# Doing Well by Doing Good?
# Risk, Return, and Environmental and Social Ratings*

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**Abstract**

We analyze the risk and return characteristics across portfolios of firms sorted by their environmental and social (ES) ratings. We document that ES ratings have no statistically significant relationship with average stock returns nor unconditional market risk. Firms with high ES ratings *do* have significantly lower downside risk than firms with low ES ratings. However, a firm's downside risk decreases by only 2–4% of its interdecile range for an interdecile-range increase in a firm's ES score. Our results suggest that the risk-return profile of ES firms cannot be the sole rationale for or against ES investing.

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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 31 trillion in 2018.[1] ESG funds have also attracted record inflows during the ongoing COVID-19 pandemic.[2] However, a recent amendment to the Employee Retirement Income Security Act of 1974 (ERISA) requires that plan fiduciaries select investments based solely on financial considerations relevant to the risk-adjusted economic value of that investment.[3] We shed light on this ongoing debate on whether ESG investments can be justified solely based on risk-return considerations by revisiting the relationship between the risk, return, and ES ratings of a firm.[4]

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." For example, a firm may economize on safety or pollution control. While this could increase profits in the short run, this exposes the firm 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* downside risk and, more generally, stronger financial performance.

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.

[1] See 2018 Global Sustainable Investment Review, page 8.

[2] `https://tinyurl.com/y2533l2c`

[3] `https://tinyurl.com/y6rzae67`

[4] As highlighted in the 2020 US Social Investment Foundation Trends Report, 84% (73%) of the institutions cited risk (return) as the motivation for considering ESG factors. But, there is still no consensus on the relationship between the ESG profile of a firm and its realized stock returns (see Hong and Kacperczyk (2009); Kempf and Osthoff (2007); Edmans (2011); Chava (2014); and Lins, Servaes, and Tamayo (2017)).

We find no meaningful relationship between the realized stock returns and ES ratings of a firm. We find that after controlling for the size effect and the strong auto-correlation of the regular beta, the relationship between ES scores and market betas is statistically insignificant. However, we find that firms with high ES ratings have statistically significantly lower downside risk than firms with low ES ratings, as measured by their downside beta, relative downside beta, coskewness, and tail risk beta. But, the economic magnitude of this decrease in downside beta for high-ES firms is small. An interdecile-range increase in a firm's ES score results in only a 2–4% interdecile-range decrease in the underlying downside risk measure. Such reductions of downside risk correspond to less than 0.07% – 0.23% per annum in expected returns—gains that are economically small.

We begin our analysis by examining patterns of future returns and unconditional market risk 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[5], we find no evidence that high-ES stocks outperform low-ES stocks. We do find that firms with high ES scores have lower market betas than low-ES firms within the same industry. However, we show that this relation is explained away by the size effect and the strong autocorrelation of regular betas.

We then analyze patterns in 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 statistically significantly lower downside risk in the future. Moreover, these relations continue to hold when we control for other firm characteristics (e.g., downside risk in the

[5]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.

past, firm size). Our results remain similar when we consider two alternative proxies for the 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.

While stocks with high ES ratings have statistically significantly lower downside risk, the magnitudes of these effects are economically small. For example, our estimates indicate that an interdecile-range move across firms in terms of their ES score is associated with a decrease in relative downside beta, whose magnitude is about 3% of the interdecile range in our sample. Such a reduction of downside risk in terms of relative downside beta corresponds to an equivalent compensation of 0.19% per annum in expected returns.[6] Of course, these humbling results may very well stem from a measurement problem: Our analysis relies on KLD ratings alone, so it may be subject to a real errors-in-variables (EIV) problem. We note that correcting this attenuation bias is unlikely to overturn our conclusion that the effect of CSR activities on downside risk is economically small. In the appendix, we find similar results using Sustainalytics ratings, another major ESG ratings provider. However, it is possible that our results can be partly attributed to the difficulty in measuring the ES profile of a firm.

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

[6]See Panel C of Table 1 in Ang, Chen, and Xing (2006): An interdecile-range move across firms in terms of $\beta^{-} - \beta$ corresponds to a change in expected returns of 6.64% per annum.

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 a reduction in downside risk can be one pecuniary benefit of investing based on ES factors, but this decrease in downside risk is not economically meaningful. Prior literature on the ES–financial performance link is mixed. If anything, investing in ES funds typically imposes large costs on mean-variance investors (Geczy, Stambaugh, and Levin (2005)). In turn, various researchers have interpreted the growth of ES-focused investment vehicles as due to irrational beliefs or non-pecuniary motives such as altruism or conformity to social norms. (See, e.g., Hartzmark and Sussman (2019) and Barber, Morse, and Yasuda (2021).) Consistent with these papers, our results suggest that growth in ES investing may be partly due to investors valuing positive societal externalities in utility in addition to wealth.

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. We use various measures of downside risk to expand on, as well as qualify, the value of resilience of ES firms during these rare episodes of market collapse for portfolio selection from 1991 to 2016.

More broadly, our study adds to recent literature addressing the risk implications of ES-focused investing by highlighting the small economic magnitude of the decrease in downside risk for ES firms (see Godfrey, Merrill, and Hansen (2009); Oikonomou, Brooks, and Pavelin (2012); Kim, Li, and Li (2014); and Krüger (2015)). Hoepner et al. (2020) find that ESG engagement reduces firms' idiosyncratic downside risk, as well as their exposure to an idiosyncratic downside-risk factor. Bolton and Kacperczyk (2020) argue that investors demand compensation for their exposure to carbon emission risk. Ilhan, Sautner, and Vilkov (2020) show that firms with more carbon emissions exhibit higher tail risk and higher variance risk. Theoretically, Albuquerque, Koskinen, and Zhang (2019) build a theoretical model which predicts that CSR decreases systematic risk, while Pástor, Stambaugh, and Taylor (2020) theoretically construct an ESG risk factor that is capable of pricing assets.

# 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. 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).

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, Servaes, 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.[7] There is considerable dispersion in ES performance

[7] Note that our measure of ES performance is linear. In unreported results, we use dummy variables for ES performance quartiles such that ES2 takes the value of one if the firm is in the second 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.

## 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 from Ibbotson Associates 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 $\beta^-$) relative to the regular beta with respect to the market portfolio (denoted by $\beta$). We consider two alternative proxies for the 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.

quartile and zero otherwise, ES2 takes the value of one if the firm is in the third ES performance quartile and zero otherwise, and ES4 takes the value of one if the firm is in the fourth ES performance quartile and zero otherwise. 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 is monotonic. Our main results are also robust: While firms with high ES ratings have statistically significantly lower downside risk, the magnitudes of these effects are economically small. The results are also very similar when we add or use dummy variables for other ES performance percentiles. All of these results are available upon request.

