ESG Risk Exposure: A Tale of Two Tails

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Abstract

This paper studies the ESG impact to the downside risk of companies in the US market by introducing a novel measure, the ESG risk contribution (△CoESGRisk). △CoESGRisk is the co-movement between the ESG risk factor and the downside risk. We find that when there is a sudden increase in the ESG risk factor, the downside risk of high-ESG companies is reduced. Such impact is positively correlated with ESG performance and company size, and it varies among different sectors. In addition, during the COVID-19 crisis period, the ESG risk contribution is higher than at normal times.

Keywords: ESG, ESG Risk Factor, Fama/MacBeth Risk Factor, Quantile Regression, CoVaR, Downside Risk

JEL codes: G12, G32, C51

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1 Introduction

The Environmental, Social and Governance (ESG) investments have experienced tremendous growth in recent years, especially during the COVID-19 crisis. The demand for high-ESG companies – companies that have high ESG scores – has been increasing.[1] According to a survey by Moody's Investors Service, inflows into ESG products grew 140% from 2019 to 2021.[2] Scholars also find that investors switch from low-ESG companies to high-ESG companies during crisis times (Dong et al., 2019 and Nofsinger and Varma, 2014). One major motivation of such behavior is that ESG investments can suffer less when there are negative shocks. Investors expect high-ESG companies to have lower downside risk than low-ESG ones during volatile times.

Studies on ESG and downside risk are still limited, but already support this motivation. Lins et al. (2017) show that high-ESG companies have high social capital that pays off during crisis times. Hoepner et al. (2021) provide evidence that firm's ESG activities, the activities that companies carry out to improve their ESG scores, improve corporate governance, and thus lead to lower downside risk. Differently, Krueger (2015) demonstrates that firms with high ESG performance are less vulnerable to company-specific negative events. Nevertheless, apart from these empirical works, there are no theoretical models that can be readily applied to explain the mechanism through which ESG affects the downside risk, nor empirical studies tackling this issue from data-driven perspective. The closest work is by Albuquerque et al. (2019), who develop an equilibrium model to explain the relationship between ESG and the general firm risk. They show that firm's ESG activities help increase product differentiation, which then allows firms to benefit from higher profit margins, and thus lower the systematic risk. However, further questions from the risk management perspective emerge: to which extent firm's ESG activities help decrease the downside risk? And what determines such benefits?

To answer these questions, we face, at least, two difficulties. First, we need to measure how much ESG activities could be realized as benefits. For example, consider a company who decides to reduce the carbon emission by 20% every year, a possible benefit would be lower corporate tax in the future, but we may not be able to know when and how much such benefit will be realized. Second, we need to measure how much these benefits can convert to deductions in the downside risk – put it in our example, the reduction of corporate tax

[1] The ESG Score is a credit-rating-like score that measures the sustainability performance of a company, usually based on a matrix of indicators. A high ESG score means high sustainability performance, for which we call companies with high ESG scores high-ESG companies.

[2] https://www.moodys.com/research/Moodys-ESG-investing-a-boon-for-asset-managers-as-product--PBC_1265808

does not necessarily mean it will suffer less when there are negative shocks in the market.

This paper aims to measure how much a company's downside risk is being affected by its ESG activities and what determines the impact. We solve the first difficulty by looking at the financial market: we measure the benefits of ESG activities by looking at how they are realized in the market. To do so, we construct the *ESG risk factor* – a type of risk factor that captures how ESG is being priced in the market.[3] The ESG risk factor is calculated as the return difference between two groups of companies: companies with high ESG score and companies with low ESG score.[4] Mathematically speaking, it is the average additional positive/negative return brought by having higher ESG scores. Economically speaking, Becchetti et al. (2018) conclude that such ESG risk factor captures the stakeholder risk – that high-ESG companies have lower stakeholder risk than low-ESG ones.[5] Ľuboš Pástor et al. (2021) show that such ESG risk factor reflects investor's ESG preference, that is, investors develop a taste for high-ESG companies and thus low-ESG ones should have a higher return to compensate the taste. Therefore, the ESG risk factor should be negative, with high-ESG companies having lower expected returns than low-ESG ones. However, the ESG risk factor can also be positive during certain periods. When there is a sudden increase in the ESG sentiment (investor's attention to ESG), investor's preference over ESG is intensified, and thus the demand for ESG products rises, pushing the price of high-ESG companies to rise quickly and thus the return of high-ESG companies is higher than that of low-ESG ones. Consequently, both tails of the ESG risk factors convey relevant information for the pricing of companies involved in ESG activities.

To address the second difficulty (i.e, to measure how and to which extent the downside risk is being affected), we propose a risk exposure measure: the *ESG Tail Risk* ($CoESGRisk$) and the *ESG Risk Contribution* ($\triangle CoESGRisk$) based on the concept of $CoVaR$ and $\triangle CoVaR$ by Adrian and Brunnermeier (2016). $CoESGRisk$ is the value at risk (VaR) of a company when the ESG risk factor becomes extremely high/low. The $\triangle CoESGRisk$ is the change of VaR when the ESG risk factor changes from the benchmark state to extremely high/low state. Thus, $\triangle CoESGRisk$ measures how the downside risk of a company changes to extreme positive/negative changes in the ESG risk factor, or, the co-movement between

[3]There are some applications in the literature. See works of Lucia et al. (2020), Becchetti et al. (2018), Hubel and Scholz (2019), Maiti (2020), Naffa and Fain (2022), Jarjir et al. (2022), **?** and Yang and Jimenez-Martin (2021).

[4]We mean High-ESG minus Low-ESG here. Of course, you can calculate the other way around, but the idea is the same.

[5]In their work, stakeholder risk is defined as the risk brought by having more conflicts with stakeholders, such as NGOs, governments, customers, suppliers, etc. For example, a company could receive fines from the government if it violates ESG-related regulation. Or, the sales could be heavily damaged if a company fails to meet the expectation of customers.

the ESG risk factor and the downside risk. Therefore, our research design focuses on the following steps: first, we calculate the ESG risk factor to capture the realization of ESG activities in the market; and second, we use the co-movement between the ESG risk factor and downside risk as how much a company's downside risk is being affected by its ESG activities.

Note that we focus on both extreme positive and negative states of the ESG risk factor, because they provide different and relevant insights on the relationship between the ESG risk factor and companies' risk exposure. As discussed above, if the ESG risk factor is in its extreme states, it means that in the market the ESG sentiment can be very high/low. This may indicate a different market condition, where ESG have stronger impacts to the downside risk of the company than normal times. Therefore, in estimating $\triangle CoESGRisk$, we also apply a more flexible setting proposed by Bonaccolto et al. (2019), where the relationship between ESG risk factor and company risk is allowed to change to the states of the ESG risk factor, for which we call it the *Quantile-located ESG Risk Contribution* ($\triangle QL - CoESGRisk$). In sum, in estimating ESG risk contribution, we apply two settings with regard to the relationship between ESG and downside risk: the conventional setting where the relationship between ESG and the company risk does not change to the states of the ESG risk factor and the more flexible setting.

Using this new measurement, we conduct an empirical analysis on the US market. Under the conventional setting, we find that when the ESG risk factor changes from normal state to extremely high state, high-ESG companies receive risk deduction benefits. That is, having high ESG scores does pay-off, which is in accordance with the literature (see, for instance, Hoepner et al., 2021 and Lins et al., 2017). Specifically, we show that the downside risk, measured by daily 5% VaR, is reduced by around 26 basis points for high-ESG companies (we express the VaR in negative quantity and by saying the downside risk is reduced, we mean the VaR has become more positive).[6] For low-ESG companies, the contribution is around -28 points. In other words, holding high-ESG companies should have 54 basis point smaller downside risk than low-ESG ones, due to the difference in their ESG performances. We show that, unless the ESG score is high (above 60% in the ranking), one should expect to have negative ESG risk contributions. Such relationship does not change over the years.

However, when we allow the states of the ESG risk factor to affect the ESG–downside risk relationship, we get different results. We find that high-ESG companies will suffer even when the market is in favor of high-ESG companies. The quantile-located ESG risk contribution to the 5% daily VaR can be -27 bps for high-ESG companies and -89 bps for low-ESG ones

[6] High-ESG means a companies with a historical average ESG score ranking above 80% quantile during our sample period 2013-2020; accordingly, low-ESG is defined as below 20% quantile

(high-ESG still suffers less). Such negative risk contribution comes from the fact that the volatility of company returns has been increased by the ESG risk factor. The result also implies that extreme states of ESG risk factor do matter, that they are linked to some certain market ESG conditions, implying a different relationship between ESG and downside risk from normal times.

In addition, unlike the conventional setting, the quantile-located ESG risk contribution changes over the years. Such changes are mainly driven by changes in the exposure of a company's downside risk to the ESG risk factor. The changing exposure is partly due to time-varying tail distributions of companies and the ESG risk factor, which is especially the case during the COVID period. However, ruling out the impacts of changing distributions, we still find a changing risk exposure over time. One possible explanation is that in different periods, extreme states of ESG risk factor may be driven by different causes, which could result in different impacts of ESG to the downside risk. Therefore, when evaluating the ESG impact, it is also needed to consider the changing relationship under different market ESG conditions.

We find that ESG risk contributions are mainly driven by company's risk exposure to ESG, for which we further study determinants of the risk exposure. The exposure is affected by corporate variables. A higher ESG score leads to a more positive exposure and thus a more positive ESG risk contribution. Apart from the ESG score, other corporate variables such as company size and profitability will also affect the ESG downside risk exposure. Specifically, large companies will suffer less under extreme market ESG conditions. We also find that higher climate sentiment and market uncertainty will lead to higher quantile beta ~~under the conventional setting~~. Differences between quantile beta under normal beta and quantile-located beta are mainly driven by market forces. The level of contribution varies among sectors, which ~~means~~ that sector characteristics should be taken into account when evaluating the impact of ESG on downside risk.

We contribute to the literature of ESG and company risk in different ways. First of all, we propose a new method to quantify how downside risk can be affected by ESG: $\triangle CoESGRisk$. Recent works find that higher ESG performance is related to lower downside risk (Hoepner et al., 2021, Ilhan et al., 2021, Lööf and Stephan, 2019, Lins et al., 2017 and Krueger, 2015). However, they fail to address how much the downside risk of a company can be affected by ESG, which is vital information for investors to form a proper sustainable investment strategies. For regulators, knowing how much is the ESG impact is crucial when evaluating the impact of ESG-related policies (e.g., new carbon tax). In addition, our results provide new implications in the literature: extreme states of the ESG risk factor could indicate extreme ESG conditions, where high-ESG companies may also suffer from being exposed to the ESG.

Our work also extends the strand of literature about ESG and financial markets. Recent studies show that ESG now becomes a systematic risk factor in the financial market (e.g., Lioui and Tarelli, 2022, Ľuboš Pástor et al., 2021 and Becchetti et al., 2018) and such realization of ESG in the financial market will affect the conditional mean of stock return (Maiti, 2020 and Lucia et al., 2020) and the connection between individual and market return (Ma et al., 2022) . In our work, we show that not only the conditional mean but also the conditional quantile is affected. Such impact to the conditional quantile is different from the conditional mean in that it varies across return distribution – we observe a larger impact to the tail than to the mean.

The paper proceeds as follows. We first describe the data and a detailed discussion of the methodology we use in Section 2. In Section 3, we present the empirical results in the US market. Section 4 analyzes determinants of $\triangle CoESGRisk$. We conclude our paper in Section 5.

2 Data and Methodology

2.1 Company Data: Equity Prices and ESG Scores

We use companies in the US market for our analysis. We download the daily price from 2013/06/03 to 2020/12/31 from Eikon (Refinitiv). The daily return is calculated as $R_{i,t} = Ln(\frac{P_{i,t}}{P_{i,t-1}})$ for each company i and time t. In total, we have 1,911 daily price observations. There are 1,867 US companies with available prices and available ESG information from 2013 to 2020 in the database (as of 2021/06).

We use the ESG combined score to represent the ESG performance of each company. The ESG combined score is also recovered from Eikon (Refinitiv), and is updated semiannually or annually, based on the fiscal year of each company. Refinitiv is one of the major ESG data providers in the world. Its ESG data covers more than 10,000 global companies in 76 countries. We have downloaded monthly ESG score data from 2013/05/31 to 2020/12/31.[7] The ESG combined score measures a company's overall sustainability performance and takes value in the range from $0 - 100$, with higher values indicating better environmental, social and governance performances of a company. The score has three components: the environmental pillar score, the social pillar score and the governance pillar score. Each pillar score has several sub-scores. Apart from three pillar scores, a controversy score is calculated for each company. The controversy score measures a company's exposure to ESG-related con-

[7]We did not use the early data because fewer companies disclosed their ESG data in early times.

troversies and negative events reflected in the global media. In summary, the ESG combined score is calculated in two steps:

$$\begin{cases} ESG_i = E_i w_E + S_i w_S + G_i w_g \\ ESG\ Combined_i = \begin{cases} ESG_i & \text{if } ESG_i > Controversy_i, \\ 0.5 \times (ESG_i + Controversy_i) & \text{otherwise} \end{cases} \end{cases} \tag{2.1}$$

where E_i, S_i,G_i are the E/S/G pillar score; w_E, w_S, w_G are the weights for each pillar score and vary among sectors according to Eikon.[8] Eq. (2.1) shows that the original ESG score should be re-adjusted (to be lower) if the controversy score is lower than the original ESG score. In other words, if one company is highly exposed to to negative events, the ESG combined score should be lower than the original ESG score. We call the ESG combined score as the ESG score in following discussions. Notably, as the ESG score is comparable across sectors, we do not have to adjust it to consider the industry characteristics.[9] A detailed description of the data and code we use is included in Appendix A.

2.2 ESG Risk Factor

Three methods are found in ESG literature to construct the ESG risk factor. The most common one is the Fama/French (FF) method.[10] Under the FF method, one constructs the risk factor as factor-mimicking portfolios by employing long-short strategies: long on stocks with low-ESG companies and short on stocks with high-ESG companies. Another method is the mimicking-portfolio approach (MP), a method formally discussed in Lamont (2001). Under the MP method, a time-series regression is conducted between the ESG score time-series (dependent) and a series of portfolio returns (independent). The portfolios are chosen to form a return space that should span the true ESG risk factor. Then, the beta in the time-series regression serves as the weight to form a tracking portfolio. In the ESG field, Engle et al. (2020) first applied the MP method to construct a tracking portfolio to mimic a climate news index.

Others (Naffa and Fain, 2022 and Ľuboš Pástor et al., 2022) construct the ESG risk factor using the Fama/MacBeth (FM) method, first appeared in the work of Fama (1976) (Ch. 9)

[8]https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf; in page 13

[9]https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf

[10]See, among the most recent contributions, Becchetti et al., 2018, Maiti, 2020, Yang and Jimenez-Martin, 2021 and Jarjir et al., 2022.

and then further discussed in Fama and French (2020). Under the FM method, in each time t, a cross-section regression is carried out. On the left side of the cross-section regression, the return of companies are used. On the right side of the regression, we use corporate variables like firm size and book-to-market ratios. Then, at each time t, the regression results will be a cross-section beta for each corporate finance variable. The final step is to stack the beta from the cross-section regression over time and obtain a time series. Similarly, in the cross-section regression step, if we add the ESG score as an explanatory variable, the corresponding beta time series can be interpreted as an estimated ESG risk factor.[11] The FM method is better in that we can control for other factors in the cross-section regression when constructing the ESG risk factor. Lioui and Tarelli (2022) further compare constructing ESG risk factor using FF method and FM method, they find that ESG risk factor under the FM method is better in being more pure (less affected by other corporate characteristics). Therefore, we will use the FM method in our paper.

We construct FM factors following the five-factor cross-section model described in Fama and French (2020). We use several corporate variables in the cross-section regression: market value (MV), the book-to-market ratio (BM), which is the book value of equity to market value of equity; operating profit (OP), calculated as the operating profit divided by book value of equity; investment growth, which measures the growth rate of total assets, and is calculated as $Ln\left(\frac{TA_{year\,t-1}}{TA_{year\,t-2}}\right)$ (TA = Total Asset). We download from Eikon the month-end value for each variable (see Appendix A for a detailed description) $OP_{i,m}$, $INV_{i,m}$, $BM_{i,m}$ and $MV_{i,m}$, where i refers to the company and m to the month. We use the ESG score standardized across the market at every month m. The standardization is performed across companies with available ESG score in month m.

