Risk, Return, and Environmental and Social Ratings*

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Abstract

We analyze the risk and return characteristics across firms sorted by their environmental and social (ES) ratings. We document that ES ratings have no significant relationship with average stock returns or unconditional market risk. Stocks of firms with higher ES ratings *do* have significantly lower systematic downside risk. Such reduction in downside risk delivers modest, yet non-trivial, gain in long-term returns of around 0.96% per annum. Realized firm news sentiment and institutional trading patterns are also consistent with these results. Our evidence suggests that investors who derive non-pecuniary benefits from ES investing need *not* sacrifice performance in the stock market.

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1 Introduction

Global assets that are managed using investment approaches that consider environmental, social, and governance (ESG) factors in portfolio selection have grown from USD 23 trillion in 2016 to USD 35 trillion in 2020.[1] ESG funds have also attracted record inflows during the ongoing COVID-19 pandemic.[2] While these trends accentuate the growing popularity of sustainable investing with investors, they also raise concerns over its financial implications.

Indeed, such trends triggered a recent amendment to the Employee Retirement Income Security Act of 1974 (ERISA) under the Trump administration, requiring that plan fiduciaries select investments based solely on investment risk and return, implicitly suggesting that integrating ESG factors is costly to investors.[3] This amendment is being amended yet again under the Biden administration, explicitly permitting plan fiduciaries to consider ESG factors when financially material, suggesting that integrating ESG factors is beneficial to investors.[4] Importantly, this policy uncertainty manifests the significant lack of consensus over the financial cost, or the benefit, of incorporating ESG factors into investment decision. We shed light on this ongoing debate by revisiting the relationship between the risk, return, and ES ratings, with a novel focus on systematic downside risk.

On one hand, ESG investing can be costly if investors who derive non-pecuniary benefits drive equilibrium asset prices.[5] On the other hand, a key premise of ESG investing is that firms "do well by doing good." As Bénabou and Tirole (2010) note, "[corporate social responsibility (CSR)] is about taking a *long-term perspective* to maximizing (intertemporal) profits," suggesting that ESG investing can provide stronger financial performance, and more specifically, *lower systematic downside risk*. For example, a firm may economize on safety or pollution control. While this could increase profits in the short run, this exposes the firm

[1] See 2020 Global Sustainable Investment Review, page 9.
[2] `https://tinyurl.com/y253312c`
[3] `https://tinyurl.com/y6rzae67`
[4] `https://tinyurl.com/2t6byr8w`
[5] See Pástor, Stambaugh, and Taylor (2021) and Pedersen, Fitzgibbons, and Pomorski (2021) for recent models that incorporate ESG investing into the asset pricing framework by modeling investor preferences for holding high-ESG assets.

to contingent liabilities (e.g., the risk of new regulations or environmental cleanup costs). Such risks are systematic to the extent that many firms suffer from managerial myopia, but high-CSR firms (in this case, environmentally friendly firms) may perform better in these periods when many firms suffer a negative shock to their value. As a result, high-CSR firms may have lower systematic risk during market declines, or lower systematic downside risk.

In this paper, we empirically analyze the implications of a firm's ES ratings on its future stock returns and on its future exposure to not only unconditional but also downside risk. We find no meaningful relationship between the realized stock returns and ES ratings of a firm. We also find that after controlling for the strong auto-correlation of the market beta, the relationship between ES scores and market betas is statistically insignificant. However, we find that firms with high ES ratings *do* have significantly lower downside risk than firms with low ES ratings, as measured by their downside beta, relative downside beta, coskewness, and tail risk beta. Such reductions of downside risk deliver modest, yet non-trivial, gain in long-term returns of around 0.96% per annum.

Our results accentuate that integrating ES factors is *not* costly, suggesting that the rapid growth of ES investing is not puzzling. ES investors do not experience significantly lower returns nor are they exposed to higher risk; in fact, such investments provide small insurance-like benefits against market declines. At the same time, ES investors can enjoy non-pecuniary benefits.[6]

We begin our analysis by examining patterns of future returns over the next month and unconditional market risk over the next 12 months for portfolios sorted on past ES scores from 1992 through 2017. We use ES ratings from MSCI KLD, a major ESG ratings provider. In line with the mixed results in the ES investment and performance literature,[7]

[6]See, e.g., Riedl and Smeets (2017); Hartzmark and Sussman (2019); and Barber, Morse, and Yasuda (2021).

[7]For example, Hong and Kacperczyk (2009) find that "sin" firms in the alcohol, tobacco, and gaming industries earn significantly higher alphas than comparable firms in other industries. In contrast, Kempf and Osthoff (2007) find that stocks with high ES ratings have significantly higher alphas than stocks with low ES ratings, while Edmans (2011) demonstrates that the firms listed in the "100 Best Companies to Work For in America" earn significant positive alphas.

we find no evidence that high-ES stocks outperform low-ES stocks. We do find that stocks of high-ES firms have lower market betas than those of low-ES firms. However, we show that this relation is explained away by the strong autocorrelation of market betas.

We then analyze patterns of future downside risk for portfolios sorted on past ES scores. Our primary measure of downside risk is the relative downside beta of Ang, Chen, and Xing (2006): downside market beta over periods when the excess market return is below its mean, controlling for the regular market beta. We find that firms with high ES scores have significantly lower future downside risk. Moreover, these relations continue to hold when we control for other firm-level characteristics (e.g., lagged downside risk, firm size). Our results remain similar when we consider two alternative proxies for downside risk: the coskewness of Harvey and Siddique (2000) and the tail risk beta of Kelly and Jiang (2014). We also find that both environmental (E) and social (S) components are equally important for predicting future downside risk. In addition, we provide suggestive evidence that lower climate change exposure also delivers lower downside risk.

Our estimates indicate that an interdecile-range increase in ES score is associated with small decreases in downside risk: The magnitude of these decreases represent about 3% of the interdecile range of the downside risk measures. However, the estimated coefficients of downside risk on ES performance, which capture only the average effect, might understate the economic significance of their relationship if the ES–downside risk link covaries negatively with the market. We confirm that this is indeed the case. A natural way to capture the joint effect is by looking at returns over the next 12 months, i.e., the contemporaneous period over which downside risk is measured.[8] Our results indicate that an interdecile-range increase in ES score delivers modest, but non-trivial, increases in annual return of around 0.96%.

Finally, we provide evidence supporting two potential mechanisms behind the downside

[8]First, returns over longer horizons capture the average effect: Even if a firm's ES performance is financially immaterial based on returns over a short horizon and unconditional risk, high-ES stock returns over longer horizons will be higher insofar as lower downside risk of high-ES firms mitigates large losses, which have a disproportionate impact on compound returns. Second, returns over a 12-month horizon account for the effect of whether the year is itself a bad year.

risk effects of firm-level ES performance. Using the firm-level news sentiment from RavenPack News Analytics as a proxy for the change in firm value, we test whether the value of high-ES firms is resilient in periods when many firms suffer a negative shock to their value. We *do* find that firm values for high-ES firms covary less with the average firm's value, especially when the average firm's value is declining. To the extent that (i) media coverage is influenced by the ES profile of the firm and (ii) returns in turn vary with media coverage, ES performance can impact the downside risk of the firm.

In addition, we examine whether the ES preferences of institutional investors can induce a pattern of institutional trading that is consistent with the negative relation between ES performance and downside risk. Using institutional trading data from Abel Noser, we find that when the market suffers extremely negative shocks, institutional investors hold on to high-ES firms which can give rise to the low downside risk of these firms. During normal times, however, institutional investors buy high-ES firms such that, unconditionally, they do not exert additional price pressure on these stocks. This is also consistent with the insignificant relation between ES ratings and unconditional market risk.

Taken together, our results highlight that reduction in downside risk is a key pecuniary benefit of incorporating ES factors into investment decisions. Prior literature on the ES–financial performance link is mixed. If anything, investing in ES funds typically imposes large costs on mean-variance investors.[9] Moving beyond mean-variance analysis, we provide strong evidence that not only is integrating ES factors *not* costly, but also it helps long-term investors mitigate downside risk. However, this insurance-like benefits against market declines alone is not large enough to explain the recent growth of ES investing. Rather, our evidence is consistent with the key role of non-pecuniary motives, coupled with the fact that there is no financial trade-off from expressing such motives.[10]

[9] See Geczy, Stambaugh, and Levin (2021)

[10] See, among others, Riedl and Smeets (2017); Hartzmark and Sussman (2019); and Barber, Morse, and Yasuda (2021).

1.1 Literature Review

Empirical studies of ES investing provide suggestive evidence that our hypothesis is plausible a priori. Lins, Servaes, and Tamayo (2017) find that firms with high ES scores had significantly higher stock returns during the 2008–2009 financial crisis, while Albuquerque et al. (2020) report a similar finding during the COVID-19 market crash. Of course, these periods are canonical examples of a declining market, i.e., precisely when high-ES firms would do well according to our ES investing proposition. Quintessentially, our measures of downside risk capture the typical benefit of ES policies during market declines that are practically more useful for portfolio selection. We discuss the relation of our paper to these papers in great detail later in Section 3.4.2.

While our focus on the implications of ES investing on systematic downside risk is novel, others have investigated its implications on standard, unconditional risk exposures or firm-specific downside risk.[11] Hoepner et al. (2021) find that successful ESG engagements by a large institutional investor shorten the negative tail of return distributions for targeted firms over time, whereas we find that publicly accessible ES information from rating agencies can be used to identify firms with lower systematic downside risk in the cross-section. Albuquerque, Koskinen, and Zhang (2019) build a theoretical model which predicts that CSR decreases systematic unconditional risk, as well as empirically documenting that systematic unconditional risk is significantly lower for firms with higher ES scores. We find that, controlling for the strong auto-correlation of systematic unconditional risk, this relationship is rendered insignificant, but we also find that systematic downside risk is significantly lower for firms with higher ES scores, providing empirical support for their theory.

Ilhan, Sautner, and Vilkov (2020) show that, using options data, firms with more carbon emissions exhibit higher tail risk, while Bolton and Kacperczyk (2021) find that stocks of such firms earn higher returns. Our results complement their evidence by showing that, using stock return data and news sentiment data, firms with better ES profiles, as well as

[11]Earlier references include Godfrey, Merrill, and Hansen (2009); Oikonomou, Brooks, and Pavelin (2012); Jo and Na (2012); Kim, Li, and Li (2014); and Krüger (2015).

those with lower climate change exposures, have lower systematic downside risk.

2 Data

Our analysis uses data from four major databases: (i) the MSCI KLD database on the ESG profile of companies, (ii) the CRSP database on stock returns, (iii) the RavenPack database on news sentiment, and (iv) the Abel Noser database on institutional trading. We also use COMPUSTAT to construct book-to-market ratios, accounting variables (return on equity (ROE), asset growth, and sales growth), and book leverage, as well as a dummy for dividend-paying firms. In this section, we describe the first two data sources in detail, and we outline the construction of the main variables used in our empirical analysis of the relationship between ES performance and downside risk. The remaining data sources are described later in Sections 4.1 and 4.2 when they are first used. The summary statistics are presented in Panel A of Table 1.

2.1 MSCI KLD Database

The data source for the firm-level ESG profile is MSCI ESG KLD Stats. This database contains annual information on the environmental, social, and governance performance of large publicly traded companies. MSCI KLD is one of the most widely used databases for ESG research by institutional investors and academics.[12]

The KLD database expanded its coverage over time, starting with S&P 500 companies during 1991–2000 then expanding to include Russell 3000 companies since 2003. The sample period is 1991–2016. MSCI KLD classifies ESG performance into 13 granular categories: *environment*, *community*, *human rights*, *employee relations*, *diversity*, *product*, *alcohol*, *firearms*, *gambling*, *military*, *nuclear power*, *tobacco*, and *corporate governance*. Similar to Lins, Ser-

[12] Recent papers that have used this database include Hong and Kostovetsky (2009); Chava (2014); Krüger (2015); Borisov, Goldman, and Gupta (2016); and Lins, Servaes, and Tamayo (2017).

vaes, and Tamayo (2017), we focus on the first six of these categories. We do not use the categories that penalize involvement in the six industries that reflect the inherent business of the firms. We do not use the corporate governance category in our main analysis because governance is generally outside the scope of CSR, but we consider this category in the robustness tests.

