Doing Well by Doing Good?

Risk, Return, and Environmental and Social Ratings

Sudheer Chava[*]   Jeong Ho (John) Kim[†]   Jaemin Lee[‡]

January 2021

Abstract

We analyze the risk and return relationship of firms sorted by environmental and social (ES) ratings. We document that ES ratings do not have a statistically significant relationship with either average stock returns or unconditional market risk measures. Firms with high ES ratings have significantly lower downside risk than firms with lower ES ratings. However, a two standard-deviation move across stocks on ES score results in a decrease in downside risk measuring only 4–8% of the underlying downside risk measure's standard deviation. This decrease in downside risk for high ES firms can be partly attributed to the news sentiment about the firms and institutional trading. Our results suggest that ES investing may not be justified solely based on the risk-return relationship of ES firms.

---

[*]Scheller College of Business, Georgia Tech, *Email:* `schava6@gatech.edu`
[†]Department of Economics, Emory University, *Email:* `jkim230@emory.edu`
[‡]Goizueta Business School, Emory University, *Email:* `jaemin.lee@emory.edu`

1 Introduction

Global assets managed under investment approaches that consider environmental, social and governance (ESG) factors in portfolio selection have grown from \$22.8 trillion in 2016 to \$30.7 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 plan fiduciaries to select investments based solely on financial considerations relevant to the risk-adjusted economic value of that investment.[3] It not clear whether ESG investments can be justified solely based on risk-return considerations as there is still no consensus on the relationship between the ESG profile of a firm and its realized stock returns.[4] In this paper, we shed light on this ongoing debate, by revisiting the relationship between the ES ratings of a firm and its risk and return profile.

A key premise of ES investing is that firms "do well by doing good." This implies that firms with better ES practices increase firm value, which in turn manifests in their stronger financial performance. As Bénabou and Tirole (2010) notes, "[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, say, risk of new regulations imposing environmental clean-up costs. Such risks are systematic to the extent that many firms suffer from managerial myopia. Of course, high ES firms (environment-friendly firms in this case) would be resilient in these periods when many firms suffer a negative shock to their value. This argument would predict that high ES stocks are less likely to deliver disappointing outcomes in periods when the stock market disappoints suggesting that high ES firms might have low downside risk.

---

[1]2018 Global Sustainable Investment Review, page 8

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

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

[4]See Hong and Kacperczyk (2009), Kempf and Osthoff (2007), Edmans (2011), Chava (2014), Lins, Servaes, and Tamayo (2017)

In this paper, we empirically analyze the relationship between ES ratings of a firm and its future stock returns and also the relationship with various risk measures including downside risk. We find that there is no meaningful relationship between the realized stock returns and ES ratings of a firm. We find that after controlling for size effect and the strong auto-correlation of regular beta, the relationship between ES scores and market beta 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 the decrease in downside beta for high ES firms is small.

We begin our analysis by looking at patterns of future returns and unconditional market risk for portfolios sorted on past ES score. We use ES ratings from MSCI KLD from 1992 through 2017. Overall, we find no evidence of high ES stocks outperforming low ES stocks. This result essentially reflects mixed results on the performance of ES investing in the literature.[5] We do find that stocks with high ES scores have low market beta than low ES stocks within the same industry. However, we show that this relation is explained away by the size effect and the strong autocorrelation of regular beta. These results highlight the importance of expanding the focus beyond unconditional risk and returns when attempting to understand the pecuniary effects of ES factors.

We then look at patterns of future downside risk for portfolios sorted on past ES score. 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 regular market beta.[6] We demonstrate that, consistent with our version of

---

[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.

[6]We consider two alternative proxies for the downside risk: the coskewness of Harvey and Siddique (2000) and tail risk beta of Kelly and Jiang (2014). These two proxies also capture some aspects of downside

the ES investing proposition, stocks with high ES scores have statistically significantly lower downside risk going forward. Moreover, these relations continue to hold when we control for other firm characteristics (e.g., downside risk in the past and firm size). We also find that both E and 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 a two-standard-deviation move across stocks in terms of ES score is associated with a decrease in relative downside beta, whose magnitude is about 6% of the standard deviation in our sample. Of course, these humbling results may very well stem from a measurement problem—our analysis that relies on KLD ratings alone will be subject to a real errors-in-variables (EIV) problem. Although, ultimately, we leave this as a task for future research, we do note that correcting the attenuation bias is unlikely to overturn our conclusion that the effect of CSR activities on downside risk is economically small.

Finally, we provide strong 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 the key assumption of our version of the ES investing proposition: is the value of high ES firms 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. Such results are consistent with firms "doing well by doing good" and they can be reflected in the cross section of stock returns to generate the downside risk effects of firm-level ES performance.

In addition, we examine whether ES preferences of institutional investors can induce a pattern of institutional trading that is consistent with the negative relation between ES performance and downside risk. Using institutional trading data from Abel Noser, we find that, when the market suffers extremely negative shocks, institutional investors hold on to

covariation. Perhaps surprisingly, we find very similar results when we use these alternative proxies.

high-ES firms which generate high returns and low downside risk of these firms. During normal times, however, institutional investors buy high-ES firms such that, unconditionally, they do not exert additional pressure on prices of these firms, which can give rise to the fact that ES ratings do not change unconditional market risk.

