0.051 | 99.969 |
| CSR strategy | 119,070 | 28.278 | 34.151 | 0.000 | 99.804 |
| **Panel C: Controls** | | | | | |
| return | 119,111 | 1.225 | 10.767 | −84.353 | 305.691 |
| volatility | 119,028 | 8.903 | 5.720 | 1.310 | 96.651 |
| beta | 117,147 | 1.199 | 1.010 | −9.380 | 12.198 |
| logassets | 119,394 | 22.941 | 1.582 | 17.766 | 28.620 |
| divnetinc | 118,206 | 0.792 | 43.731 | −162.716 | 4,300.375 |
| ebitassets | 106,927 | 0.100 | 0.090 | −0.843 | 0.917 |
| capexassets | 115,722 | 0.044 | 0.052 | 0.000 | 0.865 |
| booktomar | 119,096 | 1.025 | 48.868 | −5.945 | 4,868.352 |
| debtassets | 119,370 | 0.264 | 0.211 | 0.000 | 3.892 |

Table 2: **ESG Performance and the Cost of Protection Against Downside Risk**

Regressions are estimated at the firm-month level. The main dependent variable is the Implied Volatility Slope(IVS) which relates the implied volatility to the moneyness(measured by delta) for the standardized OTM put options with 30 days to expiration; and this captures the cost of protection against downside risk. Column (1) regress IVS on the ESG scores with controls and fixed year effects. Column (2) regress IVS on the Environmental scores with controls and fixed year effects. Column (3) regress IVS on the Social scores with controls and fixed year effects. Column (4) regress IVS on the Governance scores with controls and fixed year effects. The sample includes all US firms with ESG scores and covers the period from 2002 to 2022. The standard deviations, clustered by firm and year, are reported under the coefficients.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Cost of protection against downside risk | | | |
| | (1) | (2) | (3) | (4) |
| ESG | −0.00117*** | | | |
| | (0.0001) | | | |
| Environmental | | −0.00103*** | | |
| | | (0.0001) | | |
| Social | | | −0.00141*** | |
| | | | (0.0001) | |
| Governance | | | | 0.0002*** |
| | | | | (0.0001) |
| beta | 0.008*** | 0.007*** | 0.008*** | 0.007*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| volatility | −0.011*** | −0.011*** | −0.011*** | −0.011*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) |
| return | −0.0002 | −0.0002 | −0.0002 | −0.0002 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| logassets | −0.077*** | −0.071*** | −0.072*** | −0.084*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| divnetinc | 0.0001** | 0.0001*** | 0.0001** | 0.0001** |
| | (0.00002) | (0.00002) | (0.00002) | (0.00002) |
| ebitassets | −0.374*** | −0.365*** | −0.355*** | −0.399*** |
| | (0.014) | (0.014) | (0.014) | (0.013) |
| capexassets | −0.091*** | −0.081*** | −0.109*** | −0.075*** |
| | (0.023) | (0.023) | (0.023) | (0.023) |
| debtassets | 0.078*** | 0.073*** | 0.076*** | 0.084*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| booktomar | 0.00001 | 0.00001 | 0.00001 | 0.00001 |
| | (0.00002) | (0.00002) | (0.00002) | (0.00002) |
| Constant | 2.146*** | 1.980*** | 2.035*** | 2.258*** |
| | (0.024) | (0.027) | (0.025) | (0.023) |
| Fixed year effect | Yes | Yes | Yes | Yes |
| Observations | 103,051 | 103,051 | 103,051 | 103,051 |
| $R^2$ | 0.258 | 0.259 | 0.259 | 0.256 |
| Adjusted $R^2$ | 0.257 | 0.258 | 0.259 | 0.256 |
| Residual Std. Error (df = 103023) | 0.369 | 0.369 | 0.368 | 0.369 |
| F Statistic (df = 27; 103023) | 1,323.920*** | 1,331.071*** | 1,335.745*** | 1,312.477*** |
| *Note:* | | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 3: **ESG Performance and the Cost of Protection Against Downside Risk: Second Level of Disaggregation**

This table displays the results of the regressions of the monthly cost of protection against downside risk (IVS) on the sustainability performance based on Equation (1). This table reports only the coefficients on sustainability performance. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets, and booktomar. It also controls for a fixed-year effect. Panel A reports the environmental dimension: Resource use, Emission reduction, and Innovation. Panel B reports the social dimension: Workforce, Human rights, Community, and Product responsibility. Panel C reports the governance dimension: Management, Shareholder, and CSR strategy. The standard deviations, clustered by firm and year, are reported under the coefficients.

| Dimension | Environmental | Social | Governance |
|---|---|---|---|
| | *Dependent variable :<br>Cost of protection against downside risk* | | |
| **Panel A: Environmental** | | | |
| Resource use | −0.001***<br>(0.00004) | | |
| Emissions reduction | −0.001***<br>(0.00004) | | |
| Innovation | −0.0001***<br>(0.00004) | | |
| **Panel B: Social** | | | |
| Workforce | | −0.001***<br>(0.0001) | |
| Human rights | | −0.001***<br>(0.00004) | |
| Community | | −0.001***<br>(0.0001) | |
| Product responsibility | | −0.0004***<br>(0.00004) | |
| **Panel C: Governance** | | | |
| Management | | | 0.0004***<br>(0.00004) |
| Shareholder | | | −0.0001***<br>(0.00004) |
| CSR strategy | | | −0.001***<br>(0.00004) |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 4: **ESG Disparity based on 90th and 10th quantile.**

For each US firm in our sample, we compute the mean absolute deviation (MAD) for the E, S, and G scores. Next, we sort the firms into quantile based on the computed mean absolute deviation and extract those that belong to the 90 quantile (highest disparity) and 10 quantile (lowest disparity). Regressions are estimated at the firm-month level. The main dependent variable is the Implied Volatility Slope(IVS) which relates the implied volatility to the moneyness (measured by delta) for the standardized OTM put options with 30 days to expiration, and this captures the cost of protection against downside risk. The row "ESG" regress IVS on the ESG scores with controls and fixed year effects for the firms in 90 and 10 quantile; and report only the coefficients on the ESG scores. The row "E" regress IVS on the E scores with controls and fixed year effects for the firms in 90 and 10 quantile; and report only the coefficients on the E scores. The row "S" regress IVS on the S scores with controls and fixed year effects for the firms in 90 and 10 quantile; and report only the coefficients on the S scores. The row "G" regress IVS on the G scores with controls and fixed year effects for the firms in 90 and 10 quantile; and report only the coefficients on the G scores. The "High MAD - 90 quant" column denotes the regression result column for firms' in the 90 quantile based on the mean absolute deviation (MAD). The "Low MAD - 10 quant" column denotes the regression result column for firms' in the 10 quantile based on the mean absolute deviation (MAD). The 'High - Low MAD" represent the simple difference between the High MAD - 90 quant and the Low MAD - 10 quant. The sample includes all US firms with E, S, and G scores; and covers the period from 2002 to 2022. The t-statistics are reported under the coefficients. $*p < 0.1; **p < 0.05; ***p < 0.01$.

| | Mean Absolute Deviation (MAD) | | | |
|---|---|---|---|---|
| | High MAD - 90 Quant | | Low MAD - 10 Quant | |
| ESG | -0,00379 | *** | -0,00044 | *** |
| | (-8,93974) | | (-2,80907) | |
| E | -0,00198 | *** | -0,00009 | |
| | (-6,84420) | | (-0,57762) | |
| S | -0,00162 | *** | -0,00008 | |
| | (-7,72468) | | (-0,47048) | |
| G | 0,00070 | *** | -0,00006 | |
| | (2,49038) | | (-0,40209) | |

Table 5: **ESG Disparity as a continuous independent variable.**

This table displays the results of the regressions of the monthly cost of protection against downside risk (IVS) on the sustainability performance and the ESG disparity based on Equation (2). This table reports only the coefficients on sustainability performance and on ESG disparity. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. It also controls for a fixed-year effect. Panel A reports the environmental dimension: Resource use, Emission reduction, and Innovation. Panel B reports the social dimension: Workforce, Human rights, Community, and Product responsibility. Panel C reports the governance dimension: Management, Shareholder, and CSR strategy. The standard deviations are reported under the coefficients.