For each of the six categories we consider, MSCI KLD compiles information on both strengths and concerns. As we are interested in capturing both elements, we construct a net ES measure that adds strengths and subtracts concerns. For any given category, the maximum number of strengths and concerns varies over time; accordingly, we follow Lins, Servaes, and Tamayo (2017) and scale the strengths (concerns) in each category by dividing the number of strengths (concerns) for each firm-year by the maximum number of strengths (concerns) in that category in that year. Note that these strength and concern indices range from 0 to 1 for each category-year. Our measure of net ES involvement in each category-year therefore ranges from -1 to $+1$.

Finally, we construct the total net ES measure of a firm by summing the measures of its net ES involvement across the six categories of environment, community, human rights, employee relations, diversity, and product. This measure ranges from -6 to $+6$, and it is our primary proxy for ES performance.[13] There is considerable dispersion in ES performance across firms within the same industry: The R-squared from a Fama-MacBeth regression of ES scores on industry fixed effects is less than 0.20. In this paper, we focus on the pecuniary implications of this within-industry variation in ES performance.

[13] Note that our measure of ES performance is linear. In unreported results, we use dummy variables for ES performance quartiles. The latter specification may be more appropriate if there are nonlinearities in the relation between ES performance and risk. Indeed, we find that the impact of ES performance on risk is not entirely linear, but more importantly it is monotonic and of comparable magnitude. The results are also very similar when we include dummy variables for other ES performance percentiles.

2.2 CRSP Database

Stock return and market capitalization are constructed using the CRSP database. We confine our attention to NYSE/AMEX/Nasdaq stocks with share codes 10 and 11. We use daily and monthly returns from CRSP for the period covering January 1992 to December 2019. As usual, we use the one-month Treasury bill rate as the risk-free return rate, and we take the value-weighted return of all stocks from CRSP as the market return.

Our primary measure of downside risk is the relative downside beta (denoted by $\beta^- - \beta$), which is the downside beta of Bawa and Lindenberg (1977) (denoted by β^-) relative to the regular beta with respect to the market portfolio (denoted by β). We consider two alternative proxies for downside risk: the coskewness of Harvey and Siddique (2000) and the tail risk beta of Kelly and Jiang (2014). These two proxies also capture some aspects of downside covariation. We employ several proxies to measure a firm's downside risk because it is not clear a priori which measure is more appropriate for capturing the dimension of downside risk that may be related to the ES profile of a firm.

2.2.1 Downside Beta and Coskewness

We compute downside beta and coskewness in the same way as Ang, Chen, and Xing (2006). For each month t, we use daily returns over the 12-month period, from t to $t + 11$. Let $\widetilde{r}_{i\tau}$ denote asset i's excess return on day τ, and let $\widetilde{r}_{m\tau}$ denote the market's excess return on day τ. We exclude stocks that have more than five missing observations from our analysis. First, we demean returns within each period, and we denote the demeaned excess return of asset i and the demeaned market excess return by $\widetilde{r}_{i\tau}$ and by $\widetilde{r}_{m\tau}$, respectively. We obtain estimates of the regular market β, denoted by $\widehat{\beta}_{it}$, in the usual manner:

$$\widehat{\beta}_{it} = \frac{\sum \widetilde{r}_{i\tau}\widetilde{r}_{m\tau}}{\sum \widetilde{r}_{m\tau}^2}. \tag{1}$$

We estimate the downside beta by conditioning the observations for which the realized excess market return is below its sample mean, $\widehat{\mu}_{mt} = \sum r_{m\tau}/T_t$, where T_t is the number of trading days over the 12-month period beginning in month t.[14] We denote the demeaned excess return of asset i and the demeaned market excess return conditional on the market excess return being below the sample mean by $\widetilde{r}_{i\tau}^{-}$ and $\widetilde{r}_{m\tau}^{-}$, respectively. We then calculate $\widehat{\beta}^{-}$ as

$$\widehat{\beta}_{it}^{-} = \frac{\sum_{\{r_{m\tau} < \widehat{\mu}_{mt}\}} \widetilde{r}_{i\tau}^{-} \widetilde{r}_{m\tau}^{-}}{\sum_{\{r_{m\tau} < \widehat{\mu}_{mt}\}} \widetilde{r}_{m\tau}^{-2}}. \tag{2}$$

Finally, coskewness is estimated as

$$\widehat{\text{coskew}}_{it} = \frac{\frac{1}{T_t} \sum \widetilde{r}_{i\tau} \widetilde{r}_{m\tau}^{2}}{\sqrt{\frac{1}{T_t} \sum \widetilde{r}_{i\tau}^{2}} \left(\frac{1}{T_t} \sum \widetilde{r}_{m\tau}^{2} \right)}. \tag{3}$$

2.2.2 Tail Risk Beta

Kelly and Jiang (2014) assume that extreme return events obey a power law, in which case the common time-varying component of return tails, λ_t, can be estimated for each month as

$$\lambda_t^{Hill} = \frac{1}{K_t} \sum_{k=1}^{K_t} \ln \frac{R_{k,t}}{u_t}, \tag{4}$$

where $R_{k,t}$ is the kth daily return that falls below an extreme value threshold u_t during month t, and K_t is the total number of such exceedances within month t. We follow Kelly and Jiang and define u_t as the fifth percentile of the cross-section each period.

We estimate the tail risk β, denoted by $\widehat{\beta}_{it}^{\text{tail}}$, as the regression coefficient of firm returns on the common tail risk component λ_t using 60 months of data following portfolio formation. To calculate tail risk betas, we require that firms have nonmissing return data for at least

[14] Instead of focusing on the observations for which the excess market return is below its sample mean, another way to estimate the downside beta is by focusing on the observations for which the excess market return is negative. Using this alternative condition cannot have a material impact on the estimates of downside beta: over a typical 12-month period, the excess market return is below its sample mean for 122 trading days, of which only 8 exhibit positive excess market returns.

36 months out of the total 60 months. Since computing tail risk betas requires a long time series of returns, analysis of tail risk as the dependent variable uses data ending in 2014 rather than 2017, as in the rest of the analysis. Intuitively, stocks with high values of tail risk beta are more sensitive to tail risk, so they are deeply discounted when tail risk is high.

2.3 Our Main Sample

Panel C of Table 1 shows the number of stocks listed on NYSE, AMEX, and Nasdaq with nonmissing ESG data (in the prior year) within each size decile (based on NYSE breakpoints). Note that the MSCI KLD coverage of small firms (i.e., firms with market value below the median NYSE market equity at the beginning of the year) is saliently sparse before 2004. This pattern is consistent with the fact that the KLD database only covered S&P 500 companies until 2000. More importantly, we risk averaging risk–CSR relationships from cross-sections of stocks that are quite different over time. For this reason, we use only big firms (i.e., firms with market value above the median NYSE market equity) in our main analyses. A sensible alternative approach would be to use all firms in the period after 2001 as the sample, since this is when KLD started expanding its coverage to include smaller companies. Accordingly, we examine this sample in our robustness tests.

3 Empirical Results

3.1 Unconditional Risk and Returns of ES Score-Sorted Portfolios

It would seem that a natural starting place for any assessment of costs, or benefits, of incorporating ES factors into investment decisions is to consider traditional mean-variance investors. In this section, we begin by examining patterns of future returns over the next month and unconditional market risk for portfolios sorted on their past ES score.

3.1.1 Returns of Portfolios Sorted by ES Score

At the beginning of each month t, we sort stocks into five quintiles based on their past ES scores. In particular, since our total net ES measure is annual, we sort stocks into portfolios at the beginning of each year based on ES measures from the prior year. We then examine monthly holding period returns from t to $t+1$.

Panel A of Table 2 reports the average returns of the equal- and value-weighted portfolios over the next month from t to $t+1$, along with the return difference between the highest and the lowest past ES quintile portfolios in the column labeled "High-Low," for which we compute the t-statistic by using three Newey–West (1987) lags.

The average returns of the various ES portfolios are similar, and they do not exhibit any obvious pattern. Firms in the highest ES-score quintile earn virtually the same equal-weighted average annual returns as firms in the lowest quintile, with a t-statistic of 0.04. The value-weighted high-minus-low ES-score portfolio average return is -5 bp per month ($t = -0.37$). The average returns of the long-short portfolios are not only statistically but also economically insignificant. Similarly, portfolio alphas do not demonstrate any pattern. The alphas of the value-weighted high-minus-low ES-score portfolio are negative but small, and they are statistically insignificant for each of these models. On an equal-weighted basis, the high-minus-low ES-score portfolio alphas are typically positive but insignificant.

Panel B of Table 2 repeats the same exercise as Panel A of Table 2, except it sorts firms on their ES scores within each industry, based on two-digit Standard Industrial Classification (SIC) codes. Again, none of the return spreads, which are economically small, are statistically significant, with t-statistics between -0.8 and 0.8.

Essentially, we find no evidence of high-ES firms outperforming, or underperforming, low-ES firms. These results suggest that (abnormal) returns cannot explain the preference for (or against) ES investing.[15]

[15] We checked that these findings are unaffected by using the Fama-French 5-factor model, as well as by adding the Pastor-Stambaugh liquidity factor to our performance models.

3.1.2 Unconditional Risk of Portfolios Sorted by ES Score

In each panel of Table 2, the last row shows the average cross-sectional realized β of each quintile portfolio, where a stock's β is calculated using daily data over the next 12 months. Although these average betas are computed using multiple months of data, they are evaluated monthly. While this use of overlapping information is more efficient, it induces moving average effects. To adjust for this, we use 12 Newey–West (1987) lags in reporting t-statistics of differences in average market betas between the highest and lowest ES quintile portfolios.

The average betas for firms sorted on ES score alone (Panel A) do not demonstrate any pattern, but they do show a consistently decreasing pattern when we sort on ES score within each industry (Panel B). In this case, the difference in average market betas between quintile portfolios 5 and 1 is -0.038, which is statistically significant at the 1% level.

In summary, Table 2 demonstrates that ES scores do not have implications for return, but they seem to have implications for unconditional market risk: firms with high ES scores have low market betas in the future. These results are consistent with the model in Albuquerque, Koskinen, and Zhang (2019), which predicts that CSR decreases *systematic* risk, as well as their empirical evidence. However, this relation does not control for other firm characteristics that might be correlated with future betas. In Section 3.3.1, we show that this relation is indeed explained away by other firm characteristics.

3.2 Downside Risk of Portfolios Sorted by ES Score

Economists have long recognized that investors care differently about downside losses than about upside gains, which begs a natural extension of the traditional mean-variance analysis by taking into account the asymmetric treatment of risk. According to this extension, systematic downside risk, rather than unconditional market risk, more closely correspond to how investors actually perceive risk. We now examine patterns of future downside risk for portfolios sorted on past ES score.

Panel A of Table 3 lists the equal-weighted average downside risk characteristics of firms sorted on their ES scores into quintiles. Specifically, at the beginning of each calendar year, we sort firms into portfolios based on ES measures from the prior year. For each month, using daily data over the next 12 months, we calculate a firm's downside beta (Equation (2)) and coskewness (Equation (3)), as well as the firm's relative downside beta. We also compute a firm's tail risk beta using the next 60 months of data. Although these risk measures are computed using multiple months of data, they are evaluated monthly. To account for this, we use 12 Newey–West (1987) lags in reporting t-statistics of the differences in average realized downside risk between the highest and lowest ES quintile portfolios, except we use 60 Newey–West lags in the case of tail risk.