We run a cross-section regression every day (using the OLS estimator):

$$\begin{aligned} R_{i,t} = f_{0t} + f_{ESG,t} {Z^{ESG}}_{i,m-1} + f_{MV,t} MV_{i,m-1} + f_{BM,t} BM_{i,m-1} \\ + f_{OP,t} OP_{i,m-1} + f_{INV,t} INV_{i,m-1} + \varepsilon_{i,t}, \end{aligned} \tag{2.2}$$

where $R_{i,t}$ is the daily return of all companies with available ESG data in day t; f_{0t} is the constant and $\varepsilon_{i,t}$ is the $i.i.d.$ error term. $ESG_{i,m-1}$ is the Z-score of the ESG score. $MV_{i,m-1}$ is the market value for company i at month $m-1$. For example, for the time period of 2013/06/03 to 2013/06/30, we use the market value at 2013/05/31. $BM_{i,m-1}$ is the book-

[11] In the standard FM two-step process, the first step is to run a time series regression between company return and corporate variable time series to get one fixed beta for each company during the sample period. Then, in the second step, at each time t, we perform the cross-section regression as in Eq. (2.2) using the beta from the time-series regression (i.e. we use β_i^{ESG} to instead of $ESG_{i,m-1}$in the model). Thus, the above process to calculate ESG risk factor is different from the standard two-step FM cross-regression in that it starts directly from the second step using corporate variable as the beta in the first step.

to-market ratio, $OP_{i,m-1}$ is the operating profit and $INV_{i,m-1}$ is the investment growth. All variables will be updated monthly (if there is a change).

The result of the estimation is one beta ($f_{ESG,t}$) at each day t. We then stack the estimation result of each day over time to obtain the ESG risk factor time series. The factor is available from 2013/06/04 to 2020/12/31. In total, we have a time series of 1,910 daily estimations. Apart from estimating the ESG risk factor, we also estimate other risk factors: $f_{MV,t}$, $f_{BM,t}$, $f_{OP,t}$, $f_{INV,t}$. Following the literature (Fama and French, 2008 and Amihud, 2002), since the constructed factors could be distorted by small-cap companies, we drop penny companies, which, in our case, are defined as companies whose price went below USD 5 during our sample period. In essence, as we show in Eq. (B.5) in the Appendix B, $f_{ESG,t}$ is an ESG score-weighted portfolio: it is the return difference of (high-ESG minus low-ESG). Cross-sectionally, $f_{ESG,t}$ is the compensation brought by having higher ESG score. If $f_{ESG,t} = 0.5\%$, it means that a company with one standard deviation increase in the ESG score will have 0.5% more expected return. It is the realization (price) of firm's ESG activities in the market.

The structure used in Eq. (2.2) to capture the ESG risk factor is different from the literature. Ľuboš Pástor et al. (2021) use a two-factor structure in the cross-section regression to capture the environmental factor: the market beta and the environmental score, without intercept f_{0t}. Naffa and Fain (2022), in comparison, used 11 style factors plus one E/S/G score in the cross-section regression. As a result, Ľuboš Pástor et al. (2021) get a relatively strong factor series (statistically different from zero) while Naffa and Fain (2022) find that the ESG factor is not significant. In others words, adding too many factors in Eq. (2.2) can make the estimation of $f_{ESG,t}$ not significant, while adding too few components, as done by Ľuboš Pástor et al. (2021), though the estimation result can be significant, will make the estimation not "pure" enough, such that $f_{ESG,t}$ could capture the effect of other factors. The complexity lies in how we define "pure" and how we interpret "ESG". If we interpret ESG as something identical to other corporate variables like "total revenue" or "total asset" – that it should purely measure the "sustainability" aspect of a company – then we should add as much control variables as we can in our model to get a risk factor that only focuses on the "sustainability" part.

On the other hand, the previous literature shows that ESG affects a company's stock performance through other corporate variables. Many find that high-ESG is associated with better corporate finance indicators (see, Giese et al., 2019 and Gillan et al., 2021) (though no causality relationship has been formally proved in the literature, to the best knowledge of the authors). In that sense, putting only two factors in Eq. (2.2) as done by Ľuboš Pástor et al. (2021) also seems justified – differences in the ESG performance are reflected in differences in corporate finance variables, thus the ESG risk factor should capture effects from other corporate finance variables. Generally speaking, all approaches have pro and cons. In our case, we consider the ESG risk factor to be a factor that is *complementary* to the vastly-used and well-known five-factor structure in terms of explaining cross-section returns. Lioui and Tarelli (2022) apply a similar cross-sectional five-factor structure and show that the ESG risks factor does exist as an additional factor in terms of asset pricing.

Recent empirical studies find that the major driving force behind the return difference is the investor preference. Ľuboš Pástor et al. (2021) develop an equilibrium model in which investors preference over ESG would create a negative premia. In a similar vein, Serafeim (2020) shows that companies that are more controversial have higher returns, meaning that investors require an additional return to compensate higher risk. Becchetti et al. (2018) explain that since high-ESG companies have a lower stakeholder risk, they should thus have a lower expected return. Therefore, when in a normal market situation, high-ESG companies should under-perform low-ESG ones, this means that $f_{ESG,t}$ should be negative in normal times.

However, $f_{ESG,t}$ could be positive. One reason is that during specific periods, when there is a sudden increase in the ESG sentiment (investor's attention to ESG), investor's preference over ESG is intensified, and thus the demand for ESG products rises. As a result, the price of high-ESG companies to rise quickly and thus the return of high-ESG companies is higher than low-ESG companies. Therefore, in the next section, we study the ESG impact to the downside risk by looking at two extreme states of the ESG risk factor.

We present statistics of risk factors from Eq. (2.2) in Table 1. The t-statistic of the ESG risk factor is small during the whole sample period, indicating an average close to 0. However, when we turn to the most recent period, from 2018/6 to 2020/12, the t-statistic becomes more significant. This can also be seen in the cumulative line in Panel B of Figure 1, where there is an increasing trend in recent years. The positive shocks in recent periods means high-ESG companies outperform low-ESG companies, partly because of a sharp increase in the demand for high-ESG companies due to the increase in ESG sentiment, as found by Ľuboš Pástor et al. (2022).

As discussed before, shocks of the ESG risk factor are due to sudden changes of ESG sentiment in the market, and these changes can be associated with events related to ESG (Choi et al., 2020 and Engle et al., 2020). To examine this, we further plotted major events related to ESG (mainly climate change-related events that affected investors environmental concern). As can be seen, while we can not say that all shocks of ESG risk factor are related to major events concerning ESG, some of them are, and these events are varied in nature: political events, extreme whether, climate summits, etc.. In addition, these events are often

Table 1: **Factor Statistics**

Panel A: Factor statistics of risk factors (1910 observations)

FM	$f_{MV,t}$	$f_{BM,t}$	$f_{OP,t}$	$f_{INV,t}$	$f_{ESG,t}$	$f_{ESG,t}$ (2018–2020)
Average	0.00%	0.00%	0.00%	0.00%	0.0008%	0.0093%
Std.	0.08%	0.28%	0.20%	0.13%	0.13%	0.15%
T-stat.	0.82	-0.25	0.13	0.19	0.29	1.56
Cumulative	3.05%	-3.06%	1.11%	1.05%	1.58%	6.06%

Panel B: Correlations among FM factors

FM Risk Factors	$f_{ESG,t}$	$f_{MV,t}$	$fR_{BM,t}$	$f_{OP,t}$	$f_{INV,t}$
$f_{ESG,t}$	1				
$f_{MV,t}$	0.448	1			
$f_{BM,t}$	-0.181	-0.498	1		
$f_{OP,t}$	0.063	0.103	-0.169	1	
$f_{INV,t}$	-0.011	0.179	-0.373	0.024	1

Note: Panel A shows the factor statistics of risk factors from 2013 to 2020 (1910 observations). "Average" means the average of the factor series from 2013 to 2020. "Std." means the standard deviation of factor series from 2013 to 2020. "Cumulative" is the sum of daily factor return series from 2013 to 2020, for example, $\sum_t f_{ESG,t}$ is the cumulative return for the ESG risk factor. $f_{ESG,t}$ (2018–2020) shows the statistics of the ESG risk factor from 2018/6 to 2020/12 (652 observations). The "T-stats" is the t-statistics for the mean value, and is calculated as $t = \frac{Avg.}{std.}\sqrt{T}$,where T is the number of observations. Panel B shows the correlation the correlation among risk factors.

associated with extreme changes of the ESG risk factor, both positive (Paris Agreement) and negative (Trump Election). Shocks generated during the COVID period can be explained by the "flight-to-quality" effect (Dong et al., 2019).

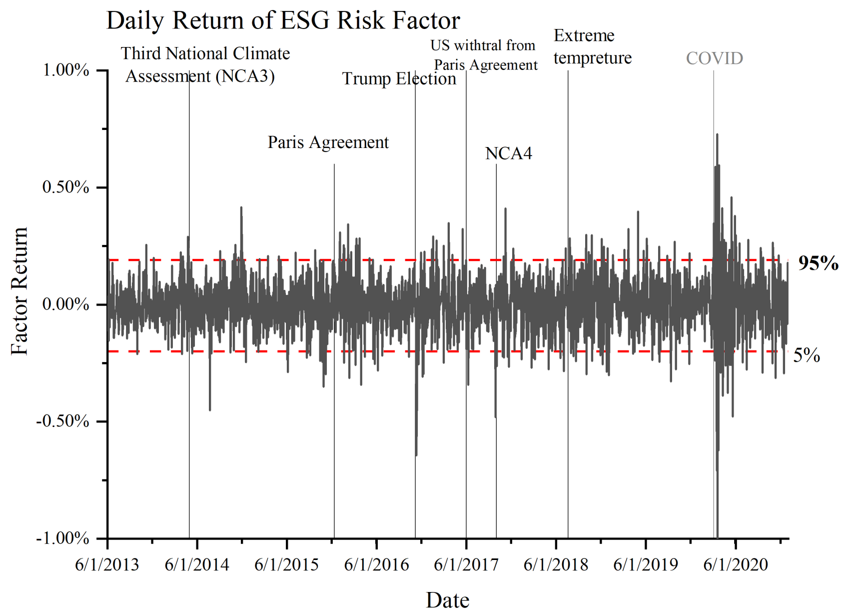
2.3 ESG Risk Factor and Downside Risk: A Conceptual Framework

If we put the discussion under the asset pricing framework, the downside risk can be regarded as a sudden large decrease of the cash flow, or a sudden large increase of the discount rate (or both). Then, ESG activities of a company reduce the downside risk through two channels: first, they mitigate the magnitude of huge changes in the cash flow or discount rate; and second, they reduce the occurrence probability of extreme events that lead to huge changes in cash flow/discount rate. Previous literature can be linked to the asset pricing framework. For example, higher social capital leads to a more stable cash flow during crisis times and thus less downside risk; if firms are less vulnerable to negative events, the probability of a large drop in the cash flow is decreased and then the downside risk is reduced.

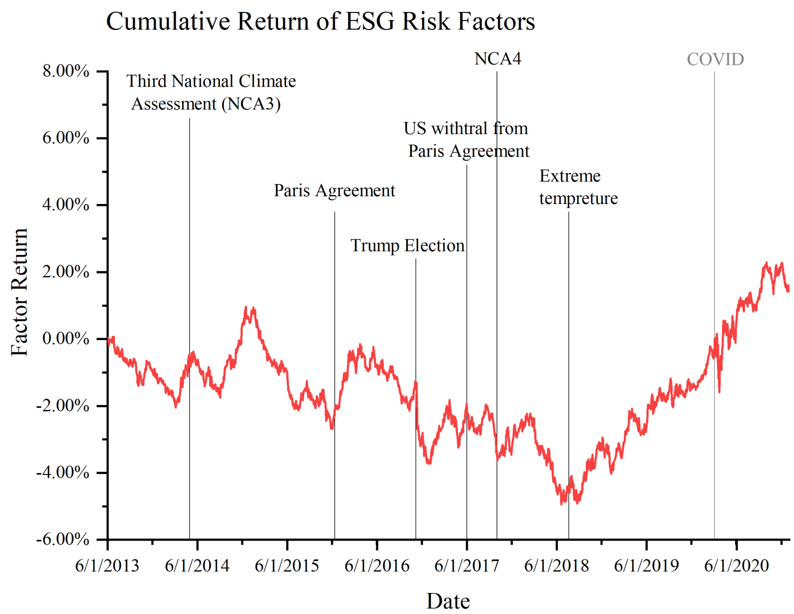
Under the framework, the ESG risk factor affects the downside risk of a company through the discount rate channel. Both the level of and the changes in the ESG risk factor matter.

Figure 1: **Time Series of the ESG Factor**

Panel A: Daily return of the ESG risk factor



Panel B: Cumulative return of the ESG risk factor



Note: The graph shows the ESG factor series. Panel A shows daily factor return of $f_{ESG,t}$. Panel B shows the the sum of daily factor return series from 2013 to 2020:$\sum_t f_{ESG,t}$.

Extreme changes (shocks) in the ESG risk factor could lead to extreme changes in the discount rate and thus may affect the downside risk of companies who have a high exposure to ESG. Extreme levels (states) of the ESG risk factor ~~mean~~ an extreme market condition where a change in the ESG performance ~~means~~ a significant change in the discount rate for companies with high exposures to ESG. In other words, the ESG becomes a source of risk.

However, following this logic, not only the ESG risk factor but also other risk factors should be associated with the downside risk. The critical difference lies in the economic interpretation of the ESG risk factor. As discussed, changes in the ESG risk factor capture shocks associated with systematic events such as ESG-related policies. Connecting the ESG risk factor with the downside risk ~~means we assume~~ those systematic events will affect the downside risk of companies, which is very likely for companies with high ESG exposure. A simple example would be high-carbon emission companies facing a new carbon tax. Similarly, extreme states of the ESG risk factor represent an extreme market condition where ESG activities are being highly over-/under-valued in the market—companies with extreme ESG performances would have a discount rate different from other companies and thus different downside risk performance. If the ESG risk factor is zero, then a company's stock return will not be affected (through the financial market channel) even if it has extremely high/low ESG performance. All these are important for investors who turn to ESG investments for downside risk deduction benefits. For this reason, the risk measures discussed in our paper are based on extreme states of the ESG risk factor.

2.4 ***CoESGRisk*** and Δ***CoESGRisk***

In the work of Adrian and Brunnermeier (2016), the CoVaR is defined as the VaR of a system conditional to one financial institution being at distress. In our case, we define the *CoESGRisk*, the **ESG tail risk**, as the VaR of a company conditional to the ESG risk factor being very high or very low (with the ESG risk factor being in its two tails), that is:

$$CoESGRisk^{\theta}_{i,\tau} \equiv VaR_{\tau}^{i|f_{ESG,t}=VaR^{\theta}_{ESG,t}}, \tag{2.3}$$

where $VaR^{\theta}_{ESG,t}$ is the VaR of the ESG risk factor at the level of θ, $\theta = 5\%$ and 95%; τ is the level of VaR for company i and in our paper we set $\tau = 5\%$. $VaR^{\theta}_{ESG,t}$ refers to the ESG risk factor ($f_{ESG,t}$) being high and positive or low and negative. In other words, we set $f_{ESG,t}$ to be in two extreme states: when the price of ESG is very high ($f_{ESG,t} = VaR^{95\%}_{ESG,t}$) and very low ($f_{ESG,t} = VaR^{5\%}_{ESG,t}$) in market.