### 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 $\tau$, and let $\widetilde{r}_{m\tau}$ denote the market's excess return on day $\tau$. 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 $\beta$, 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 the 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 $t$. We calculate the demeaned excess return of asset $i$ and the demeaned market excess return conditional on the market excess return being below the sample mean, which we denote 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, $\lambda_t$, 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 $k$th 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 $\beta$, denoted by $\widehat{\beta}_{it}^{\text{tail}}$, as the regression coefficient of firm returns on the common tail risk component $\lambda_t$ using 60 months of data following portfolio formation. To calculate tail risk betas, we require that firms have nonmissing return data for at least 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 December 2014 rather than December 2017, as in the rest of 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

In this section, we begin by examining patterns of future returns and unconditional market risk for portfolios sorted on their past ES score. To the extent that high-ES firms provide high returns and/or low market risk exposure going forward, it can be straightforward to explain why investors demand the stocks of these firms.

### 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, certainly not increasing from the low-ES to high-ES portfolios. Firms in the highest ES-score quintile earn value-weighted average annual returns that are 0.60% lower than firms in the lowest quintile, with a $t$-statistic of $-0.4$. The equal-weighted high-minus-low ES-score portfolio average return is virtually zero ($t = 0.04$). The average returns of the long-short portfolios are not only statistically insignificant 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. For the three-factor model, the alpha is $-0.96\%$ per annum ($t = -0.7$). On an equal-weighted basis, the high-minus-low ES-score portfolio alphas are typically positive but insignificant. For example, the three-factor alpha is only 0.12% ($t = 0.1$).

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 low-ES firms. If anything, high-ES firms appear to be underperforming low-ES firms, but it depends on whether we use value-weighted portfolios. Importantly, the underperformance of high-ES firms is small, and it is never statistically significant. These results suggest that (abnormal) returns cannot explain the preference for (or against) ES investing.

#### 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 $\beta$ of each quintile portfolio. Using daily data over the next 12 months, we calculate a stock's regular beta, as described in Equation (1). 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 quintile portfolio 5 (high ES) and quintile portfolio 1 (low ES).

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 1 and 5 is $-0.038$, which is statistically significant at the 1% level.

In summary, Table 2 demonstrates that ES scores do not have return implications, but they do seem to have implications for unconditional risk exposure: 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. 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

We now examine patterns of future downside risk for portfolios sorted on past ES score. To the extent that high-ES stocks provide low downside risk exposure going forward, investors who care more about downside losses than upside gains would demand these stocks.

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 as in Equation (2) and its coskewness as in Equation (3), as well as 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 quintile portfolio 5 (high ES) and quintile portfolio 1 (low ES), 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 statistically significant at the 1% level. In other words, the prices of high-ES stocks tend to decrease less than those of low-ES stocks *with comparable market risk exposure.* Note that this implies that the prices of high-ES stocks also tend to increase more 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.

We examine whether the cross-sectional implications of ES score on downside risk are robust to controlling for industry. Industry can be an important driver of these results (as well as those in Panel A of Table 2) for several reasons. First, some industries are considered more controversial than others.[8] Second, Fama and French (1997) show that market risk exposure varies substantially across industries. Therefore, in Panel B, we control for industry by sorting stocks within each industry into quintiles according to their ES scores.

That firms' ES scores predict their downside risk is robust to controlling for industry: High-ES firms continue to have low relative downside betas and high coskewness. Controlling for industry preserves the statistical significance of spreads in these measures of downside risk. They are 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 a significant role in delivering a negative relation between ES score and downside risk, even though it does not fully explain away the relation.

On the other hand, past ES score seems to be a poor predictor of future tail risk. 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 between the first and fifth ES quintile portfolios is still statistically insignificant, with a $t$-statistic of $-1.4$. Perhaps surprisingly, 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.

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

Finally, while Panel A shows that 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, which is highly statistically significant, with a $t$-statistic of $-4.2$. This result can be consistent with high-ES firms' low downside risk, but another possible explanation is that it mechanically reflects the relation between past ES scores and future regular betas. Panel B of Table 1 shows that $\beta$ and $\beta^{-}$ are highly correlated, with a correlation around 0.83. Given this correlation, it is not surprising that patterns of $\beta$ and $\beta^{-}$ sorted on past ES score are qualitatively the same. Therefore, we must be cautious when measuring downside risk to control for the regular beta by focusing on relative downside beta, $(\beta^{-} - \beta)$, in lieu of downside beta.

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 low regular, unconditional betas. These results suggest that, in an economy where investors care more about downside losses than upside gains, the low downside risk of high-ES firms can account for why investors demand the stocks of these firms. However, these relations do not control for firm characteristics (with the exception of industry) that are correlated with future downside risk (e.g., downside risk in the past) or contemporaneously correlated with ES scores (e.g., firm size).

## 3.3 ES Score as a Predictor of Future Risk Exposure

There is little theoretical guidance regarding which firm characteristics determine the riskiness of a stock, but a number of studies, including Daniel and Titman (1997); Harvey and Siddique (1999); and Ang, Chen, and Xing (2006); have empirically explored how risk exposures are related to firm characteristics. In Table 4, we examine the negative relationship between high ES scores and future risks for holding such stocks, 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) that are known ex ante and on past risk characteristics that are also measured ex ante.

### 3.3.1 ES Score Does Not Predict Future Unconditional Risk Exposure

In Panel A, we first consider regressions of future realized regular 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 the following: (i) ES score and log of market capitalization, (ii) industry fixed effects, and (iii) risk measures (i.e., regular beta, relative downside beta, coskewness, and tail risk beta) over the past months. 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 betas over the next 12 months. On the other hand, past betas are a strong predictor of future betas. Hence, the strong predictive pattern of past ES scores and future regular betas in Panel B of Table 2 is explained away by the size effect and the strong 12-month autocorrelation of regular betas. Column 3 adds additional stock characteristics, only to confirm the robustness of this negative result.

In summary, we find no empirical support for a reward for ES investing in terms of unconditional risk exposure. 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 suggest that the unconditional risk and return of ES investing cannot rationalize it. In contrast, 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 past ES score can predict future realized measures of downside risk—relative downside beta, coskewness, and tail risk beta—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 evidence for ES score as a predictor of future relative downside beta is negative, with $t$-statistics around $-4$. Consider a one-point increase in ES score, which is about the same order of magnitude as the interdecile range in our sample (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 about 0.016, controlling for the full list of firm characteristics 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 highly statistically significant effects of ES investing on decreasing relative downside beta are essentially independent of other firm characteristics and risk characteristics.

Moreover, there is strong evidence that high-ES firms tend to have high future coskewness and low future exposure to tail risk. Since firms with high coskewness or low tail risk tend to have low covariation with the market when the market declines, these results are consistent with high-ES firms having low downside risk. The estimated coefficients on ES score indicate that a one-point increase in ES score is associated with an increase in coskewness of about 0.012 (Columns 2 and 4 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 in Table 3 are insignificant. According to the last column of Panel B of Table 4, changing the ES score by one point is associated with a statistically significant decrease in tail risk exposure of 0.021.