| | *Dependent variable :* | |
|---|---|---|
| | *Cost of protection against downside risk* | |
| Coefficients | Sustainability - $\beta_1$ | ESG disparity - $\lambda_1$ |
| **Panel A: Aggregate** | | |
| ESG | $-0.001^{***}$ | $0.001^{***}$ |
| | (0.0001) | (0.0001) |
| **Panel B: First level:** | | |
| Environmental | $-0.001^{***}$ | $0.001^{***}$ |
| | (0.0001) | (0.0001) |
| Social | $-0.001^{***}$ | $0.001^{***}$ |
| | (0.0001) | (0.0001) |
| Governance | 0.0001 | $0.001^{***}$ |
| | (0.0001) | (0.0001) |
| **Panel C: Second level:** | | |
| **Environmental:** | | |
| Resource use | $-0.001^{***}$ | $0.001^{***}$ |
| | (0.00004) | (0.0001) |
| Emissions reduction | $-0.001^{***}$ | $0.001^{***}$ |
| | (0.00005) | (0.0001) |
| Innovation | $-0.00001$ | $0.001^{***}$ |
| | (0.00004) | (0.0001) |
| **Social:** | | |
| Workforce | $-0.001^{***}$ | $0.001^{***}$ |
| | (0.0001) | (0.0001) |
| Human rights | $-0.001^{***}$ | $0.001^{***}$ |
| | (0.00004) | (0.0001) |
| Community | $-0.001^{***}$ | $0.001^{***}$ |
| | (0.0001) | (0.0001) |
| Product responsibility | $-0.0004^{***}$ | $0.001^{***}$ |
| | (0.00004) | (0.0001) |
| **Governance:** | | |
| Management | $0.0003^{***}$ | $0.001^{***}$ |
| | (0.00004) | (0.0001) |
| Shareholder | $-0.0002^{***}$ | $0.002^{***}$ |
| | (0.00004) | (0.0001) |
| CSR strategy | $-0.001^{***}$ | $0.001^{***}$ |
| | (0.00004) | (0.0001) |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 6: **ESG Exposure to Aggregate Downside Risk(ADR).**

This table presents the average beta at each time t aggregated over the sample period from 2003 to 2021. For each firm at each time t, we perform 12-month regression based on the following regression equation: $R_{i,m,t} = \alpha_0 + \beta_0 ADR_{m,t} + \epsilon_{i,m,t}$ where $\beta_0$ is the firm exposure to aggregate downside risk. Next, we group the firms into high, medium, and low sustainability performance quantiles at time t-1 and compute the average beta at time t. Finally, we averaged the beta over the sample period from 2003 to 2021. Since the aggregate downside risk is decreasing in downside beta, the most negative downside risk betas connote the highest downside risk.

| Sustainability measures | High | Medium | Low |
|---|---|---|---|
| | | $\beta_0$ | |
| **Panel A: ESG performance** | | | |
| ESG | $-0,026$ | $-0,034$ | $-0,052$ |
| Environmental | $-0,022$ | $-0,041$ | $-0,047$ |
| Social | $-0,028$ | $-0,041$ | $-0,042$ |
| Governance | $-0,034$ | $-0,037$ | $-0,040$ |
| **Panel B: ESG disparity** | | | |
| ESG disparity | $-0,045$ | $-0,033$ | $-0,033$ |

Table 7: **Pricing of Aggregate Downside Risk based on the full sample.**

This table presents the results of Fama and MacBeth (1973) regressions of month t + 1 excess stock returns on month t $\lambda_{ADR}$ and different risk factors betas ($\lambda_{riskfactors}$) for the full sample. The t-stats are adjusted for data-driven Newey West and are reported in parenthesis. ADR, MKT, SMB(small minus big), HML(high minus low), RMW(robust minus weak), and CMA (conservative minus aggressive) are the returns on the downside, market, size, value, profitability, and investment factors respectively.

| Portfolio | $\alpha$ | $\lambda_{ADR}$ | $\lambda_{MKT}$ | $\lambda_{SMB}$ | $\lambda_{HML}$ | $\lambda_{RMW}$ | $\lambda_{CMA}$ |
|---|---|---|---|---|---|---|---|
| **ADR** | 0.010 | $-0.116$ | | | | | |
| | (2.980) | (-2.121) | | | | | |
| **One Factor + ADR** | 0.007 | $-0.087$ | 0.004 | | | | |
| | (2.932) | (-2.059) | (2.059) | | | | |
| **Fama 3 Factor + ADR** | 0.007 | $-0.084$ | 0.003 | 0.002 | 0.0006 | | |
| | (2.891) | (-2.284) | (2.079) | (0.355) | (0.400) | | |
| **Fama 5 Factor + ADR** | 0.008 | $-0.084$ | 0.003 | 0.002 | 0.0007 | $-0.0005$ | $-0.0006$ |
| | (3.091) | (-1.870) | (1.746) | (2.943) | (0.661) | (-0.975) | (-1.135) |

Table 8: **Pricing of Aggregate Downside Risk conditioned on the ESG performance.**

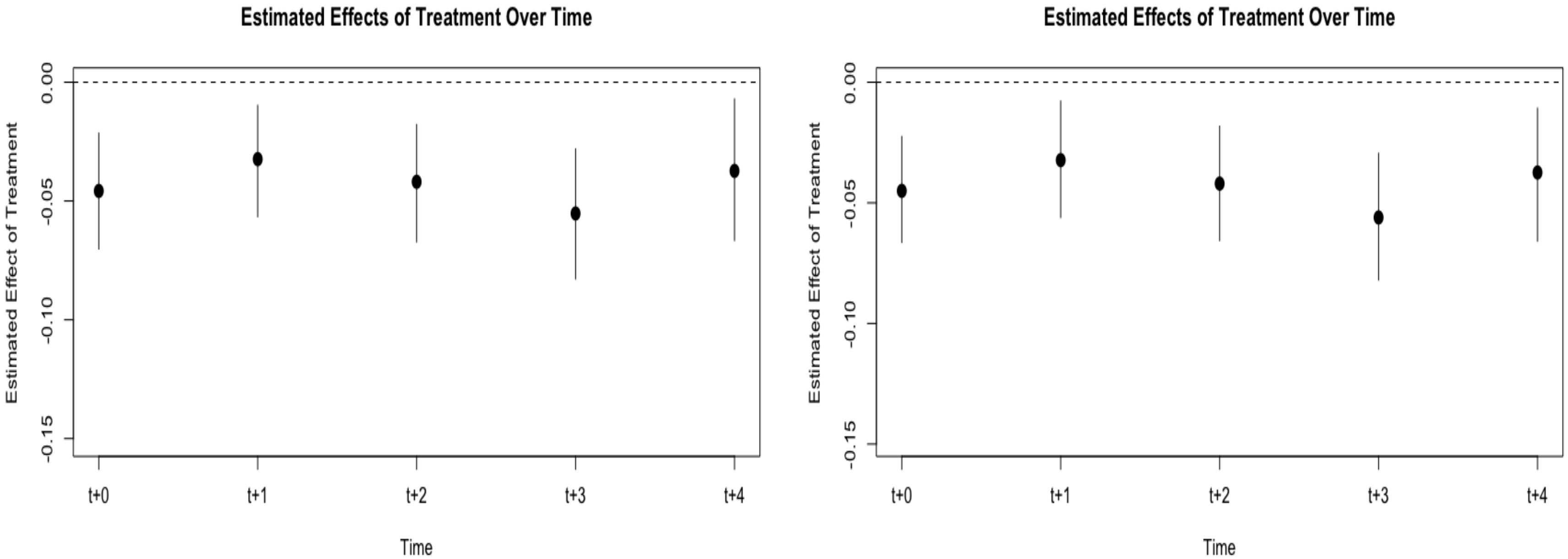
This table presents the results of Fama and MacBeth (1973) regressions of month t + 1 excess stock returns on month t $\lambda_{ADR}$ and different risk factors betas ($\lambda_{riskfactors}$) conditioned on the ESG performance. The t-stats are adjusted for data-driven Newey West and are reported in parenthesis. ADR, MKT, SMB(small minus big), HML(high minus low), RMW(robust minus weak), and CMA (conservative minus aggressive) are the returns on the downside, market, size, value, profitability, and investment factors respectively.