Thus, *CoESGRisk* looks at the level of downside risk of a company under the extreme situation where the pricing of ESG in the market is extremely high/low. A comparison between $CoESGRisk$ and unconditional VaR would reveal how the downside risk of a company would be different when the ESG risk factor changes to extreme states. For example, if $CoESGRisk_{i,5\%}^{95\%} = -3\%$ and $VaR_{i,5\%} = -1\%$, then it means that for company i, when there is a sudden increase in the ESG risk factor, the downside risk of the company becomes more negative. One possible explanation could be that company i is less favored by investors in that situation. Such concerns by investors put downward pressure on the stock price and thus it has lower returns and higher losses. Accordingly, the change of $CoESGRisk$ from $CoESGRisk_{i,5\%}^{95\%}$ to $CoESGRisk_{i,5\%}^{50\%}$ can be regarded as the **ESG risk contribution**, for which we introduce $\triangle CoESGRisk_{i,\tau}^{\theta}$, an indicator similar to $\triangle CoVaR$, as set out below:[12]

$$\triangle CoESGRisk_{i,\tau}^{\theta} \equiv CoESGRisk_{i,\tau}^{\theta} - CoESGRisk_{i,\tau}^{50\%}. \tag{2.5}$$

Eq. (2.5) measures the change of VaR of company i when the ESG risk factor changes from normal state to extreme state. It is the difference between the VaR of two conditional distributions and measures how the conditional distribution changes in the lower part when the ESG risk factor changes.[13] Economically speaking, $\triangle CoESGRisk$ tells to which extent the downside risk is exposed to ESG. Therefore, it explains how much the VaR of company i at the level τ will change if the ESG risk factor changes drastically. A positive value of $\triangle CoESGRisk$ indicates that the VaR of a company becomes more positive (less risky) due to the extreme change of ESG risk factor.

2.5 *CoESGRisk* and $\triangle$*CoESGRisk* Estimation: Quantile Regression

The financial econometric literature includes several approaches for conditional VaR estimation: from quantile regression, to multivariate GARCH, or to copula. We use the quantile regression because the betas estimated at the quantile of interest allow us to better identify

[12] Girardi and Ergün (2013) calculate the $\Delta CoVaR$ as the percentage change of CoVaR from the benchmark situation to extreme situation, which, in our case, should be:

$$\triangle CoESGRisk_{i,\tau}^{\theta}(\mathrm{GE}) \equiv \frac{CoESGRisk_{i,\tau}^{\theta} - CoESGRisk_{i,\tau}^{50\%}}{CoESGRisk_{i,\tau}^{50\%}}. \tag{2.4}$$

The problem with the above percentage change definition, as is discussed in Caporin et al. (2021), is that in calmer times, $CoESGRisk_{i,\tau}^{50\%}$ may be close to zero and thus $\triangle \mathrm{CoESGRisk}_{i,\tau}^{\theta}$ may be very large. Therefore, under this definition, the large value of $\triangle CoESGRisk_{i,\tau}^{\theta}$ does not necessarily come from $CoESGRisk_{i,\tau}^{\theta}$ but the small value of $CoESGRisk_{i,\tau}^{50\%}$.

[13] To be more specific, $CoESGRisk_{5\%}^{95\%}$ is the 5% VaR of the conditional distribution that conditions on the ESG risk factor being at 95% level (the conditional VaR); $CoESGRisk_{5\%}^{50\%}$ is the 5% VaR of the conditional distribution that conditions on the ESG risk factor being at 50% level.

how the downside risk of a company is exposed to ESG.

We first run quantile regressions at the level of $\tau = 5\%$, the bear market condition, for the whole period,

$$\begin{aligned} F^{-1}(\tau, R_{it}|covariates) = \delta^{\tau}_{0,i} + \delta^{\tau}_{1,i} f_{M,t} + \delta^{\tau}_{2,i} f_{MV,t} + \delta^{\tau}_{3,i} f_{BM,t} \\ +\delta^{\tau}_{4,i} f_{OP,t} + \delta^{\tau}_{5,i} f_{INV,t} + \beta^{ESG,\tau}_{i} f_{ESG,t} \end{aligned}, \tag{2.6}$$

where $f_{M,t}$ is the market risk factor (since on the left side we use company return $R_{i,t}$ instead of excess return $r_{i,t}$, here $f_{M,t}$ is the market return) and is from the Kenneth R. French database.[14] $f_{MV,t}$, $f_{BM,t}$, $f_{OP,t}$ and $f_{INV,t}$ come from Eq. (2.2). The quantile beta measures the exposure of the downside risk of a company to ESG. Note that here we use factors from the FM method instead of the FF method (e.g., SMB or HML) to run the quantile regression to be coherent with the ESG risk factor construction.

Then, we use Eq.(2.6) to calculate the conditional ESG risk as

$$\begin{gathered} CoESGRisk^{\theta}_{\tau,i,t} = \\ \hat{\delta}^{\tau}_{0,i} + \hat{\delta}^{\tau}_{1,i} f_{M,t} + \hat{\delta}^{\tau}_{2,i} f_{MV,t} + \hat{\delta}^{\tau}_{3,i} f_{BM,t} + \hat{\delta}^{\tau}_{4,i} f_{OP,t} + \hat{\delta}^{\tau}_{5,i} f_{INV,t} + \hat{\beta}^{ESG,\tau}_{i} VaR^{\theta}_{ESG,t} \end{gathered},$$

for company i and $\tau = 5\%$; θ is the quantile for the ESG risk factor, and we set θ= 95%, 50% and 5%. $CoESGRisk^{50\%}_{\tau,i,t}$ is the VaR at τ level of company i conditioned on the ESG risk factor being at its median (or the 'benchmark state', as is called in the literature). Finally, the $\triangle CoESGRisk^{\theta}_{i,\tau}$ is calculated as:

$$\Delta CoESGRisk^{\theta}_{\tau,i,t} = \hat{\beta}^{ESG,\tau}_{i} (VaR^{\theta}_{ESG,t} - VaR^{50\%}_{ESG,t}), \tag{2.7}$$

for the two extreme tails θ= 95% and θ= 5%.

To estimate the VaR for the ESG risk factor, we use the *conditional auto-regressive value at risk (CAViaR)* proposed by Engle and Manganelli (2004), where the VaR is estimated by directly modeling the quantile using:

$$VaR^{\theta}_{ESG,t} = \beta_0 + \beta_1 VaR^{\theta}_{t-1} + \beta_2 (f_{ESG,t-1})^{+} + \beta_3 (f_{ESG,t-1})^{-}, \tag{2.8}$$

with the initial value VaR^{θ}_{0} given by the historical VaR of the whole sample period. $(f_{ESG,t-1})^{+} = \max(f_{ESG,t-1}, 0)$ and $(f_{ESG,t-1})^{-} = -\min(f_{ESG,t-1}, 0)$. For details on model estimation, we refer the reader to Engle and Manganelli (2004).

[14] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

2.6 *CoESGRisk* and Δ*CoESGRisk* Estimation: Non-parametric Quantile Regression

According to Eq. (2.7), the sign and size of $\Delta CoESGRisk^{\theta}_{\tau,i,t}$ depend on the interaction between two elements: the quantile beta ($\beta_i^{ESG,\tau}$) and the quantile of the ESG risk factor. The quantile beta is fixed no matter how the ESG risk factor changes. That is, the relationship between the tail of the company and the ESG risk factor is independent from the state of the ESG risk factor.

However, this assumption may not be fair enough to describe the actual situation with regard to ESG, because the extreme state of the ESG risk factor is not like the extreme state of an individual company. While the extreme state of a company may only be due to some individual extreme events, the extreme state of the ESG risk factor represents the extreme market environment where, for example, the ESG sentiment is very high/low. Under such extreme market environment, ESG may have stronger impacts to companies than during normal times. In other words, the relationship between the tail of the company and the ESG risk factor may also change according to the state of the ESG risk factor.

Therefore, in estimating $\Delta CoESGRisk^{\theta}_{\tau,i,t}$, $\beta_i^{ESG,\tau}$ should also be conditioned to the extreme state of the ESG risk factor. To do so, we apply the method by Bonaccolto et al. (2019), who propose a more flexible setting of $CoVaR$ compared to Adrian and Brunnermeier (2016). In concrete, in estimating the quantile regression of Eq. (2.6), they resort to non-parametric quantile regression, modifying the standard quantile regression problem:

$$\underset{\beta_i^{ESG,\tau},\gamma_t^{\tau}}{\operatorname{argmin}} \Sigma_{t=1}^{T}\rho\left[R_{it} - \beta_i^{ESG,\tau} f_{ESG,t} - \gamma_i^{\tau} M_t - a_i^{\tau}\right],$$

into:

$$\underset{\beta_i^{ESG,\tau|\theta},\gamma_t^{\tau|\theta}}{\operatorname{argmin}} \Sigma_{t=1}^{T}\rho_{\theta}\left[R_{it} - \beta_i^{ESG,\tau|\theta} f_{ESG,t} - \gamma_i^{\tau|\theta} M_t - a_i^{\tau|\theta}\right] \times K\left(\frac{F\left(f_{ESG,t}\right)-\theta}{h}\right),$$

where M_t is the set of control variables. The only difference between the two minimization problems is the kernel function $K\left(\frac{F\left(f_{ESG,t}\right)-\theta}{h}\right)$. $F\left(f_{ESG,t}\right)$ is the empirical quantile of the ESG risk factor (the actual state of $f_{ESG,t}$). θ represents the extreme state of the ESG risk factor, 95% or 5%. h is the bandwidth, for which we set it to 0.15.[15] The form of the kernel function is 1-D Gaussian. Bonaccolto et al. (2019) refer to this improved CoVaR as

[15] Bonaccolto et al. (2019) show that the for other bandwidth values. We set a bandwidth of 0.15 instead of smaller values to allow for more data points around the θ states to be considered.

Quantile-Located CoVaR given the dependence on the conditioning of company's quantile.

Following Bonaccolto et al. (2019), when $\theta = 95\%$, in estimating the quantile regression, we assign a lower weight to (or filtering out) points of $f_{ESG,t}$ that are further away from the $VaR^{95\%}_{ESG,t}$. Therefore, $\beta_i^{ESG,\tau|\theta}$ is conditioned to the θ state of the ESG risk factor.

Accordingly, the new quantile-located $CoESGRisk^{\theta}_{\tau,i,t}$ is calculated as:

$$\begin{cases} QL - CoESGRisk^{\tau|\theta}_{\tau,i,t} = \hat{a}_i^{\tau|\theta} + \hat{\gamma}_i^{\tau|\theta} M_t + \hat{\beta}_i^{ESG,\tau|\theta} VaR^{\theta}_{ESG,t} \\ QL - CoESGRisk^{\tau|50\%}_{\tau,i,t} = \hat{a}_i^{\tau|50\%} + \hat{\gamma}_i^{\tau|50\%} M_t + \hat{\beta}_i^{ESG,\tau|50\%} VaR^{50\%}_{ESG,t} \end{cases},$$

and the quantile-located $\Delta CoESGRisk^{\theta}_{\tau,i,t}$ is calculated as

$$\Delta QL - CoESGRisk^{\theta}_{\tau,i,t} = QL - CoESGRisk^{\tau|\theta}_{\tau,i,t} - QL - CoESGRisk^{\tau|50\%}_{\tau,i,t}. \tag{2.9}$$

3 ESG Risk Contribution

In this section, we first show the ESG risk contribution calculated with Eq. (2.7) and compare them with quantile-located ESG risk contribution calculated with Eq. (2.9). Then, we evaluate the time-variation in ESG risk contribution. For a better comparison, we group companies into different ESG levels. To do so, we calculate the average ESG score for each company using their available ESG scores during the sample period. We then calculate the 20%, 40%, 60% and 80% quantile of the average ESG score and classify companies into each group. We call low-ESG companies with an average ESG score lower than 20% quantile, while high-ESG companies are those with the average ESG score higher than 80%.[16] Another interesting angle is to see whether at different return quantiles, the ESG have similar/different contributions. For this purpose, we calculate the ESG risk contribution for τ = 5%,10%, 20% and 50%.

3.1 Δ *CoESGRisk*

Before showing the ESG risk contribution, we first present a general view of how the entire tail is being affected by the ESG risk factor. To do so, we compare $CoESGRisk^{\theta}_{\tau,i}$ and

[16]It should be noted that when evaluating the whole period ESG risk contribution, we use the average ESG score for the whole period and when it comes to annual ESG risk contribution, we classify company only using ESG score of that year

$VaR_{i,\tau}$. We first estimate the point value of $CoESGRisk^{\theta}_{\tau,i}$ as:

$$CoESGRisk^{\theta}_{\tau,i} = \hat{a}^{\tau}_{i} + \hat{\gamma}^{\tau}_{i} E\left(M_t\right) + \hat{\beta}^{ESG,\tau}_{i} VaR^{\theta}_{ESG},$$

where $\theta = 95\%$ and 5% and τ ranges from 5% to 95%, that is, we fix the θ and change the τ. $E\left(M_t\right)$ is the unconditional expectation of control variables. For VaR^{θ}_{ESG}, we first estimate the CAViaR model and calculate the average of the estimated series. For comparison purposes, we also estimate the conditional quantile as:

$$Va\hat{R}_{i,\tau} = \hat{a}^{\tau}_{i} + \hat{\gamma}^{\tau}_{i} E\left(M_t\right) + \hat{\beta}_{i}^{ESG,\tau} E\left(ESG_t\right),$$

where it is calculated under normal ESG condition, that is, when the ESG risk factor is at its mean value. Since $E\left(M_t\right)$ is close to zero, $CoESGRisk^{\theta}_{\tau,i}$ is mainly driven by the intercept and the quantile of the ESG risk factor. Also, because the $E\left(ESG_t\right)$is close to zero, the major difference between $CoESGRisk^{\theta}_{\tau,i}$ and $Va\hat{R}_{i,\tau}$ is the component $\hat{\beta}^{ESG,\tau}_{i} VaR^{\theta}_{ESG}$.

Based on the estimated $CoESGRisk^{\theta}_{\tau,i}$ and $Va\hat{R}_{i,\tau}$, we plot the whole probability density function (PDF) for both high-ESG companies and low-ESG companies in Figure 2. The probability density is constructed by calculating $CoESGRisk^{\theta}_{\tau,i}$ and $Va\hat{R}_{i,\tau}$ at different tau levels (from $\tau = 5\%$ to 95%, with step size of 5%) and then conducting linear interpolation.[17]

Panel A shows the distribution of high and low-ESG when conditioned on $\theta = 95\%$. The dashed vertical line shows the $\tau = 5\%$ and $\tau = 50\%$ quantile. We note that for high-ESG companies, when conditioned on $\theta = 95\%$ (blue), compared to the normal one (yellow), the whole tail moves to the right. The situation is the reverse for low-ESG companies. We find that high-ESG companies have smaller downside risk[18] than low-ESG ones (comparing between the yellow one and the purple one). Such difference is widened when the market is in favor of high-ESG companies ($\theta = 95\%$). In addition, such shift in the distribution from normal to conditional is not parallel, the movement is larger at tail than at the middle. This happens because $\beta^{ESG,\tau}_{i}$ is τ-dependent and the size of $\beta^{ESG,5\%}_{i}$is larger than that of $\beta^{ESG,50\%}_{i}$. Panel B shows distributions under $\theta = 5\%$. The situation is reversed: for high-ESG companies, the whole tail moves to the left, which implies that the downside risk has been increased. The movement in the tail is also larger than the middle.