Panel A shows a consistently decreasing pattern between past ES scores and realized downside risk, based on relative downside beta and coskewness. The difference in average relative downside beta is -0.047, with a corresponding difference in average coskewness 0.019. These differences are significant at the 1% level. That is, when the market declines, the prices of high-ES stocks tend to decrease less than those of low-ES stocks *with comparable market risk exposure.* Moreover, high-ES firms with high coskewness tend to do better than low-ES firms with low coskewness when market volatility is high. These are also typically—though not always—periods of low market returns. Taken together, our results are consistent with high-ES firms' low downside risk.

In Panel B, we examine the robustness of ES score's implications for downside risk to controlling for industry by sorting stocks within each industry into quintiles according to their ES scores. Industry can be an important driver of the results in Panel A of Table 3 (and Table 2) for several reasons. First, some industries are considered more controversial than others.[16] Second, Fama and French (1997) show that market risk exposure varies substantially across industries.

Controlling for industry, high-ES firms continue to have low relative downside betas and

[16] For example, KLD classifies participation in the production of alcohol, gambling, firearms, military, nuclear, and tobacco as "sinful."

high coskewness, and spreads in these measures of downside risk are still highly significant, with t-statistics of -2.6 and 3.1, respectively. Nevertheless, these differences are about half the magnitude of the corresponding differences in Panel A. This indicates that industry plays an important role in the negative relations between ES score and downside risk, even though it does not fully explain away the relation.

On the other hand, past ES score does not seem to predict future tail risk well. Panel A shows that tail risk betas across the ES quintiles do not demonstrate any pattern. Panel B shows that high-ES firms exhibit lower tail risk than low-ES firms within the same industry, but the corresponding spread in tail risk beta is still insignificant. However, in Section 3.3.2, we show that, controlling for other firm characteristics, past ES score does negatively predict future tail risk, consistent with high-ES firms' low downside risk.

Finally, Table 3 shows that, while realized downside betas for portfolios sorted by ES score alone do not demonstrate any pattern, the 5–1 difference in downside betas for ES portfolios controlling for industry is negative and highly significant, with a t-statistic of -4.2. This result can be consistent with high-ES firms' low downside risk, but it can also be mechanically reflecting the relation between ES scores and future unconditional betas. Panel B of Table 1 shows that β and β^- are highly correlated, with a correlation around 0.83. Given this correlation, it is not surprising that patterns of β and β^- sorted on ES score are qualitatively the same. Therefore, we must be cautious to control for the effect of unconditional risk when measuring downside risk by focusing on relative downside beta, $(\beta^- - \beta)$, in lieu of downside beta, β^-.

In summary, Table 3 demonstrates that ES scores do have significant implications for downside risk based on relative downside risk and coskewness. Firms with high ES scores have low future downside risk that is not mechanically driven by their low unconditional market risk. These novel results suggest that, to investors who care more about downside losses than upside gains, the low downside risk of high-ES firms can be one pecuniary benefit of incorporating ES factors into their investment decisions. However, these relations do not control for various other firm characteristics that are related to future downside risk (e.g., past downside risk) or contemporaneously correlated with ES scores (e.g., firm size).

3.3 ES Score as a Predictor of Future Systematic Risk Exposure

There is little theoretical guidance regarding which firm characteristics determine the riskiness of a stock, but a number of studies have empirically explored how a stock's risk exposure is related to its firm characteristics.[17] In Table 4, we examine the negative relationship between ES scores and future systematic risks, controlling for the standard list of known cross-sectional effects. We run Fama–MacBeth (1973) regressions of realized risk exposure on various firm characteristics, including ES score, and past risk characteristics, all of which are known ex ante.

3.3.1 ES Score Does Not Predict Future Unconditional Risk Exposure

In Panel A, we first consider regressions of future unconditional beta and downside beta over the next 12 months on past variables at the individual firm level. All the independent variables in these regressions are measured in a period before the realization of risk measures. These regressions are run monthly, so we use 12 Newey–West (1987) lags.

Independent variables in the first two columns include: (i) ES score, (ii) log of market capitalization, (iii) risk measures (i.e., unconditional β, relative downside β, coskewness, and tail risk β) over the past months, and (iv) industry fixed effects. The last two columns also include other firm characteristics: (i) the firm book-to-market ratio, (ii) its excess returns over the past 12 months, (iii) accounting measures of performance (i.e., return on equity (ROE), asset growth, and sales growth), (iv) book leverage, and (v) a dummy for firms that pay dividends.

The first column shows that past ES scores do not predict future unconditional betas.

[17] See, e.g., Daniel and Titman (1997); Harvey and Siddique (1999); and Ang, Chen, and Xing (2006).

On the other hand, past betas are a strong predictor of future betas. Hence, the strong predictive pattern of future unconditional betas across portfolios sorted by ES score in Table 2 is explained away by the size effect and the strong 12-month autocorrelation of betas. Column 3 adds additional stock characteristics, only to confirm the robustness of this negative result.

In summary, we find no significant evidence that ES scores have unconditional risk implications. Recall from Table 2 that the average returns (risk-adjusted or not) from high-ES firms are no different than those from low-ES firms. Taken together, these two results accentuate the importance of moving beyond unconditional risk and return for assessing the financial implications of incorporating ES factors into investment decisions. Indeed, the predictive relation between ES score and future downside beta persists (Columns 2 and 4), highlighting the key difference between unconditional and downside risk.

3.3.2 ES Score Predicts Future Downside Risk Exposure

Panel B of Table 4 repeats the same exercise as Panel A, except we now examine whether future measures of downside risk—relative downside β, coskewness, and tail risk β—can be predicted by past ES score, controlling for other firm characteristics and risk characteristics. Note that relative downside beta and coskewness are computed over the next 12 months, so we use 12 Newey–West (1987) lags; tail risk beta is computed over the next 60 months, so we use 60 Newey–West lags.

The estimated coefficients of future relative downside beta on past ES score are negative, with t-statistics around -4. Consider a 1.05-point increase in ES score, which corresponds to the interdecile range of ES score (Panel A of Table 1). The coefficient estimate in Column 4 of Panel B of Table 4 indicates that such an increase in ES score is associated with a decrease in relative downside beta of 0.017, controlling for the full list of firm and risk characteristics. This effect is of the same order of magnitude as the difference in relative downside beta between the highest and lowest quintile ES portfolios that control for industry (Panel B of Table 3). Hence, the significant effects of ES investing on decreasing relative downside beta are essentially independent of other firm characteristics and risk characteristics.

Moreover, high-ES firms tend to have high future coskewness and low future tail risk. Since firms with high coskewness or low tail risk tend to covary less with the market during market declines, these results are consistent with high-ES firms having low downside risk. The estimated coefficient on ES score indicates that a 1.05-point increase in ES score is associated with an increase in coskewness of about 0.013 (Column 5 of Panel B of Table 4), compared to the 5–1 quintile difference of 0.010 in coskewness for the ES quintiles within each industry (Panel B of Table 3). Recall that the 5–1 quintile differences in tail risk betas for the ES quintiles are insignificant. According to the last column of Panel B of Table 4, changing the ES score by 1.05 point is associated with a statistically significant decrease in tail risk exposure of 0.021.

In summary, we continue to find that ES scores have significant benefits in terms of downside risk, which are stronger after controlling for other cross-sectional effects: High-ES firms have low relative downside betas and high coskewness, as well as low tail risk betas. Not only are these effects statistically significant, they are larger than those of the portfolio analysis in Table 3. Taken together with our results on unconditional risk and return, reduction of downside risk seems to be a key pecuniary benefit of ES investing.

3.4 Interpreting the Magnitude of the Estimated Coefficients

The preceding analysis shows that stocks with high ES ratings have statistically significantly lower downside risk. This is consistent with the findings in the literature that these stocks had higher returns during the 2008–2009 financial crisis (Lins, Servaes, and Tamayo 2017) and during the COVID-19 market crash (Albuquerque et al. 2020). While these effects are statistically significant, we should gauge their economic significance.

To interpret the economic magnitudes of the estimated coefficients reported in the Fama–MacBeth regressions, we consider an interdecile-range move across stocks in terms of ES score, or a 1.05-point increase in ES score. The coefficient estimates indicate that such an increase in ES score is associated with (i) a decrease in relative downside beta of 0.017 (which represents about 3% of relative downside beta's interdecile range), (ii) an increase in coskewness of 0.013 (which represents about 4% of the interdecile range of coskewness), and (iii) a decrease in tail risk beta of 0.022 (which represents about 2% of tail risk beta's interdecile range). Such reductions of downside risk seem economically small.

However, the economic effects of such reductions of downside risk might be understated if the downside risk of high ES stocks is varying over time, as suggested by Figure 1. In particular, the estimated coefficients of downside risk regressed on lagged ES performance might understate the economic significance of the ES-downside risk link if the downside risk advantage of high ES stocks covaries negatively with the market, i.e., the resilience of high ES stocks during the worse part of a year is heightened if the year is itself a bad year. We explore this possibility. The results are in Table 5.

In Panel A, we first consider panel regressions of realized risk—unconditional beta, downside beta, relative downside beta, and coskewness—in each year on past variables at the individual firm level. We include all the independent variables in Table 4, except including firm fixed effects in lieu of industry fixed effects.[18] All standard errors are double clustered by firm and time. Consistent with the results of our Fama–MacBeth regressions, ES ratings have no significant unconditional risk implications, whereas they do have significant benefits in terms of downside risk. Compared to the estimated coefficients on ES score from the Fama–MacBeth regressions, those from the panel regressions are similar, but slightly larger.

Panel B repeats the same exercise as Panel A, except we now interact ES performance with $1(NegMktRet)$ and $1(PosMktRet)$, where $1(NegMktRet)$ ($1(PosMktRet)$) is a dummy variable that is equal to 1 if the market's excess return is negative (positive) in a given year.[19] ES ratings continue to have no significant unconditional risk implications, whereas they do have significant downside risk benefits in both good and bad years. More importantly, the downside risk advantage of high ES stocks typically doubles in bad years,

[18]Including industry fixed effects as in the Fama–MacBeth regressions leads to the same conclusions.
[19]Again, all standard errors are double clustered by firm and time.

indicating that the ES-downside risk link covaries negatively with the market. Therefore, the estimated coefficients of downside risk on ES performance, which capture only the average effect, plausibly understate the economic significance of their relationship.

A natural way to capture the joint effect is by looking at realized returns over the next 12 months, i.e., the contemporaneous period over which our downside risk measures are calculated. First, returns over longer horizons capture the average effect: Even if a firm's ES performance is financially immaterial based on returns over a short horizon (Table 2) and standard, unconditional risk exposures (Tables 4 and 5), high-ES stock returns over longer horizons will be higher to the extent that lower downside risk of high-ES firms mitigates large losses, which have a disproportionate impact on compound returns. Second, returns over a 12-month horizon account for the effect of whether the year is itself a bad year.

In Table 6, we run Fama–MacBeth (1973) regressions of realized excess and DGTW-adjusted returns over the next 12 months on past ES scores.[20] In the first two columns, we control for realized market beta computed over the next 12 months. The last two columns instead control for realized downside beta and upside beta computed over the same period.[21] In all columns, we control for log-size, book-to market ratio, and past 12-month excess returns at the beginning of the period t, as well as realized return volatility and coskewness.

Again, we consider an interdecile-range move across stocks in terms of ES score, or a 1.05-point increase in ES score. The coefficient estimates indicate that such an increase in ES score is associated with a future increase in annual returns of around 0.96%. While these gains in long-term returns are modest in economic terms, they are non-trivial and substantially larger than what the estimated coefficients of downside risk on ES performance suggest, consistent with our results in Panel B of Table 5.

In summary, not only do our results provide strong evidence that integrating ES factors is *not* costly, they also explain why long-term investors care more about ES issues (Starks,

[20]We compute the standard errors of the coefficients by using 12 Newey–West (1987) lags.