In summary, the reward for ES investing, in terms of downside risk, is 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 when controlling for industry alone. Taken together with our negative results on unconditional risk and return, downside risk seems to be the singular rationale for why investors might care about CSR.

### 3.3.3 Interpreting the Economic 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 earlier 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 $1.05 \times 0.016 = 0.017$ (which represents about 3% of the interdecile range in our sample), (ii) an increase in coskewness of $1.05 \times 0.012 = 0.013$ (which represents about 4% of the interdecile range in our sample), and (iii) a decrease in tail risk beta of $1.05 \times 0.021 = 0.022$ (which represents about 2% of the interdecile range in our sample). These quantities imply reductions of downside risk in terms of relative downside $\beta$, coskewness, and tail risk $\beta$ that correspond to equivalent compensations of 0.19%, 0.23%, and 0.071% per annum in expected returns, respectively.[9]

[9] See Panel C of Table 1 in Ang, Chen, and Xing (2006): An interdecile-range move across stocks in terms of $\beta^{-} - \beta$ corresponds to a change in expected returns of 6.64% per annum. See Panel B of Table 3 in Ang, Chen, and Xing (2006): An interdecile-range movement across coskewness changes expected returns by 6.22% per annum. See Panel A of Table 4 in Kelly and Jiang (2014): An interdecile-range move across stocks in terms of $\beta^{\text{tail}}$ corresponds to a change in expected returns of 3.96% per annum.

In sum, such reductions of downside risk do not seem economically meaningful.

Of course, these humbling results may very well stem from a measurement problem: Our proxies for CSR may not accurately measure a firm's CSR activities. Indeed, the ESG ratings of leading agencies disagree substantially (Chatterji et al. (2016) and Berg, Koelbel, and Rigobon (2020)). Therefore, our analysis, which relies on KLD ratings alone, is subject to a real errors-in-variables (EIV) problem. We did not worry about the EIV problem when establishing statistical significance, as it works against us. However, the EIV problem introduces an attenuation bias that is of first-order importance for assessing the economic significance of the estimates in Table 4. Unfortunately, correcting the attenuation bias is unlikely to overturn our conclusion that the effect of CSR activities on downside risk is economically small. For example, a naive back-of-the-envelope calculation suggests that 97% of the variation in our ES scores must be noise if, in reality, a two-standard-deviation move across stocks in terms of ES score is associated with one-standard-deviation decrease in relative downside beta. Nevertheless, it would surely be interesting to address the attenuation bias by using ES ratings from multiple raters or by proposing a more accurate measure of CSR activities. We leave this task for future research.

On one hand, our results can explain why long-term investors care more about ES issues (Starks, Venkat, and Zhu 2020): Such investors are more exposed to downside risk and rationally ought to be more concerned about ES issues, which can help them mitigate downside risk. On the other hand, our discussion suggests a cautionary investing note: Purely financial considerations may not be enough to justify ES investing.

## 3.4 Robustness

### 3.4.1 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 net 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 in order to avoiding stocks that covary strongly when the market dips. We also examine the G score (i.e., the corporate governance category in the MSCI KLD database) 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 aggregate ES performance. The results are shown in Panel A of Table 5. We also find similar results when we use all three ESG components simultaneously.

Interestingly, we find negative relations between all measures of downside risk and each specific component of the aggregate ES score. The estimated coefficients on the E score are statistically significant, with $t$-statistics around $-3$, 7, and $-2$ for relative downside beta, coskewness, and tail risk beta, respectively. Similarly, the coefficients on the S score are highly statistically significant, except in the case of tail risk beta.

Note that the E score has a cross-sectional standard deviation of 0.12, while the S score's standard deviation is 0.39. These standard deviations arise mechanically: 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 $+5$. The standard deviation of the E score is one third of the S score's standard deviation. At the same time, the coefficients on the E score are three times larger than the coefficients on the S score for relative downside beta and coskewness. In turn, our results indicate that both the E and S elements of ES are of similar importance for predicting these proxies of downside risk. Only in the case of tail risk beta is the coefficient on the E score significantly larger than the coefficient on the S score.

On the other hand, the G score is not important for 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 aggregate ES performance, or one of its two components, and downside risk, controlling for the G score (Panel B). Overall, the negative relation between a firm's CSR activities and downside risk appear to be driven by its environmental and social performance. Both components are equally important for predicting future downside beta and coskewness, while the E component dominates in the case of tail risk beta.

#### 3.4.2 ES Score Predicts Downside Risk in the Universe After 2001

In Panel A of Table 6, we consider the same Fama–MacBeth (1973) regressions in the last three columns of Panel B of Table 4, except we use the period after 2001, when KLD started expanding its coverage to include smaller companies. We find that our main results in the extended sample of big firms are robust: High-ES firms have low relative downside betas and high coskewness, as well as low tail risk betas in the full cross-section of firms in recent times. While these effects remain statistically significant, they are clearly smaller than those in Table 4.

To understand this evidence, we interact the aggregate 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 6. In all columns, we find significant slopes on ES Score$\times 1(BigCap)$ that are similar in magnitude to those in Table 4. The interactions that involve $1(SmlCap)$ are never statistically significant, though all estimates do indicate negative relations between ES score and downside risk for small firms as well.

In short, we obtain the downside risk effects of ES performance that are robust and stable in magnitude across various measures of downside risk and over time, primarily in the cross-section of large firms (Figure 1).[10] These relations are strong enough to produce 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.[11]

### 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

[10] A natural explanation is that these effects are due to patterns of institutional trading, as discussed later.

[11] 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)).

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 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 7. 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[12] 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 7 reports the time-series averages of relative sentiment downside betas

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

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.[13] Panel C conducts the same analysis as in Panel B but controlling for industry. The differences in relative downside and unconditional 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. But such patterns are modest in economic terms: The 5–1 differences in relative sentiment downside betas between ES portfolios are less than half 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 25% of the variation in returns, these effects are not strong enough to produce economically meaningful relations between ES and downside risk.

## 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.[14]

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

[13] All the $t$-statistics in Panels B and C of Table 7 are computed using 12 Newey–West (1987) lags.

[14] 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)).

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 minus shares sold, or trading imbalance).[15] 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 $\beta^-$. 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 8, 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

[15]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.

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 8). 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, 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 economically small, our results indicate that the ES preferences of institutional investors, albeit significant, are quite weak: Trading downside betas decrease by only 3–4% of their interdecile range for an interdecile-range increase in ES score.