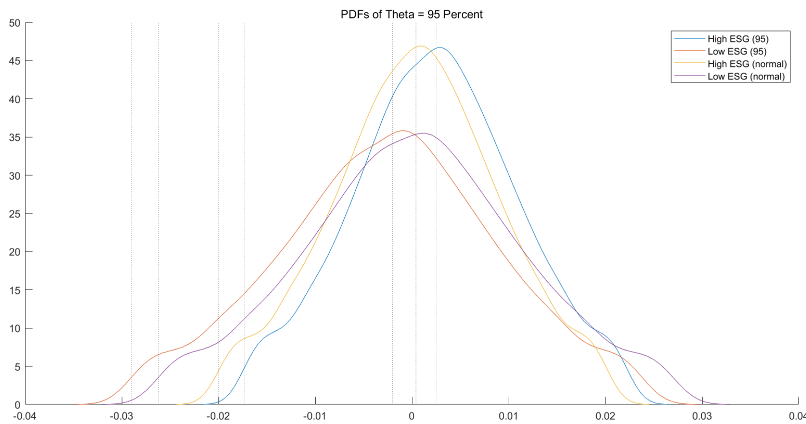
To see the size of ESG risk contribution, we present the $\triangle CoESGRisk$ in Table 2. We report the $\triangle CoESGRisk$ value in basis points. A positive value of $\triangle CoESGRisk$ means

[17] For more detail of how we draw the PDF, please refer to the ksdensity function of MATLAB (https://ww2.mathworks.cn/help/stats/ksdensity.html?requestedDomain=cn)

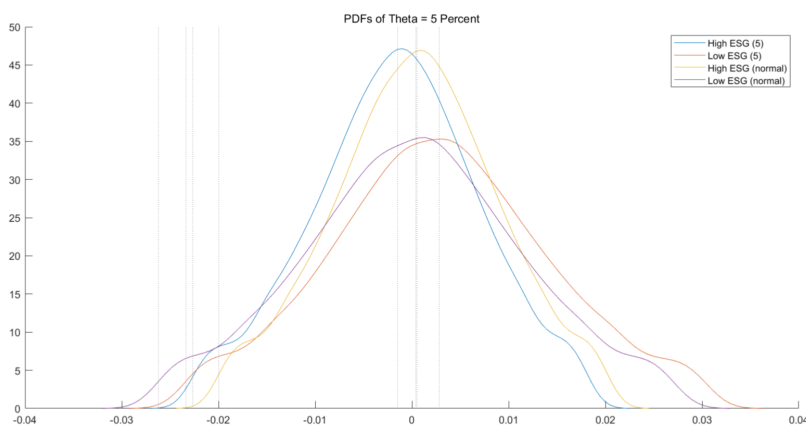
[18] We proxy downside risk with the unconditional and conditional distribution quantiles (i.e., the VaR).

Figure 2: **PDFs under Different θs**

Panel A: PDFs of both high- and low-ESG groups conditioned on the ESG risk factor being at 95%



Panel B: PDFs of both high- and low-ESG groups conditioned on the ESG risk factor being at 5%



Note: the graph shows the PDFs under different θ conditions. Panel A shows the PDFs of both high-ESG group and low-ESG group under $\theta = 95\%$ and Panel B shows PDFs under $\theta = 5\%$. In each panel, the blue and yellow line shows the PDF of high-ESG group. The red line is $Va\hat{R}_{i,\tau}$ (with a legend of "normal"). The dashed line shows the 5% and 50% quantile of the distribution. The value is shown in basis points.

Table 2: **Average $\triangle CoESGRisk$ for Different ESG Groups**

$VaR^{95\%}_{ESG,t}$	High	80-60	60-40	40-20	Low	$VaR^{5\%}_{ESG,t}$	High	80-60	60-40	40-20	Low
OLS	23.43	6.15	-12.54	-23.59	-26.39	OLS	-24.48	-6.43	13.11	24.66	27.58
$\tau = 50\%$	19.42	2.75	-12.89	-23.31	-24.46	$\tau = 50\%$	-20.30	-2.87	13.47	24.36	25.57
$\tau = 20\%$	21.13	3.47	-13.26	-24.19	-27.01	$\tau = 20\%$	-22.08	-3.62	13.86	25.29	28.23
$\tau = 10\%$	22.43	3.99	-13.55	-25.07	-28.01	$\tau = 10\%$	-23.44	-4.17	14.16	26.20	29.28
$\tau = 5\%$	26.14	5.52	-11.88	-24.69	-28.18	$\tau = 5\%$	-27.32	-5.77	12.42	25.80	29.45

Note: The table presents the average $\triangle CoESGRisk$ for different ESG level groups. We first calculate the $\triangle CoESGRisk$ series for each companies from 2013 to 2020 using Eq.(2.7). Then, we calculate the average of the $\triangle CoESGRisk$ series and get one $\triangle CoESGRisk$ for each company. We then group companies and calculate the group average. The left panel shows the $\triangle CoESGRisk$ when the ESG risk factor changes from normal state to extremely high state ($f_{ESG,t} = VaR^{95\%}_{ESG,t}$) and the right panel shows the $\triangle CoESGRisk$ when the ESG risk factor changes from normal state to extremely low state ($f_{ESG,t} = VaR^{5\%}_{ESG,t}$).

that the downside risk is reduced and a negative value means that the risk is increased. $\triangle CoESGRisk^{95\%}_{\tau}$ represents a situation where the ESG risk factor changes from 50% to 95%, or when there is a sudden increase in the ESG risk factor. In that situation, the risk contribution is positive for high-ESG group (26.14 basis points, at $\tau = 5\%$), and the contribution is negative for ESG groups below 60% quantile.

The contribution can be as low as -28.18 basis points for the low-ESG group (5% VaR). In other words, if we hold a portfolio of high-ESG companies, compared to holding a portfolio of low-ESG companies, the downside risk of the high-ESG portfolio (measured by 5% VaR) is (26.56 + 28.63 = 55.19 basis points) smaller. For comparison purposes, we also add a row containing the results estimated at the mean level ("OLS"). We do observe a difference between the mean level and the 50% quantile level – the impact to the mean is larger than the 50% quantile but smaller than the 5% quantile. This is because the impact to the mean is the averaged impact to all quantiles.

Mathematically speaking, the negative shift from $\theta = 95\%$ to $\theta = 5\%$ observed in Figure 2 results from fact that, given a τ level, by definition, the only difference between $CoESGRisk^{5\%}_{\tau,i}$ and $CoESGRisk^{95\%}_{\tau,i}$ is the quantile of ESG risk factor. It is expected (and mathematically logical) that under the linear regression, the $\hat{\beta}^{ESG,OLS}_i$ is positive for high-ESG companies and negative for low-ESG ones, because ESG risk factor is constructed as the return difference between high- and low-ESG companies. However, it is still interesting (and not expected a-prior) to see that for high-ESG companies, $\beta^{ESG,\tau}_i$ is positive and for low-ESG ones, $\beta^{ESG,\tau}_i$ is negative. It is also not expected that the impact to the tail is larger than the impact to the middle, as $\triangle CoESGRisk^{95\%}_{\tau}$ gradually increase as τ goes from 50% to 5%.

Economically speaking, the above result implies that when the market is in favor of high-ESG companies, the return level of high-ESG companies is increased and thus downside risk is also decreased. In addition, such decrease in the downside risk not only comes from the increase in the mean, but also comes from the decrease in the volatility, because $\triangle CoESGRisk_{5\%}^{95\%}$ is larger than $\triangle CoESGRisk_{OLS}^{95\%}$. Similarly, when $\theta = 5\%$, for high-ESG companies, both the return level as well as the volatility become worse.

3.2 Quantile-located $\Delta CoESGRisk$

Until now, the conclusion we get is in accordance with the common view in the literature: high-ESG companies have downside risk benefits when the market is in favor of high-ESG ones. One crucial assumption of the above results is that the relationship between the ESG risk factor and the tail of the company does not change to the status of ESG risk factor. In this section, we relax this assumption and present the results of the quantile-located $\Delta CoESGRisk_{\tau}^{\theta}$.

Same as the previous subsection, we first give a comparison between $QL - CoESGRisk_{\tau}^{\theta}$ and $Va\hat{R}_{i,\tau}$. We estimate the point value of $QL - CoESGRisk_{\tau,i}^{\theta}$ as

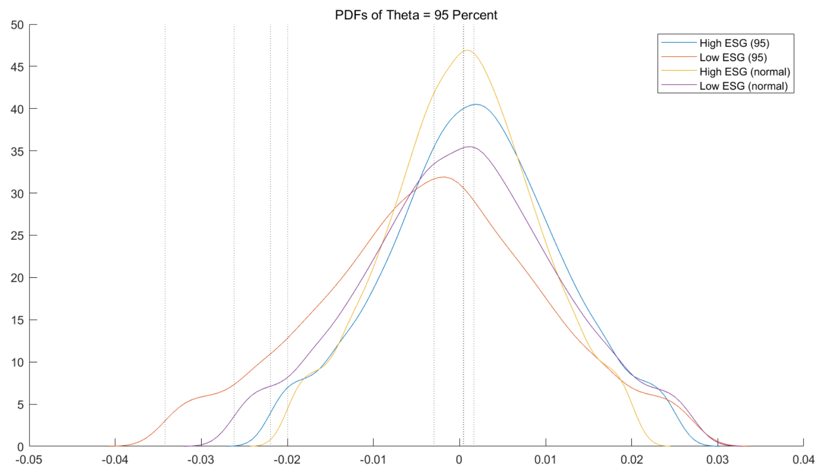
$$QL - CoESGRisk_{\tau,i}^{\theta} = \hat{a}_i^{\tau|\theta} + \hat{\gamma}_i^{\tau|\theta} E\left(M_t \times K\left(\frac{F^{-1}\left(F_{ESG,t}\right) - \theta}{h}\right)\right) + \hat{\beta}_i^{ESG,\tau|\theta} VaR_{ESG}^{\theta}.$$

The $Va\hat{R}_{i,\tau}$ is the same as the previous section. We first present in Figure 3 the comparison between the $QL - CoESGRisk_{\tau,i}^{\theta}$ and $Va\hat{R}_{i,\tau}$for both high-ESG and low-ESG group. In Panel A, we first note that, conditioned on $\theta = 95\%$,while the high-ESG group is still benefiting at $\tau = 50\%$, it is suffering at $\tau = 5\%$ (comparing between yellow and blue). That is, unlike the previous case, the downside risk of the high-ESG group is increased although the market favors the high-ESG group. From Panel C, we see that when $\theta = 95\%$,below $\tau = 20\%$, $QL - CoESGRisk_{\tau,i}^{\theta} < Va\hat{R}_{i,\tau}$ for the high-ESG group (left, black line). That being said, at $\theta = 95\%$, high-ESG companies still suffer less than low-ESG ones in the tail. This can be seen from Panel A that the tail of the low-ESG companies moves furthest towards left (red line). Then, because at $\theta = 5\%$ low-ESG companies suffer less than high-ESG ones, the distance between tail of the two groups under $\theta = 5\%$ is closer than the distance under unconditional situations (Panel B).

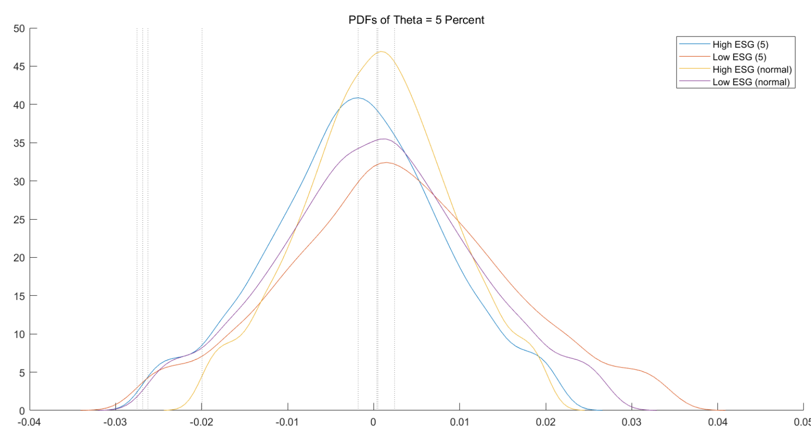
We further provide in Table 3 a comparison between statistics of the conditional distribution generated from $QL - CoESGRisk_{\tau,i}^{\theta}$, $CoESGRisk_{\tau,i}^{\theta}$ and $Va\hat{R}_{i,\tau}$. Panel A shows the results of high-ESG group under both $\theta = 5\%$ and $\theta = 95\%$. Compared to the unconditional one (column 1), when conditioned on $\theta = 95\%$, we observe an increase in the volatility of

Figure 3: **PDFs for Different θs (cont.)**

Panel A: PDFs of both high- and low-ESG groups conditioned on the ESG risk factor being at 95%



Panel B: PDFs of both high- and low-ESG groups conditioned on the ESG risk factor being at 5%



Note: the graph shows the PDFs under different θ conditions. Panel A shows the PDFs of both high-ESG group and low-ESG group under $\theta = 95\%$ and Panel B shows PDFs under $\theta = 5\%$. In each panel, the blue and yellow line shows the PDF of high-ESG group. The red and purple line represent the PDF of low-ESG group. The dashed line shows the 5% and 50% quantile of the distribution. The value is shown in basis points.

Table 3: **Statistics of Conditional Distributions**

Panel A: Distribution statistics for high-ESG companies

	$\hat{VaR}$	$QL-Co(95\%)$	$Co(95\%)$	$QL-Co(5\%)$	$Co(5\%)$
Column	(1)	(2)	(3)	(4)	(5)
Mean	0.0398%	0.1634%	0.2451%	-0.2004%	-0.1679%
Std.	0.8571%	0.9997%	0.8507%	1.0120%	0.8637%
Kurtosis	2.6220	2.6594	2.5960	2.7113	2.6511
Skewness	-0.0421	-0.0197	0.0022	-0.0768	-0.0867

Panel B: Distribution statistics for low-ESG companies

	$\hat{VaR}$	$QL-Co(95\%)$	$Co(95\%)$	$QL-Co(5\%)$	$Co(5\%)$
Column	(1)	(2)	(3)	(4)	(5)
Mean	0.0256%	-0.3222%	-0.2363%	0.2728%	0.2905%
Std.	1.1376%	1.3045%	1.1334%	1.2988%	1.1421%
Kurtosis	2.6343	2.6603	2.6120	2.7013	2.6609
Skewness	0.0158	-0.0504	-0.0401	0.0704	0.0724

Note: The table presents the statistics of conditional distributions. Panel A shows the results for high-ESG group and Panel B low-ESG group. In both panels, "Std." means standard deviation. Column (1) is the one without the conditional status of the ESG risk factor. Column (2) and (3) are conditioned on $\theta = 95\%$. Column (4) and (5) are conditioned on $\theta = 5\%$.

$QL-CoESGRisk^{\theta}_{\tau,i}$ (column 2), which explains the fatter tail of $QL-CoESGRisk^{\theta}_{\tau,i}$ over $CoESGRisk^{\theta}_{\tau,i}$. We also observe a slight decrease in the volatility of $CoESGRisk^{\theta}_{\tau,i}$ (column 3), which confirms the findings in Panel A of Figure 2, where the movement in the tail is larger than the movement in the middle. In the meantime, changes in the kurtosis and skewness are quite limited from column 1 – 6. The same thing happens to low-ESG companies as is shown in Panel B. Therefore, the above results indicate a very different finding from the traditional view in terms of ESG and downside risk: if we assume that extreme states of the ESG risk factor indicate a extreme market ESG condition, then under such market ESG condition, the downside risk will be larger both for high-ESG and low-ESG companies.

We provide in Table 4 the $\Delta QL-CoESGRisk^{\theta}_{\tau}$ for each ESG group. The row "OLS" is calculated by applying the kernel function to both dependent and independent variable and then fitting a linear regression. In the middle (row "τ =50%") and mean (row "OLS"), the results of $\Delta QL-CoESGRisk^{\theta}_{\tau}$ are close to $\Delta CoESGRisk^{\theta}_{\tau}$ as reported Table 2.