| Portfolio | $\alpha$ | $\lambda_{ADR}$ | $\lambda_{MKT}$ | $\lambda_{SMB}$ | $\lambda_{HML}$ | $\lambda_{RMW}$ | $\lambda_{CMA}$ |
|---|---|---|---|---|---|---|---|
| **ADR:** | | | | | | | |
| Low ESG Score | 0.010 | -0.124 | | | | | |
| | (2.838) | (-2.220) | | | | | |
| Medium ESG Score | 0.010 | -0.090 | | | | | |
| | (2.945) | (-1.589) | | | | | |
| High ESG Score | 0.0092 | -0.140 | | | | | |
| | (3.119) | (-2.199) | | | | | |
| **One Factor + ADR:** | | | | | | | |
| Low ESG Score | 0.0079 | -0.0997 | 0.0031 | | | | |
| | (2.757) | (-2.176) | (1.443) | | | | |
| Medium ESG Score | 0.0064 | -0.0743 | 0.0041 | | | | |
| | (2.361) | (-1.548) | (2.291) | | | | |
| High ESG Score | 0.0063 | -0.0900 | 0.0045 | | | | |
| | (2.779) | (-2.200) | (2.066) | | | | |
| **Fama 3 Factor + ADR:** | | | | | | | |
| Low ESG Score | 0.0072 | -0.09292 | 0.00272 | 0.0031 | 0.0009 | | |
| | (2.816) | (-2.186) | (1.313) | (4.494) | (0.759) | | |
| Medium ESG Score | 0.0071 | -0.0734 | 0.0030 | 0.0022 | 0.0003 | | |
| | (2.546) | (-1.614) | (1.795) | (3.0247) | (0.269) | | |
| High ESG Score | 0.0066 | -0.0875 | 0.0044 | 0.0003 | 0.0004 | | |
| | (2.891) | (-2.284) | (2.079) | (0.355) | (0.400) | | |
| **Fama 5 Factor + ADR:** | | | | | | | |
| Low ESG Score | 0.0077 | -0.1002 | 0.0025 | 0.0035 | 0.0011 | 0.0003 | -0.0009 |
| | (2.923) | (-2.139) | (1.165) | (4.086) | (0.897) | (0.338) | (-1.888) |
| Medium ESG Score | 0.0078 | -0.0698 | 0.0021 | 0.0022 | -0.00002 | -0.0003 | -0.0003 |
| | (2.623) | (-1.55) | (1.104) | (2.495) | (-0.018) | (-0.607) | (-0.505) |
| High ESG Score | 0.0066 | -0.0785 | 0.0041 | 0.0002 | 0.0005 | 0.0002 | -0.0009 |
| | (2.926) | (-2.080) | (1.974) | (0.193) | (0.434) | (0.258) | (-1.390) |

Table 9: **Pricing of Aggregate Downside Risk conditioned on the ESG Disparity.**

This table presents the results of Fama and MacBeth (1973) regressions of month t + 1 excess stock returns on month t $\lambda_{ADR}$ and different risk factors betas ($\lambda_{riskfactors}$) conditioned on the ESG disparity. Panel A reports the regression result on all firms in our sample. Panel B reports the regression result conditioned on firms with low ESG performance. Panel C reports the regression result conditioned on firms with high ESG performance. The t-stats are adjusted for data-driven Newey West and are reported in parenthesis. ADR, MKT, SMB(small minus big), HML(high minus low), RMW(robust minus weak), and CMA (conservative minus aggressive) are the returns on the downside, market, size, value, profitability, and investment factors respectively.

| Portfolio | $\alpha$ | $\lambda_{ADR}$ | $\lambda_{MKT}$ | $\lambda_{SMB}$ | $\lambda_{HML}$ | $\lambda_{RMW}$ | $\lambda_{CMA}$ |
|---|---|---|---|---|---|---|---|
| **Panel A: All firms** | | | | | | | |
| Low ESG Disparity | 0.008 | -0.123 | 0.002 | 0.003 | 0.001 | 0.0006 | -0.0008 |
| | (3.136) | (-2.068) | (1.105) | (3.470) | (1.254) | (0.783) | (-1.602) |
| Medium ESG Disparity | 0.007 | -0.078 | 0.003 | 0.002 | 0.0009 | -0.0004 | -0.0009 |
| | (2.786) | (-1.944) | (1.662) | (2.313) | (0.978) | (-0.509) | (-1.603) |
| High ESG Disparity | 0.008 | -0.065 | 0.004 | 0.002 | 0.0002 | -0.001 | -0.0002 |
| | (2.863) | (-1.440) | (2.034) | (2.255) | (0.205) | (-1.815) | (-0.338) |
| **Panel B: Low ESG performance** | | | | | | | |
| Low ESG Disparity | 0.006 | -0.178 | 0.008 | 0.004 | 0.002 | 0.004 | -0.0001 |
| | (1.710) | (-2.297) | (1.956) | (4.041) | (0.986) | (-1.359) | (-0.182) |
| Medium ESG Disparity | -0.029 | 0.220 | 0.023 | 0.006 | 0.016 | -0.002 | -0.002 |
| | (0.785) | (-0.865) | (1.127) | (1.463) | (0.976) | (-2.007) | (-2.748) |
| High ESG Disparity | 0.012 | -0.050 | -0.001 | 0.002 | 0.004 | -0.0009 | -0.0004 |
| | (3.276) | (-1.208) | (-0.377) | (0.446) | (1.080) | (-1.565) | (-0.538) |
| **Panel C: High ESG performance** | | | | | | | |
| Low ESG Disparity | -0.016 | -0.096 | 0.040 | -0.012 | -0.041 | -0.024 | -0.0003 |
| | (-0.836) | (-2.374) | (1.150) | (-0.705) | (-0.929) | (-1.043) | (-0.462) |
| Medium ESG Disparity | 0.005 | -0.157 | 0.008 | 0.001 | 0.0003 | 0.0003 | -0.0011 |
| | (1.607) | (-2.353) | (1.736) | (0.770) | (0.103) | (0.380) | (-1.598) |
| High ESG Disparity | 0.009 | -0.053 | 0.005 | -0.005 | -0.005 | 0.0002 | -0.0009 |
| | (2.570) | (-0.053) | (2.186) | (-0.414) | (-0.620) | (0.297) | (-1.224) |




(a) CBPS Weighting

(b) PS Weighting

Figure 1: **Estimated Average Treatment Effect of ESG status (treatment) on the Cost of Protection Against Downside Risk based on the Weighting Method.** The estimates are based on the weighting method that adjusts for treatment and covariates histories during the period of 12 months prior to the treatment. The estimates for the average effects of ESG treatment are shown for the period of four (4) months after the immediate effect, with 95% asymptotic confidence intervals as vertical bars. The bootstrap method is used for the standard error calculation.