# 5 Conclusion

In the past few decades, there has been a substantial increase in the assets invested based on ESG considerations, both in absolute dollars and relative to other investments. However, there is no consensus on whether ESG investing is associated with stronger financial performance. Understanding the risk-return profile of ESG firms is especially important in light of the recent ERISA amendments that require fiduciaries to select investments based solely on their risk and return. In this paper, we analyze how systematic downside risk and, more generally, financial performance of firms vary with their environmental and social ratings. We find strong evidence that firms with high ES ratings have statistically significantly lower downside risk, whereas such firms do not differ from the others based on standard, unconditional market risk or average returns. However, this decrease in downside risk is not economically large. An interdecile-range increase in ES score is associated with a decrease of only 2–4% of the interdecile range of the underlying downside risk measure, amounting to 0.07%–0.23% in expected returns per annum. The economically insignificant association between risk, returns, and ES ratings suggests that a case for or against investing in ES stocks cannot be rationalized based solely on risk and return considerations. Our results suggest that growth in ES investing may be partly due to investors valuing positive societal externalities in utility in addition to wealth.

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# A Appendix: Additional Robustness Tests

In this appendix, we examine the negative relationship between high ES scores and future risks for holding such stocks, except we use ESG performance from Sustainalytics as a robustness check. Specifically, we run Fama-MacBeth (1973) regressions of realized risk exposures on various firm characteristics, including Sustainalytics' total ESG score, that are known ex ante, and on past risk characteristics also measured ex ante.

Sustainalytics analyzes performance against ESG issues by examining a comprehensive set of core and sector-specific metrics, scored and weighted to determine a company's overall ESG performance. It then measures how well companies are prepared for the ESG issues that are the most material to their business by using a customized weight matrix that defines the relative importance of each indicator and reflects the emphasis on key ESG issues for each industry.[16] In turn, Sustainalytics aggregates these raw scores to produce a company's total ESG score (out of 100), as well as its three components: Environmental, Social and Governance. The sample period is from August 2009 to December 2017.

In each panel, we consider regressions of future realized measures of downside risk—relative downside beta, coskewness, and tail risk beta—on past variables at the individual firm level, including Sustainalytics' total ESG score. 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.[17]

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

[17]We have also examined if past total ESG score from Sustainalytics can predict future realized regular beta and downside beta over the next 12 months, controlling for other firm characteristics and risk characteristics. In summary, we continue to find no empirical support for the reward in terms of unconditional risk exposures for investing in high-CSR firms: not only are the estimated slopes on total ESG score never significant, they flip signs depending on the sample we use. In contrast, the negative relation between a firm's CSR activities and future downside beta continues to persist when we use Sustainalytics' total ESG score, though it is no longer statistically significant. Less important but also noteworthy is that the ESG-$\beta^-$ slope estimates are similar in magnitude to those of the ESG-($\beta^- - \beta$) relation in Table 9.

The first three columns use, as the main independent variable, the raw total ESG score from Sustainalytics, while the last three columns use its natural logarithm.[18]

Just like MSCI KLD, Sustainalytics' coverage of small firms (i.e., market value below the median NYSE market equity at the beginning of the year) is sparse: slightly more than 10% of its coverage are small firms. Accordingly, we only use big firms (i.e., market value above the median NYSE market equity) in Panel A, just like in our main analyses.

There is no evidence that high ESG stocks tend to have low future relative downside beta or low future exposure to tail risk, though the ESG-$\beta^{-} - \beta$ slope estimates are consistently negative. We do find that ESG score positively predicts future coskewness, with $t$-statistics around $-2$. Regardless, these coefficient estimates indicate that an interdecile-range increase in Sustainalytics' total ESG score is associated with even smaller reductions of downside risk than those implied by such an increase in our ES score.

Panel B examines a subsample that further excludes firms with negative book value, in which the ESG-$\beta^{-} - \beta$ slope estimate is negative and marginally significant (see column 4 of Panel B). Regardless, the ESG slope estimates are similar in magnitude to those in Panel A and thus not economically meaningful.

Finally, Panels C and D of Table 9 repeat the same exercise as Panels A and B, except that we use the average of Sustainalytics' E(nvironmental) and S(ocial) scores in lieu of its total ESG score. These coefficient estimates indicate that an interdecile-range increase in the average E & S scores is associated with even smaller reductions of downside risk than those implied by such an increase in the total ESG score.

In summary, we continue to find negative relations between a firm's CSR activities and downside risk using Sustainalytics' ESG performance, but the effects are not only economically small but also mostly statistically insignificant. That is, using ES ratings from multiple raters is unlikely to overturn the economically small effect of CSR activities on downside risk.

[18] We also include all those firm characteristics in the last three columns of Panel B of Table 4 other than the ES score that we construct from MSCI KLD.

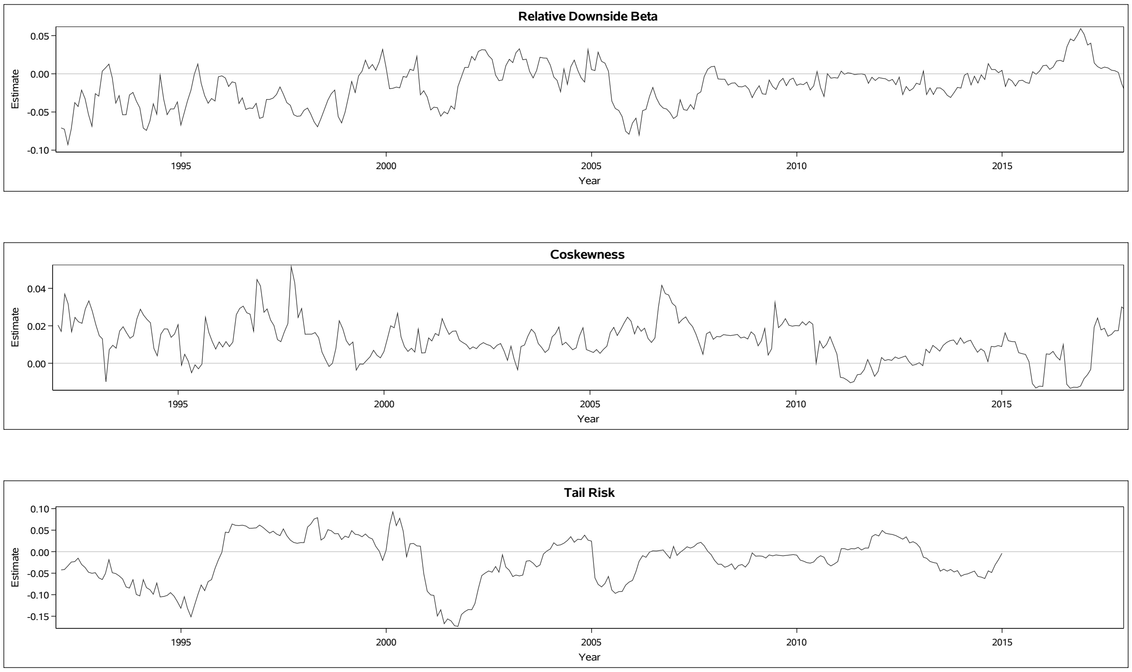


**Figure 1: Monthly ES Coefficient Estimates**

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.