[21]Upside beta is effectively the covariance of a firm's stock return with the market return conditional on upside movements of the market.

Venkat, and Zhu 2020): Such investors are more exposed to downside risk, so they rationally should be more concerned about ES issues, which can help them mitigate downside risk.

3.4.1 Role of Measurement Error

The economic significance of the negative relation between ES ratings and downside risk might still be understated because of a measurement problem: Our proxy for ES may not accurately measure a firm's ES activities. On one hand, the ESG ratings of leading agencies disagree substantially.[22] On the other hand, Eccles and Stroehle (2018) and Eccles, Lee, and Stroehle (2020) point out that there are data construction and integrity issues with MSCI KLD since 2013: in essence, post-2013 data are not updated properly since MSCI is phasing out KLD to MSCI IVA dataset.

Therefore, our analysis, which relies on KLD ratings alone and which contains post-2013 data, can be subject to a real errors-in-variables (EIV) problem. We did not worry about the EIV problem when establishing statistical significance, as it would work against us. But the EIV problem can lead to an attenuation bias that is of first-order importance for assessing the economic significance of the estimates in Table 4.

Nevertheless, addressing the potential attenuation bias is unlikely to lead to downside risk mitigation effects of ES activities that are much larger than what we obtain. First, a back-of-the-envelope calculation suggests that 97% of the variation in our ES scores must be noise if, in reality, an interdecile-range move across stocks in terms of ES score is associated with interquartile-range decrease in relative downside beta (which is half of the interdecile range). Second, in the appendix, we find similar results using Sustainalytics ratings, another major ESG ratings provider: using ES ratings from multiple raters is unlikely to substantially increase the magnitude of the downside risk effect of ES activities. Third, using ES ratings from MSCI KLD before 2013 only, we also find similar results, albeit slightly stronger.[23]

[22] See Chatterji et al. (2016) and Berg, Koelbel, and Rigobon (2020).
[23] All of these results are available upon request.

3.4.2 Relation to the Literature

This is not the first paper to show that high ES stocks do better during market downturns. Specifically, Lins, Servaes, and Tamayo (2017) find that high-ES firms had significantly higher stock returns during the 2008–2009 financial crisis, while Albuquerque et al. (2020) report a similar finding during the COVID-19 market crash. The economic effects we obtain are consistent with those of ES policies on stock returns surrounding unparalleled market-wide, negative events such as the 2008–2009 financial crisis or the COVID-19 market crash.

Our measures of downside risk estimate the benefit of ES policies during market-wide, negative events in a conservative way, entertaining a range of downside market outcomes instead of considering only the single most catastrophic event. Such events occur rarely by definition, so the substantial economic effects conditional on such events translate to relatively small reduction in our downside risk measures. To the extent that our measures of downside risk capture the typical benefit of ES policies during market declines, they are practically more useful for portfolio selection. In summary, using conservative measures of downside risk, we highlight that not only are ES firms resilient during rare episodes of market collapse considered in the literature, they continue to be resilient during more typical market declines. At the same time, we elucidate how the substantial economic effects found in this literature can be still consistent with modest, yet non-trivial, value for long-term investors.

3.5 Robustness

3.5.1 Both E and S Predict Future Downside Risk Exposure (and G Does Not)

Before we turn to potential explanations for the negative relation between ES performance and downside risk, we split the total ES score into two components: (i) E(nvironmental) score (i.e., the environment category in the MSCI KLD database) and (ii) S(ocial) score (i.e., the five categories of community, human rights, employee relations, diversity, and product). We seek to determine whether a firm's aggregate ES performance or a specific component of a firm's ES score is important for avoiding stocks that covary strongly when the market dips. We also examine the G score (i.e., the corporate governance category) here.

We run Fama–MacBeth (1973) regressions analogous to those in the last three columns of Panel B of Table 4, except that we use one ESG component at a time in lieu of the total ES score.[24] The results are shown in Panel A of Table 7.

We find strong negative relations between both components of the total net ES score and all measures of downside risk. The estimated coefficients on the E score are significant, with t-statistics around -3, 7, and -2 for relative downside beta, coskewness, and tail risk, respectively; those on the S score are also highly significant, except in the case of tail risk. Moreover, the coefficient estimates indicate that both the E and S elements of ES activities are equally important for mitigating downside risk, based on relative downside beta and coskewness. To see this, first note that the standard deviations of the E and S scores are 0.12 and 0.39, respectively (Table 1),[25] so the standard deviation of the E score is one third of that of the S score. At the same time, the coefficients on the E score are three times larger than those on the S score for relative downside beta and coskewness. Only in the case of tail risk beta is the coefficient on the E score substantially larger than that on the S score.

In contrast, we find that the G score has no predictive ability for future downside risk. The estimated coefficients on the G score are not only substantially smaller than those on the E or S scores, but they are statistically insignificant when we control for other cross-sectional effects. These results are consistent with Hong, Kubik, and Scheinkman (2012); Servaes and Tamayo (2013); and Krüger (2015).

Finally, the same conclusions continue to hold when we analyze the relation between the total ES score, or one of its two components, and measures of downside risk, controlling for the G score (Panel B of Table 7). In summary, both the environmental and the social

[24] We find similar results when we use all three ESG components simultaneously.

[25] Note that this difference in the standard deviations of the E and S scores is mechanical: The E score is computed using only one category, thus ranging from -1 to $+1$, whereas the S score is computed using the five social categories, thus ranging from -5 to $+5$.

aspects of a firm's ES activities appear to be of similar importance for mitigating the firm's future downside risk.

3.5.2 Climate Change Concerns Predict Future Downside Risk Exposure

No other aspect of ESG has attracted more attention than those related to climate change concerns. In addition to analyzing the relations between two components of ES performance and downside risk, we analyze the relation between a firm's climate change exposure and measures of its risk. Similar to Chava (2014), we define the firm's climate change score as its clean energy strength minus its climate change concern score, both of which are part of the KLD environment category. We note that focusing on the firm's climate change score reduces the sample period to 2000–2013: climate change concern score is available from 2000 onward, while clean energy strength score experienced a major change in definition in 2013 when it was split into multiple indicators, many of which are missing.[26]

We run Fama–MacBeth (1973) regressions analogous to those in Table 4, except that we use the firm's climate change score in lieu of its total ES score. The results are shown in Panel A of Table 7.

Similar to the results of Table 4, climate change score has no significant unconditional risk implications, whereas stocks with high climate change score (i.e., stocks with low climate change exposure) have significantly lower future downside risk, based on downside beta, relative downside beta, and coskewness. Such stocks also have lower future tail risk, although the relation is statistically insignificant.

While climate change score has significant benefits in terms of lowering downside risk, the economic effects are much smaller than those of the total ES score. This may very well stem from the fact that our climate change score, constructed using two MSCI KLD dummies, may not accurately measure a firm's climate change exposure. In addition, our

[26]We speculate that this issue is related to the data construction and integrity issues with MSCI KLD since 2013, as discussed earlier in Section 3.4.1.

sample period does not cover more recent times, especially since the Paris Climate Accords in 2015, when climate change concerns have substantially heightened. In this sense, we provide only suggestive evidence. A more accurate measurement of a firm's climate change exposure or a study of more recent times could reveal a much stronger downside risk mitigation effects. We hope that such a task will be undertaken by future research.

3.5.3 ES Score Predicts Downside Risk in the Universe After 2001

In Panel A of Table 8, we consider the same regressions in the last three columns of Panel B of Table 4, except we use the sample of all firms in the period after 2001. We find that our main results, which uses the sample of big firms since 1991, the beginning of our sample, are robust: High-ES firms have low relative downside betas and high coskewness, as well as low tail risk betas in the cross-section of all firms in recent years. While these effects continue to be statistically significant, they are certainly smaller than those in Table 4.

This result can be due to the dependence of ES-downside link on size. To test this idea, we interact ES performance with $1(SmlCap)$ and $1(BigCap)$, where $1(SmlCap)$ ($1(BigCap)$) is a dummy variable that is equal to 1 if the firm's market value is below (above) the median NYSE market equity. The results are shown in Panel B of Table 8. The estimated slopes on ES Score$\times 1(BigCap)$ are significant and of similar magnitude to those in Table 4 in all columns. In contrast, the interactions that involve $1(SmlCap)$ are never significant, though their slopes indicate negative relations between ES score and downside risk for small firms.

In short, we find robust negative relations between ES performance and downside risk that are stable over time, primarily in the cross-section of large firms. A natural explanation is that these effects are due to patterns of institutional trading, as discussed in Section 4.2. These negative relations in the cross-section of large firms are strong enough to keep up the statistical significance of the same relations when pooled with small firms.

4 Potential Explanations

In this section, we discuss two general explanations that can give rise to the downside risk effects of firm-level ES performance.

4.1 Doing Well by Doing Good

A key assumption of our version of the ES investing proposition is that the value of high-ES firms is resilient in periods when many firms suffer a negative shock to their value, which can be reflected in the cross-section of stock returns to generate the negative relation between ES score and downside risk documented in Section 3. In turn, we test whether the firm values of high-ES firms covary less with the average firm's value when the average firm's value is declining. We find strong empirical support for this.

Ideally, we would construct a direct measure of changes in firm value due to corporate actions that raise ES scores. But this is a challenge in itself. Instead, we use the firm-level news sentiment from RavenPack Analytics as a proxy for changes in firm value.[27]

4.1.1 RavenPack Database

For each news story analyzed, RavenPack produces a sentiment score ranging from 0–100, where values above 50 indicate positive sentiment and values below 50 show negative sentiment. As advised by the RavenPack user guide, we filter for news stories in which the firm was prominent (i.e., a relevance score of 100), and we filter for the first story that reports a categorized event (i.e., a novelty score of 100). We measure daily news sentiment for each firm as the average of RavenPack's sentiment scores across all news for each firm-day observation.

We notice that in a significant fraction of the observations, the firm is missing daily

[27] Our approach is motivated by the literature which indicates that media releases contain a large amount of value-relevant information (e.g., Tetlock, Saar-Tsechansky, and Macskassy (2008)).

news sentiment. In turn, betas computed using data on news sentiment at the firm level would be noisy. To address this concern, we conduct our analysis using news sentiment data by examining the quintile portfolios sorted by ES scores, as in Sections 3.1 and 3.2.

If a firm's news sentiment is a good proxy for its value change, we would expect an increasing relationship between realized returns and realized news sentiment at a high frequency, which we *do* find at the portfolio level in Panel A of Table 9. These relations are both statistically and economically significant: News sentiment alone explains 25% of the variation in contemporaneous returns across the portfolios. Similarly, there is a strong positive contemporaneous relation between market return and aggregate news sentiment[28] that is visually plain in Figure 2, which plots their daily values at the start of each month over time.

4.1.2 Patterns of Sentiment Covariation Across Portfolios Sorted by ES Score

The exploratory analysis in the previous section indicates that the negative relation between ES score and downside risk may very well stem from a similar relation in the cross-section of firm values, as proxied by news sentiment. We now examine whether news sentiment for high-ES firms covaries less with the aggregate news sentiment during periods of low aggregate news sentiment by constructing sentiment-based measures of downside covariation in the same way as the corresponding measures based on stock returns.

Panel B of Table 9 reports the time-series averages of relative sentiment downside betas and sentiment unconditional betas for each quintile portfolio. Both measures of sentiment covariation demonstrate essentially monotonic patterns that are decreasing in ES score. Furthermore, the differences in the column labeled "High-Low" are significantly negative, with t-statistics of -6.0 and -4.7, respectively.[29] Panel C conducts the same analysis as in Panel B but controlling for industry. The differences in relative downside and unconditional

[28]Specifically, we measure daily aggregate news sentiment as the value-weighted average of daily firm news sentiment across all firms on each day.