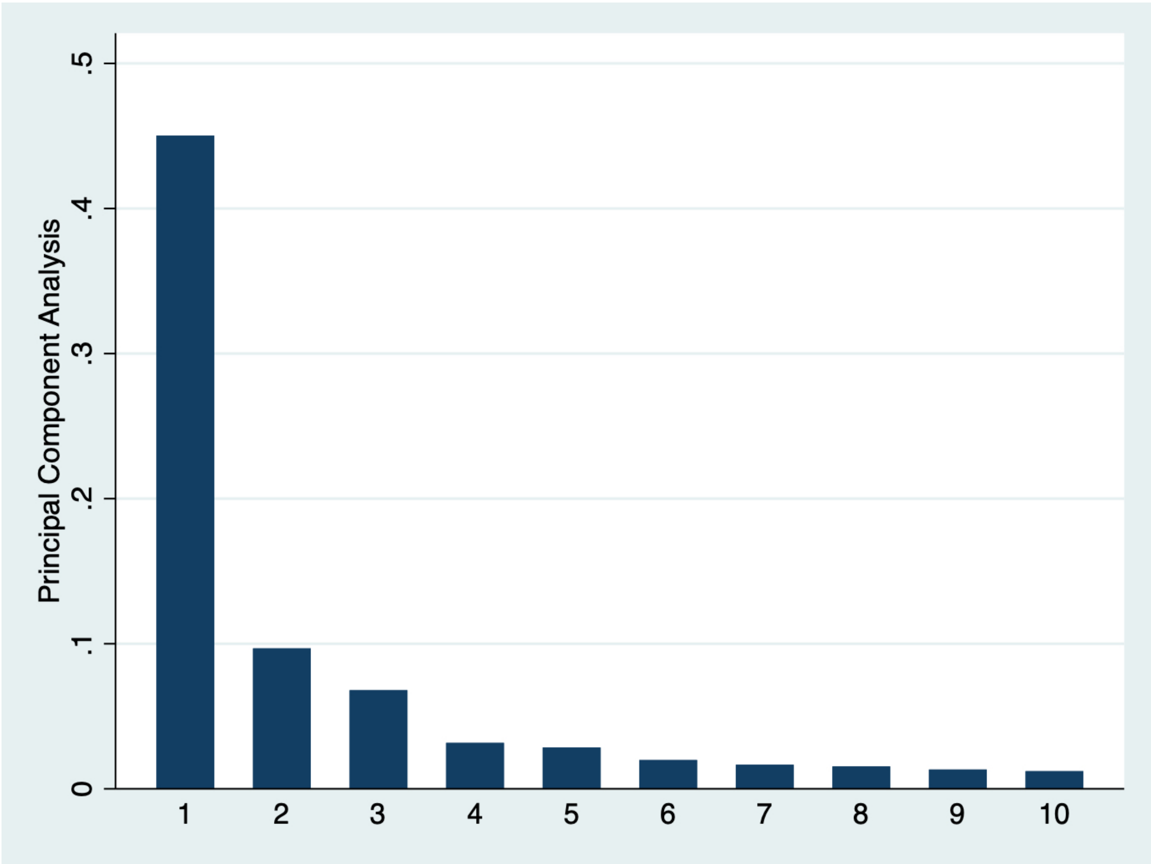



Figure 2: **Principal Component Analysis based on the Firm Downside Risk.** This shows the first 10 Principal Component Analysis on the correlation matrix of the firm downside risk measure, $FDR_i$, extracted from option prices. For the computation of the principal component analysis, a firm must have at least 18 daily observations in a month to be included. The principal component analysis is conducted on the correlation matrix of the monthly $FDR_i$. This analysis applies to a set of firms with at least 192 of its monthly observations and we also fill in the missing value as their mean. The data range is from January 2001 to December 2021 and the frequency is monthly.

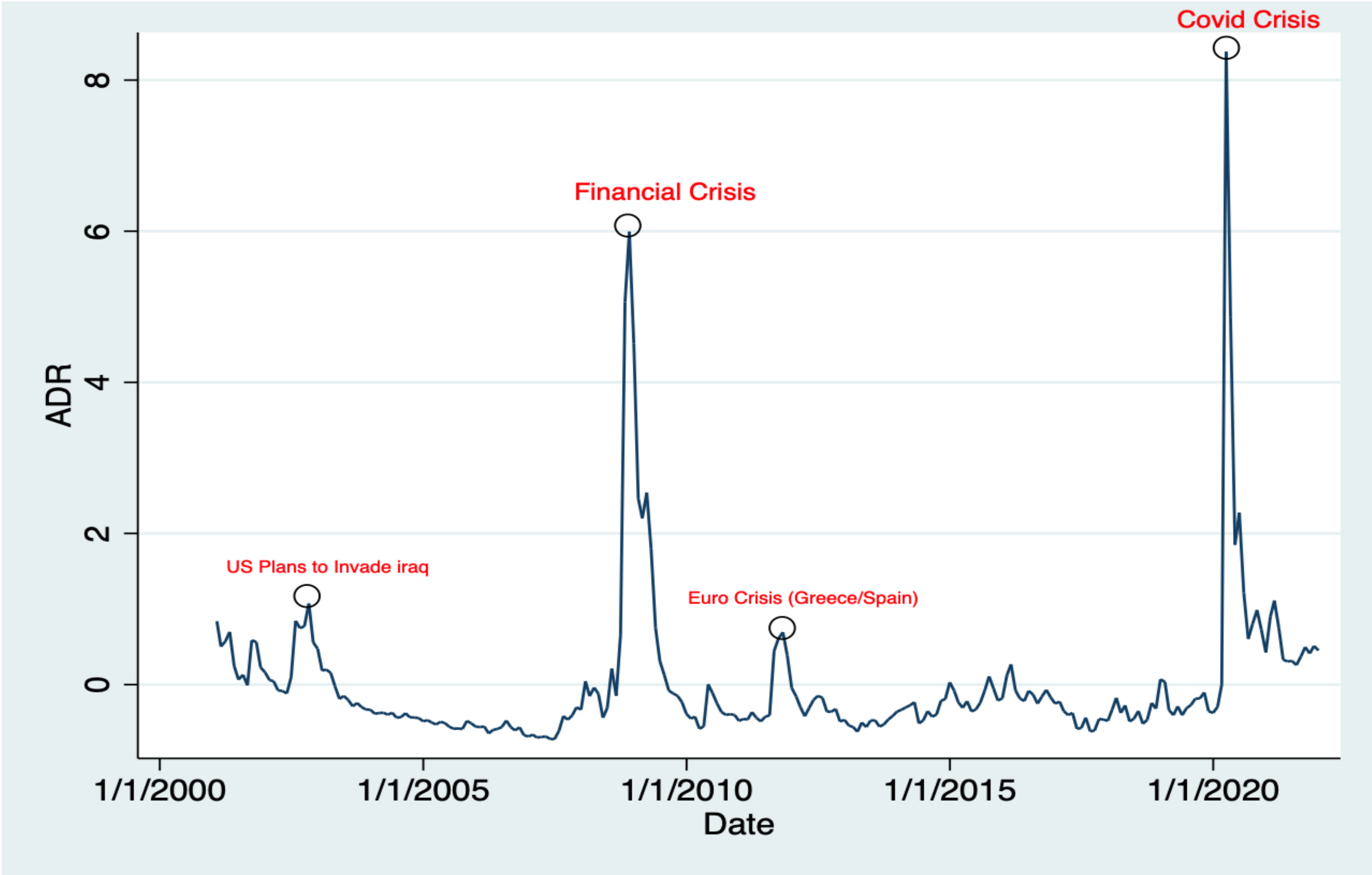



Figure 3: **Time-series of the risk-neutral probability of downside events termed as the "Aggregate Downside risk".** The risk-neutral probability of downside events is the first principal component extracted from the panel of firm downside risk measures, $FDR_i$, extracted from option prices. The probability is constructed following Siriwardane (2015). A firm must have at least 18 daily observations in a month to be included. Principal component analysis is conducted on the correlation matrix of the monthly $FDR_i$. This analysis applies to a set of firms with at least 192 of their monthly observations and we also fill in the missing value as their mean. The data range is from January 2001 to December 2021 and the frequency is monthly.

# Appendix

Table A1: Variable definitions for risk measures, sustainability measures and controls.

| Variable | Definitions |
|---|---|
| **Panel A: Risk Measures** | |
| smfiv | Simple model-free implied volatility from Martin (2011, 2017). |
| mfiv_bkm | Model-free implied volatility from Bakshi et al. (2003). This is equation A2 in this paper. |
| mfiv_bjn | Model-free implied volatility from Britten-Jones and Neuberger (2000). This is equation A1 in this paper. |
| smfivd | Simple model-free implied volatility for OTM puts (downside) from Martin (2011, 2017) |
| mfivd_bkm | Model-free implied volatility for OTM puts (downside) from Bakshi et al. (2003). This is equation A4 in this paper. |
| mfivd_bjn | Model-free implied volatility for OTM puts (downside) from Britten-Jones and Neuberger (2000). This is equation A3 in this paper. |
| mfis | Model-free implied skewness based on Bakshi et al. (2003). |
| mfik | Model-free implied kurtosis based on Bakshi et al. (2003). |
| cvix_sigma2 | Corridor volatility index from Andersen and Bondarenko (2007), Andersen et al. (2015) measured on the relative deviation of 2 sigmas from the At-the-Money (ATM) moneyness of 1. |
| rix | Rare disaster concern index (rix) from Gao et al. (2018). This is the difference between mfivd_bjn and mfivd_bkm. This is equation A5 in this paper. |
| **Panel B: Sustainability Measures** | |
| Environmental, Social and Governance (ESG) score | "The term ESG used in this study is the ESG combined (ESGC) score which takes into consideration the ESG controversies." ESGC overlays the ESG score with ESG controversies to provide a comprehensive evaluation of the company's sustainability impact and conduct over time. ESGC scores provide a rounded and comprehensive scoring of a company's ESG performance, based on the reported information pertaining to the ESG pillars, with the ESG controversies overlay captured from global media sources. |
| Environmental (E) score | "Resource use score, Emissions reduction score, and Innovation score are aggregated to form the Environmental Score" |
| Social (S) score | "Workforce score, Human rights score, Community score, and Product responsibility score are aggregated to form the Social score." |