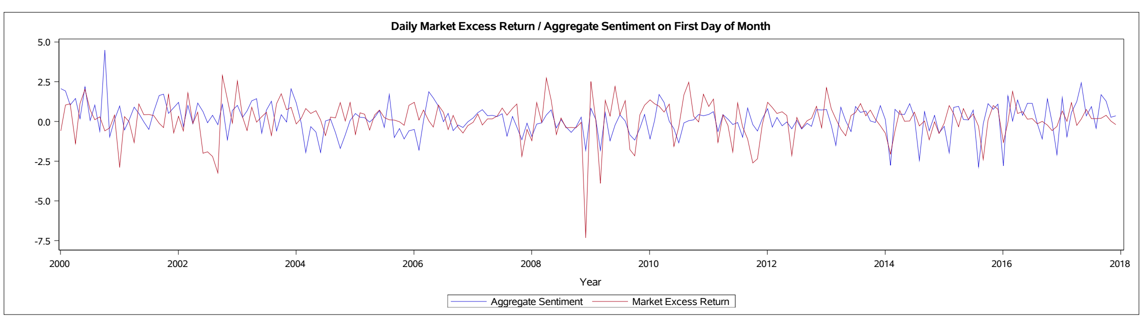


**Figure 2: Aggregate News Sentiment and Market Excess Return**

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 summary statistics of ES scores, realized market risk measures, control variables, and returns, as well as number of firms with ES scores during sample period from 1992 to 2017. Panel A reports time-series averages of monthly cross-sectional summary statistics of ES scores, realized market risk measures, and control variables. The sample consists of firms with common shares listed on NYSE, AMEX, or NASDAQ, with market capitalization above 50th percentile of NYSE breakpoint, and with ES scores provided by MSCI. The sample period is from January 1992 to December 2017 except realized tail risk, which is estimated using future monthly returns of 5 years, and therefore spans until December 2014. Control variables are winsorized at the 1% level and 99% level within each month. Panel B provides time-series averages of monthly cross-sectional summary statistics of monthly raw return and abnormal returns using the same sample. For each firm at month $t$, using past 36 monthly excess returns, we estimate factor loadings and compute abnormal return for month $t$. We consider CAPM, 3-Factor model of Fama and French (1992), and 4-Factor model augmented with momentum factor of Carhart (1997). We also compute DGTW characteristics-adjusted return of Daniel, Grinblatt, Titman, and Wermers (1997). In Panel C, we report number of firms with ES scores provided by MSCI within NYSE market capitalization decile breakpoint at the end of each year. All firms have common shares listed on NYSE, AMEX, or NASDAQ.

**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 | 14374 | 30644 | 1896 | 2748 | 5201 | 12461 | 30576 |
| 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 | 1 | 1 |
| 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 | 0.8311 | -0.1246 | -0.0413 | 0.4828 |
| Downside beta | 0.8311 | 1 | 0.4291 | -0.3901 | 0.4440 |
| Rel. downside beta | -0.1246 | 0.4291 | 1 | -0.6624 | -0.0047 |
| Coskewness | -0.0413 | -0.3901 | -0.6624 | 1 | -0.0603 |
| Tail risk | 0.4828 | 0.4440 | -0.0047 | -0.0603 | 1 |

**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 | 1060 |
| 2002 | 13 | 24 | 22 | 46 | 85 | 158 | 186 | 189 | 178 | 152 | 1053 |
| 2003 | 387 | 553 | 373 | 310 | 255 | 217 | 184 | 189 | 180 | 153 | 2801 |
| 2004 | 471 | 619 | 322 | 281 | 236 | 213 | 202 | 180 | 172 | 155 | 2851 |
| 2005 | 450 | 577 | 354 | 280 | 249 | 201 | 192 | 187 | 169 | 156 | 2815 |
| 2006 | 466 | 593 | 326 | 267 | 268 | 177 | 188 | 173 | 166 | 158 | 2782 |
| 2007 | 339 | 555 | 391 | 302 | 225 | 191 | 195 | 167 | 164 | 150 | 2679 |
| 2008 | 404 | 503 | 382 | 324 | 222 | 210 | 174 | 158 | 162 | 153 | 2692 |
| 2009 | 611 | 446 | 349 | 255 | 218 | 197 | 161 | 169 | 161 | 151 | 2718 |
| 2010 | 641 | 433 | 343 | 272 | 227 | 180 | 164 | 170 | 169 | 150 | 2749 |
| 2011 | 518 | 447 | 286 | 294 | 210 | 175 | 178 | 165 | 165 | 147 | 2585 |
| 2012 | 462 | 419 | 291 | 286 | 205 | 186 | 169 | 164 | 175 | 157 | 2514 |
| 2013 | 154 | 333 | 315 | 256 | 221 | 186 | 191 | 163 | 166 | 159 | 2144 |
| 2014 | 93 | 279 | 352 | 300 | 237 | 185 | 211 | 167 | 182 | 172 | 2178 |
| 2015 | 54 | 265 | 335 | 286 | 237 | 216 | 205 | 180 | 176 | 174 | 2128 |
| 2016 | 77 | 338 | 300 | 248 | 221 | 212 | 185 | 168 | 170 | 163 | 2082 |
| Total | 5252 | 6532 | 5020 | 4317 | 3770 | 3572 | 3638 | 3732 | 4159 | 4102 | 44094 |

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

This table reports the average realized returns and realized unconditional market risk for portfolios sorted on past ES scores. The sample consists of firms with common shares listed on NYSE, AMEX, or NASDAQ, with market capitalization above 50th percentile of NYSE breakpoint, and with ES scores provided by MSCI. The sample period is from January 1992 to December 2017. Because our ES measure is reported annually, we sort firms into quintile at the beginning of each year based on ES measures from previous year. For each month $t$, we compute monthly average portfolio return and report the time-series average excess return, as well as alphas by regressing the excess returns on monthly factor returns. We consider alphas with respect to CAPM, 3-Factor model of Fama and French (1992), and 4-Factor model augmented with momentum factor of Carhart (1997). We also compute average realized unconditional market risk measured from $t$ to $t+11$, which is estimated as in equation (1). We also report the average difference between the highest and the lowest ES quintile, along with its corresponding $t$-statistics. Standard errors for return difference are adjusted for serial correlation as in Newey and West (1987) allowing for 3 months lag for returns, and 12 months lag for unconditional market risk. Panel A reports results when we sort firms at the beginning of each year based on ES measures from previous year, as described previously. The time-series average number of firms in each portfolio ranges from 143 to 149. Panel B reports results when we sort firms using ES measure from prior year within industry as classified by two-digit Standard Industrial Classication (SIC) codes. The time-series average number of firms in each portfolio ranges from 118 to 163. *** 1%, ** 5%, * 10% significance.