Taken together, our results highlight downside risk as the unique pecuniary benefit from ES factors.[7] 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 (e.g., altruism or social norms).[8] This interpretation, were it true, would be troubling from an economic point of view. If all ES demand is due to irrational beliefs or non-pecuniary utility, reasons to invest in ES-focused investment vehicles would be shaky at best under the standard neoclassical assumptions. Expanding the focus beyond the standard, mean-variance paradigm, we accentuate the fact that at least some ES demand is rational.

This result also has clear policy implications. The U.S. Department of Labor (DOL) recently announced a final rule "preventing [retirement plan] fiduciaries from selecting investments based on non-pecuniary considerations and requiring them to base investment decisions on financial factors," and the final rule was motivated "in light of recent trends involving environmental, social and governance (ESG) investing."[9] Overall, our results strongly support that a firm's CSR activities, in addition to more traditional characteristics, *do* warrant the attention of investors based solely on financial factors. But they warn against ES-focused investment vehicles, confirming prior concerns by the DOL.

Empirical studies of ES investing provide suggestive evidence that our hypothesis is

---

[7]Our results also help explain why institutional investors with longer horizons exhibit stronger ES preferences (Starks, Venkat, and Zhu 2020): such investors have longer holding period and are more exposed to extreme events. Thus, they can rationally demand ES factors to alleviate their downside risk exposure.

[8]See, e.g., Hartzmark and Sussman (2019) and Barber, Morse, and Yasuda (2021).

[9]https://www.dol.gov/newsroom/releases/ebsa/ebsa20201030

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 precisely when high ES stocks would do well according to our ES investing proposition. We expand on, as well as qualify, the implications of resiliency of ES firms during these rare episodes of market collapse for portfolio selection by using various measures of downside risk.

More broadly, our study adds to a recent literature addressing the risk implications of ES-focused investing.[10] Hoepner et al. (2020) find that ESG engagement reduces firms' idiosyncratic downside risk, as well as their exposures to an idiosyncratic-downside-risk factor. Bolton and Kacperczyk (2020) argue that investors demand compensation for their exposure to carbon emission risk. Theoretically, Albuquerque, Koskinen, and Zhang (2019) builds a theoretical model that predicts CSR decreases systematic risk, while Pástor, Stambaugh, and Taylor (2020) theoretically construct an ESG risk factor that is capable of pricing assets.

The rest of the paper is organized as follows. Section 2 describes our data sources and main variable construction. We present our empirical results on the relationship between the ES profile of a firm and its downside risk measures in Section 3. We explore some potential explanations for why high ES firms have lower downside risk in Section 4. We conclude in Section 5.

2   Data

Our analysis uses data from four major databases: (1) MSCI KLD database on the ESG profile of companies, (2) CRSP database on stock return, (3) RavenPack database on news

---

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

sentiment, and (4) Abel Noser database on institutional trading.[11] In this section, we describe each of the first two data sources in detail and 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, as soon as 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 has information on environmental, social, and governance performance of large publicly traded companies on an annual basis. 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).

KLD database expanded its coverage over time starting with S&P 500 companies during 1991–2000, 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.[12] While we do not use the corporate governance category in our main analysis because governance is generally outside the scope of CSR, we consider this category in 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

---

[11]We also use COMPUSTAT to construct book-to-market ratio, accounting variables (return on equity, ROE; asset growth; and sales growth), as well as book leverage, and a dummy for dividend-paying firms.

[12]We do not use the ESG Stats categories that penalize involvement in the six industries that are considered controversial, as there is nothing to be done by firms operating in these industries to change their scores (in addition, we eventually control for industry in all of our test).

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) for each category by dividing the number of strengths (concerns) for each firm-year by the maximum number of strength (concern) for that category in that year. Note that these strength and concern indices range from zero to one 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 for 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 is our primary proxy for ES performance that ranges from -6 to $+6$.

2.2 CRSP Database

Stock return data are obtained from the CRSP database.[13] 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 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 $\beta^- - \beta$): the downside beta of Bawa and Lindenberg (1977) (denoted by β^-) relative to the regular beta with respect to the market portfolio (denoted by β). We consider two alternative proxies for the downside risk: the coskewness of Harvey and Siddique (2000) and 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.

---

[13]We also collect market capitalizations for each stock.

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 $\tilde{r}_{i\tau}$ denote asset i's excess return on day τ, and let $\tilde{r}_{m\tau}$ denote the market's excess return on day τ. We exclude stocks with more than 5 missing observations from our analysis. First, we demean returns within each period, and denote the demeaned excess return of asset i and demeaned market excess return by $\tilde{r}_{i\tau}$ and by $\tilde{r}_{m\tau}$, respectively. We obtain estimates of the regular market β, denoted $\hat{\beta}_{it}$, in the usual manner as:

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

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

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

Finally, coskewness is estimated as:

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

2.2.2 Tail Risk Beta

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

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

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

We estimate the tail risk β, denoted $\widehat{\beta}_{it}^{\text{tail}}$, as the regression coefficient of firm returns on the common tail risk component λ_t using 60 months of data following portfolio formation.[14] Note that we compute tail risk beta in the same way as Kelly and Jiang (2014), except we use 60 months of data rather than 120.[15] Intuitively, stocks with high values of tail risk beta are more sensitive to tail risk, and so 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 non-missing ESG data (in the prior year) within each size decile (based on NYSE breakpoints). Note that MSCI KLD coverage of small firms (i.e., 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 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 only use big firms (i.e., market value above the median NYSE market equity) in our main analyses. A sensible alternative approach would be to use, as the sample, the period after 2001 when KLD started expanding its coverage to include smaller companies. Accordingly, we examine this sample in robustness tests.