Continued on next page

**Table A1 – continued from previous page**

| Variable | Definitions |
|---|---|
| Governance (G) score | "Management score, Shareholders score, and CSR strategy score are aggregated to form the Governance score." |
| Resource use score | The resource use score reflects a company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management. |
| Emissions reduction score | The emission reduction score measures a company's commitment and effectiveness towards reducing environmental emissions in its production and operational processes. |
| Innovation score | The innovation score reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes, or eco-designed products. |
| Workforce score | The workforce score measures a company's effectiveness in terms of providing job satisfaction, a healthy and safe workplace, maintaining diversity and equal opportunities, and development opportunities for its workforce. |
| Human rights score | The human rights score measures a company's effectiveness in terms of respecting fundamental human rights conventions. |
| Community score | The community score measures the company's commitment to being a good citizen, protecting public health and respecting business ethics. |
| Product responsibility score | The product responsibility score reflects a company's capacity to produce quality goods and services, integrating the customer's health and safety, integrity and data privacy. |
| Management score | The management score measures a company's commitment and effectiveness towards following best practice corporate governance principles. |
| Shareholders score | The shareholders score measures a company's effectiveness towards equal treatment of shareholders and the use of anti-takeover devices. |
| CSR strategy score | The CSR strategy score reflects a company's practices to communicate that it integrates economic (financial), social and environmental dimensions into its day-to-day decision-making processes. |
| **Panel C: Controls** | |
| Return | Monthly return for the individual US firms |
| Volatility | 12-month rolling window of the firm standard deviation based on the firm's return. |
| Beta | 12-month rolling window of the firm beta based on the regression of the firm's return on S&P 500 return (market return). |
| Logassets | Natural logarithms of total assets |

Continued on next page

**Table A1 – continued from previous page**

| Variable | Definitions |
|---|---|
| Divnetinc | Gross dividends-common stocks divided by net income after taxes |
| Ebitassets | Normalized Earnings before interest and taxes (EBIT) divided by total assets |
| Capexassets | Capital expenditure (Capex) divided by total assets |
| Booktomar | Book value(computed as book value per share multiply by total common shares outstanding) divided by market capitalization |
| Debtassets | Total debt divided by total assets |

Firm downside risk (FDR) is the firm's price of a downside insurance contract. To understand the foundation for the construction of the FDR, please refer to Gao et al. (2018). The computation to extract the firm downside risk (FDR) is as follows:

$$IV_{it} = \frac{2e^{r\tau}}{\tau}\{\int_{K>S_{it}} \frac{1}{K^2} C_{it}(S_{it}; K, T)dK + \int_{K<S_{it}} \frac{1}{K^2} P_{it}(S_{it}; K, T)dK\} \tag{A1}$$

$$\begin{aligned} V_{it} = \frac{2e^{r\tau}}{\tau}\{&\int_{K>S_{it}} \frac{1 - ln(K/S_{it})}{K^2} C_{it}(S_{it}; K, T)dK \\ &+ \int_{K<S_{it}} \frac{1 - ln(K/S_{it})}{K^2} P_{it}(S_{it}; K, T)dK\} \end{aligned} \tag{A2}$$

where r is the constant interest rate. $\tau$ is the time to maturity or time to expiration. $C_{it}(S_{it}; K, T)$ is the price of the firm's i call options with strike price T and maturity K. $P_{it}(S_{it}; K, T)$ is the price of firm's i put options with strike price T and maturity K. The difference between $V_{it}$ and $IV_{it}$ is $-ln(K/S_{it})$ in $V_{it}$ which implies that larger (smaller) weights are assigned to more deeply OTM put(call) options. This allows us to extract extreme price deviation. The difference between the $V_{it}$ and $IV_{it}$ captures investors' expectations about the distribution of large price variation Gao et al. (2018).

Next, we obtain only the downside measures of the firm's IV and V which leaves us with only the OTM put options:

$$IV_{it}^{-} = \frac{2e^{r\tau}}{\tau} \int_{K<S_{it}} \frac{1}{K^2} P_{it}(S_{it}; K, T)dK \tag{A3}$$

$$V_{it}^{-} = \frac{2e^{r\tau}}{\tau} \int_{K<S_{it}} \frac{1 - ln(K/S_{it})}{K^2} P_{it}(S_{it}; K, T)dK \tag{A4}$$

$$FDR_{it} = V_{it}^{-} - IV_{it}^{-} = \frac{2e^{r\tau}}{\tau} \int_{K<S_{it}} \frac{ln(K/S_{it})}{K^2} P_{it}(S_{it}; K, T)dK \tag{A5}$$

$FDR_{it}$ is the difference between $V_{it}^{-}$ and $IV_{it}^{-}$ which captures investors' expectation of extreme downside price movement of firm's i. It can also be interpreted as the risk-neutral probability of firm i extreme downside movement. $FDR_{it}$ can also be seen as the value of a simple portfolio of put options on firm i and form at date t to extract extreme downside movement.

Table A2: **Second level of disaggregation for Sustainability disparity.**

This table displays the results of the regressions of the monthly cost of protection against downside risk (IVS) on sustainability performance and sustainability disparity. This table reports only the coefficients on sustainability performance. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. It also controls for fixed year effect. Panel A reports the aggregate ESG. Panel B report the first level of disaggregation. Panel C reports the second level of disaggregation. The standard deviations are reported under the coefficients. Clustered standard errors around year and sector.

| Dimension | ESG disparity | E disparity | S disparity | G disparity |
|---|---|---|---|---|
| | *Dependent variable :* *Cost of protection against downside risk* | | | |
| **Panel A: Aggregate** | | | | |
| ESG | 0.001*** (0.0001) | | | |
| **Panel B: First level of Aggregation** | | | | |
| Environmental | 0.001*** (0.0001) | 0.0002*** (0.0001) | | |
| Social | 0.001*** (0.0001) | | 0.0003*** (0.0001) | |
| Governance | 0.001*** (0.0001) | | | 0.001*** (0.0001) |
| **Panel C: Second level of Aggregation** | | | | |
| **Environmental** | | | | |
| Resource use | 0.001*** (0.0001) | 0.0005*** (0.0001) | | |
| Emissions reduction | 0.001*** (0.0001) | 0.0003*** (0.0001) | | |
| Innovation | 0.001*** (0.0001) | −0.0002** (0.0001) | | |
| **Social** | | | | |
| Workforce | 0.001*** (0.0001) | | 0.001*** (0.0001) | |
| Human rights | 0.001*** (0.0001) | | −0.0005*** (0.0001) | |
| Community | 0.001*** (0.0001) | | 0.001*** (0.0001) | |
| Product responsibility | 0.001*** (0.0001) | | 0.0003*** (0.0001) | |
| **Governance** | | | | |
| Management | 0.001*** (0.0001) | | | 0.001*** (0.0001) |
| Shareholder | 0.001*** (0.0001) | | | 0.001*** (0.0001) |
| CSR strategy | 0.001*** (0.0001) | | | 0.0003*** (0.0001) |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 | | |

Table A3: **Heterogeneous of ESG disparity across sectors.**

This table displays the results of the regressions of the monthly cost of protection against downside risk (IVS) on the sustainability performance and the ESG disparity based on Equation (2). This table reports only the coefficients on sustainability performance ($\beta$) and on ESG disparity ($\lambda$) for each sector. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. It also controls for a fixed-year effect. We classify firms into sectors based on the Global Industry Classification Standard (GICS). The GICS classifies firms into 12 sectors: Energy, Material, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, and Real Estate. We label firms that we could not match to any sector as "No sector identified".