**Panel A: ES Sort**

| | Low | 2 | 3 | 4 | High | High-Low | $t$-stat |
|---|---|---|---|---|---|---|---|
| | | | *Return (Equal-weighted)* | | | | |
| Excess return | 1.04 | 1.05 | 1.02 | 1.05 | 1.04 | 0 | 0.04 |
| CAPM alpha | 0.4 | 0.36 | 0.31 | 0.4 | 0.36 | -0.04 | -0.33 |
| 3F alpha | 0.25 | 0.23 | 0.21 | 0.29 | 0.26 | 0.01 | 0.11 |
| 4F alpha | 0.32 | 0.37 | 0.31 | 0.35 | 0.36 | 0.04 | 0.37 |
| | | | *Return (Value-weighted)* | | | | |
| Excess return | 0.91 | 0.97 | 0.88 | 0.9 | 0.86 | -0.05 | -0.37 |
| CAPM alpha | 0.35 | 0.35 | 0.19 | 0.26 | 0.21 | -0.14 | -1.03 |
| 3F alpha | 0.32 | 0.31 | 0.16 | 0.24 | 0.24 | -0.08 | -0.68 |
| 4F alpha | 0.3 | 0.39 | 0.17 | 0.19 | 0.28 | -0.01 | -0.1 |
| *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 | 1.03 | 1.02 | 1.04 | 1.08 | 1.03 | 0 | -0.04 |
| CAPM alpha | 0.33 | 0.33 | 0.39 | 0.42 | 0.36 | 0.04 | 0.42 |
| 3F alpha | 0.2 | 0.19 | 0.26 | 0.31 | 0.26 | 0.07 | 0.84 |
| 4F alpha | 0.32 | 0.31 | 0.36 | 0.37 | 0.34 | 0.02 | 0.28 |
| | | | *Return (Value-weighted)* | | | | |
| Excess return | 0.91 | 0.92 | 0.88 | 0.9 | 0.88 | -0.03 | -0.31 |
| CAPM alpha | 0.33 | 0.27 | 0.28 | 0.25 | 0.24 | -0.09 | -0.77 |
| 3F alpha | 0.29 | 0.24 | 0.23 | 0.27 | 0.25 | -0.04 | -0.42 |
| 4F alpha | 0.29 | 0.27 | 0.24 | 0.24 | 0.3 | 0 | 0.03 |
| *Market Beta* | 1.0262 | 1.0057 | 0.9921 | 1.0032 | 0.9882 | -0.0380*** | -2.92 |

## Table 3. ES-sorted Portfolio Downside Market Risks

This table reports the average realized downside market risks for portfolios sorted on past ES scores. For downside market risk, we consider downside beta, relative downside beta, coskewness (Ang et al, 2006), and tail risk (Kelly and Jiang, 2014). The sample consists of firms with common shares listed on NYSE, AMEX, or NASDAQ, with market capitalization above 50th percentile of NYSE breakpoint, and with ES scores provided by MSCI. The sample period is from January 1992 to December 2017 except tail risk, which is estimated using monthly return of 5 years, and therefore spans until December 2014. For each firm at the beginning of month $t$, we compute downside beta as in equation (2) and coskewness as in equation (3) using daily return data over the next 12 months ($t \sim t+11$), as well as relative downside beta as the difference between downside beta and unconditional beta, following Ang et al (2006). We also compute tail risk using monthly return data over the next 60 months ($t \sim t+59$), following Kelly and Jiang (2014). Because our ES measure is reported annually, we sort firms into quintile at the beginning of each year based on ES measures from the previous year. At the beginning of each month $t$, we compute average downside market risk during the following one year (5 years for tail risk), and report its time-series average. We also report the average difference between the highest and the lowest ES quintile, along with its corresponding $t$-statistics. Standard errors are adjusted for serial correlation as in Newey and West (1987) allowing for 12 months lag (60 months for tail risk). Panel A reports results when we sort firms at the beginning of each year based on ES measures from the previous year, as described previously. The time-series average number of firms in each portfolio ranges from 143 to 149. Panel B reports results when we sort firms using ES measure from prior year within industry as classified by two-digit Standard Industrial Classification (SIC) codes. The time-series average number of firms in each portfolio ranges from 118 to 163. *** 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 |
| 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*** | 3.1 |
| 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 result of Fama-MacBeth (1973) regression of realized market risks on past ES score and firm characteristics. The sample consists of firms with common shares listed on NYSE, AMEX, or NASDAQ, with market capitalization above 50th percentile of NYSE breakpoint, and with ES scores provided by MSCI. The sample period is from January 1992 to December 2017 except tail risk, which is estimated using monthly return of 5 years, and therefore spans until December 2014. For each firm at the beginning of month $t$, we compute unconditional beta as in equation (1), downside beta as in equation (2), and coskewness as in equation (3) using daily return data over the next 12 months ($t \sim t+11$), as well as relative downside beta as the difference between downside beta and unconditional beta, following Ang et al (2006). We also compute tail risk using monthly return data over the next 60 months ($t \sim t+59$), following Kelly and Jiang (2014). All regressions include lagged risk variables measured over $t-12 \sim t-1$ ($t-60 \sim t-1$ for tail risk) as control variables. In subset of specifications, we also include the most recent quarter-end or year-end firm characteristics as control variables. These include 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. We also include industry fixed effect, in which the industry of a firm is identified by two-digit Standard Industrial Classification (SIC) codes. All independent variables except ES scores are winsorized at the 1% level and 99% level, following Ang et al (2006). Standard errors are adjusted for serial correlation as in Newey and West (1987) allowing for 12 months lag (60 months for tail risk). $t$-statistics are reported in parenthesis. *** 1%, ** 5%, * 10% significance.

### Panel A: Beta Measures

| | Dependent Variables | | | |
|---|---|---|---|---|
| | Beta | Downside Beta | Beta | Downside Beta |
| *ES Score* | -0.0047 | -0.0233*** | -0.001 | -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 | 0.03 | -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) |
| $\mathbf{1}$(*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 ($R^2$) | 0.7132 | 0.5593 | 0.7451 | 0.598 |
| 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 | -0.039 |
| | | | | (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* | | | | -0.004 | -0.003 | -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 ($R^2$) | 0.286 | 0.3066 | 0.464 | 0.3158 | 0.3364 | 0.4942 |
| Mean (# obs) | 672 | 672 | 603 | 668 | 668 | 599 |