---

[14]To calculate tail risk betas for individual stocks, we require stocks to at least 36 months out of 60 with nonmissing returns.

[15]Because estimating the tail loading for each stock requires a long time series of returns, the estimates of tail sensitivities are only available before December 2014. Thus, analysis of tail risk as the dependent variable uses data ending in December 2014 rather than December 2017 for all other analyses.

3 Empirical Results

3.1 Unconditional Risk and Returns of ES Score-Sorted Portfolios

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

3.1.1 Returns of ES Score-Sorted Portfolios

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 ESG quintile portfolios in the column labeled "High-Low," for which we compute the t-statistic by using 3 Newey-West (1987) lags. We consider excess returns, as well as alphas with respect to the market factor and factor returns based on size (SMB), book-to-market (HML), and momentum (up minus down, UMD).

The average returns of the different ES portfolios are similar, and do not exhibit any obvious pattern, certainly not increasing from the low-ES to high-ES portfolios. Stocks in the highest ES score quintile earn value-weighted average annual returns 0.60% lower than stocks 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 ($t = 0.04$). Average returns of the long-short portfolios are not only statistically, but also economically insignificant.

Similarly, portfolio alphas do not demonstrate any pattern. Alphas of the value-weighted

high minus low ES score portfolio are negative, but small, and 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. It is only 0.12% for the three-factor model ($t = 0.1$).

Panel B of Table 2 repeats the same exercise as Panel A of Table 2, except it sorts stocks on ES score within each industry.[16] 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 stocks outperforming low ES stocks. If anything, high ES stocks appear to be underperforming low ES stocks, but it depends on whether we use value-weighted portfolios. Importantly, the underperformance of high-ES stocks is small in magnitude, 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 ES Score-Sorted Portfolios

In each panel of Table 2, the last row shows the average cross-sectional realized β 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 at a monthly frequency. While more efficient, this use of overlapping information induces moving average effects. We adjust for this by reporting t-statistics of differences in average market betas between quintile portfolio 5 (high ES) and quintile portfolio 1 (low ES) using 12 Newey-West (1987) lags.

While average betas for stocks sorted on ES score alone (Panel A) do not demonstrate any pattern, 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 in this case is -0.038, which is statistically significant at the 1% level.

---

[16]Industry classifications are based on groupings of two-digit Standard Industrial Classification (SIC) codes.

In summary, Table 2 demonstrates that ES scores do not have return implications, but they do seem to have implications for unconditional risk exposures: stocks with high ES scores have low market beta going forward.[17] However, this relation does not control for other firm characteristics that might be correlated with future beta. In Section 3.3.1, we show that this relation is indeed explained away by other firm characteristics.

3.2   Downside Risk of ES Score-Sorted Portfolios

We now look at patterns of future downside risk for portfolios sorted on past ES score. To the extent that high ES stocks provide low downside risk exposures 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 stocks sorted by ES scores into quintiles.[18] For each month, using daily data over the next 12 months, we calculate a stock's downside beta as in Equation (2) and coskewness as in equation (3), as well as relative downside beta. We also compute a stock'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 at a monthly frequency. We account for this by reporting t-statistics of differences in average realized downside risk between quintile portfolio 5 (high ES) and quintile portfolio 1 (low ES) using 12 Newey-West (1987) lags, except for tail risk, in which case we use 60 Newey-West lags.

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, high ES stocks

---

[17]These results, as well as the more robust empirical results in what follows that high ES stocks have low downside risk going forward, are consistent with Albuquerque, Koskinen, and Zhang (2019), whose theoretical model predicts that CSR decreases *systematic* risk.

[18]Specifically, at the beginning of each year, we sort stocks into portfolios based on ES measures from the prior year.

tend to move downward less than low ES stocks *with comparable market risk exposures.* Note that this implies high ES stocks also tend to move upward more than low ES stocks with comparable market risk exposures. Moreover, high ES stocks with high coskewness tend to do better than low ES stocks 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 stocks' low downside risk.

We examine the robustness of ES score's cross-sectional downside risk implications 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.[19] Second, Fama and French (1997) show that market risk exposures vary substantially across industries. Therefore, in Panel B, we control for industry by sorting stocks within each industry into quintiles according to ES scores.

ES score's predictive ability for low downside risk is robust to controlling for industry: high ES stocks continue to have low relative downside beta and high coskewness. Controlling for industry preserves the statistical significance of spreads in these measures of downside risk, which are highly significant with t-statistics of -2.6 and 3.1, respectively. Nevertheless, these differences are about half the size in 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 the relation away.

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 stocks exhibit lower tail risk than low ES stocks within the same industry, but the corresponding spread in tail risk beta between the first and fifth ES portfolio 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 stocks' low downside risk.