| | *Dependent variable : Cost of protection against downside risk* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | ESG | | Environmental | | Social | | Governance | |
| Coefficients | $\beta_1$ | $\lambda_1$ | $\beta_1$ | $\lambda_1$ | $\beta_1$ | $\lambda_1$ | $\beta_1$ | $\lambda_1$ |
| **Industry:** | | | | | | | | |
| Energy | −0.001*** | 0.003*** | −0.002*** | 0.002*** | −0.001*** | 0.003*** | −0.00001 | 0.003*** |
| | (0.0003) | (0.0004) | (0.0002) | (0.0004) | (0.0002) | (0.0004) | (0.0002) | (0.0004) |
| Material | 0.001*** | 0.001 | 0.001*** | 0.001** | 0.001*** | 0.001* | 0.0003* | 0.0003 |
| | (0.0002) | (0.0004) | (0.0002) | (0.0004) | (0.0002) | (0.0004) | (0.0002) | (0.0004) |
| Industrials | −0.001*** | 0.001** | −0.0004** | 0.001* | −0.001*** | 0.001** | 0.001*** | 0.001** |
| | (0.0002) | (0.0003) | (0.0002) | (0.0003) | (0.0002) | (0.0003) | (0.0002) | (0.0003) |
| Consumer | −0.001*** | 0.002*** | −0.001*** | 0.001*** | −0.001*** | 0.002*** | −0.0004*** | 0.002*** |
| Discretionary | (0.0002) | (0.0002) | (0.0001) | (0.0002) | (0.0001) | (0.0002) | (0.0001) | (0.0002) |
| Consumer | −0.0004* | 0.002*** | −0.0001 | 0.002*** | −0.001*** | 0.002*** | 0.0003 | 0.002*** |
| Staples | (0.0002) | (0.0004) | (0.0002) | (0.0004) | (0.0002) | (0.0004) | (0.0002) | (0.0004) |
| Health Care | −0.002*** | 0.001*** | −0.001*** | 0.0003 | −0.002*** | 0.001** | −0.0001 | 0.001*** |
| | (0.0002) | (0.0003) | (0.0002) | (0.0003) | (0.0002) | (0.0003) | (0.0002) | (0.0003) |
| Financials | −0.0002 | 0.004*** | −0.001** | 0.004*** | 0.001** | 0.005*** | −0.00002 | 0.004*** |
| | (0.001) | (0.001) | (0.0003) | (0.001) | (0.0005) | (0.001) | (0.0003) | (0.001) |
| Information | −0.001*** | 0.003*** | −0.001*** | 0.002*** | −0.001*** | 0.003*** | 0.0002 | 0.003*** |
| Technology | (0.0002) | (0.0003) | (0.0001) | (0.0003) | (0.0002) | (0.0003) | (0.0002) | (0.0003) |
| Communication | 0.004*** | −0.001** | −0.001*** | −0.001 | −0.002*** | −0.0003 | 0.002*** | −0.001** |
| Services | (0.001) | (0.001) | (0.0004) | (0.001) | (0.0005) | (0.001) | (0.0003) | (0.001) |
| Utilities | 0.0005 | 0.0001 | 0.002*** | 0.001 | 0.001** | 0.0002 | 0.001** | −0.0003 |
| | (0.0004) | (0.001) | (0.0003) | (0.001) | (0.0004) | (0.001) | (0.0003) | (0.001) |
| Real Estate | −0.001*** | −0.001** | −0.001*** | −0.002*** | 0.00001 | −0.001** | −0.0004* | −0.001* |
| | (0.0003) | (0.0004) | (0.0002) | (0.0005) | (0.0003) | (0.0004) | (0.0002) | (0.0005) |
| No sector | 0.006*** | 0.001 | 0.001** | 0.003** | 0.005*** | 0.002* | 0.002*** | 0.001 |
| identified | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table A4: **Quantile regression of Cost of protection against downside risk.**

This table displays the quantile results of the regressions of the monthly cost of protection against downside risk (IVS) on the sustainability performance based on Equation (1). This table reports only the coefficients on sustainability performance. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. It also controls for fixed year effect and includes constant. Column (20) reports the 20th Quantile result of the regression. Column (40) reports the 40th Quantile result of the regression. Column (60) reports the 60th Quantile result of the regression. Column (80) reports the 80th Quantile result of the regression. The standard deviations are reported under the coefficients.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Cost of protection against downside risk | | | |
| | Quantile | | | |
| | (20) | (40) | (60) | (80) |
| ESG | $-0.0003^{***}$ | $-0.001^{***}$ | $-0.001^{***}$ | $-0.002^{***}$ |
| | (0.00001) | (0.00002) | (0.00004) | (0.0001) |
| E | $-0.0003^{***}$ | $-0.001^{***}$ | $-0.001^{***}$ | $-0.001^{***}$ |
| | (0.00001) | (0.00002) | (0.00003) | (0.0001) |
| S | $-0.0004^{***}$ | $-0.001^{***}$ | $-0.001^{***}$ | $-0.001^{***}$ |
| | (0.00002) | (0.00002) | (0.00003) | (0.0001) |
| G | $-0.0001^{***}$ | $-0.00001$ | 0.00004 | $0.0001^{**}$ |
| | (0.00001) | (0.00002) | (0.00003) | (0.0001) |
| Fixed Year Effect | Yes | Yes | Yes | Yes |
| Controls and constant | Yes | Yes | Yes | Yes |
| Observations | 103,051 | 103,051 | 103,051 | 103,051 |
| *Note:* | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table A5: **Regression on sub-sample.**

This table presents the results of the sub-sample regressions of the monthly cost of protection against downside risk (IVS) on the sustainability performance and the ESG disparity based on Equation (2). This table reports only the coefficients on sustainability performance and on ESG disparity. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. It also controls for a fixed-year effect. Panel A runs a regression of the sample from January 2010 to December 2021. Panel B runs on the sample excluding firms with zero environmental scores. The standard deviations are reported under the coefficients.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Cost of protection against downside risk | | | |
| | (1) | (2) | (3) | (4) |
| **Panel A: Sample from 2010 onwards** | | | | |
| ESG | −0.001*** | | | |
| | (0.0001) | | | |
| E | | −0.001*** | | |
| | | (0.0001) | | |
| S | | | −0.001*** | |
| | | | (0.0001) | |
| G | | | | 0.0002*** |
| | | | | (0.0001) |
| ESG disparity | 0.002*** | 0.001*** | 0.002*** | 0.002*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Constant and Controls | Yes | Yes | Yes | Yes |
| Observations | 82,528 | 82,528 | 82,528 | 82,528 |
| $R^2$ | 0.224 | 0.224 | 0.225 | 0.223 |
| Adjusted $R^2$ | 0.224 | 0.224 | 0.225 | 0.223 |
| Residual Std. Error (df = 82505) | 0.401 | 0.401 | 0.401 | 0.401 |
| F Statistic (df = 22; 82505) | 1,081.669*** | 1,082.779*** | 1,091.286*** | 1,075.681*** |
| **Panel B: Exclude firms with zero E score** | | | | |
| ESG | −0.001*** | | | |
| | (0.0001) | | | |
| E | | −0.001*** | | |
| | | (0.0001) | | |
| S | | | −0.001*** | |
| | | | (0.0001) | |
| G | | | | 0.00004 |
| | | | | (0.0001) |
| ESG disparity | 0.001*** | 0.001*** | 0.001*** | 0.001*** |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Constant and Controls | Yes | Yes | Yes | Yes |
| Observations | 80,395 | 80,395 | 80,395 | 80,395 |
| $R^2$ | 0.275 | 0.275 | 0.275 | 0.274 |
| Adjusted $R^2$ | 0.275 | 0.275 | 0.275 | 0.274 |
| Residual Std. Error (df = 80366) | 0.364 | 0.364 | 0.364 | 0.365 |
| F Statistic (df = 28; 80366) | 1,091.023*** | 1,089.241*** | 1,091.353*** | 1,082.686*** |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 | |

Table A6: **Regression based on MSCI ESG data.**

This table presents the results of the regressions of the monthly cost of protection against downside risk (IVS) on the MSCI sustainability performance and the ESG disparity based on Equation (2). This table reports only the coefficients on sustainability performance and on ESG disparity. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. It also controls for a fixed-year effect. The standard deviations are reported under the coefficients.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Cost of protection against downside risk | | | |
| | (1) | (2) | (3) | (4) |
| **Panel A: MSCI raters** | | | | |
| ESG | $-0.021^{***}$ | | | |
| | (0.002) | | | |
| E | | $-0.018^{***}$ | | |
| | | (0.001) | | |
| S | | | $-0.004^{***}$ | |
| | | | (0.001) | |
| G | | | | $0.005^{***}$ |
| | | | | (0.001) |
| ESG disparity | $0.006^{***}$ | $0.008^{***}$ | $0.006^{***}$ | $0.006^{***}$ |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Fixed Effects | Yes | Yes | Yes | Yes |
| Constant and Controls | Yes | Yes | Yes | Yes |
| Observations | 79,167 | 79,167 | 79,167 | 79,167 |
| $R^2$ | 0.185 | 0.187 | 0.184 | 0.184 |
| Adjusted $R^2$ | 0.184 | 0.186 | 0.183 | 0.184 |
| Residual Std. Error (df = 79146) | 0.457 | 0.457 | 0.458 | 0.457 |
| F Statistic (df = 20; 79146) | $896.532^{***}$ | $907.718^{***}$ | $889.728^{***}$ | $891.151^{***}$ |
| *Note:* | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table A7: **Other risk measures.**