## Table 5. Fama MacBeth Regression Analysis - ES Score Decomposition

This table shows the result of Fama-MacBeth (1973) regression of realized market risks on decomposed past E, S, and G score and firm characteristics. The sample consists of firms with common shares listed on NYSE, AMEX, or NASDAQ, with market capitalization above 50th percentile of NYSE breakpoint, and with ES scores provided by MSCI. The sample period is from January 1992 to December 2017 except tail risk, which is estimated using monthly return of 5 years, and therefore spans until December 2014. For each firm at the beginning of month $t$, we compute unconditional beta as in equation (1), downside beta as in equation (2), and coskewness as in equation (3) using daily return data over the next 12 months ($t \sim t+11$), as well as relative downside beta as the difference between downside beta and unconditional beta, following Ang et al (2006). We also compute tail risk using monthly return data over the next 60 months ($t \sim t+59$), following Kelly and Jiang (2014). All regressions include lagged risk variables measured over $t-12 \sim t-1$ ($t-60 \sim t-1$ for tail risk) as control variables. In subset of specifications, we also include the most recent quarter-end or year-end firm characteristics as control variables. These include 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. We also include industry fixed effect, in which the industry of a firm is identified by two-digit Standard Industrial Classification (SIC) codes. All independent variables except ES scores are winsorized at the 1% level and 99% level, following Ang et al (2006). Standard errors are adjusted for serial correlation as in Newey and West (1987) allowing for 12 months lag (60 months for tail risk). $t$-statistics are reported in parenthesis. *** 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 ($R^2$) | 0.3152 | 0.3156 | 0.3154 | 0.3358 | 0.336 | 0.3355 | 0.4941 | 0.4942 | 0.4945 |
| 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** | | |
| | (-2.83) | | | (6.09) | | | (-2.05) | | |
| *E Score* | | -0.0425** | | | 0.0337*** | | | -0.0832* | |
| | | (-2.33) | | | (5.22) | | | (-1.88) | |
| S *Score* | | | -0.0150*** | | | 0.0116*** | | | -0.0181 |
| | | | (-2.85) | | | (6.24) | | | (-1.57) |
| G *Score* | -0.0094 | -0.0112 | -0.0103 | -0.0061 | -0.0048 | -0.0055 | -0.0205 | -0.0248 | -0.0208 |
| | (-0.97) | (-1.12) | (-1.06) | (-1.36) | (-1.03) | (-1.22) | (-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 ($R^2$) | 0.3172 | 0.3167 | 0.317 | 0.3375 | 0.337 | 0.3372 | 0.496 | 0.4957 | 0.4961 |
| Mean (# obs) | 668 | 668 | 668 | 668 | 668 | 668 | 599 | 599 | 599 |

## Table 6. Fama MacBeth Regression Analysis - Robustness Check

This table shows the result of Fama-MacBeth (1973) regression of realized market risks on past ES score and firm characteristics, using alternative sample. The sample consists of firms with common shares listed on NYSE, AMEX, or NASDAQ, and with ES scores provided by MSCI. The sample period is from January 2002—when MSCI began expanding its coverage—to December 2017 except tail risk, which is estimated using monthly return of 5 years, and therefore spans until December 2014. For each firm at the beginning of month $t$, we compute coskewness as in equation (3) using daily return data over the next 12 months ($t \sim t+11$), as well as relative downside beta as the difference between downside beta and unconditional beta, following Ang et al (2006), in which unconditional beta and downside beta is computed as in equation (1) and (2) respectively. We also compute tail risk using monthly return data over the next 60 months ($t \sim t+59$), following Kelly and Jiang (2014). All regressions include lagged risk variables measured over $t-12 \sim t-1$ ($t-60 \sim t-1$ for tail risk) as control variables. In subset of specifications, we also include the most recent quarter-end or year-end firm characteristics as control variables. These include 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. We also include industry fixed effect, in which the industry of a firm is identified by two-digit Standard Industrial Classification (SIC) codes. All independent variables except ES scores are winsorized at the 1% level and 99% level, following Ang et al (2006). Standard errors are adjusted for serial correlation as in Newey and West (1987) allowing for 12 months lag (60 months for tail risk). In Panel B, we estimate the effect of ES Score separately for large and small firms. **1***(SmlCap)* (**1***(BigCap))* is a dummy variable that is equal to one if the rm's market value is below (above) the median NYSE market equity. $t$-statistics are reported in parenthesis. *** 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) |
| **1**(*Dividend*) | -0.0089 | 0.0001 | -0.0290** |
| | (-1.59) | (0.05) | (-2.43) |
| *Lag(12mth exret)* | -0.006 | 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 ($R^2$) | 0.1958 | 0.2431 | 0.3307 |
| Mean (# obs) | 1989 | 1989 | 1822 |

**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 ($R^2$) | 0.1968 | 0.2443 | 0.331 |
| Mean (# obs) | 1989 | 1989 | 1822 |

## Table 7. Doing Well by Doing Good: News Sentiment Covariation Patterns

This table test whether firm values for high ES firms covary less with the average firm's value when the average firm's value is declining, using data from Ravenpack. The sample period is from January 2000—when Ravenpack started its news coverage—to December 2017. 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. We also compute ES-sorted portfolio-level sentiment using sample of firms with market capitalization above 50th percentile of NYSE breakpoint, and with ES scores provided by MSCI. Because our ES measure is reported annually, we sort firms into quintile at the beginning of each year based on ES measures from the previous year. For each portfolio, we compute daily portfolio sentiment by value-weighting daily news sentiment of firms with at least one news. Panel A reports the result of Fama-MacBeth (1973) regression of ES-sorted portfolio daily excess return on contemporaneous ES-sorted daily portfolio sentiment measures. We compute daily portfolio excess return by equal- or value-weighting daily excess return within each portfolio. Standard errors are adjusted for serial correlation as in Newey and West (1987) allowing for 5 days lag. Panel B reports the average realized portfolio sentiment betas sorted on past ES scores. For each portfolio at the beginning of month $t$, we compute unconditional sentiment beta by regressing daily portfolio sentiment on daily aggregate sentiment using daily sentiment data over next 12 months ($t \sim t+11$). Similarly as in Ang et al (2006), we compute downside sentiment beta by regressing daily portfolio sentiment on daily aggregate sentiment using days with daily aggregate sentiemnt below the average daily aggregate sentiment over next 12 months ($t \sim t+11$). Relative downside sentiment beta is computed as the difference between downside sentiment beta and unconditional sentiment beta. We report their time-series averages, as well as the average difference between the highest and the lowest ES quintile and their corresponding $t$-statistics. Standard errors are adjusted for serial correlation as in Newey and West (1987) allowing for 12 months lag. We report result when we sort firms using solely ES measure from prior year, as well as when we sort firms using ES measure from prior year within industry as classified by two-digit Standard Industrial Classification (SIC) codes. *** 1%, ** 5%, * 10% significance.