---

[19]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 on 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 stocks' low downside risk, but another possible explanation is that it mechanically reflects the relation between past ES scores and future regular beta. Panel B of Table 1 shows that β and β^- are highly correlated with a correlation around 0.83. Given this correlation, it is not surprising that patterns of β and β^- sorted on past ES score are qualitatively the same. Therefore, we need to take care in controlling for the regular beta in measuring downside risk 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. Stocks with high ES scores have low downside risk going forward that is not mechanically driven by low regular, unconditional betas. These results suggest that, in an economy with investors placing greater emphasis on downside risk than upside gains, low downside risk of high ES stocks can account for why investors demand these stocks. However, these relations do not control for firm characteristics other than 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

While there is little theoretical guidance regarding which firm characteristics determine riskiness of a stock, 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 stocks 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 exposures on various firm characteristics, including ES score, that are known ex ante,

and on past risk characteristics 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 prior to the realization of risk measures. The regressions are run at a monthly frequency, so we use 12 Newey-West (1987) lags.

The first two columns include, as independent variables, ES score and log of market capitalization, in addition to industry fixed effects and risk measures—regular beta, relative downside beta, coskewness, and tail risk beta—over the past months. The last two columns also include other firm characteristics, which are the firm book-to-market ratio, past 12-month excess returns, accounting measures of performance (return on equity, ROE; asset growth; and sales growth), as well as book leverage, and a dummy for dividend-paying firms.

The first column shows that past ES score does not predict future beta over the next 12 months. On the other hand, past beta is a strong predictor of future beta. Hence, the strong predictive pattern of past ES score and future regular beta in Panel B of Table 2 is explained away by the size effect and the strong 12-month autocorrelation of regular beta. Column 3 adds additional stock characteristics only to confirm the robustness of this negative result.

In summary, we do not find empirical support for the reward in terms of unconditional risk exposures for ES investing. Recall from Table 2 that the average returns (risk-adjusted or not) from high ES stocks are no different than those on low ES stocks. Taken together, these two results suggest that 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 if 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 stocks tend to have high future coskewness and low future exposure to tail risk. Since stocks 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 stocks 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 0.009 in average coskewness for the ES quintiles within each industry in Table 3. Recall that the 5–1 quintile differences in tail risk beta in Table 3 are insignificant. According to the last column of Panel B of Table 4, changing ES score by one point is associated with a statistically significant decrease in tail risk exposure of 0.021.

In summary, the reward in terms of downside risk for ES investing is stronger after controlling for other cross-sectional effects: high ES stocks have low relative downside beta and high coskewness, as well as low tail risk beta. Not only are these effects statistically significant, they are larger in magnitude compared to portfolio analyses in Table 3 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 can 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, 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 ought to gauge their economic significance.

To interpret the economic magnitudes of the estimated coefficients reported in the Fama-MacBeth regressions, consider a two-standard-deviation move across stocks in terms of ES score, or a $2 \times 0.44 = 0.89$ point increase in ES score. The coefficient estimates indicate that such an increase in ES score is associated with a decrease in relative downside beta of $0.89 \times 0.016 = 0.014$ (which represents about 6% of the standard deviation in our sample), an increase in coskewness of $0.89 \times 0.012 = 0.011$ (which represents about 8% of the standard deviation in our sample), and a decrease in tail risk beta of $0.89 \times 0.021 = 0.019$ (which represents about 4% of the standard deviation in our sample). These quantities imply humbling effects that are economically small, regardless of how we measure downside risk.

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, ESG ratings from leading agencies disagree substantially (Chatterji et al. 2016). Therefore, our analysis that relies on KLD ratings alone will be subject to a real errors-in-variables (EIV) problem. While we do not worry about the EIV problem for establishing statistical significance, as it

works against us, it introduces attenuation bias that is of first-order importance for assessing the economic significance of the estimates in Table 4. But 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 score needs to be noise if in reality, 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 ESG issues (Starks, Venkat, and Zhu 2020): such investors are more exposed to downside risk and rationally ought to be more concerned about ESG issues, which can help them mitigate downside risk. On the other hand, our discussion suggests a cautionary investing note: ES investing by itself cannot be wise on the basis of financial considerations. Rather, investors can improve their current investment process by incorporating ES criteria on the side.

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 MSCI KLD) and (ii) S(ocial) score (i.e., the five categories of community, human rights, employee relations, diversity, and product). We seek to identify whether it is a firm's ES performance in aggregate or a specific component of ES that is important for avoiding stocks that covary strongly when the market dips. We also examine the G score (i.e., the corporate governance category in MSCI KLD) here.

We run Fama-MacBeth (1973) regressions analogous to those in the last three columns

of Panel B of Table 4, except that we on one ESG component at a time in lieu of the aggregate ES performance. The results are in Panel A of Table 5.[20]

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 $+5$. While the standard deviation for E score is one third of that for S score, the coefficients on E score are three times those on S score for relative downside beta and coskewness. In turn, our results indicate that both 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 E score significantly larger in magnitude than that on S score.

On the other hand, the G score is not important for downside risk. Not only are the estimated coefficients on G score are substantially smaller in magnitude compared to those on E or S score, they are statistically insignificant controlling for other cross-sectional effects. These results are consistent with prior literature suggesting corporate governance is generally not part of a firm's CSR activities.[21]

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 in 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

---

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

[21]See, e.g., Hong, Kubik, and Scheinkman (2012), Servaes and Tamayo (2013), and Krüger (2015).