[29]All the t-statistics in Panels B and C of Table 9 are computed using 12 Newey–West (1987) lags.

betas continue to be consistently negative and highly significant.

Taken together, our results are consistent with firms "doing well by doing good" such that they can explain the downside risk effects of firm-level ES performance in stock returns. Firm values for high-ES firms covary less with the average firm's value, especially when the average firm's value is declining. These patterns are also economically significant: The 5–1 differences in relative sentiment downside betas between ES portfolios represent about 44% of the interdecile range of the relative sentiment downside beta (based on 25 portfolios formed on size and book-to-market). Considering the fact that news sentiment explains about 25% of the variation in stock returns, these patterns translate to relatively small reductions in downside risk due to ES performance in the stock market.

4.2 ES Preferences of Institutional Investors

Another possible explanation for the negative relation between ES score and downside risk documented in Section 3 is that a group of large investors have preference for high-ES firms such that, during market declines, these firms are less susceptible to selling pressure and they covary less with the market. Institutional investors potentially represent such a group.[30]

In particular, we examine how the direction of institutional trading covaries with market returns depending on firm-level ES performance. We hypothesize that, conditional on market declines, institutional investors tend not to sell high-ES stocks as the market falls: The institutional trading downside beta with respect to the market is negatively related to ES score. We use Abel Noser institutional trading data, which contain trading records of institutional investors that use Abel Noser's transaction cost analysis services.

For each firm-day observation, we calculate the net shares traded (i.e., shares purchased

[30]First, institutional investors increasingly exhibit preferences for high-ESG firms (Starks, Venkat, and Zhu (2020) and Cao et al. (2020)). Second, institutional trading exerts significant price pressure in equity markets (Coval and Stafford (2007) and Lou (2012)). Finally, our results obtain primarily in the cross-section of large firms, which are exactly what institutional investors tend to invest in (Gompers and Metrick (2001)).

minus shares sold, or trading imbalance).[31] We then scale the trading imbalance by focusing on its direction, taking a value of 1 for net institutional buying, -1 for net institutional selling, and 0 for zero net position. Our sample contains trades of large firms (firms above the median NYSE market equity) by 762 institutions between 2000 and 2010, for a total of USD 31.3 trillion in trading.

4.2.1 ES Score Matters for Patterns of Institutional Trading

We consider two versions of trading downside beta. The first version estimates betas by regressing the direction of institutional trading of each firm on the market excess return using only the observations for which the realized market excess return is below its mean in each period, just as when computing β^-. It is not clear a priori when institutional investors step in, if at all, to alleviate the selling pressure on prices of high-ES firms; therefore, the second version uses only the observations for which the realized market excess return is below the 25th percentile of its distribution in each period. We then calculate the relative trading downside beta as the raw trading downside beta minus the trading unconditional beta.

In Table 10, we examine whether past ES scores can predict future realized measures of how institutional trading covaries with the market, where the t-statistics are computed using 12 Newey–West (1987) lags. The first column shows that past ES scores do not statistically significantly predict future trading unconditional betas over the next 12 months. ES scores exhibit consistently negative relations with both versions of trading downside beta, raw or relative, but the estimated slopes on ES scores are statistically significant only for the second version of the trading downside beta (see the last two columns of Table 10). These results suggest that institutional investors *do* supply liquidity to high-ES firms during market declines, but they do so mainly during times of extreme market declines.

Taken together, we obtain institutional trading patterns that can explain the downside risk effects of firm-level ES performance: When the market suffers extremely negative shocks,

[31] If a firm is not traded by any institution on a given day, but it has been traded at least once in the database, we assume that the institutions traded 0 shares that day.

institutional investors hold on to high-ES firms, which induces high returns and low downside betas for these firms. Consistent with the fact that the downside risk effects of firm-level ES performance are not large, our results indicate that the ES preferences of institutional investors, albeit significant, are not strong: Trading downside betas decrease by only 3–4% of their interdecile range for an interdecile-range increase in ES score.

5 Conclusion

Over recent decades, there has been a substantial growth (both in absolute dollars and relative to other investments) in the assets that are invested based on ESG considerations. Yet, the recent amendment to the ERISA, requiring fiduciaries to select investments based solely on investment risk and return, and its subsequent reversal highlight the fact that there is still no consensus on the financial implications of ESG investing. In this paper, we empirically analyze how a firm's systematic downside risk and, more generally, a firm's financial performance vary with its environmental and social ratings. We find strong evidence that stocks of firms with high ES ratings have significantly lower downside risk, whereas stocks of such firms do not differ from comparable stocks based on standard, unconditional market risk or average returns. We show that the downside risk reduction effect of ES policies delivers modest, yet non-trivial, gain in future annual returns of around 0.96%. Our results suggest that investors deriving non-pecuniary benefits from ES investing need not sacrifice financial performance and therefore help explain the rapid growth of ES investing.

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A Robustness Tests with Sustainalytics' ESG Ratings

In this appendix, we re-examine the relationship between ES performance and future risks, except we use Sustainalytics' data for the firm-level ESG profile. Sustainalytics measures how well companies are prepared for their most material ESG issues by using a customized weight matrix that defines the relative importance of each indicator and emphasizes the key ESG issues for each industry.[32] In turn, these raw scores are aggregated to produce a company's total ESG score (out of 100), as well as its three component scores: Environmental, Social and Governance. The sample period is from August 2009 to December 2017.

We run Fama–MacBeth (1973) regressions of future downside risk measures—relative downside β, coskewness, and tail risk β—on all the independent variables in Table 4, except we now use Sustainalytics' total ESG score instead of ES score constructed from KLD.[33] The results are in Table 11. The first three columns in each panel use the scores as is, while the last three columns use their natural logarithms.

Just like MSCI KLD, the Sustainalytics coverage of small firms (i.e., market value below the median NYSE market equity) is sparse: Slightly more than 10% of its firms are small. Accordingly, we examine the sample of big firms (i.e., market value above the median NYSE market equity), just like in our main analyses, in Panel A. Panel B examines a subsample that further excludes firms with negative book value.

In Panel A, the estimated coefficients of future relative downside beta on Sustainalytics ESG score are consistently negative, but insignificant. However, Panel B shows that stocks with high Sustainalytics ESG scores have significantly lower future relative downside beta by focusing on big firms with positive book value (Column 4).

[32] Importantly, this helps account for the fact that whether a given ESG issue is material likely varies systematically across firms and industries (Khan, Serafeim, and Yoon (2016)).

[33] We also considered regressions of future β and β^- on Sustainalytics' total ESG score, analogous to those in the last two columns of Panel A of Table 4. In summary, we continue to find no evidence that ES scores have unconditional risk implications. While the negative relation between ES score and future downside beta persists, it is no longer significant. This result is likely due to the fact that β^- is not a good measure of downside risk, as discussed earlier in Section 3.2.

Moreover, firms with high Sustainalytics ESG scores have significantly lower future downside risk, based on coskewness, in both panels. On the other hand, we find no evidence that Sustainalytics ESG scores have implications for tail risk beta: Focusing on tail risk beta reduces the sample period to little more than 5 years, so our estimated coefficients could just be too noisy in this case.

In summary, we continue to find that a firm's CSR activities, as measured by Sustainalytics' total ESG score, have significant, but weaker, downside risk benefits. Therefore, using ES ratings from multiple raters is unlikely to lead to downside risk mitigation effects of ES activities that are substantially larger than what we obtain in this paper.

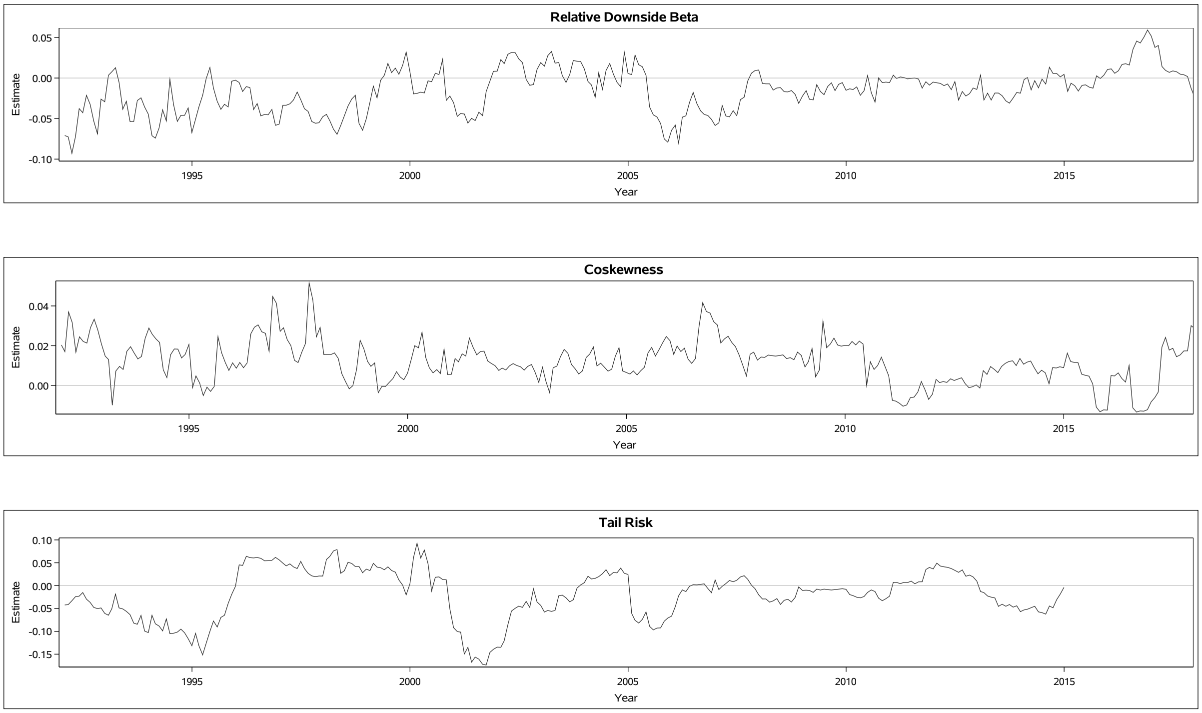

Figure 1: Monthly ES Coefficient Estimates

Plotted is the monthly ES coefficient estimate from monthly cross-sectional regression of downside risk measures on ES score and control variables. The control variables include lagged risk measures, log-normalized market capitalization in previous month, book-to-market ratio, standard deviation of daily return measured over past one year, excess return during past 12 months, dividend dummy, asset growth, sales growth, leverage, and return on equity.

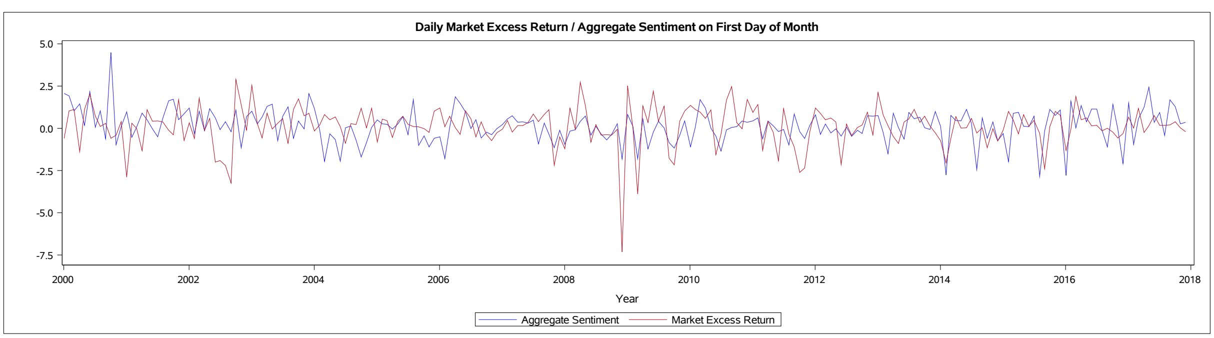

Figure 2: Aggregate News Sentiment and Market Excess Return

Plotted is the daily aggregate news sentiment and daily excess market return, on the first trading day of each month. Using all firms listed on NYSE, AMEX, or Nasdaq, we construct daily firm-level news sentiment as the average sentiment score of daily firm-level news. News published after 4:00 PM are attributed to the next trading day. We compute corresponding daily aggregate sentiment measures by value-weighting daily news sentiment of firms with at least one news. For comparison, both series are normalized to have mean zero and variance one. The time-series correlation during our sample period is 0.21.