### 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* | -0.01015*** | -0.02028*** | -0.00548*** | -0.01731*** |
| | (-4.65) | (-6.49) | (-3.77) | (-6.81) |
| *AggSent* | 0.000212*** | 0.000413*** | 0.000118*** | 0.000353*** |
| | (4.87) | (6.58) | (4.07) | (6.95) |
| *N (# of days)* | 4,528 | 4,528 | 4,528 | 4,528 |
| $R^2$ | 0.2522 | 0.2615 | 0.2560 | 0.2601 |

### 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 8. ES Preferences of Institutional Investors: Institutional Trading Patterns

This table shows the result of Fama-MacBeth (1973) regression of realized institutional trading betas on past ES score and firm characteristics. The sample consists of firms with common shares listed on NYSE, AMEX, or NASDAQ, with market capitalization above 50th percentile of NYSE breakpoint, and with ES scores provided by MSCI. We also require a firm to be traded by institutional investors as reported by Abel Noser Database. The sample period is from January 1999 to January 2010, which is the sample period for Abel Noser Database and the period during which we can estimate trading beta over one year horizon. From Abel Noser Database, for each firm, we aggregate daily net trades across all institutional investors. All trades executed after 4:00 PM are attributed to the next trading day. For each firm-day, we assign trading direction variable 1 when institutional investors in aggregate bought the firm, 0 when they did not trade in aggregate, and -1 when they sold in aggregate. For each firm at the beginning of month $t$, we compute unconditional trading beta by regressing daily market excess return on daily trading direction variable over next 12 months ($t \sim t+11$). Similarly as in Ang et al (2006), we compute downside trading beta by regressing daily portfolio sentiment on daily trading direction variable using days with daily market excess return below the average market excess return over next 12 months ($t \sim t+11$). We also compute downside trading beta by using alternative downside period criteria, using days with daily market excess return below the bottom 25th percentile market excess return over next 12 months ($t \sim t+11$). Relative downside trading beta is computed as the difference between downside trading beta and unconditional trading beta. All regressions include lagged risk variables measured over $t-12 \sim t-1$ ($t-60 \sim t-1$ for tail risk) as control variables. In subset of specifications, we also include the most recent quarter-end or year-end firm characteristics as control variables. These include 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. We also include industry fixed effect, in which the industry of a firm is identified by two-digit Standard Industrial Classification (SIC) codes. All independent variables except ES scores are winsorized at the 1% level and 99% level, following Ang et al (2006). Standard errors are adjusted for serial correlation as in Newey and West (1987) allowing for 12 months lag. $t$-statistics are reported in parenthesis. *** 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 | -0.277 | -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* | -0.089 | 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 | 0.091 | -0.0221 | 0.6501 | 0.537 |
| | (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 ($R^2$) | 0.1511 | 0.1247 | 0.1179 | 0.1248 | 0.1216 |
| Mean (# obs) | 696 | 696 | 696 | 696 | 696 |

## Table 9. Sustainalytics

This table shows the result of Fama-MacBeth (1973) regression of realized market risks on past Sustainalytics' total ESG score (Panels A and B) or ES score, i.e., the average of Sustainalytics' E and S scores (Panels C and D). The sample consists of firms with common shares listed on NYSE, AMEX, or NASDAQ, with market capitalization above 50th percentile of NYSE breakpoint, and with Sustainalytics score. In Panels B and D, we further exclude firms with negative book value. The sample period is from September 2009 to December 2017 except tail risk, which is estimated using monthly return of 5 years, and therefore spans until December 2014. For each firm at the beginning of month $t$, we compute unconditional beta as in equation (1), downside beta as in equation (2), and coskewness as in equation (3) using daily return data over the next 12 months ($t \sim t + 11$), as well as relative downside beta as the difference between downside beta and unconditional beta, following Ang et al (2006). We also compute tail risk using monthly return data over the next 60 months ($t \sim t + 59$), following Kelly and Jiang (2014). The last three columns in each panel use the natural logarithm of one plus Sustainalytics scores. All regressions include lagged risk variables measured over $t - 12 \sim t - 1$ ($t - 60 \sim t - 1$ for tail risk) as control variables. We also include the most recent quarter-end or year-end firm characteristics as control variables. These include 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. We also include industry fixed effect, in which the industry of a firm is identified by two-digit Standard Industrial Classification (SIC) codes. All independent variables except except Sustainalytics score are winsorized at the 1% level and 99% level, following Ang et al (2006). Standard errors are adjusted for serial correlation as in Newey and West (1987) allowing for 12 months lag (60 months for tail risk). $t$-statistics are reported in parenthesis. *** 1%, ** 5%, * 10% significance.

### Panel A: Big Firms

| | Dependent Variables | | | | | |
|---|---|---|---|---|---|---|
| | Relative Downside Beta | Coskewness | Tail Risk | Relative Downside Beta | Coskewness | Tail Risk |
| | | *Raw Score* | | | *Log Score* | |
| *ESG Score* | -0.000101 | 0.000358* | 0.00131 | -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 | 0.371 | 0.56 | 0.34 | 0.371 | 0.56 |
| Mean (# obs) | 651 | 651 | 622 | 651 | 651 | 622 |

### Panel B: Big Firms, Excluding Those With Negative Book Values

| | Dependent Variables | | | | | |
|---|---|---|---|---|---|---|
| | Relative Downside Beta | Coskewness | Tail Risk | Relative Downside Beta | Coskewness | Tail Risk |
| | | *Raw Score* | | | *Log Score* | |
| *ESG Score* | -0.000156 | 0.000322* | 0.00137 | -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 ($R^2$) | 0.346 | 0.377 | 0.567 | 0.346 | 0.377 | 0.567 |
| Mean (# obs) | 633 | 633 | 607 | 633 | 633 | 607 |

## Panel C: Big Firms

| | Dependent Variables | | | | | |
|---|---|---|---|---|---|---|
| | Relative Downside Beta | Coskewness | Tail Risk | Relative Downside Beta | Coskewness | Tail Risk |
| | | *Raw Score* | | | *Log Score* | |
| *ES Score* | -0.0000337 | 0.000297* | 0.0014 | -0.00734 | 0.0160* | 0.0727 |
| | (-0.20) | (1.85) | (1.52) | (-0.87) | (1.82) | (1.46) |
| 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 | 0.371 | 0.56 | 0.339 | 0.371 | 0.56 |
| Mean (# obs) | 651 | 651 | 622 | 651 | 651 | 622 |

## Panel D: Big Firms, Excluding Those With Negative Book Values

| | Dependent Variables | | | | | |
|---|---|---|---|---|---|---|
| | Relative Downside Beta | Coskewness | Tail Risk | Relative Downside Beta | Coskewness | Tail Risk |
| | | *Raw Score* | | | *Log Score* | |
| *ES Score* | -0.0000992 | 0.000280* | 0.00139 | -0.0107 | 0.0152* | 0.0727 |
| | (-0.68) | (1.70) | (1.60) | (-1.43) | (1.68) | (1.53) |
| 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 ($R^2$) | 0.346 | 0.377 | 0.567 | 0.346 | 0.377 | 0.567 |
| Mean (# obs) | 633 | 633 | 607 | 633 | 633 | 607 |