19

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 that 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 stocks have low relative downside beta and high coskewness, as well as low tail risk beta in the full cross-section of stocks in recent times. While these effects remain statistically significant, they are clearly smaller in magnitude compared to 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 one if the firm's market value is below (above) the median NYSE market equity. The results are in Panel B of Table 6. In all columns, we find significant slopes on ES Score$\times 1(BigCap)$ that are similar in magnitude compared 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).[22] These relations are strong enough to give rise to the statistical significance of the same relations when pooled with small firms.

---

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

4 Potential Explanations

In this section, we discuss two general explanations that can give rise to 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 firm values for high ES firms covary less with the average firm's value when the average firm's value is declining, and find strong empirical support for it.

Ideally, we would directly construct a measure of changes in firm value attributable to corporate actions that raise ES scores. But this is a challenge in itself. Instead, we use the firm-level news sentiment from RavenPack News Analytics as a proxy for the change in firm value. If news detects most events of material relevance to firms, and if news sentiment corresponds to the direction of the impact (positive or negative), a firm's news sentiment is a good proxy for high-frequency change in its value.[23]

4.1.1 RavenPack Database

RavenPack provides real-time structured sentiment data for firms and financially relevant events by analyzing unstructured content from Dow Jones Newswires. We use RavenPack's millisecond time-stamped data from 2000 to 2017.

For each news story analyzed, RavenPack contains a timestamp, company identifier,

---

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

scores for relevance (i.e., how strongly related the firm is to the underlying news story), novelty (i.e., how "new" or novel a news story is) and sentiment (i.e., the news sentiment for a given firm). Importantly, the event sentiment score ranging from 0-100, where values above 50 indicate positive sentiment and values below 50 show negative sentiment, is determined by matching stories typically categorized by experts as having short-term positive or negative impact on firm value.

As per the RavenPack user guide, we filter for the news story in which the firm was prominent (i.e., relevance score of 100), and filter for the first story reporting a categorized event (i.e., novelty score of 100). We assign a news story to a given trading day if the news is released on that day before the market close at 16:00 and to the next trading day if the news is released at or after 16:00, including news released on a nontrading day (e.g., a weekend or a holiday). 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: a typical firm is covered in the news only 80 times in any given year. In turn, betas computed using data on news sentiment at the firm level would be noisy. To address this concern, we conduct our analysis with news sentiment data by examining the quintile portfolios sorted by ES scores, just like 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. We run Fama-Macbeth regressions of the value- and equal-weighted portfolios' excess returns on their average news sentiment.[24] Since the regressions are run at the daily frequency, we compute the standard errors of the coefficients by using 5 Newey-West (1987) lags for within-week autocorrelation. Panel A of Table 7 reports the results: the first two columns use portfolios sorted only on past ES scores; the last two columns repeats the same exercise, except they sort stocks on ES score within each industry. Indeed, we find increasing

---

[24]Specifically, we measure daily news sentiment for each portfolio as the value-weighted average of daily firm news sentiment across all firms within that portfolio on each day.

relationships between realized returns, equal-weighted or not, and realized news sentiment. These relations are both statistically and economically significant: news sentiment alone explains 25% of variation in contemporaneous returns across the portfolios.

Similarly, there is a strong positive contemporaneous relation between market return and aggregate news sentiment,[25,26] which is visually obvious from Figure 2 that plots their daily values as of the beginning of each month over time.[27]

To summarize, the news sentiment explains daily returns both at the portfolio level and at the aggregate level.

4.1.2 Patterns of Sentiment Covariation for ES Score-Sorted Portfolios

The exploratory analysis in the previous section indicates that news sentiment explains daily returns. In turn, 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 covary less with the aggregate news sentiment during periods of low aggregate news sentiment.

We construct sentiment-based measures of downside covariation, sentiment downside beta, for each portfolio-month observation. For each month t, we use daily sentiment over the 12-month period, from t to $t+11$. We obtain estimates of the sentiment unconditional β by regressing the news sentiment of each portfolio on the average news sentiment over each 12-month period. We estimate sentiment downside beta by regressing the news sentiment of each portfolio on the average news sentiment using only the observations for which the realized average news sentiment is below its mean within each period. We then calculate

---

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

[26]In unreported results, we run a daily-frequency time-series regression of the market's excess return on aggregate news sentiment (i.e., the pooled cross-sectional average of news sentiment). We find that the market return statistically significantly increases in aggregate news sentiment, and their correlation is 0.21.

[27]For plotting purposes only, we standardize the two variables to facilitate their comparison.

relative sentiment downside beta as the raw sentiment downside beta minus the sentiment unconditional β. Note that these measures are deliberately constructed 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 beta and sentiment unconditional beta for each quintile portfolio, as well as their differences between the highest and the lowest ES quintile portfolios. Both average relative sentiment downside and sentiment unconditional betas 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.[28]

Panel C conducts the same analysis as in Panel B but we control for industry by sorting stocks within each industry into quintiles according to ES scores. The differences in relative sentiment downside beta and sentiment unconditional beta between the high and low ES quintiles 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 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. Decreasing patterns between sentiment-based downside covariation and ES are consistent with the presence of the negative relation between ES performance and downside risk. On the other hand, sentiment-based unconditional covariation and ES show a relatively weak relationship that is not strong enough to give rise to a statistically significant relation between ES and unconditional risk, albeit negative.[29]

---

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

[29]The differences in relative sentiment downside beta (sentiment unconditional beta) are larger (smaller) than its time-series average cross-sectional standard deviation.