Table 1. Summary Statistics

This table presents the summary statistics of the main variables used in our empirical analysis. Panel A reports time-series averages of the cross-sectional summary statistics of (i) measures of ESG profile (see Section 2.1), (ii) measures of risk (see Section 2.2) and (iii) firm characteristics, in our main sample (firms with market value above the median NYSE market equity since 1991). All firm characteristics, i.e., control variables, are winsorized at the 1% and 99% level within each month. Panel B shows the correlations among our risk measures in our main sample. Panel C shows the number of stocks listed on NYSE, AMEX, and Nasdaq with nonmissing ESG data (in the prior year) within each size decile (based on NYSE breakpoints).

Panel A: Time-series Averages of Cross-sectional Summary Statistics

Variable	T	N	Mean	STD	10th	25th	50th	75th	90th
ES Score	312	727	0.0249	0.4445	-0.4792	-0.2253	-0.0070	0.2730	0.5754
E Score	312	727	-0.0010	0.1230	-0.1206	-0.0220	0.0041	0.0359	0.1394
S Score	312	727	0.0258	0.3936	-0.4165	-0.2045	-0.0078	0.2426	0.5141
G Score	312	727	-0.0583	0.1443	-0.1853	-0.1383	-0.0569	0.0000	0.0859
MktCap ($ mil)	312	727	14,374	30,644	1,896	2,748	5,201	12,461	30,576
Beta	312	700	1.0030	0.4190	0.5323	0.7156	0.9451	1.2256	1.5568
Downside beta	312	700	1.0016	0.4659	0.4730	0.6894	0.9451	1.2538	1.6022
Rel. downside beta	312	700	-0.0014	0.2592	-0.2989	-0.1461	-0.0020	0.1441	0.2941
Coskewness	312	700	-0.1305	0.1339	-0.2988	-0.2203	-0.1316	-0.0406	0.0405
Tail risk	276	626	0.6972	0.5151	0.1234	0.3511	0.6339	0.9613	1.3386
Dividend dummy	312	721	0.7566	0.4073	0.1731	0.3846	1.0000	1.0000	1.0000
Book-to-Market	312	723	0.4289	0.2773	0.1317	0.2322	0.3789	0.5738	0.7895
Past 12 mth exret	312	724	0.1288	0.3129	-0.2159	-0.0639	0.0947	0.2749	0.4975
Past 12 mth ret STD	312	724	0.0211	0.0076	0.0131	0.0158	0.0194	0.0245	0.0316
Return on equity	312	723	0.0370	0.0769	-0.0089	0.0183	0.0361	0.0559	0.0883
Asset growth	312	722	0.1194	0.2398	-0.0534	0.0040	0.0665	0.1589	0.3243
Sales growth	312	722	0.1011	0.2370	-0.1002	-0.0087	0.0659	0.1597	0.3243
Leverage	312	722	1.5371	2.6626	0.1210	0.2758	0.6136	1.4022	3.9901

Panel B: Time-series Averages of Cross-sectional Correlation of Risk Measures

	Beta	Downside beta	Rel. downside beta	Coskewness	Tail risk
Beta	1.0000	0.8311	-0.1246	-0.0413	0.4828
Downside beta		1.0000	0.4291	-0.3901	0.4440
Rel. downside beta			1.0000	-0.6624	-0.0047
Coskewness				1.0000	-0.0603
Tail risk					1.0000

Panel C: MSCI Coverage by NYSE Market Capitalization Breakpoint

	NYSE Size Breakpoint Decile										
Year	1	2	3	4	5	6	7	8	9	10	Total
1991	9	9	25	35	48	68	87	91	132	120	624
1992	12	11	30	26	52	63	79	97	129	134	633
1993	11	12	23	25	48	67	69	107	122	143	627
1994	10	7	23	30	41	59	59	103	139	152	623
1995	8	11	32	21	33	62	64	94	137	164	626
1996	8	17	28	23	30	44	61	103	147	170	631
1997	9	12	29	27	29	37	67	85	157	180	632
1998	8	11	20	28	31	47	47	92	157	179	620
1999	11	15	22	28	32	42	57	89	155	177	628
2000	13	20	24	26	34	40	67	79	146	170	619
2001	13	23	23	41	76	139	196	203	183	163	1,060
2002	13	24	22	46	85	158	186	189	178	152	1,053
2003	387	553	373	310	255	217	184	189	180	153	2,801
2004	471	619	322	281	236	213	202	180	172	155	2,851
2005	450	577	354	280	249	201	192	187	169	156	2,815
2006	466	593	326	267	268	177	188	173	166	158	2,782
2007	339	555	391	302	225	191	195	167	164	150	2,679
2008	404	503	382	324	222	210	174	158	162	153	2,692
2009	611	446	349	255	218	197	161	169	161	151	2,718
2010	641	433	343	272	227	180	164	170	169	150	2,749
2011	518	447	286	294	210	175	178	165	165	147	2,585
2012	462	419	291	286	205	186	169	164	175	157	2,514
2013	154	333	315	256	221	186	191	163	166	159	2,144
2014	93	279	352	300	237	185	211	167	182	172	2,178
2015	54	265	335	286	237	216	205	180	176	174	2,128
2016	77	338	300	248	221	212	185	168	170	163	2,082
Total	5,252	6,532	5,020	4,317	3,770	3,572	3,638	3,732	4,159	4,102	44,094

Table 2. ES-sorted Portfolio Returns and Unconditional Market Risk

This table presents patterns of future 1-month returns and unconditional market risk for portfolios sorted on their past ES score. Panel A reports the average returns of the equal- and value-weighted portfolios over the next month from t to $t+1$, along with the return difference between the highest and the lowest past ES quintile portfolios in the column labeled "High-Low". Panel B repeats the same exercise as Panel A, except it sorts firms on their ES scores *within* each industry, based on two-digit Standard Industrial Classification (SIC) codes. The last row in each panel shows the average cross-sectional realized β of each quintile portfolio, along with the difference between "High-Low", where a stock's β is calculated using daily data over the next 12 months. t-statistic of "High-Low" return (β) is computed using 3 (12) Newey–West (1987) lags. *** 1%, ** 5%, * 10% significance.

Panel A: ES Sort

	Low	2	3	4	High	High-Low	t-stat
				Return (Equal-weighted)			
Excess return	0.0104	0.0105	0.0102	0.0105	0.0104	0.0000	0.04
CAPM alpha	0.0040	0.0036	0.0031	0.0040	0.0036	-0.0004	-0.33
3F alpha	0.0025	0.0023	0.0021	0.0029	0.0026	0.0001	0.11
4F alpha	0.0032	0.0037	0.0031	0.0035	0.0036	0.0004	0.37
				Return (Value-weighted)			
Excess return	0.0091	0.0097	0.0088	0.0090	0.0086	-0.0005	-0.37
CAPM alpha	0.0035	0.0035	0.0019	0.0026	0.0021	-0.0014	-1.03
3F alpha	0.0032	0.0031	0.0016	0.0024	0.0024	-0.0008	-0.68
4F alpha	0.0030	0.0039	0.0017	0.0019	0.0028	-0.0001	-0.10
Market Beta	0.9790	1.0128	1.0258	0.9904	1.0030	0.0240	1.01

Panel B: ES Sort Within Industry

	Low	2	3	4	High	High-Low	t-stat
				Return (Equal-weighted)			
Excess return	0.0103	0.0102	0.0104	0.0108	0.0103	0.0000	-0.04
CAPM alpha	0.0033	0.0033	0.0039	0.0042	0.0036	0.0004	0.42
3F alpha	0.0020	0.0019	0.0026	0.0031	0.0026	0.0007	0.84
4F alpha	0.0032	0.0031	0.0036	0.0037	0.0034	0.0002	0.28
				Return (Value-weighted)			
Excess return	0.0091	0.0092	0.0088	0.0090	0.0088	-0.0003	-0.31
CAPM alpha	0.0033	0.0027	0.0028	0.0025	0.0024	-0.0009	-0.77
3F alpha	0.0029	0.0024	0.0023	0.0027	0.0025	-0.0004	-0.42
4F alpha	0.0029	0.0027	0.0024	0.0024	0.0030	0.0000	0.03
Market Beta	1.0262	1.0057	0.9921	1.0032	0.9882	-0.0380***	-2.92

Table 3. ES-sorted Portfolio and Downside Market Risks

This table presents patterns of future downside risks for portfolios sorted on their past ES score. Panel A reports the average realized downside β, relative downside β, coskewness, and tail risk β of each portfolio, along with the differences between the highest and the lowest past ES quintile portfolios in the column labeled "High-Low". Panel B repeats the same exercise as Panel A, except it sorts firms on their ES scores *within* each industry, based on two-digit Standard Industrial Classification (SIC) codes. All risk measures are computed using daily data over the next 12 months, except tail risk β which is computed using data over the next 60 months. t-statistic of "High-Low" is computed using 12 Newey–West (1987) lags except tail risk β, for which we use 60 lags. *** 1%, ** 5%, * 10% significance.

Panel A: ES Sort

	Low	2	3	4	High	High-Low	t-stat
Downside beta	1.0028	1.0218	1.0210	0.9775	0.9801	-0.0227	-1.00
Rel downside beta	0.0238	0.0090	-0.0048	-0.0129	-0.0229	-0.0468***	-4.92
Coskewness	-0.1409	-0.1307	-0.1324	-0.1258	-0.1220	0.0189***	3.39
Tail risk	0.6784	0.7192	0.7241	0.6794	0.6863	0.0079	0.28

Panel B: ES Sort Within-industry

	Low	2	3	4	High	High-Low	t-stat
Downside beta	1.0309	1.0115	0.9972	0.9914	0.9764	-0.0545***	-4.18
Rel downside beta	0.0047	0.0058	0.0051	-0.0119	-0.0117	-0.0165***	-2.62
Coskewness	-0.1360	-0.1337	-0.1313	-0.1255	-0.1262	0.0098***	3.10
Tail risk	0.7116	0.7222	0.7003	0.6814	0.6725	-0.0391	-1.44

Table 4. Fama MacBeth Regression Analysis

This table shows the results of Fama–MacBeth (1973) regressions of realized risk exposure on past ES score, risk characteristics, and other firm characteristics. All independent variables are measured in a period before the realization of risk measures. In Panel A, we use future unconditional β and downside β as dependent variables. In Panel B, we use future downside risks—relative downside β, coskewness, and tail risk β—as dependent variables. We include industry fixed effects, based on two-digit Standard Industrial Classification (SIC) codes. The regressions are run monthly. Because unconditional β, downside β, relative downside β, and coskewness are computed over the next 12 months, we use 12 Newey–West (1987) lags for standard error; tail risk β is computed over the next 60 months, so we use 60 Newey–West lags. *** 1%, ** 5%, * 10% significance.