At the tail, we do observe differences. When the market is in favor of high-ESG companies ($\theta = 95\%$), the $\Delta QL-CoESGRisk^{\theta}_{\tau}$ is negative even for high-ESG companies. The contribution to the 5% tail can be -27 bps for high-ESG companies and -89 bps for low-ESG ones. One thing is the same: although both are suffering, high-ESG companies suffer less than low-ESG ones. The distance between high- and low-ESG companies for the $\Delta QL-CoESGRisk^{\theta}_{\tau}$ is also larger than that of $\Delta CoESGRisk^{\theta}_{\tau}$. We further provide in

Table 4: **Average $\triangle QL - CoESGRisk$ for the Whole Sample Period**

$VaR_{ESG,t}^{95\%}$	High	80-60	60-40	40-20	Low	$VaR_{ESG,t}^{5\%}$	High	80-60	60-40	40-20	Low
OLS	19.97	7.65	-14.16	-23.08	-26.54	OLS	-29.40	-10.14	10.82	19.99	25.13
$\tau = 50\%$	19.27	4.26	-12.60	-22.02	-23.97	$\tau = 50\%$	-21.12	-2.69	12.93	24.39	25.13
$\tau = 20\%$	2.29	-14.54	-32.89	-43.84	-49.77	$\tau = 20\%$	-40.47	-20.30	-4.80	6.40	8.14
$\tau = 10\%$	-13.35	-30.62	-49.00	-61.89	-68.98	$\tau = 10\%$	-57.21	-37.74	-19.53	-8.52	-5.84
$\tau = 5\%$	-27.35	-50.32	-67.55	-83.69	-89.22	$\tau = 5\%$	-81.74	-60.61	-37.80	-29.22	-26.10

Note: The table presents the average $\triangle QL - CoESGRisk$ for different ESG level groups. We first calculate the $\triangle QL - CoESGRisk$ series for each companies from 2013 to 2020 using Eq.(2.9). Then, we calculate the average of the $\triangle QL - CoESGRisk$ series and get one $\triangle QL - CoESGRisk$ for each company. We then group companies and calculate the group average. The left panel shows the $\triangle QL - CoESGRisk$ when the ESG risk factor changes from normal state to extremely high state ($f_{ESG,t} = VaR_{ESG,t}^{95\%}$) and the right panel shows the $\triangle QL - CoESGRisk$ when the ESG risk factor changes from normal state to extremely low state.

Appendix C a discussion of the statistical significance of the ESG risk contribution, where we show that for most companies ESG risk contributions are statistically different from zero.

3.3 Decompose ESG Risk Contributions

To study what contributes to such difference between $\Delta QL{-}CoESGRisk_{\tau}^{\theta}$ and $\Delta CoESGRisk_{\tau}^{\theta}$, we follow Bonaccolto et al. (2019) to further write Eq. (2.9) and get four major components of the quantile-located ESG risk contribution:

$$
\begin{aligned}
\Delta QL - CoESGRisk_{\tau,i,t}^{\theta} &= \hat{a}_i^{\tau|\theta} - \hat{a}_i^{\tau|50\%} + \left(\hat{\gamma}_i^{\tau|\theta} - \hat{\gamma}_i^{\tau|50\%}\right) M_t + \\
&\quad \hat{\beta}_i^{ESG,\tau|\theta} VaR_{ESG,t}^{\theta} - \hat{\beta}_i^{ESG,\tau|50\%} VaR_{ESG,t}^{50\%} \\
&= \hat{a}_i^{\tau|\theta} - \hat{a}_i^{\tau|50\%} + \left(\hat{\gamma}_i^{\tau|\theta} - \hat{\gamma}_i^{\tau|50\%}\right) M_t + \hat{\beta}_i^{ESG,\tau|\theta} VaR_{ESG,t}^{\theta} - \hat{\beta}_i^{ESG,\tau|\theta} VaR_{ESG,t}^{50\%} \\
&\quad + \hat{\beta}_i^{ESG,\tau|\theta} VaR_{ESG,t}^{50\%} - \hat{\beta}_i^{ESG,\tau|50\%} VaR_{ESG,t}^{50\%} \\
&= \underbrace{\left(\hat{a}_i^{\tau|\theta} - \hat{a}_i^{\tau|50\%}\right)}_{\textbf{Part 1}} + \underbrace{\left(\hat{\gamma}_i^{\tau|\theta} - \hat{\gamma}_i^{\tau|50\%}\right) M_t}_{\text{Part 2}} + \underbrace{\hat{\beta}_i^{ESG,\tau|\theta}\left(VaR_{ESG,t}^{\theta} - VaR_{ESG,t}^{50\%}\right)}_{\textbf{Part 3}} + \\
&\quad \underbrace{VaR_{ESG,t}^{50\%}\left(\hat{\beta}_i^{ESG,\tau|\theta} - \hat{\beta}_i^{ESG,\tau|50\%}\right)}_{\textbf{Part 4}}
\end{aligned}
, \tag{3.1}
$$

where:

- Part 1: $\left(\hat{a}_i^{\tau|\theta} - \hat{a}_i^{\tau|50\%}\right)$ represents changes in the level of downside risk due to changes of ESG risk factor. It is the shift in the conditional distribution of the company when the ESG factor moves along its distribution from 50% quantile to θ quantile.
- Part 2: $\left(\hat{\gamma}_i^{\tau|\theta} - \hat{\gamma}_i^{\tau|50\%}\right) M_t$ is the change in the contribution of control variables.

- Part 3: $\hat{\beta}_i^{ESG,\tau|\theta}\left(VaR_{ESG,t}^{\theta} - VaR_{ESG,t}^{50\%}\right)$. This part corresponds to the definition of $\Delta CoESGRisk_{\tau}^{\theta}$. The only difference is that $\hat{\beta}_i^{ESG,\tau|\theta}$ is estimated conditioned on the ESG risk factor being at θ state, while $\hat{\beta}_i^{ESG,\tau}$ is estimated using all values of ESG risk factor.
- Part 4: $VaR_{ESG,t}^{50\%}\left(\hat{\beta}_i^{ESG,\tau|\theta} - \hat{\beta}_i^{ESG,\tau|50\%}\right)$. The part measures how changing relationship (measured by quantile beta) affects the downside risk of a company.

We present in Table 5 the four components for high-ESG and low-ESG companies. Part 4 is close to zero, due to the fact that $VaR_{ESG,t}^{50\%}$ during our sample period is close to zero. Part 2 is close to zero, which means that the contribution of control variables does not change when ESG risk factor change from normal state to extreme states. The major contributors are part 1 and part 3. Part 1 does not change to the ESG scores – high-ESG and low-ESG have the same part 1. We also find that part 1 changes to the τ level: shift in the tail ($\tau = 5\%$) is larger than shift in the middle ($\tau = 50\%$).

Since part 1 is positive at all τ levels, part 3 then becomes the main contributor to the negative ESG risk contribution we observed in Table 4. Part 3 corresponds to the ESG risk contribution and is quite close to $\Delta CoESGRisk$ at $\tau = 50\%$. However, at $\tau = 5\%$, part 3 becomes negative for $\triangle QL - CoESGRisk_{\tau}^{95\%}$, which means that $\hat{\beta}_i^{ESG,\tau|95\%}$ changes from positive to negative as τ changes from 50% to 5%. In addition, because the only difference between part 3 and $\Delta CoESGRisk$ is the quantile beta, it can be fairly concluded that the major difference between $\triangle QL - CoESGRisk_{\tau}^{\theta}$ and $\Delta CoESGRisk$ is caused by the difference between $\hat{\beta}_i^{ESG,\tau}$ and $\hat{\beta}_i^{ESG,\tau|\theta}$.

Quantile beta measures the dependency between the τth conditional quantile of the company and the distribution of the ESG risk factor. Then, when we calculate $\hat{\beta}_i^{ESG,\tau|\theta}$ conditioning on the θ state of ESG risk factor, what we are actually doing is selecting a group of observations of the ESG risk factor that is around the θ status (by applying a kernel weight vector in the minimization problem) and then running quantile regression between the sub-group and the downside risk of a company. Therefore, $\hat{\beta}_i^{ESG,\tau|\theta}$ measures the dependency between the τ conditional quantile of the company and a sub-group observation of the ESG risk factor.

Economically speaking, if the relationship between ESG and tail of the return distribution does not change according to the state of the ESG risk factor, $\hat{\beta}_i^{ESG,\tau|\theta}$ should be equal (or at least close) to $\hat{\beta}_i^{ESG,\tau}$ – this is what we observe in the middle of the return distribution (i.e., when $\tau = 50\%$, $\hat{\beta}_i^{ESG,\tau|\theta} \approx \hat{\beta}_i^{ESG,\tau}$), which implies that the impact of ESG to the middle of the return distribution is the same regardless whether the ESG risk factor is in its normal

Table 5: **Components of $\triangle QL - CoESGRisk$ for the Whole Sample Period**

Panel A: Components of $\triangle QL - CoESGRisk_{\tau}^{95\%}$ ($f_{ESG,t} = VaR_{ESG,t}^{95\%}$) (basis points)

High	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$	**Low**	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$
Part 1	0.44	19.12	32.38	45.42	Part 1	-0.57	19.58	34.19	48.26
Part 2	0.03	-0.39	-0.73	-1.06	Part 2	0.08	-0.43	-0.83	-1.08
Part 3	18.81	-15.87	-43.95	-70.21	Part 3	-23.49	-68.29	-101.17	-134.73
Part 4	0.00	-0.58	-1.04	-1.50	Part 4	0.01	-0.62	-1.18	-1.68
Sum	19.26	2.27	-13.36	-27.37	Sum	-23.95	-49.74	-68.95	-89.19

Panel B: Components of $\triangle QL - CoESGRisk_{\tau}^{5\%}$ ($f_{ESG,t} = VaR_{ESG,t}^{5\%}$) (basis points)

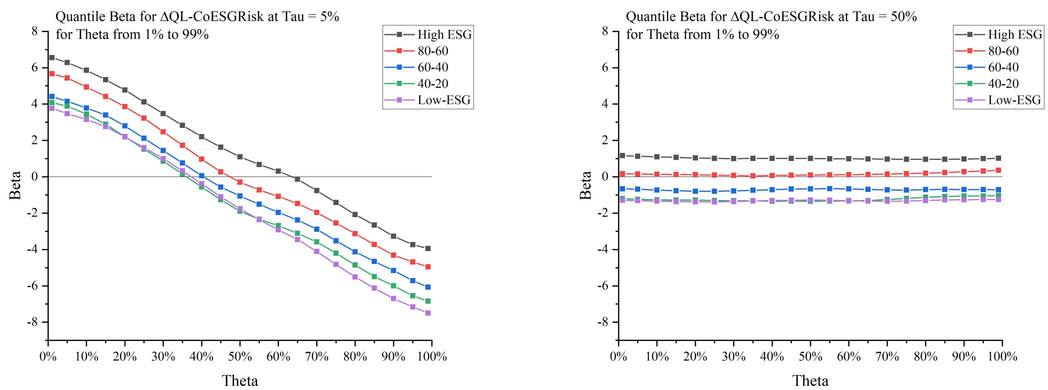
High	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$	**Low**	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$
Part 1	0.95	17.59	28.92	40.09	Part 1	-0.81	18.90	30.18	40.44
Part 2	0.09	0.18	0.19	0.14	Part 2	0.15	0.24	0.27	0.27
Part 3	-22.19	-58.85	-87.38	-123.59	Part 3	25.81	-11.68	-37.38	-68.44
Part 4	0.04	0.62	1.07	1.61	Part 4	-0.01	0.69	1.08	1.63
Sum	-21.12	-40.47	-57.21	-81.74	Sum	25.13	8.14	-5.84	-26.10

Note: The table presents the four parts of $\triangle QL - CoESGRisk_{\tau}^{\theta}$ calculated in Eq. (3.1) for high- and low-ESG groups. Panel A shows the results of for $\theta = 95\%$ and Panel B shows the results for $\theta = 5\%$. "High" means high-ESG company group and "low" means low-ESG company group.

state or extreme states. However, when we come to the tail, $\hat{\beta}_i^{ESG,\tau|\theta}$ is more negative than $\hat{\beta}_i^{ESG,\tau}$, and as a result, ESG risk contribution is negative even for high-ESG companies under a market condition where high-ESG is preferred ($\theta = 95\%$). A plausible explanation is that, as we have shown in Table 3, the volatility of companies is increased by being exposed to ESG, whether the exposure is positive or negative. In other words, extreme states of ESG risk factor do represent extreme market ESG conditions, where exposure to ESG will bring additional volatility to the return distribution. The increased volatility could be due to increased trading activities regarding high- and low-ESG companies during extreme market conditions. As a robustness check, we provide in Appendix D the results using different ESG data provider – the Bloomberg ESG score. Although the correlation of ESG score between the two is only around 0.5, we get similar results in terms of the ESG risk contribution.

As a final check, we provide in Figure 4 the $\beta_i^{ESG,5\%|\theta}$ and $\beta_i^{ESG,50\%|\theta}$ from $\theta = 1\%$ to $\theta = 99\%$. That is, we fix the τ level and check how ESG risk contribution changes across θ levels. As can be seen, at the lower tail, we observe a monotonic change in the $\beta_i^{ESG,5\%|\theta}$ (Panel A). In comparison, at $\tau = 50\%$ (Panel B), $\beta_i^{ESG,5\%|\theta}$ remains quite stable across θ levels, with high-ESG companies having positive quantile beta. This is in line with our previous results that at $\tau = 50\%$, $\triangle QL - CoESGRisk$ is quite close to $\triangle CoESGRisk$, where $\beta_i^{ESG,5\%|\theta}$ does not change to θ levels.

Figure 4: **Quantile Beta under Different θs**



Note: the graph shows the quantile-located quantile beta. We fix τ level to be 5% and 50% and let θ to change from 1% to 99%. The left panel shows the results at $\tau = 5\%$ and the right panelshows the results at

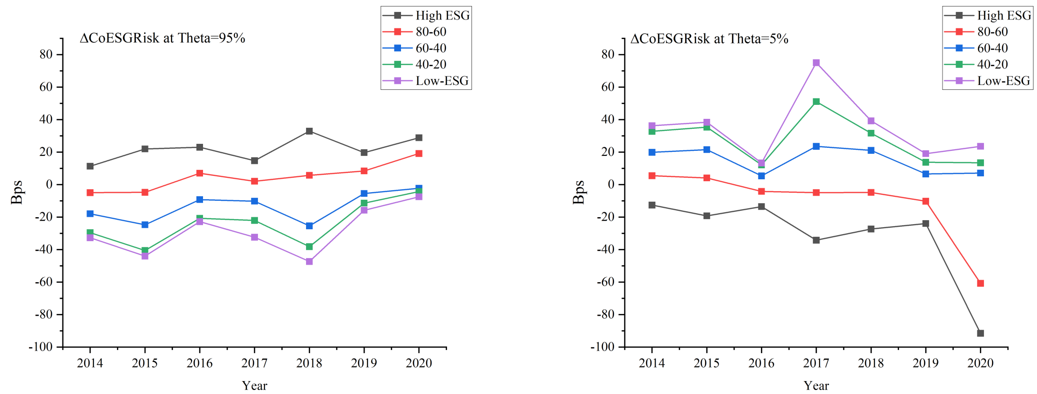
3.4 How ESG Risk Contribution Changes Over Time

To show if the impact of ESG to the downside risk of a company can change over time, we estimate the ESG risk contribution for each year from 2014/01/01 to 2020/12/31 (seven years in total). We focus on the impact to the tail ($\tau = 5\%$).

We present in Figure 5 the yearly results for $\Delta CoESGRisk$. For $\theta = 95\%$ (left panel), we do not observe big changes across the years. When $\theta = 5\%$ (right panel), we find that the risk contribution becomes more negative for high-ESG companies in recent years. Since the major components of $\Delta CoESGRisk$ are quantile beta ($\beta_i^{ESG,\tau}$) and the quantile of ESG risk factor ($VaR^{\theta}_{ESG,t}$ and $VaR^{50\%}_{ESG,t}$), we present in Figure 6 the changes of the two components. We see that the relationship between the tail and the ESG risk factor is quite stable across the years (left panel) and the major changes brought to $\Delta CoESGRisk$ is the change in the quantile of the ESG risk factor (right panel). For example, the distance between $VaR^{50\%}_{ESG,t}$ and $VaR^{5\%}_{ESG,t}$ in 2020 increased drastically, which contributes to the sharp decrease of $\Delta CoESGRisk^{5\%}_{5\%}$ of high-ESG group in the same year.