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, they are less susceptible to selling pressure and they covary less with the market. Institutional investors potentially represent such group of large investors for several reasons. First, institutional investors, especially those with longer horizons, increasingly exhibit preferences for firms with high-ESG profiles.[30] Second, trading by institutional investors is capable of exerting meaningful price pressure in the stock market.[31] Finally, recall that our results regarding the downside risk effects of ES performance are obtained primarily in the cross section of large firms, which are exactly the type of stocks that institutional investors tend to invest in.[32]

In particular, we examine how the direction of institutional trading covaries with the market return depending on firm-level ES performance. We hypothesize that, conditional on down moves of the market, institutional investors tend not to sell high ES stocks as the market falls: institutional trading downside beta with respect to the market is negatively related to ES score. On the other hand, conditional on the upside movements of the market, institutional investors might buy high ES stocks as the market rises: institutional trading upside beta with respect to the market is positively related to ES score, which is the opposite of the relation when the market declines. Thus, we also hypothesize that, unconditionally, institutional trading beta with respect to the market is not significantly related to ES score. Our analysis of these two hypotheses relies on institutional trading data from Abel Noser.[33]

---

[30]See, for example, Starks, Venkat, and Zhu (2020) and Cao et al. (2020).

[31]See, for example, Coval and Stafford (2007) and Lou (2012).

[32]For evidence on institutional preferences for stock characteristics, see Gompers and Metrick (2001).

[33]This data set has several advantages. First, the data are not likely to suffer from self-reporting bias because clients submit this information to receive objective evaluations of their trading costs, not to publicize their performance. Moreover, Abel Noser includes information about institutions that report in the past but at some point terminated their relationship with Abel Noser, which implies that the data is free of survivorship bias.

4.2.1 Abel Noser Database

We use Abel Noser institutional trading data, which contain trading records of institutional investors that use Abel Noser's transaction cost analysis services. The set of investors covered by Abel Noser data are mainly plan sponsors (e.g., United Airlines) and mutual fund families (e.g., Fidelity Investments). For each transaction, Abel Noser provides, among other things, the unique client code for each institution, the unique identifier for each stock traded, the time of execution, whether the trade is a buy or sell, the execution price, and the number of shares traded. Hu et al. (2018), who provide a detailed description of the Abel Noser data, estimate that Abel Noser data covers 12% of CRSP trading volume from 1999 to 2011.[34]

Similar to the timing of a news release, we assign a trade to a given day if the trade is executed on that day before or at the market close (16:00) and to the next trading day if the trade is executed after 16:00. For each firm-day observation, we calculate the net shares traded (i.e., shares purchased minus shares sold, or trading imbalance).[35] We then scale the trading imbalance by focusing on its direction, taking values 1 for net institutional buying, -1 for net institutional selling and zero for zero.

In the end, our sample contains trades of big firms (i.e., market value above the median NYSE market equity) by 762 institutions, with 203 money managers and 559 plan sponsors, between 2000 and 2010 that total \$31.3 trillion.

4.2.2 ES Score Matters for Patterns of Institutional Trading

We measure the covariation of institutional trading with the market each firm-month observation. For each month t, we use the direction of daily trading imbalance over the 12-month period, from t to $t + 11$. We obtain estimates of the trading unconditional β with respect

---

[34]Previous studies (e.g., Anand et al. 2012) show that the characteristics of stocks held and traded by institutions in the Abel Noser database are comparable to those in the 13F database.

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

to the market by regressing the direction of institutional trading of each firm on the market excess return over each 12-month period. We consider two versions of trading downside beta. The first version estimates 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 within each period, just like in computing β^-. Given that it is not clear a priori when institutional investors step in, if at all, to take the selling pressure off on prices of high ES firms, the second version uses only the observations for which the realized market excess return is below the 25th percentile of its distribution within each period. We then calculate relative trading downside beta as the raw trading downside beta minus the trading unconditional β.

In Table 8, we examine if past ES score can predict future realized measures of how institutional trading covaries with the market, controlling for other firm characteristics and risk characteristics.[36] The first column shows that past ES score does not statistically significantly predict future trading unconditional beta over the next 12 months. On the other hand, we find that ES score exhibits consistently negative relations with both versions of trading downside beta, raw or relative. However, the estimated slopes on ES score are statistically significant only for the second version of trading downside beta (see the last two columns of Table 8). While institutional investors *do* step in to supply liquidity to high ES firms during market declines, they do so mainly during times of extreme market declines.

Taken together, we obtain institutional trading patterns that can explain downside risk effects of firm-level ES performance in stock returns, and our results are consistent with the following narrative based on ES preferences of institutional investors: when the market suffers extremely negative shocks, institutional investors hold on to high-ES firms which generate high returns and low downside betas of these firms. During normal times, however, institutional investors buy high-ES firms such that, unconditionally, they do not exert additional pressure on prices of these firms, which can give rise to the fact that ES ratings do not change unconditional market risk.

---

[36] All the *t*-statistics in Table 8 are computed using 12 Newey-West (1987) lags.