This table displays the results of the regressions of the monthly different risk measures on the sustainability performance based on Equation (1). This table reports only the coefficients on sustainability performance. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. It also controls for a fixed-year effect. Panel A considers closely related downside risk measures to the baseline downside risk measure termed as the "cost of protection against downside risk". Panel B reports the regressions of the monthly different general risk measures on the sustainability performance based on Equation (1). The definition of the different risk measures is provided in the appendix.

| Dimension | ESG | Environmental | Social | Governance |
|---|---|---|---|---|
| **Panel A: Related downside risk** | | | | |
| smfivd | −0.0002*** | −0.0002*** | −0.0001*** | −0.00001 |
| | (0.00002) | (0.00001) | (0.00001) | (0.00001) |
| mfivd_bkm | −0.0004*** | −0.0003*** | −0.0001*** | 0.00003 |
| | (0.00003) | (0.00002) | (0.00003) | (0.00003) |
| mfivd_bjn | −0.0003*** | −0.0002*** | −0.0001*** | 0.00001 |
| | (0.00003) | (0.00002) | (0.00002) | (0.00002) |
| **Panel B: General risk** | | | | |
| smfiv | −0.001*** | −0.0003*** | −0.0001 | 0.0001** |
| | (0.00005) | (0.00003) | (0.00004) | (0.00003) |
| mfiv_bkm | −0.001*** | −0.0004*** | −0.0001*** | 0.00004 |
| | (0.00005) | (0.00003) | (0.00004) | (0.00003) |
| mfiv_bjn | −0.001*** | −0.0004*** | −0.0001*** | 0.00004 |
| | (0.00004) | (0.00003) | (0.00004) | (0.00003) |
| mfis | 0.00004 | 0.0003*** | 0.001*** | −0.00004 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| mfik | −0.001*** | −0.003*** | −0.005*** | 0.002*** |
| | (0.0003) | (0.0002) | (0.0003) | (0.0003) |
| cvix_sigma2 | −0.001*** | −0.0004*** | −0.0001*** | 0.00004 |
| | (0.00005) | (0.00003) | (0.00004) | (0.00003) |
| rix | −0.0001*** | −0.0001*** | −0.00001* | 0.00002*** |
| | (0.00001) | (0.00001) | (0.00001) | (0.00001) |

*Note:* *p<0.1; **p<0.05; ***p<0.01

Table A8: **Credit Default Swap as a dependent variable.**

This table displays the results of the regressions of the monthly credit default swap on the sustainability performance and the ESG disparity based on Equation (2). This table reports only the coefficients on sustainability performance and on ESG disparity. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets and booktomar. It also controls for a fixed-year effect. Panel A reports the aggregate ESG. Panel B reports the first level of disaggregation. Panel C reports the second level of disaggregation. The standard deviations are reported under the coefficients.

| | *Dependent variable :* *Credit Default Swap* | |
|---|---|---|
| Coefficients | Sustainability - $\beta_1$ | ESG disparity - $\lambda_1$ |
| **Panel A: Aggregate** | | |
| ESG | $-0.276^{***}$ | $0.179^{**}$ |
| | (0.055) | (0.088) |
| **Panel B: First level:** | | |
| Environmental | $-0.145^{***}$ | 0.136 |
| | (0.041) | (0.091) |
| Social | $-0.032$ | $0.217^{**}$ |
| | (0.047) | (0.088) |
| Governance | $-0.038$ | $0.230^{***}$ |
| | (0.042) | (0.088) |
| **Panel C: Second level:** | | |
| **Environmental:** | | |
| Resource use | $-0.001$ | $0.222^{**}$ |
| | (0.032) | (0.090) |
| Emissions reduction | $-0.103^{***}$ | $0.158^{*}$ |
| | (0.033) | (0.090) |
| Innovation | $-0.047$ | $0.206^{**}$ |
| | (0.029) | (0.088) |
| **Social:** | | |
| Workforce | $-0.011$ | $0.220^{**}$ |
| | (0.038) | (0.088) |
| Human rights | $0.251^{***}$ | $0.305^{***}$ |
| | (0.029) | (0.088) |
| Community | $-0.087^{*}$ | $0.216^{**}$ |
| | (0.045) | (0.087) |
| Product responsibility | $-0.143^{***}$ | $0.207^{**}$ |
| | (0.030) | (0.087) |
| **Governance:** | | |
| Management | $-0.035$ | $0.235^{***}$ |
| | (0.033) | (0.088) |
| Shareholder | $0.188^{***}$ | $0.190^{**}$ |
| | (0.032) | (0.087) |
| CSR strategy | $-0.171^{***}$ | 0.141 |
| | (0.029) | (0.088) |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table A9: **Different regression models based on Thomson ESG data.**

This table presents the results of the different regression models of the monthly cost of protection against downside risk (IVS) on the sustainability performance and the ESG disparity based on Equation (2). This table reports only the coefficients on sustainability performance and on ESG disparity. The control variables are beta, volatility, return, logassets, divnetinc, ebitaseets, capexaseets, debtassets, and booktomar. It also controls for a fixed-year effect. Column(1) provides regression results that incorporate year fixed effect but no clustered standard deviation error. Column(2) provides regression results that incorporate year-sector fixed effect but no clustered standard deviation error. Column(3) provides regression results that incorporate year-sector fixed effect and year-clustered standard deviation error. Column(4) provides regression results that incorporate year-sector fixed effect and year-sector clustered standard deviation error. The standard deviations are reported under the coefficients.

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | cost of protection against downside risk | | | |
| | (1) | (2) | (3) | (4) |
| **Panel A : Thomson ESG Data** | | | | |
| ESG | $-0.001^{***}$ | $-0.001^{***}$ | $-0.001^{***}$ | $-0.001^{***}$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| ESG disparity | $0.001^{***}$ | $0.001^{***}$ | $0.001^{***}$ | $0.001^{***}$ |
| | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Constant and controls | Yes | Yes | Yes | Yes |
| Fixed effect | Year | Year + Sector | Year + Sector | Year + Sector |
| Clustered SD error | No | No | Year | Year + Sector |
| *Note:* | | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