As for $\Delta QL - CoESGRisk$, we provide the four parts in each year from 2014 – 2020 in Figure 7. We also present the results of $\beta_i^{ESG,\tau|\theta}$ across time in Figure 8. The first thing we observe is that part 3 changes over the years, both in signs and size. For example, in 2018, the $\Delta QL - CoESGRisk^{95\%}_{5\%}$ is positive for high-ESG companies (Panel A, left graph) and is even more positive than $\Delta CoESGRisk$ in the same year (Figure 5, Panel A, black line), which is different from the result using the full sample period, where $\Delta QL - CoESGRisk^{95\%}_{5\%}$ is negative for high-ESG companies. In the meantime, for the year 2020, the ESG risk contribution is negative for both high-ESG and low-ESG, regardless of $\theta = 5\%$ and 95%. Apart from part 3, we also observe a huge increase in the size of part 4 in year 2020. This is because $VaR^{50\%}_{ESG,t}$ has largely increased in the year 2020, as is shown in Figure 6.

Figure 5: $\Delta CoESGRisk$ **from 2014 − 2020**



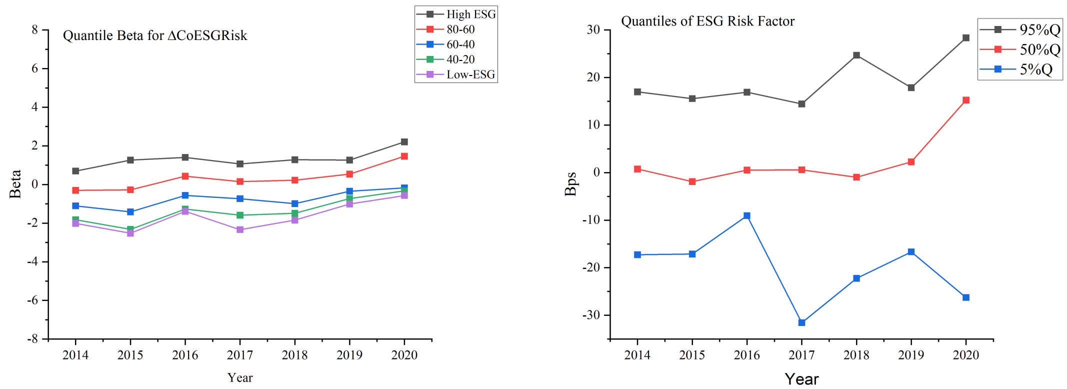
Note: the graph shows $\triangle CoESGRisk^{\theta}_{5\%}$ for each year from 2014 to 2020. The left panel presents $\triangle CoESGRisk^{95\%}_{5\%}$ and the right panel is the results for $\triangle CoESGRisk^{5\%}_{5\%}$.

If the part 3 is changing in sign, it means that the quantile beta $\beta_i^{ESG,\tau|\theta}$ is changing in sign. A changing $\beta_i^{ESG,\tau|\theta}$ implies that the relationship between the tail of the company and the tail of the ESG risk factor is time-varying. Such changing relationship could be due to three possible reasons: first, the tail of the company is changing (the relationship is changing due to heteroskedasticity); second, the return distribution of the ESG risk factor is changing (heteroskedasticity); and third, how ESG is affecting the downside risk of a company is time-varying (the relationship is really changing).

To examine the three possibilities, we provide in Figure 9 and Table 6 the results after standardizing the company return and the ESG risk factor. To standardize the two, we first use EGARCH(1,1) conditional volatility model, with t-student distribution, to estimate the time varying volatility. We then standardize the time series as $z_t = \frac{r_t - \mu}{\sigma_t}$, where μ is the empirical mean of the sample period and σ_t is the conditional volatility time series estimated by the EGARCH model. In Panel A of Figure 9, by only standardizing the ESG risk factor, the results of 2020 at $\theta = 95\%$ are different from Figure 8 (left): the sign does not change from positive to negative. The same happens in Panel B, where we estimate the quantile beta using only standardized company returns. Therefore, the changing relationship between the tail of ESG and the tail of the company can be driven by the changing distributions of both company returns and the ESG risk factor. This is especially the case during crisis times.

In Panel C, we estimate the quantile beta by standardizing both company return and the ESG risk factor. We find that that although $\beta_i^{ESG,\tau|95\%}$ (left graph) of 2020 now becomes

Figure 6: **Components of $\Delta CoESGRisk$ from 2014 to 2020**



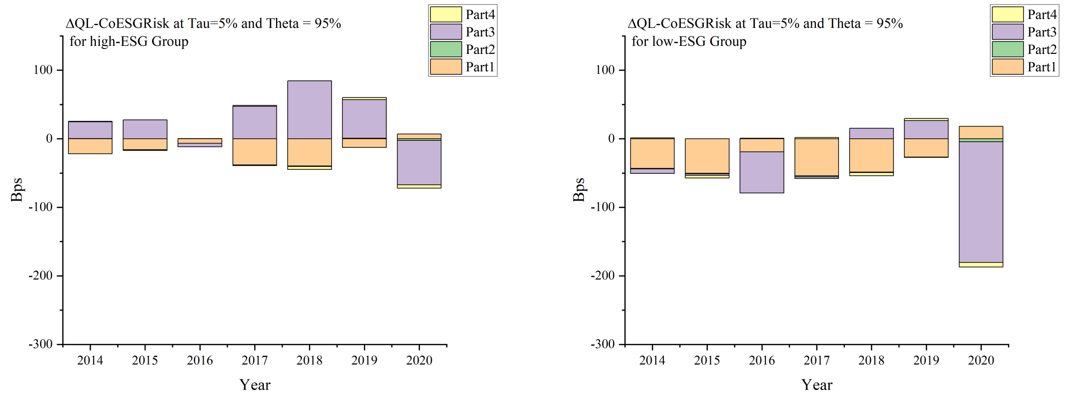
Note: the graph shows the components of $\Delta CoESGRisk$ over the years. The left panel shows the quantile beta at $\tau = 5\%$. The right panel shows the 5%, 50% and 95% of the ESG risk factor. The quantiles of the ESG risk factor is estimated using the CAViaR model of (2.8) and then we calculate one average value of that year.

positive, the overall trend is quite similar to the results in Figure 8. We still observe $\beta_i^{ESG,\tau|5\%}$ of 2020 changing from negative to positive (middle graph). Similarly, the results in Table 6 is close to the results in Table 5 in that part 3 changes from positive to negative when τ change from 50% to 5% (the size is different because we use standardized time series of the ESG risk factor and company return), which means that our whole-period results also holds after taking out the heteroskedasticity issue. In sum, ruling out heteroskedasticity possibilities, we still find a time-varying relationship between the tail of the company and the tail of the ESG risk factor.

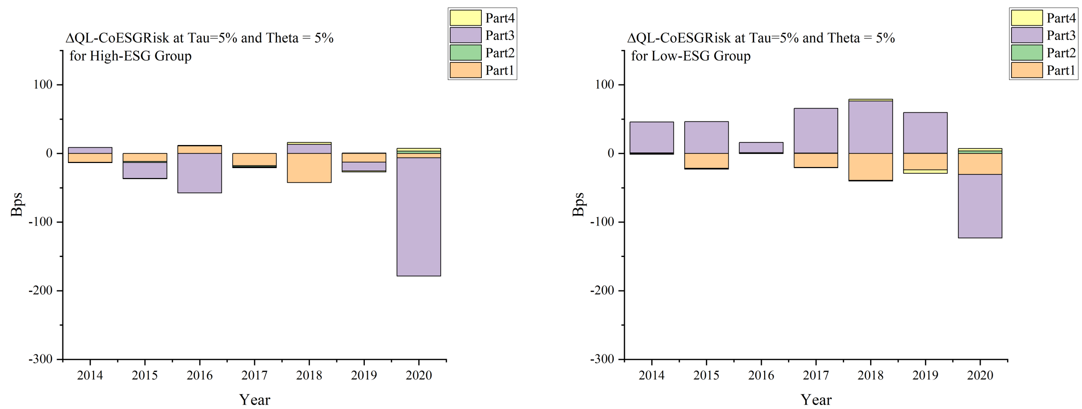
Then, the question is: why the relationship between tail of the company and tail of the ESG risk factor is changing over time? One possible explanation is that, if $\hat{\beta}_i^{ESG,\tau|\theta}$ depends on extreme states of ESG, then the level and sign of $\hat{\beta}_i^{ESG,\tau|\theta}$ also depend on why the ESG risk factor is driven towards extreme states during the sample period. In other words, how ESG affects the downside risk in one period may depends on the the very same reason pushing the ESG factor towards extreme states. This explains why we observe a drastic change from negative to positive in 2020 at $\theta = 5\%$ (Figure 9, middle of Panel C): extreme values of the ESG risk factor observed in 2020 can be due to the "flight-to-quality" effect (Dong et al., 2019), which might be different from early non-crisis years. Recent literature on ESG risk factor show that investor ESG sentiment is the main driver of the ESG risk factor (Lioui and Tarelli, 2022 and Ľuboš Pástor et al., 2021). A sudden increase in the ESG sentiment will increase in the ESG risk factor. Our results show that why there are shocks in the ESG sentiment is also important, because different shocks to drive the ESG risk factor could mean different investor behaviors and thus different impacts to the downside risk, as is shown in

Figure 7: **Components of $\Delta QL - CoESGRisk$ from 2014 to 2020**

Panel A: Four components of $\Delta QL - CoESGRisk^{95\%}_{5\%}$ for each year

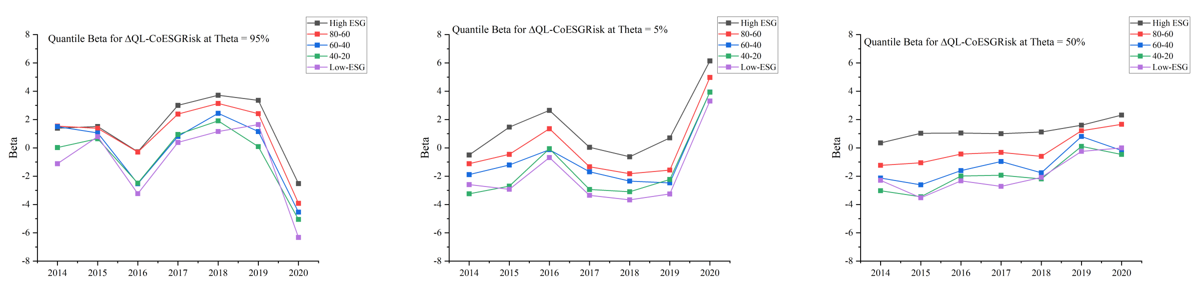


Panel B: Four components of $\Delta QL - CoESGRisk^{5\%}_{5\%}$ for each year



Note: the graph shows the four components of the quantile–located ESG risk contribution for each year from 2014 to 2020. Panel A shows the results conditioned on $\theta = 95\%$ and Panel B shows the results for $\theta = 5\%$.

Figure 8: $\beta_i^{ESG,\tau|\theta}$ **under Different** θ**s**



Note: the graph shows the quantile beta under quantile–located scheme ($\beta_i^{ESG,5\%|\theta}$) for different ESG levels in each year, with $\tau = 5\%$ and $\theta = 95\%$

Panel B of Figure 1.

That being said, the results in previous sub-sections (i.e., $\Delta QL - CoESGVaR^{\theta}_{\tau}$ using the full sample period and the $\Delta CoESGVaR^{\theta}_{\tau}$), even though they are different from what we observe in this sub-section, are still useful in showing the relationship between ESG and downside risk. First, the $\Delta QL - CoESGVaR^{\theta}_{\tau}$ under the full sample period provides us with an averaged effect of ESG on downside risk over the long-term. Actually, we calculate the results using the pre-COVID data as in Table 7, and they are quite similar with the full sample period results. Second, $\Delta CoESGVaR^{\theta}_{\tau}$ measures the ESG risk contribution considering whole distribution of ESG risk factors, while $\Delta QL - CoESGVaR^{\theta}_{\tau}$ considers only part of ESG risk factors. The key assumption of $\Delta QL - CoESGVaR^{\theta}_{\tau}$ is that the changing ESG risk factor indicates a changing market ESG condition, which could happen only over some periods because $\hat{\beta}_i^{ESG,\tau|\theta}$ and $\hat{\beta}_i^{ESG,\tau}$ are quite similar in early years (2014 and 2015). Meanwhile, $\Delta CoESGVaR^{\theta}_{\tau}$ measures the "averaged" relationship. Therefore, the results of $\Delta CoESGVaR^{\theta}_{\tau}$ and $\Delta QL - CoESGVaR^{\theta}_{\tau}$ are mutually supplementary in showing how and to which extent the ESG could affect the downside risk of a company. However, our empirical evidence does strongly support the need for adopting non-parametric quantile regression for the evaluation of the ESG factor role in driving the downside risk of companies. In fact, we have clearly shown that the ESG factor impact on the downside risk strongly depends on the state of the ESG factor.

4 Determinants of Quantile Beta

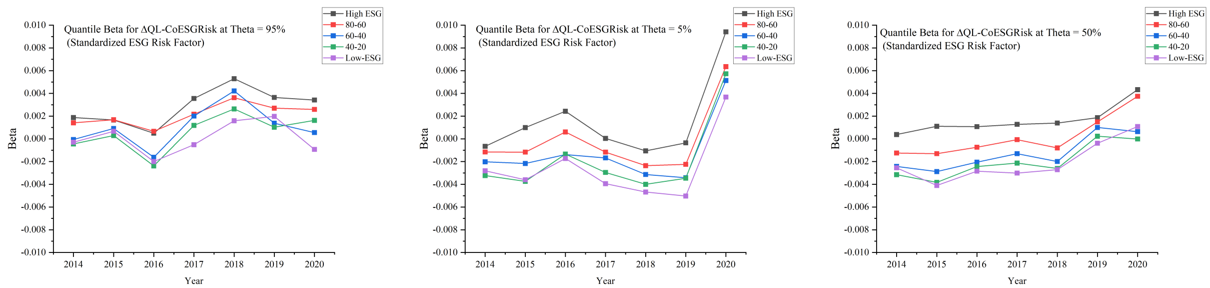
The $\triangle CoESGRisk$ and $\Delta QL - CoESGVaR^{\theta}_{\tau}$ provide us with numerical measurements of how much the downside risk is contributed by ESG. It is also of paramount importance to identify what determines the contribution. According to the previous analysis, the major difference observed between $\triangle CoESGRisk$ and $\Delta QL - CoESGVaR^{\theta}_{\tau}$ is driven by the quantile beta. In this section, we apply panel data method to study what determines the quantile beta.