Panel A: Beta Measures

	Dependent Variables			
	Beta	Downside Beta	Beta	Downside Beta
ES Score	-0.0047	-0.0233***	-0.0010	-0.0171***
	(-0.91)	(-3.77)	(-0.21)	(-3.01)
lag(Beta)	0.6381***	0.5879***	0.4615***	0.3640***
	(21.28)	(18.23)	(17.28)	(11.41)
lag(Coskewness)	-0.0086	0.0300	-0.0836***	-0.0634*
	(-0.23)	(0.57)	(-3.02)	(-1.73)
lag(Rel down beta)	0.0166	0.0971***	-0.0361*	0.0263
	(0.68)	(3.27)	(-1.84)	(1.18)
lag(Tail risk)	0.0887***	0.1066***	0.0865***	0.0987***
	(7.02)	(6.35)	(7.90)	(6.62)
log(Size)	0.0036	-0.0072	0.0129*	0.0062
	(0.51)	(-1.12)	(1.72)	(0.98)
Asset Growth			0.0165*	0.0211*
			(1.76)	(1.89)
B/M			0.0256	0.0292
			(1.57)	(1.59)
1(*Dividend*)			-0.0284**	-0.0226
			(-2.48)	(-1.59)
Lag(12mth exret)			0.0956***	0.1088***
			(3.17)	(3.22)
Lag(12mth ret std)			9.1411***	12.5405***
			(8.93)	(9.01)
Leverage			0.0072***	0.0120***
			(3.99)	(5.95)
ROE			-0.0781**	-0.1630***
			(-2.35)	(-2.77)
Sales Growth			0.0203	0.0163
			(1.38)	(1.02)
Industry FE	Yes	Yes	Yes	Yes
# of months	312	312	312	312
Mean (R^2)	0.71	0.56	0.75	0.60
Mean (# obs)	672	672	668	668

Panel B: Downside Risk Measures

	Dependent Variables					
	Relative Downside Beta	Coskewness	Tail Risk	Relative Downside Beta	Coskewness	Tail Risk
ES Score	-0.0186***	0.0125***	-0.0276**	-0.0161***	0.0120***	-0.0208**
	(-4.14)	(6.87)	(-2.28)	(-3.81)	(7.67)	(-2.01)
lag(Beta)	-0.0502***	0.0049	0.3602***	-0.0975***	-0.0065	0.2114***
	(-3.22)	(0.57)	(5.68)	(-6.47)	(-0.48)	(3.97)
lag(Coskewness)	0.0387	0.0476**	0.0737**	0.0202	0.0256**	0.0157
	(1.51)	(2.42)	(2.09)	(0.92)	(2.38)	(0.49)
lag(Rel down beta)	0.0805***	-0.0021	0.0905***	0.0624***	-0.0098*	0.0293
	(4.93)	(-0.22)	(5.42)	(4.76)	(-1.72)	(1.62)
lag(Tail risk)	0.0179**	-0.0158***	0.1209***	0.0122	-0.0146***	0.1216***
	(2.39)	(-3.79)	(8.58)	(1.48)	(-2.79)	(5.91)
log(Size)	-0.0108**	-0.0007	-0.0555***	-0.0067*	0.0004	-0.0396***
	(-2.38)	(-0.25)	(-4.50)	(-1.68)	(0.16)	(-3.61)
Asset Growth				0.0046	0.0067*	0.0233
				(0.54)	(1.81)	(1.40)
B/M				0.0036	-0.0022	0.1021**
				(0.27)	(-0.40)	(2.42)
1(*Dividend*)				0.0058	-0.0025	-0.0390
				(0.67)	(-0.93)	(-1.55)
Lag(12mth exret)				0.0132	-0.0004	0.0017
				(1.10)	(-0.08)	(0.07)
Lag(12mth ret std)				3.3994***	1.304	8.5756***
				(4.05)	(1.60)	(4.44)
Leverage				0.0048***	-0.0023***	0.0138***
				(4.78)	(-2.83)	(3.78)
ROE				-0.0850*	0.0390**	-0.2074*
				(-1.73)	(2.39)	(-1.81)
Sales Growth				-0.0040	-0.0030	-0.0307*
				(-0.44)	(-0.63)	(-1.71)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
# of months	312	312	276	312	312	276
Mean (R^2)	0.29	0.31	0.46	0.32	0.34	0.50
Mean (# obs)	672	672	603	668	668	599

Table 5. Panel Regression Analysis

This table shows the results of panel regressions of realized risk in each year—unconditional β, downside β, relative downside β, and coskewness—on past ES score. The observations are at firm-year level. We include all control variables included in Table 4, except including firm fixed effects in lieu of industry fixed effects. We also include year fixed effects. $\mathbf{1}(\mathit{NegMktRet})$ ($\mathbf{1}(\mathit{PosMktRet})$) is a dummy variable that is equal to 1 if the market's realized excess return in a given year is negative (positive), and 0 otherwise. Standard errors are double clustered by firm and time. *** 1%, ** 5%, * 10% significance.

Panel A: Aggregate ES effect

	Dependent Variables			
	Beta	Downside Beta	Relative Downside Beta	Coskewness
ES Score	-0.0304 (-1.68)	-0.0528** (-2.64)	-0.0224** (-2.46)	0.0147*** (3.10)
Control Variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.6678	0.5203	0.1902	0.6412
Nobs	17,299	17,299	17,299	17,299

Panel B: ES effect conditional on market excess return

	Dependent Variables			
	Beta	Downside Beta	Relative Downside Beta	Coskewness
ES Score $\times\mathbf{1}(\mathit{PosMktRet})$	-0.0298 (-1.63)	-0.0498** (-2.44)	-0.0200** (-2.07)	0.0135*** (2.80)
ES Score $\times\mathbf{1}(\mathit{NegMktRet})$	-0.0359 (-0.84)	-0.0788* (-1.90)	-0.0429*** (-3.91)	0.0246** (2.49)
Control Variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.6678	0.5204	0.1903	0.6413
Nobs	17,299	17,299	17,299	17,299

Table 6. Fama MacBeth Regression Analysis - 12 months return

This table shows the results of Fama–MacBeth (1973) regressions of realized excess and DGTW-adjusted return over the next 12 months on past ES score. In the first (last) two columns, we control for realized market beta (downside and upside beta) computed over the next 12 months using daily returns. In all specifications, we control for realized return volatility and coskewness over the next 12 months, as well as past log-size, past book-to-market ratio, and past 12-month excess return. We include industry fixed effects, based on two-digit Standard Industrial Classification (SIC) codes. The regressions are run monthly. We use 12 Newey–West (1987) lags for standard error. *** 1%, ** 5%, * 10% significance.

	Dependent Variables: log(1+Cumulative 12 months return)			
	Excess Return	DGTW-adj Return	Excess Return	DGTW-adj Return
ES Score	0.0084*	0.0088**	0.0094**	0.0098**
	(1.84)	(1.99)	(1.99)	(2.15)
Beta	0.1709***	0.1761***		
	(5.18)	(6.02)		
Downside Beta			0.0751***	0.0679***
			(4.00)	(3.61)
Upside Beta			0.0702***	0.0792***
			(4.34)	(4.49)
log(MktCap)	-0.0193***	-0.0105***	-0.0179***	-0.0094***
	(-4.34)	(-4.09)	(-4.00)	(-3.99)
B/M	0.0058	-0.0050	0.0045	-0.0066
	(0.41)	(-0.34)	(0.32)	(-0.44)
lag(12mth exret)	-0.0109	-0.0180	-0.0078	-0.0160
	(-0.59)	(-1.10)	(-0.43)	(-1.05)
12mth ret std	-15.6415***	-13.8976***	-14.5843***	-12.6262***
	(-11.38)	(-13.47)	(-9.51)	(-10.57)
Coskewness	-0.0054	-0.0010	-0.0023	-0.0210
	(-0.20)	(-0.05)	(-0.06)	(-0.51)
Industry FE	Yes	Yes	Yes	Yes
# of months	312	312	312	312
Mean (R^2)	0.3934	0.3229	0.3938	0.3237
Mean (# obs)	693	672	693	672

Table 7. Fama MacBeth Regression Analysis - ES Score Decomposition and Climate Score

This table shows the results of Fama–MacBeth (1973) regressions analogous to those in the last three columns of Panel B of Table 4, which regresses the realized downside risks on past total ES score. In lieu of the total ES score, Panel A uses one ESG component at a time. Panel B uses total ES score, or one of its two components, while controlling for the G(overnance) score. Panel C uses, in lieu of the total ES score, the firm's climate change score, which is defined as the firm's clean energy strength minus its climate change concern score, both of which are part of the environment category in the MSCI KLD database. Note that focusing on the firm's climate change score reduces the sample period to only 2000–2013. *** 1%, ** 5%, * 10% significance.

Panel A: Separate Effect

	Dependent Variables								
	Relative Downside Beta			Coskewness			Tail Risk		
E Score	-0.0421***			0.0329***			-0.0848*		
	(-3.25)			(6.68)			(-1.90)		
S *Score*		-0.0153***			0.0114***			-0.0175	
		(-3.44)			(7.04)			(-1.55)	
G *Score*			-0.0137			-0.0033			-0.0237
			(-1.11)			(-0.51)			(-0.66)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of months	312	312	312	312	312	312	276	276	276
Mean (R^2)	0.32	0.32	0.32	0.34	0.34	0.34	0.50	0.50	0.50
Mean (# obs)	668	668	668	668	668	668	599	599	599

Panel B: Controlling for Governance

	Dependent Variables								
	Relative Downside Beta			Coskewness			Tail Risk		
ES Score	-0.0160***			0.0122***			-0.0211**		
	(-3.83)			(7.73)			(-2.05)		
E Score		-0.0425**			0.0337***			-0.0832*	
		(-3.26)			(6.74)			(-1.88)	
S *Score*			-0.0150***			0.0116***			-0.0181
			(-3.47)			(7.11)			(-1.57)
G *Score*	-0.0094	-0.0112	-0.0103	-0.0061	-0.0048	-0.0055	-0.0205	-0.0248	-0.0208
	(-0.77)	(-0.90)	(-0.85)	(-0.92)	(-0.72)	(-0.84)	(-0.58)	(-0.73)	(-0.57)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of months	312	312	312	312	312	312	276	276	276
Mean (R^2)	0.32	0.32	0.32	0.34	0.34	0.34	0.50	0.50	0.50
Mean (# obs)	668	668	668	668	668	668	599	599	599

Panel C: Climate Change Score

	Dependent Variables				
	Beta	Downside Beta	Relative Downside Beta	Coskewness	Tail Risk
ClimateChg Score	-0.0041	-0.0128***	-0.0087**	0.0061**	-0.0192
	(-0.92)	(-2.74)	(-1.98)	(2.27)	(-1.11)
Control variables	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
# of months	168	168	168	168	168
Mean (R^2)	0.7690	0.6245	0.3230	0.3437	0.5266
Mean (# obs)	732	732	732	732	680

Table 8. Fama MacBeth Regression Analysis - Robustness Check

This table shows the results of Fama–MacBeth (1973) regressions analogous to those in Table 4, which uses firms with market value above median NYSE market equity during period 1993–2017. Instead, we use the alternative sample of all firms in the period after 2001. Panel A considers the same regressions in the last three columns of Panel B of Table 4. Panel B interacts ES performance with $\mathbf{1}(SmlCap)$ and $\mathbf{1}(BigCap)$, where $\mathbf{1}(SmlCap)$ ($\mathbf{1}(BigCap)$) is a dummy variable that is equal to 1 if the firm's market value is below (above) the median NYSE market equity, and 0 otherwise. *** 1%, ** 5%, * 10% significance.