5   Conclusion

We empirically analyze risk and return of environmental and social firms. 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. While these results suggest downside risk as the unique pecuniary benefit from ES factors, the effect is not materially large enough to support ES-focused investment vehicles based solely on economic considerations. But, it is possible that this weak result may stem from the fact that our proxies for CSR might be too noisy. We leave the task of addressing the attenuation bias for future research.

Finally, we provide empirical evidence for two general explanations that can give rise to downside risk effects of firm-level ES performance. First, patterns of realized firm news sentiment show that firms "do well by doing good": firm values for high ES firms covary less with the average firm's value, especially when the average firm's value is declining. Second, patterns of institutional trading show that institutional investors have preference for high-ES stocks: they hold on to these stocks when the market suffers extremely negative shocks. Overall, our results strongly support that a firm's CSR activities, in addition to more traditional characteristics, warrant the attention of investors interested in hedging their downside risk.

References

Albuquerque, R., Y. Koskinen, S. Yang, et al. (2020). "Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash". In: *Review of Corporate Financial Studies* 9.3, pp. 593–621.

Albuquerque, R., Y. Koskinen, and C. Zhang (2019). "Corporate Social Responsibility and Firm Risk: Theory and Empirical Evidence". In: *Management Science* 65.10, pp. 4451–4469.

Anand, A. et al. (2012). "Performance of Institutional Trading Desks: An Analysis of Persistence in Trading Costs". In: *Review of Financial Studies* 25.2, pp. 557–598.

Ang, A., J. Chen, and Y. Xing (2006). "Downside Risk". In: *Review of Financial Studies* 19.4, pp. 1191–1239.

Barber, B. M., A. Morse, and A. Yasuda (2021). "Impact investing". In: *Journal of Financial Economics* 139.1, pp. 162–185.

Borisov, A., E. Goldman, and N. Gupta (2016). "The Corporate Value of (Corrupt) Lobbying". In: *Review of Financial Studies* 29.4, pp. 1039–1071.

Cao, J. et al. (2020). "ESG Preference, Institutional Trading, and Stock Return Patterns". Working Paper.

Chava, S. (2014). "Environmental Externalities and Cost of Capital". In: *Management Science* 60.9, pp. 2223–2247.

Coval, J. and E. Stafford (2007). "Asset fire sales (and purchases) in equity markets". In: *Journal of Financial Economics* 86.2, pp. 479–512.

Daniel, K. and S. Titman (1997). "Evidence on the Characteristics of Cross Sectional Variation in Stock Returns". In: *Journal of Finance* 52.1, pp. 1–33.

Edmans, A. (2011). "Does the stock market fully value intangibles? Employee satisfaction and equity prices". In: *Journal of Financial Economics* 101.3, pp. 621–640.

Fama, E. F. and J. D. MacBeth (1973). "Risk, Return, and Equilibrium: Empirical Tests". In: *Journal of Political Economy* 81.3, pp. 607–636.

Geczy, C. C., R. F. Stambaugh, and D. Levin (2005). "Investing in Socially Responsible Mutual Funds". Working Paper.

Godfrey, P. C., C. B. Merrill, and J. M. Hansen (2009). "The relationship between corporate social responsibility and shareholder value: an empirical test of the risk management hypothesis". In: *Strategic Management Journal* 30.4, pp. 425–445.

Gompers, P. A. and A. Metrick (2001). "Institutional Investors and Equity Prices". In: *Quarterly Journal of Economics* 116.1, pp. 229–259.

Hartzmark, S. M. and A. B. Sussman (2019). "Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows". In: *Journal of Finance* 74.6, pp. 2789–2837.

Harvey, C. and A. Siddique (2000). "Conditional Skewness in Asset Pricing Tests". In: *Journal of Finance* 55.3, pp. 1263–1295.

Hoepner, A. G. F. et al. (2020). "ESG Shareholder Engagement and Downside Risk". Working Paper.

Hong, H. and M. Kacperczyk (2009). "The price of sin: The effects of social norms on markets". In: *Journal of Financial Economics* 93.1, pp. 15–36.

Hong, H. and L. Kostovetsky (2012). "Red and blue investing: Values and finance". In: *Journal of Financial Economics* 103.1, pp. 1–19.

Hong, H., J. D. Kubik, and J. Scheinkman (2012). "Financial Constraints on Corporate Goodness". Working Paper.

Hu, G. et al. (2018). "Institutional trading and Abel Noser data". In: *Journal of Corporate Finance* 52, pp. 143–167.

Kelly, B. and H. Jiang (2014). "Tail Risk and Asset Prices". In: *Review of Financial Studies* 27.10, pp. 2841–2871.

Kempf, A. and P. Osthoff (2007). "The Effect of Socially Responsible Investing on Portfolio Performance". In: *European Financial Management* 13.5, pp. 908–922.

Kim, Y., H. Li, and S. li (2014). "Corporate social responsibility and stock price crash risk". In: *Journal of Banking Finance* 43, pp. 1–13.

Krüger, P. (2015). "Corporate goodness and shareholder wealth". In: *Journal of Financial Economics* 115.2, pp. 304–329.

Lins, K. V., H. Servaes, and A. Tamayo (2017). "Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis". In: *Journal of Finance* 72.4, pp. 1785–1824.

Lou, D. (2012). "A Flow-Based Explanation for Return Predictability". In: *Review of Financial Studies* 25.12, pp. 3457–3489.