In concrete, we estimate the following panel regression using fixed effects with robust standard error:

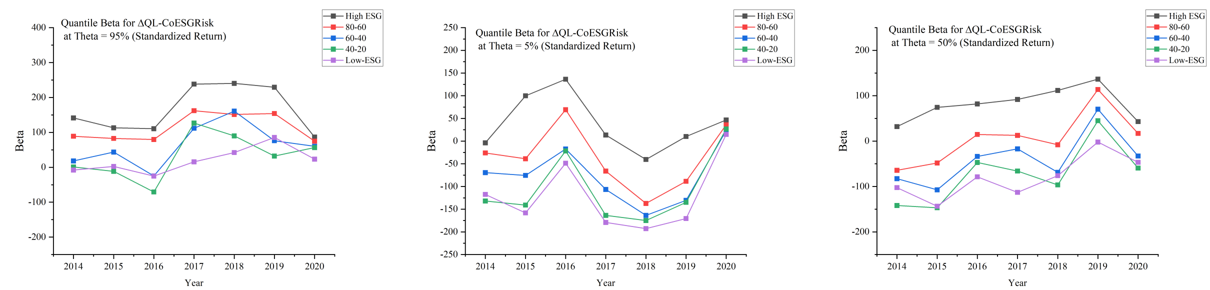
$$\begin{aligned} \beta^{ESG}_{i,t} &= \alpha_0 + \beta_1 Z(ESG_{i,t}) + \beta_3 log(MV_{i,t}) \\ &+ \beta_4 LEV_{i,t} + \beta_5 ROA_{i,t} + \beta_5 BM_{i,t} + \beta_6 VIX_t + \beta_7 Sent_t + \varepsilon_t \end{aligned}, \tag{4.1}$$

Figure 9: $\beta_i^{ESG,\tau|\theta}$ **under Different** θ**s (Standardized Return)**

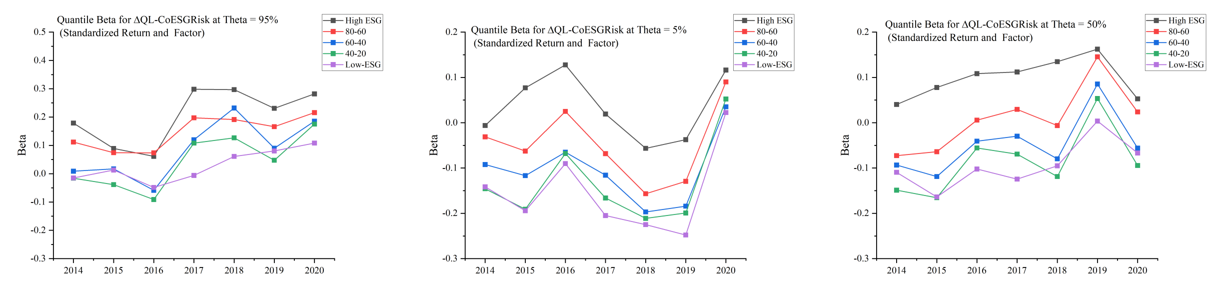
Panel A: $\beta_i^{ESG,\tau|\theta}$ for each year by only standardizing the ESG risk factor



Panel B: $\beta_i^{ESG,\tau|\theta}$ for each year by only standardizing company returns



Panel C: $\beta_i^{ESG,\tau|\theta}$ for each year by standardizing both company returns and the ESG risk factor



Note: the graph shows the quantile beta under quantile–located scheme ($\beta_i^{ESG,5\%|\theta}$) for different ESG levels in each year (with $\tau = 5\%$). Panel A shows the results when standardizing the ESG risk factor. Panel B shows the results when standardizing the company return. Panel C shows the results when standardizing both the ESG risk factor and company returns.

Table 6: **Components of $\triangle QL - CoESGRisk$ for the Whole Sample Period (Standardized Return)**

Panel A: Components of $\triangle QL - CoESGRisk_{\tau}^{95\%}$ ($f_{ESG,t} = VaR_{ESG,t}^{95\%}$) (basis points)

High	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$	**Low**	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$
Part 1	105.41	373.94	369.01	352.98	Part 1	-36.73	200.58	269.03	472.95
Part 2	-54.58	-80.02	-103.55	-112.06	Part 2	-44.10	-59.53	-76.94	-79.24
Part 3	509.93	-209.77	-726.41	-1348.06	Part 3	-1544.87	-2430.57	-3130.08	-4035.13
Part 4	-1.69	-7.38	-11.13	-16.17	Part 4	-0.49	-5.85	-9.66	-16.16
Sum	559.08	76.77	-472.09	-1123.32	Sum	-1626.19	-2295.37	-2947.65	-3657.58

Panel B: Components of $\triangle QL - CoESGRisk_{\tau}^{5\%}$ ($f_{ESG,t} = VaR_{ESG,t}^{5\%}$) (basis points)

High	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$	**Low**	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$
Part 1	178.63	625.03	931.55	1156.78	Part 1	170.73	579.20	801.89	945.11
Part 2	-29.79	-28.07	-23.76	-25.44	Part 2	-18.50	-12.64	-13.20	-13.25
Part 3	-859.47	-1854.66	-2646.21	-3583.76	Part 3	1420.20	676.01	241.47	-260.67
Part 4	0.44	5.78	10.44	15.44	Part 4	0.59	5.76	9.29	11.90
Sum	-710.19	-1251.92	-1727.98	-2436.98	Sum	1573.03	1248.34	1039.44	683.10

Note: The table presents the four parts of $\triangle QL - CoESGRisk_{\tau}^{\theta}$ calculated in Eq. (3.1) for high- and low-ESG groups. Panel A shows the results of for $\theta = 95\%$ and Panel B shows the results for $\theta = 5\%$. "High" means high-ESG company group and "low" means low-ESG company group. Both return and the ESG risk factor is being standardized.

Table 7: **Components of $\triangle QL - CoESGRisk$ for the Pre-COVID Period**

Panel A: Components of $\triangle QL - CoESGRisk_{\tau}^{95\%}$ ($f_{ESG,t} = VaR_{ESG,t}^{95\%}$) (basis points)

High	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$	**Low**	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$
Part 1	-1.11	3.67	4.57	5.44	Part 1	-1.92	1.72	4.08	4.63
Part 2	-0.06	-0.02	-0.01	-0.10	Part 2	-0.04	-0.03	-0.11	-0.19
Part 3	16.73	6.21	0.63	-2.24	Part 3	-22.50	-38.48	-49.80	-60.69
Part 4	0.01	-0.14	-0.23	-0.31	Part 4	0.04	-0.13	-0.28	-0.38
Sum	15.57	9.72	4.95	2.79	Sum	-24.42	-36.91	-46.12	-56.63

Panel B: Components of $\triangle QL - CoESGRisk_{\tau}^{5\%}$ ($f_{ESG,t} = VaR_{ESG,t}^{5\%}$) (basis points)

High	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$	**Low**	$\tau = 50\%$	$\tau = 20\%$	$\tau = 10\%$	$\tau = 5\%$
Part 1	1.66	7.39	11.43	13.89	Part 1	0.73	9.45	11.42	13.10
Part 2	0.01	0.10	0.22	0.21	Part 2	-0.01	-0.03	0.07	0.18
Part 3	-19.38	-35.97	-49.06	-57.86	Part 3	24.04	8.19	5.57	-1.10
Part 4	0.04	0.31	0.50	0.60	Part 4	0.03	0.36	0.42	0.60
Sum	-17.67	-28.17	-36.90	-43.16	Sum	24.80	17.97	17.47	12.78

Note: The table presents the four parts of $\triangle QL - CoESGRisk_{\tau}^{\theta}$ calculated in Eq. (3.1) for high- and low-ESG groups. The sample period is from 2013 to 2019 covering the pre-COVID period. Panel A shows the results of for $\theta = 95\%$ and Panel B shows the results for $\theta = 5\%$. Both return and the ESG risk factor is being standardized.

where $\beta_{i,t}^{ESG}$ is the estimated quantile beta and the quantile-located quantile beta for each company in each year at $\tau = 5\%$. We have three types of dependent variables: $\beta_{i,t}^{ESG,5\%}$, $\beta_{i,t}^{ESG,5\%|5\%}$ and $\beta_{i,t}^{ESG,5\%|95\%}$. We also check the deviation from normal beta to quantile-located beta, defined as $D^{95\%} = \left|\beta_{i,t}^{ESG,5\%} - \beta_{i,t}^{ESG,5\%|95\%}\right|$ and $D^{5\%} = \left|\beta_{i,t}^{ESG,5\%} - \beta_{i,t}^{ESG,5\%|5\%}\right|$. We have seven years of observations for each company ($t = 1, ..., 7$). The first observation is year 2014, which is calculated using all the return data from 2014/1/1 to 2014/12/31. $Z(ESG_{i,t})$ is the Z-score of the average monthly ESG score in year t.

In model (4.1), we study two types of determinants of quantile beta. We control for several firm characteristics. We add the size ($log(MV_{i,t})$), leverage level ($LEV_{i,t}$, leverage ratio, defined here as total debt/total capital), profitability ($ROA_{i,t}$, return on assets) and book-to-market ratio ($BM_{i,t}$), which are documented in the literature to be related to the ESG performance of a company (Gillan et al., 2021). We download the month-end value of the firm-level market value, the leverage ratio and the return on asset from the Eikon Database. Since we have yearly data frequency in the panel data, $MV_{i,t}$, $LEV_{i,t}$, $ROA_{i,t}$, and $BM_{i,t}$ are the average value of month-end values in year t, for each company i.

We also consider two market-related factors~~. We add~~ the market volatiliy index (VIX_t)~~.~~ The volatility index is the estimation of 30-day implied volatility of the S&P 500 index in the US. A high value of the volatility index means large overall uncertainty in the corresponding financial market. ~~We also include the climate sentiment index ($Sent_t$). As~~ discussed in the previous section, the difference between the quantile-located beta and the normal beta may be related to the extreme climate sentiment. Therefore, a higher climate sentiment may indicate a larger deviation. The climate sentiment index ~~here~~ ~~is~~ the Google Trends index for the topic of "climate change", and is calculated based on the amount of searches in a given period for a given region. A higher index value means a higher sentiment.

Table 8 shows summary statistics. Panel A shows the average and number of observations of the ESG score and β^{ESG}. The average ESG score has small variations across the years, while the quantile betas have a larger magnitude of changes. The data frequency of 2020 decreased because the ESG information of some companies has not been released as at the data downloading date (2021/11).

Table 9 reports the results of the model (4.1). Columns 1 is the regression for $\beta_t^{ESG,\tau}$. The coefficient for $Z(ESG)$ is significant and positive: one standard deviation increase in the ESG score will increase the quatile beta by 0.59. In addition to the ESG score, we also observe a significant impact of other control variables. The coefficient of $log(MV_{i,t})$ is negative and significant, which implies that companies with a larger size should have a more negative quantile beta. A higher leverage ratio is associated with a more negative beta. The

Table 8: Summary Statistics of Variables

Panel A: Statistics of $\beta_{i,t}^{ESG}$ and ESG score

Year	Frequency	Percent	$\beta_{i,t}^{ESG,5\%}$	$\beta_{i,t}^{ESG,5\%\|95\%}$	$\beta_{i,t}^{ESG,5\%\|5\%}$	ESG Score
2014	771	8.1%	-0.1648	0.6671	-1.0574	40.58
2015	1200	12.6%	-0.4435	1.0783	-0.5607	38.65
2016	1483	15.6%	-0.2439	-1.7624	0.6638	37.91
2017	1521	16.0%	-0.6821	1.5044	-1.8293	39.90
2018	1528	16.1%	-0.5620	2.4724	-2.3142	40.93
2019	1525	16.0%	-0.0567	1.7376	-1.7586	43.08
2020	1492	15.7%	0.5268	-4.4486	4.4986	45.05
Total	9520	100.0%	-0.2323	0.1784	-0.3368	40.87

Panel B: Statistics of other dependent variables

Variable	N	Mean	Std.	P25	Median	P75
Log(MV)	11327	8.15	1.59	7.02	8.02	9.19
Leverage Ratio	11306	42.56	71.82	21.27	40.52	56.14
ROA (%)	11256	3.90	16.59	1.34	4.65	8.47
Book-to-Market	11313	0.44	2.82	0.23	0.43	0.71

Note: The table shows descriptive statistics of dependent and independent variables. Panel A shows the mean and frequency of quantile betas and ESG score for each year. Panel B presents a summary of other corporate variables.

coefficient for $ROA_{i,t}$ and book-to-market ratio are insignificant. The coefficients for the VIX index and climate sentiment are positive, which means that higher market uncertainity and climate sentiment leads to a larger beta (and thus high-ESG companies will have more risk deduction benefit).

Columns 2 and 3 are coefficients for the the quantile-located quantile beta. The coefficient for the ESG score is significant and positive when $\theta = 5\%$, which corresponds to our previous results that when market is in favor of low-ESG companies ($\theta = 5\%$), high-ESG companies suffer more. The coefficients of $log(MV_{i,t})$ have opposite sign under two conditions: a larger size indicates a more positive $\beta_{i,t}^{ESG,5\%|95\%}$ and a more negative $\beta_{i,t}^{ESG,5\%|5\%}$. Since $\beta_{i,t}^{ESG,5\%|95\%}$ corresponds to a contribution of $\beta_{i,t}^{ESG,5\%|95\%}\left(VaR_{ESG,t}^{95\%} - VaR_{ESG,t}^{50\%}\right)$ and $\beta_{i,t}^{ESG,5\%|5\%}$ corresponds to a contribution of $\beta_{i,t}^{ESG,5\%|5\%}\left(VaR_{ESG,t}^{5\%} - VaR_{ESG,t}^{50\%}\right)$, it implies that under extreme market ESG conditions, companies with larger size will receive higher benefits. The coefficient for the VIX index is opposite between $\beta_{i,t}^{ESG,5\%|95\%}$ (negative) and $\beta_{i,t}^{ESG,5\%|5\%}$ (positive), which implies that, when conditioned on the status of the ESG risk factor, the ESG contribution will become smaller when the market uncertainity increases. This is also in-line with the results in Table 8, where we find that the quantile-located quantile beta changes drastically when the COVID happened (with $\beta_{i,t}^{ESG,5\%|5\%}$ becoming more positive and $\beta_{i,t}^{ESG,5\%|95\%}$ more negative). The coefficient of climate sentiment is positive for

Table 9: **Regression on Determinants of β_t^{ESG}**

Dep. var. =	$\beta_{i,t}^{ESG,5\%}$	$\beta_{i,t}^{ESG,5\%\|95\%}$	$\beta_{i,t}^{ESG,5\%\|5\%}$	$D^{95\%}$	$D^{5\%}$
Column	(1)	(2)	(3)	(4)	(5)
$Z(ESG)$	0.5194*** (6.90)	-0.1815 (-0.89)	0.5837*** (2.99)	-0.1833 (-1.39)	-0.1160 (-0.81)
$log(MV_{i,t})$	-0.6835*** (-2.61)	2.9747*** (5.47)	-2.4142*** (-3.38)	-0.8381* (-1.75)	-0.7599* (-1.73)
Leverage	-0.0496** (-2.05)	-0.0887 (-0.83)	0.0443 (0.71)	0.0006 (0.01)	0.0156 (0.37)
$ROA_{i,t}$	-0.0362 (-0.18)	0.3536 (0.88)	-0.5287 (-1.44)	-0.4084 (-1.12)	-0.5224 (-1.45)
Book-to-Market	1.0679 (1.42)	0.9012 (0.87)	2.7954 (1.18)	0.3864 (0.43)	0.5265 (0.56)
VIX	0.4580*** (10.90)	-1.6337*** (-17.88)	1.9513*** (18.87)	0.4806*** (7.37)	0.1783*** (2.61)
Sentiment	0.2615*** (7.41)	0.2203*** (2.39)	0.1166 (1.20)	0.2648*** (4.18)	-0.3859*** (-6.29)
Observations	9454	9454	9454	9454	9454
Adjusted R^2	0.039	0.061	0.094	0.011	0.013

Note: The table shows the regression results under fixed-effects, with robust errors clustered at the company level. Column 1 is the regression for quantile beta. Column 2 and 3 are the regression for the quantile-located quantile beta. The number in the parenthesis is the t-statistic. Coefficients are standardized after the estimation as $\beta_{stdardardized} = \beta_{original}\sigma_{indepent}$.
* Statistical significance at the 10% level. ** Statistical significance at the 5% level. *** Statistical significance at the 1% level.

$\beta_{i,t}^{ESG,5\%|95\%}$.

Columns 4 and 5 are the coefficients for the beta deviation. Larger companies have smaller deviations. Apart from the company size, other firm characteristics play a limited role in determining the deviation. Instead, we observe the market-related forces being the major determinants. A higher VIX index means a higher deviation. A higher climate sentiment means a larger $D^{95\%}$, which is sensible because $\beta_{i,t}^{ESG,5\%|95\%}$ means $f_{ESG,t} = VaR_{ESG,t}^{95\%}$ and thus corresponds to a high climate sentiment market condition. We further provide the regression results for the pre-COVID period, the results are quite similar to that of the whole period.