Panel A: Full Sample

	Dependent Variables		
	Relative Downside Beta	Coskewness	Tail Risk
ES Score	-0.0100**	0.0094***	-0.0159**
	(-2.09)	(4.47)	(-2.28)
lag(Beta)	-0.1062***	-0.0006	0.2138***
	(-9.18)	(-0.06)	(4.65)
lag(Coskewness)	0.0151	0.0300**	-0.0427
	(0.69)	(2.36)	(-1.16)
lag(Rel down beta)	0.0425***	-0.0068	-0.0018
	(4.95)	(-1.41)	(-0.10)
lag(Tail risk)	0.0096	-0.0130***	0.1047***
	(1.23)	(-3.55)	(6.31)
log(Size)	0.0162***	-0.0099***	-0.0230*
	(3.77)	(-2.75)	(-1.90)
Asset Growth	-0.0092	0.0048	0.0216
	(-0.84)	(1.17)	(1.04)
B/M	0.0092	-0.0081**	0.0853**
	(0.74)	(-2.59)	(2.32)
$\mathbf{1}(Dividend)$	-0.0089	0.0001	-0.0290**
	(-1.59)	(0.05)	(-2.43)
Lag(12mth exret)	-0.0060	0.0065	-0.0247
	(-0.54)	(1.56)	(-1.34)
Lag(12mth ret std)	3.6785***	0.5969	3.7840***
	(3.93)	(1.07)	(4.53)
Leverage	0.0046***	-0.0014***	0.0216**
	(3.84)	(-3.06)	(2.00)
ROE	-0.0224	-0.0003	-0.1874***
	(-1.32)	(-0.06)	(-3.16)
Sales Growth	0.0015	0.0013	0.0026
	(0.18)	(0.67)	(0.35)
Industry FE	Yes	Yes	Yes
# of months	192	192	156
Mean (R^2)	0.20	0.24	0.33
Mean (# obs)	1,989	1,989	1,822

Panel B: Separate Estimation Based on Size

	Dependent Variables		
	Relative Downside Beta	Coskewness	Tail Risk
ES Score $\times\mathbf{1}$*(BigCap)*	-0.0159**	0.0143***	-0.0140*
	(-2.52)	(6.34)	(-1.85)
ES Score $\times\mathbf{1}$*(SmlCap)*	-0.0053	0.0017	-0.0227
	(-0.46)	(0.33)	(-0.89)
lag(Beta)	-0.1067***	-0.0004	0.2133***
	(-9.38)	(-0.03)	(4.65)
lag(Coskewness)	0.0174	0.0290**	-0.0402
	(0.80)	(2.30)	(-1.11)
lag(Rel down beta)	0.0425***	-0.0067	-0.0019
	(4.97)	(-1.40)	(-0.10)
lag(Tail risk)	0.0093	-0.0130***	0.1043***
	(1.19)	(-3.54)	(6.37)
log(Size)	0.0155***	-0.0096***	-0.0232*
	(3.57)	(-2.64)	(-1.94)
Asset Growth	-0.0088	0.0046	0.0221
	(-0.79)	(1.11)	(1.06)
B/M	0.0094	-0.0082***	0.0860**
	(0.75)	(-2.66)	(2.35)
$\mathbf{1}$(*Dividend*)	-0.0088	0.0001	-0.0287**
	(-1.56)	(0.03)	(-2.45)
Lag(12mth exret)	-0.0056	0.0063	-0.0245
	(-0.51)	(1.51)	(-1.34)
Lag(12mth ret std)	3.7109***	0.5832	3.8088***
	(3.96)	(1.05)	(4.58)
Leverage	0.0045***	-0.0014***	0.0215**
	(3.82)	(-3.05)	(2.00)
ROE	-0.0217	-0.0007	-0.1880***
	(-1.28)	(-0.13)	(-3.17)
Sales Growth	0.0012	0.0014	0.0024
	(0.15)	(0.68)	(0.33)
Industry FE	Yes	Yes	Yes
# of months	192	192	156
Mean (R^2)	0.20	0.24	0.33
Mean (# obs)	1,989	1,989	1,822

Table 9. Doing Well by Doing Good: News Sentiment Patterns

We measure daily news sentiment for each firm as the average of RavenPack's sentiment scores across all news for each firm-day observation. We filter for news stories in which the firm was prominent (i.e., a relevance score of 100), and for the first story that reports a same categorized event (i.e., a novelty score of 100). Note that focusing on RavenPack's firm-level news sentiment data reduces the sample period to 2000–2017.

This table shows the results of our analysis using the portfolio news sentiment measures by examining the quintile portfolios sorted on their past ES scores, as detailed in Section 4.1.2. Note that we value-weight firm-level news sentiment to construct portfolio news sentiment. Panel A shows the results of Fama–MacBeth (1973) regressions of daily portfolio excess returns on contemporaneous, daily portfolio news sentiment, where we compute the t-statistics by using 5 Newey–West (1987) lags. We construct sentiment-based measures of downside covariation in the same way as the corresponding measures based on stock returns. Panel B reports the time-series averages of relative sentiment downside betas and sentiment unconditional betas for each quintile portfolio. Panel C conducts the same analysis as in Panel B, except it sorts firms on their ES scores *within* each industry, based on two-digit Standard Industrial Classification (SIC) codes. All the t-statistics in Panels B and C are computed using 12 Newey–West lags.

Panel A: Fama MacBeth Regression of Portfolio Excess Return on Portfolio Sentiment

	ES Sort		ES Sort Within-industry	
Return	*Equal-Weighted*	*Value-Weighted*	*Equal-Weighted*	*Value-Weighted*
Intercept	-0.0102***	-0.0203***	-0.0055***	-0.0173***
	(-4.65)	(-6.49)	(-3.77)	(-6.81)
AggSent	0.0002***	0.0004***	0.0001***	0.0004***
	(4.87)	(6.58)	(4.07)	(6.95)
N (# of days)	4,528	4,528	4,528	4,528
R^2	0.25	0.26	0.26	0.26

Panel B: Sentiment Beta Analysis - ES Sort

	Low	2	3	4	High	High-Low	t-stat
Beta	1.2274	0.9949	0.8714	0.8152	0.9238	-0.3036***	-4.67
Rel. Downside Beta	0.1329	-0.0126	0.0529	0.0088	-0.1573	-0.2901***	-5.96

Panel C: Sentiment Beta Analysis - ES Sort within Industry

	Low	2	3	4	High	High-Low	t-stat
Beta	1.2523	1.0323	0.8701	0.8242	0.9343	-0.3180***	-4.14
Rel. Downside Beta	0.1547	-0.0195	-0.0117	-0.0516	-0.1144	-0.2691***	-3.88

Table 10. ES Preferences of Institutional Investors: Trading Patterns

We measure daily institutional trading for each firm using Abel Noser institutional trading data. For each firm on a given day, we calculate the aggregate net shares traded by institutional investors, then scale the trading imbalance by focusing on its direction: 1 for net institutional buying, -1 for net selling, and 0 for zero net position. Note that focusing on Abel Noser's institutional trading data reduces the sample period to January 1999–January 2010.

This table shows the result of Fama-MacBeth (1973) regression of realized institutional trading β on past ES score, risk characteristics, and other firm characteristics. All independent variables are measured in a period before the realization of institutional trading pattern. For each firm, trading βs are computed using the direction of daily aggregate institutional trading over the next 12 months, as detailed in Section 4.2.1. We include industry fixed effects, based on two-digit Standard Industrial Classification (SIC) codes. The regressions are run monthly. We use 12 Newey–West (1987) lags for standard error. *** 1%, ** 5%, * 10% significance.

Dependent Variable	Trading Beta	Downside Trading Beta	Rel. Downside Trading Beta	Downside Trading Beta	Rel. Downside Trading Beta
Downside criteria		$MktEx_t < \overline{Daily\_MktEx}$		$MktEx_t <$ 25th $Daily\_MktEx$	
ES Score	0.2151	-0.0618	-0.2770	-1.2958**	-1.5109**
	(1.36)	(-0.24)	(-0.76)	(-1.98)	(-2.16)
lag(Beta)	0.6908***	1.7067**	1.0159	1.4032	0.7124
	(2.95)	(2.39)	(1.35)	(1.62)	(0.77)
lag(Coskewness)	-0.5191	-0.8699	-0.3507	2.9802	3.4994
	(-0.54)	(-0.55)	(-0.27)	(0.97)	(1.10)
lag(Rel down beta)	-0.6993**	0.1576	0.8569*	-0.0890	0.6103
	(-2.18)	(0.30)	(1.81)	(-0.10)	(0.68)
lag(Tail risk)	0.3475***	0.3014	-0.0461	0.7154	0.3679
	(3.88)	(1.26)	(-0.20)	(1.45)	(0.79)
log(Size)	0.5138***	0.2851	-0.2288*	-0.3467	-0.8606***
	(5.29)	(1.42)	(-1.84)	(-1.36)	(-3.44)
Asset Growth	0.1131	0.0910	-0.0221	0.6501	0.5370
	(0.46)	(0.22)	(-0.04)	(0.67)	(0.60)
B/M	-0.8282***	-0.9339	-0.1057	-2.5668**	-1.7386
	(-2.65)	(-1.54)	(-0.25)	(-2.07)	(-1.56)
$\mathbf{1}$(*Dividend*)	-0.0026	-0.3889	-0.3863	0.3405	0.3432
	(-0.02)	(-1.06)	(-1.27)	(0.57)	(0.63)
Lag(12mth exret)	0.1626	-0.2086	-0.3713	-0.2329	-0.3955
	(0.88)	(-0.34)	(-0.62)	(-0.30)	(-0.49)
Lag(12mth ret std)	31.8699**	17.7926	-14.0774	0.4765	-31.3935
	(2.60)	(0.42)	(-0.38)	(0.01)	(-0.89)
Leverage	0.1471***	0.3330***	0.1859***	0.4405***	0.2934***
	(3.65)	(6.93)	(5.55)	(3.39)	(2.64)
ROE	0.7760*	3.3676**	2.5916*	2.5014	1.7254
	(1.81)	(2.10)	(1.69)	(0.85)	(0.61)
Sales Growth	0.0031	0.5117	0.5086	1.8231**	1.8200**
	(0.01)	(0.92)	(0.98)	(2.21)	(2.39)
Industry FE	Yes	Yes	Yes	Yes	Yes
# of months	133	133	133	133	133
Mean (R^2)	0.15	0.12	0.12	0.12	0.12
Mean (# obs)	696	696	696	696	696

Table 11. Sustainalytics

This table shows the results of Fama–MacBeth (1973) regressions of realized risk exposure on past ESG profile from Sustainalytics. Following our main analysis in Table 4, we include the same control variables, and focus on big firms (i.e., market value above median NYSE market equity), except we use Sustainalytics' total ESG score in lieu of ES score constructed from KLD. The first three columns in each panel use the scores as it is, while the last three columns use their natural logarithms. In Panel B, we use subset of firms after excluding those with negative book value. The sample period is September 2009–December 2017. Industry fixed effects are based on two-digit Standard Industrial Classification (SIC) codes. The regressions are run monthly. Because relative downside β and coskewness are computed over the next 12 months, we use 12 Newey–West (1987) lags for standard error; tail risk β is computed over the next 60 months, so we use 60 Newey–West lags. *** 1%, ** 5%, * 10% significance.

Panel A: Full Sample

	Dependent Variables					
	Relative Downside Beta	Coskewness	Tail Risk	Relative Downside Beta	Coskewness	Tail Risk
	Raw Score			*Log Score*		
ESG Score	-0.0001	0.0004*	0.0013	-0.0125	0.0212**	0.0677
	(-0.61)	(1.96)	(1.19)	(-1.37)	(1.99)	(1.07)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
# of months	100	100	64	100	100	64
Mean (R^2)	0.34	0.37	0.56	0.34	0.37	0.56
Mean (# obs)	651	651	622	651	651	622

Panel B: Excluding Firms with Negative Book Value

	Dependent Variables					
	Relative Downside Beta	Coskewness	Tail Risk	Relative Downside Beta	Coskewness	Tail Risk
	Raw Score			*Log Score*		
ESG Score	-0.0002	0.0003*	0.0014	-0.0152*	0.0191*	0.0725
	(-1.01)	(1.72)	(1.33)	(-1.75)	(1.76)	(1.23)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
# of months	100	100	64	100	100	64
Mean (R^2)	0.35	0.38	0.57	0.35	0.38	0.57
Mean (# obs)	633	633	607	633	633	607