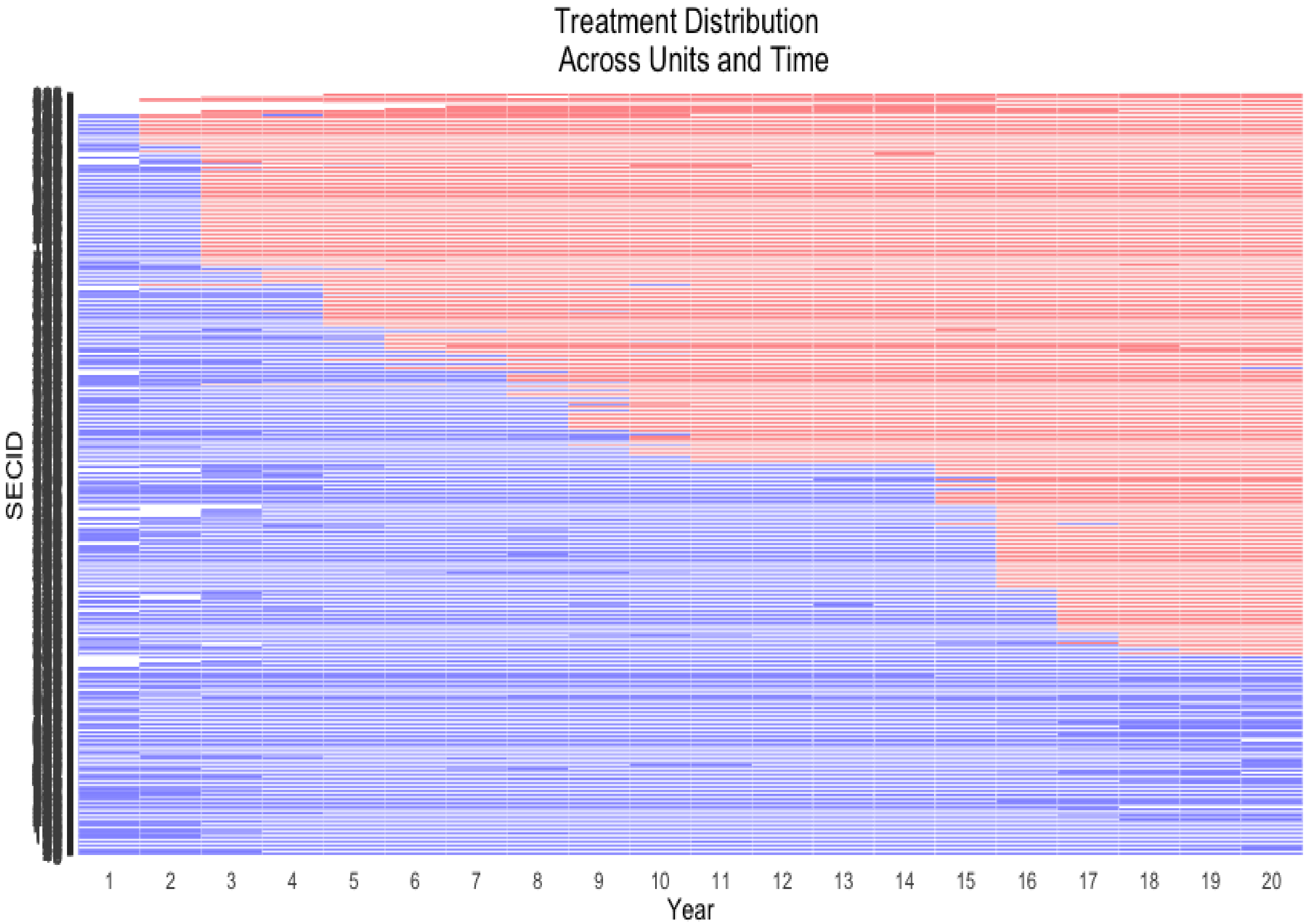
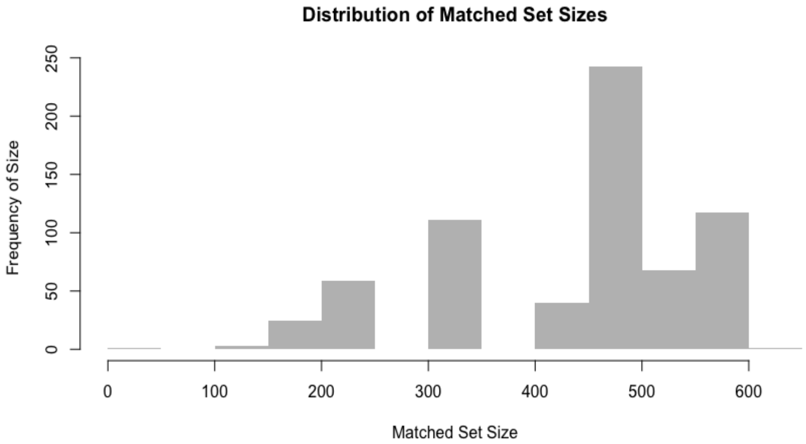
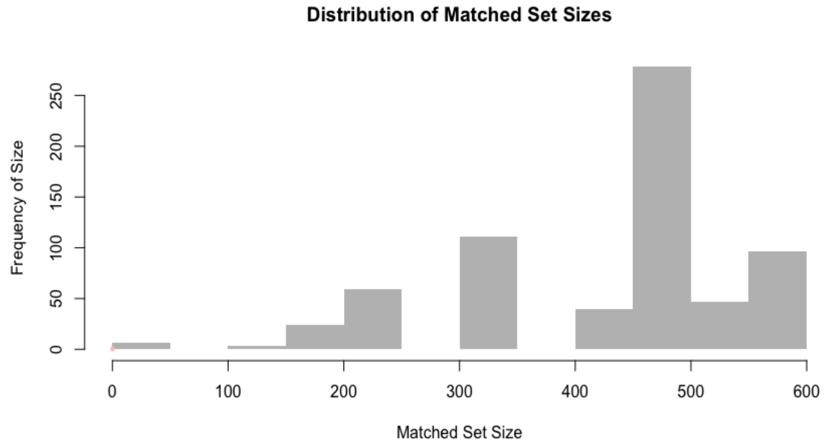


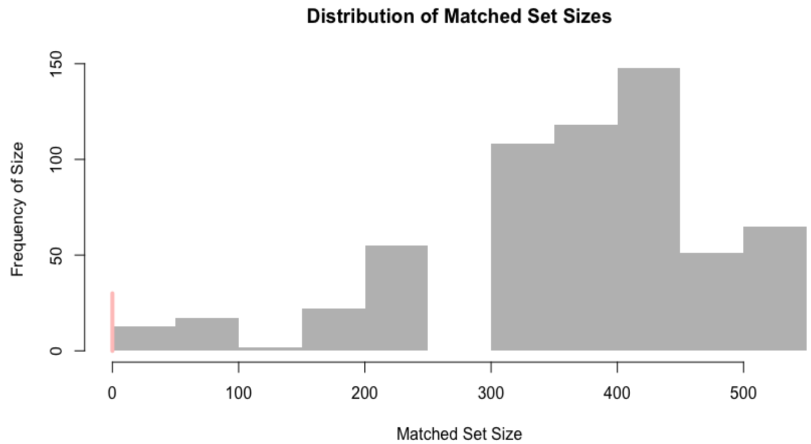

Figure A1: **Treatment Variation Plot for the distribution of ESG treatment across Units (firms) and time.** The red (blue) rectangle represents the ESG treatment(control) firm-year observation. The white area represents the year when a firm is not assigned ESG score. The plot starts in the year 2001 and ends in the year 2020.




(a) Up to 6 identical treatment periods

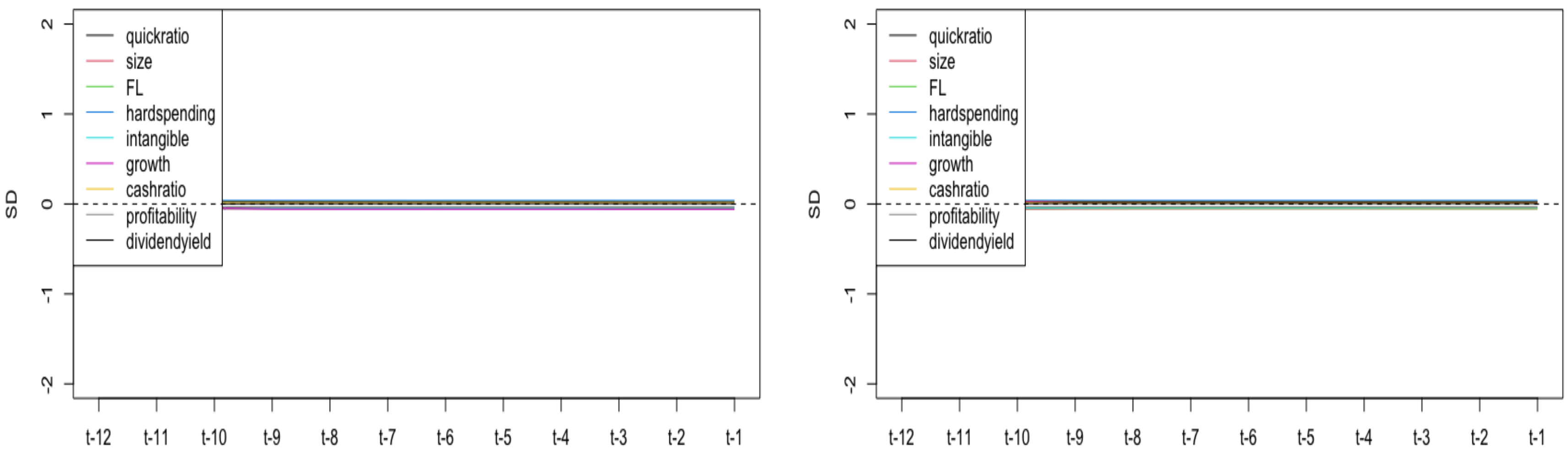



(b) Up to 12 identical treatment periods




(c) Up to 24 identical treatment periods

Figure A2: **Frequency Distribution of the Number of Matched Control Firms.** The bar represents the number of control matched firms that share the same treatment history as the treated observation prior to the treatment period. The frequency distribution is presented for the control matched firms that share up to 6, 12, and 24 identical treatment histories as the treated observation prior to the treatment period. Thinner vertical bars at zero represent the number of treated observations that have no matched control units.




(a) CBPS Weighting

(b) PS Weighting

Figure A3: **Covariates Balance based on weighting method:** Improved Covariate Balance of matching over 12 months pre-treatment period based on weighting method. Plot (a) plots the standardized mean difference between treated observations and the matched control observations based on the Covariates balance propensity score (CBPS) weighting method over the pretreatment period of 12 months. Plot (b) plots the standardized mean difference between treated observations and the matched control observations based on the Propensity score (PS) weighting method over the pretreatment period of 12 months.