Newey, W. K. and K. D. West (1987). "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix". In: *Econometrica* 55.3, pp. 703–708.

Oikonomou, I., C. Brooks, and S. Pavelin (2012). "The Impact of Corporate Social Performance on Financial Risk and Utility: A Longitudinal Analysis". In: *Financial Management* 41.2, pp. 483–515.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2020). "Sustainable investing in equilibrium?" In: *Journal of Financial Economics* forthcoming.

Servaes, H. and A. Tamayo (2013). "The Impact of Corporate Social Responsibility on Firm Value: The Role of Customer Awareness". In: *Management Science* 59.5, pp. 1045–1061.

Starks, L., P. Venkat, and Q. Zhu (2020). "Corporate ESG Profiles and Investor Horizons". Working Paper.

Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy (2008). "More Than Words: Quantifying Language to Measure Firms' Fundamentals". In: *Journal of Finance* 63.3, pp. 1437–1467.
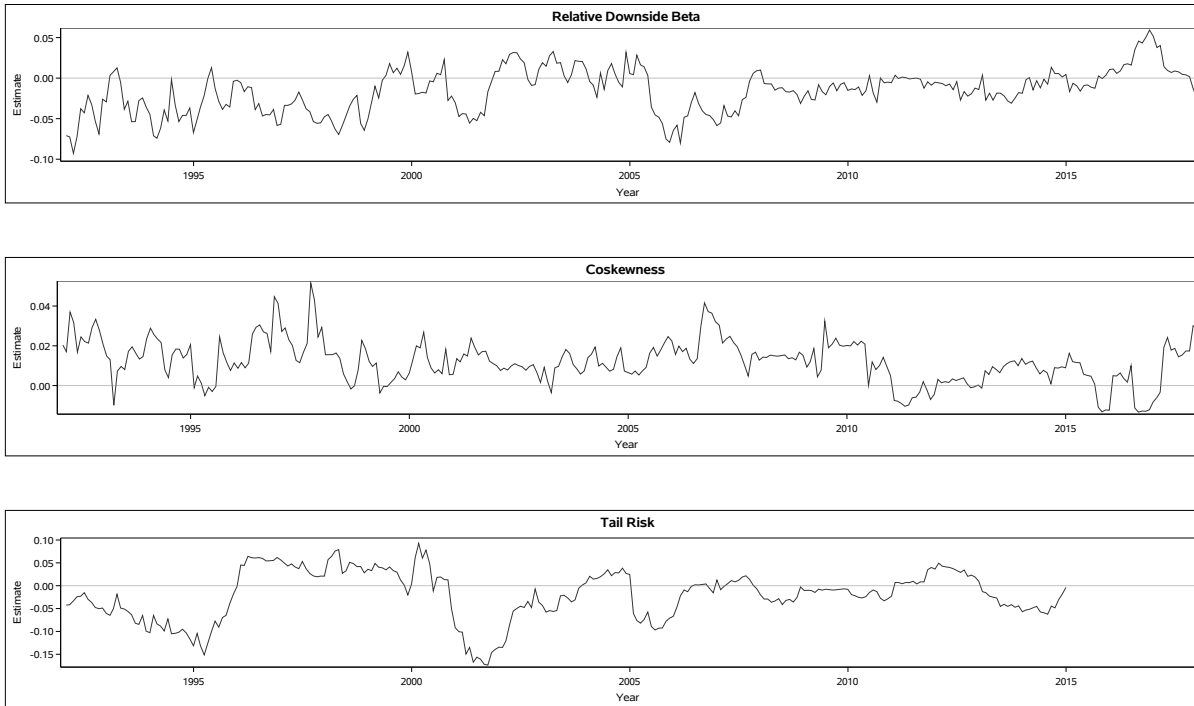
Figure 1: Monthly ES Coefficient Estimates

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.
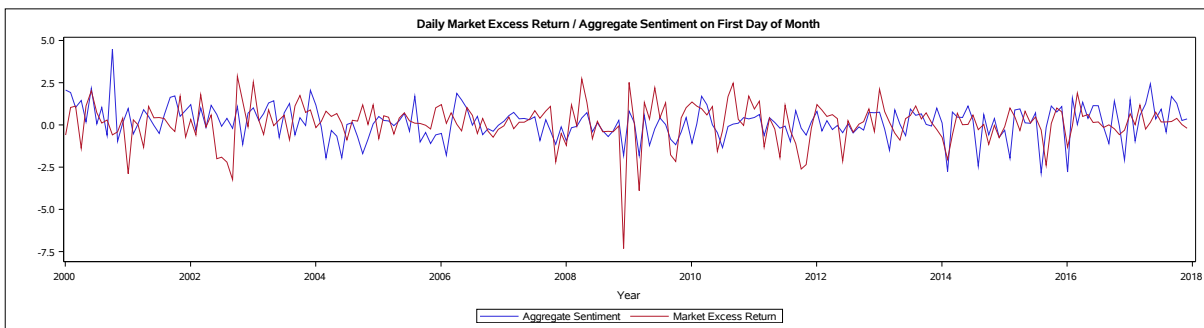
Figure 2: Aggregate News Sentiment and Market Excess Return

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	553	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)
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

39

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. $\mathbf{1}(SmlCap)$ ($\mathbf{1}(BigCap)$) 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)
$\mathbf{1}(Dividend)$	-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)
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