We further explored if sector characteristics have impacts on the level of ESG risk contribution by adding sector dummies in the OLS regression setting (non-constant). We present in Table 11 the coefficient for the sector dummy, with the last column the market average. We do observe differences in the quantile beta among sectors, which means that sector

Table 10: **Regression on Determinants of β_t^{ESG} (Pre-COVID)**

Dep. var. =	$\beta_{i,t}^{ESG,5\%}$	$\beta_{i,t}^{ESG,5\%\|95\%}$	$\beta_{i,t}^{ESG,5\%\|5\%}$	$D^{95\%}$	$D^{5\%}$
Column	(1)	(2)	(3)	(4)	(5)
$Z(ESG)$	0.5313*** (6.15)	-0.0519 (-0.21)	0.6275*** (2.83)	-0.2857* (-1.96)	-0.1772 (-1.12)
$log(MV_{i,t})$	-0.1602 (-0.59)	3.2509*** (4.73)	-2.0837*** (-2.78)	0.5658 (1.13)	0.6393 (1.23)
Leverage	-0.0729*** (-3.35)	-0.1461* (-1.89)	-0.0073 (-0.18)	-0.0136 (-0.37)	-0.0095 (-0.26)
$ROA_{i,t}$	0.2454 (1.16)	0.3737 (0.74)	-0.1517 (-0.37)	-0.2558 (-0.71)	-0.5941 (-1.47)
Book-to-Market	3.1753*** (4.29)	1.7879 (0.83)	2.2182 (1.30)	0.6687 (0.51)	-0.1089 (-0.08)
VIX	0.2331*** (2.53)	0.4185* (1.65)	0.1888 (0.88)	1.5482*** (9.99)	0.9192*** (5.30)
Sentiment	0.2110*** (5.94)	0.3700*** (3.91)	-0.0591 (-0.64)	0.3249*** (5.09)	-0.3550*** (-5.66)
Observations	7970	7970	7970	7970	7970
Adjusted R^2	0.022	0.009	0.004	0.016	0.015

Note: The table shows the regression results for under fixed-effects estimator, with robust errors clustered at the company level. Column 1 is the regression for quantile beta. Column 2 and 3 are the regression for the quantile-located quantile beta. The number in the parenthesis is the t-statistic. Coefficients are standardized after the estimation as $\beta_{stdardardized} = \beta_{original}\sigma_{indepent}$.
* Statistical significance at the 10% level. ** Statistical significance at the 5% level. *** Statistical significance at the 1% level.

characteristics do play a role in affecting the relationship between ESG and downside risk. For example, the Energy sector has the most negative quantile beta in all conditions, which means that companies in this sector will suffer from exposing to ESG. Meanwhile, the Utility sector has the most positive quantile beta (more positive than the market).

5 Conclusion

Investors turn to ESG investments for risk deduction benefits. This is especially the case during the COVID period, when ESG investments in the market have almost doubled within two years. Since ESG investments are evidenced both in practice and by the literature to have lower downside risk, whether and how the downside risk of a company is affected by its ESG activities is of particular interest to investors and regulators. Our paper provides

Table 11: **Sector Impact on β_t^{ESG}**

Dep. var. =	$\beta_{i,t}^{ESG,5\%}$	$\beta_{i,t}^{ESG,5\%\|95\%}$	$\beta_{i,t}^{ESG,5\%\|5\%}$	$D^{95\%}$	$D^{5\%}$
Column	(1)	(2)	(3)	(4)	(5)
Consumer Non-Cyclical	-6.7214***	-0.9811	-9.0442***	5.39141***	13.2500***
Consumer Cyclical	-6.3952***	0.0577	-9.0653***	5.34885***	13.1507***
Technology and Telecomun.	-7.8203***	-1.7373*	-11.5515***	5.08974***	12.8643***
Utility	-4.4121***	2.2781**	-7.1520***	3.52405***	12.7593***
Energy	-8.2406***	-3.8393***	-9.3906***	5.96094***	14.8643***
Health	-7.7854***	-0.6644	-10.8236***	5.77113***	13.5235***
Financial	-6.6302***	-1.4985	-9.7536***	3.51172***	11.006***
Basic Materials	-6.7855***	-0.8202	-10.4731***	4.46075***	12.4808***
Industrial	-7.1233***	-1.2042	-10.0481***	4.25917***	12.3677***
Market Average	-6.5954***	-0.8584	-9.7118***	4.11143***	11.9063***

Note: The table shows the coefficient of regression results for model (4.1). Coefficients are standardised after the estimation as $\beta_{stdardardized} = \beta_{original}\sigma_{indepent}$.
* Statistical significance at the 10% level. ** Statistical significance at the 5% level. *** Statistical significance at the 1% level.

a new measurement – the ESG risk contribution ($\triangle CoESGRisk$) – to quantify how ESG affects the downside risk of a company. In concrete, we construct the ESG risk factor to represent how ESG activities of companies are being realized in the market. Then, we use the co-movement between the ESG risk factor and the downside risk to measure the risk contribution of ESG to a company. Using this measurement, we study companies in the US market. In estimating the ESG risk contribution, apart from the plain quantile regression, we apply a more flexible setting where the market ESG condition changes to the status of the ESG risk factor, such that the relationship between ESG risk factor and the downside risk of a company also changes.

Under our proposed setting, high-ESG companies would suffer even when the market is in favor of high-ESG companies, mainly due to the increase in the volatility. In addition, ESG risk contributions under this setting change over time. A possible explanation is that, if we only measure the relationship between the tail of the ESG risk factor and the tail of the companies, the relationship between the two could change, because what drives the ESG risk factor to extreme states may also change.

In comparison, results from the conventional setting are closer to the literature. When there is a sudden increase in the ESG risk factor, the average ESG contribution to downside risk (represented by daily 5% VaR) is around 26 basis points for the high-ESG group and -28 basis points for the low-ESG group. The risk deduction benefits for high-ESG group are mainly due to the increase in the mean and a slight decrease in the volatility of the conditional distribution. The ESG risk contribution under this setting does not change over time.

We extend our analysis by studying the determinants of the quantile beta, the main driver of the ESG risk contribution. We find that a higher ESG score leads to a more positive exposure and thus a more positive contribution. Apart from the ESG score, other corporate variables such as size or leverage will also affect the contribution. Specifically, large and profitable companies will suffer less under extreme market ESG conditions. Apart from firm characteristics, we also examine if market forces determines the quantile beta. We find that higher climate sentiment and market uncertainty will lead to higher quantile beta under conventional setting. In fact, apart from company size, differences between quantile beta under conventional setting and our proposed setting are mainly driven by market forces. The level of contribution varies among sectors, which means that sector characteristics should be taken into account when evaluating the impact of ESG on downside risk.

$\triangle CoESGRisk$ provides regulators with an effective tool to quantify the downside risk impact of ESG-related policies. For example, an incentive plan to promote carbon emission reductions in the energy sector may stimulate the environmental concerns of investors and might thus cause investors to further increase their investment in high-ESG companies in the sector, such that high-ESG companies outperform low-ESG companies to a large extent (with the ESG risk factor becomes high and positive). Then, the ESG risk contribution also changes. In other words, changes in the ESG policy will finally be reflected in the changes in the ESG risk contribution. Therefore, $\triangle CoESGRisk$ can then be used to show the downside risk impact of such policy both at individual company level and at the sector level.

Finally, when calculating $\triangle CoESGRisk$, we assume that the ESG risk factor changes from 50% state to two extremes states. This assumption may be too radical in calmer times. At any event, the central idea behind our method is that we use the co-movement between a company's downside risk and the ESG risk factor as a measurement of ESG risk contribution. Therefore, the new measurement can be used in a more flexible way by regulators, market participants, and risk managers: by setting the ESG risk factor state to a value that fits the actual economic condition or that is coherent with the current perception/interest to ESG (i.e., the ESG sentiment).

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A Company Variable and ESG Data in Eikon Database

We provide the list of data and the corresponding code we use in the data base of Eikon Datastream as in Table 12.

Table 12: Data Description and Code

Name	**Frequency**	**Period**	**Code**
Price	Daily	2013/06/01 - 2020/12/31	P
Market Value	Monthly, Month-end	2013/05/31 - 2020/11/31	MV
Book Value	Monthly, Month-end	2013/05/31 - 2020/11/31	WC03501
Total Asset	Monthly, Month-end	2011/05/31 - 2019/12/31	WC02999
Operating Income	Monthly, Month-end	2013/05/31 - 2020/11/31	WC01250
Market to Book Ratio	Monthly, Month-end	2013/05/31 - 2020/11/31	MTBV
Leverage Ratio	Monthly, Month-end	2013/05/31 - 2020/12/31	WC08231
Return on Assets	Monthly, Month-end	2013/05/31 - 2020/12/31	WC08326
ESG Combined Score	Monthly, Month-end	2013/05/31 - 2020/12/31	TRESGCS

B Discussion on the Property of FM Factors

For illustration purposes, assume we have a one-factor structure in the cross-section regression, a constant plus one ESG property at time $t-1$[19]. All ESG scores are standardized to z-score (with 0 mean and a standard deviation of 1) among all companies in time t. In concrete, we have

$$\begin{cases} r_{it} = F_{0t} + F_{ESG,t} ESG_{i,t-1} + \eta_{it} \\ \mu_{ESG_{t-1}} = \frac{\sum ESG_{i,t-1}}{n} = 0 \Rightarrow \sum ESG_{i,t-1} = 0 \\ \sigma^2_{ESG_{t-1}} = \frac{\sum (ESG_{i,t-1} - 0)^2}{n} = 1 \Rightarrow \sum (ESG_{i,t-1})^2 = n \end{cases} \tag{B.1}$$

The matrix form of Eq. (B.1) is:

$$R_t = X_{t-1}\Gamma_t + \Phi_t, \tag{B.2}$$

where R_t is the return matrix with a size of $(n \times 1)$: $R_t = [r_{1t}, r_{2t}, r_{3t}, ..., r_{nt}]^T$; X_{t-1} is the variable matrix with a value of time (t-1) with a size of $(n \times 2)$:

[19] At time t, we only know the value of those variables in the previous period (t-1)

$$X_{t-1} = \begin{bmatrix} 1 & ESG_{1,t-1} \\ 1 & ESG_{2,t-1} \\ ... & ... \\ 1 & ESG_{n,t-1} \end{bmatrix}_{(n\times 2)} . \tag{B.3}$$

The Γ_t is the matrix of factor returns with a size of (2×1) : $\left[\hat{F}_{0,t}, \hat{F}_{ESG,t}\right]^T$ and the error term $\Phi_t = [\eta_{1t}, \eta_{2t}, ..., \eta_{nt}]^T$. And the Ordinary Least Square (OLS) estimation of Γ_t is:

$$\begin{aligned} \Gamma_t &= (X_{t-1}^T X_{t-1})^{-1} X_{t-1}^T R_t \\ &= \left(\begin{bmatrix} 1 & ... & 1 \\ ESG_{1,t-1} & ... & ESG_{n,t-1} \end{bmatrix} \begin{bmatrix} 1 & ESG_{1,t-1} \\ 1 & ESG_{2,t-1} \\ ... & ... \\ 1 & ESG_{n,t-1} \end{bmatrix} \right)^{-1} \begin{bmatrix} 1 & ... & 1 \\ ESG_{1,t-1} & ... & ESG_{n,t-1} \end{bmatrix} R_t \\ &= \left(\begin{bmatrix} n & \sum_{i=1}^n ESG_{i,t-1} \\ \sum_{i=1}^n ESG_{i,t-1} & \sum_{i=1}^n (ESG_{i,t-1})^2 \end{bmatrix} \right)^{-1} \begin{bmatrix} 1 & ... & 1 \\ ESG_{1,t-1} & ... & ESG_{n,t-1} \end{bmatrix} R_t \\ &= \left(\begin{bmatrix} n & 0 \\ 0 & n \end{bmatrix} \right)^{-1} \begin{bmatrix} 1 & ... & 1 \\ ESG_{1,t-1} & ... & ESG_{n,t-1} \end{bmatrix} R_t = \frac{1}{n^2} \begin{bmatrix} n & 0 \\ 0 & n \end{bmatrix} \begin{bmatrix} 1 & ... & 1 \\ ESG_{1,t-1} & ... & ESG_{n,t-1} \end{bmatrix} R_t \\ &= \begin{bmatrix} \frac{1}{n} & \frac{1}{n} & ... & \frac{1}{n} \\ \frac{ESG_{1,t-1}}{n} & \frac{ESG_{2,t-1}}{n} & .. & \frac{ESG_{n,t-1}}{n} \end{bmatrix} R_t = [R_{0,t}, R_{ESG,t}]^T \end{aligned} , \tag{B.4}$$

so that we have:

$$\begin{cases} f_{0,t} = & \frac{1}{n} r_{1t} + \frac{1}{n} r_{2t} + ... + \frac{1}{n} r_{nt} \\ f_{ESG,t} = & \frac{1}{n}(ESG_{1,t-1} r_{1t} + ESG_{2,t-1} r_{2t} + ... + ESG_{n,t-1} r_{nt}) \end{cases} . \tag{B.5}$$

Eq. (B.5) says that the ESG risk factor ($f_{ESG,t}$) is a portfolio, with the standardized ESG score as weights. Note that the ESG score is standardized cross-sectional to have zero mean, which means that for high-ESG companies the $ESG_{i,t-1}$ is positive and for low-ESG companies, the $ESG_{i,t-1}$ is negative. In that sense, $f_{ESG,t}$ is the return difference between high- and low-ESG companies. It is the “performance premium”: the additional positive/negative return brought by additional ESG performance.

C Significance of ESG Risk Contribution

To formally test if the ESG risk contribution is significantly different from zero, we follow the method of Reboredo et al. (2016), who uses the two-sample Kolmogorov–Smirnov test (the KS test, Abadie, 2002) to show if the conditional VaR is equal to unconditional VaR in terms of the cumulative distribution function (CDF). In our case, we intend to compare the CDFs of $CoESGVaR^{\theta}_{\tau,i,t}$ and $CoESGVaR^{50\%}_{\tau,i,t}$ of each company. The test statistic of the KS test is defined as follows:

$$D_{mn} = \left(\frac{mn}{m+n}\right)^{\frac{1}{2}} sup_x \mid A_m(x) - B_n(x) \mid,$$

where $A_m(x)$ and $B_n(x)$ are the cumulative distribution functions of $CoESGVaR^{\theta}_{\tau,i,t}$ and $CoESGVaR^{50\%}_{\tau,i,t}$, respectively, and n and m are the size of the two samples. The null hypothesis is defined as:

$$H_0 : CoESGVaR^{\theta}_{\tau,i,t} = CoESGVaR^{50\%}_{\tau,i,t} \text{ or } \triangle CoESGVaR^{\theta}_{\tau,i,t} = 0, \tag{C.1}$$

where $\theta = 95\%$ or 5% and τ ranges from 50% to 5% , for company i. If we reject the null hypothesis, it means that the CDFs of the two are different and the $\triangle CoESGVaR^{\theta}_{\tau,i,t}$ is significantly different from zero.

We present in Table 13 the percentage of KS test with a p-value smaller than 1% in each group for both $\Delta CoESGVaR^{\theta}_{\tau}$ and $\Delta QL - CoESGVaR^{\theta}_{\tau}$. First, most companies have a significant KS test statistics, which means that for most companies the ESG risk contribution is significantly different from zero. We do find that companies with more extreme ESG scores (either extremely high or extremely low) have a higher ESG risk contribution, especially for $\Delta CoESGVaR^{\theta}_{\tau}$. Same to the conclusion we get in the section 3.2, the impact is higher in the tail than in the middle (with higher percentage of companies having significant KS test statistics), especially for $\Delta QL - CoESGVaR^{\theta}_{\tau}$.

D Robustness: Changing the Data Provider

The ESG score is often known as noisy and inconsistent across different data providers, which means that a change of data provider could change our results (Berg et al., 2022). To check if our results are robust to ESG databases, we provide the results under the Bloomberg ESG score in this sub-section. The Bloomberg ESG score is calibrated using various data sources offered on the Bloomberg Terminal service, mainly company-reported sustainability

Table 13: **Percentage of KS Test with p-value Smaller than 1%**

Panel A: Percentage of companies with p-value <1% in the KS test for $\triangle CoESGRisk_{\tau}^{\theta}$

$\triangle CoESGRisk_{\tau}^{95\%}$	High-ESG	80-60	60-40	40-20	Low-ESG
OLS	87.25%	82.35%	83.01%	85.29%	86.27%
$\tau = 50\%$	83.99%	78.10%	83.99%	83.99%	85.62%
$\tau = 20\%$	83.99%	80.07%	82.35%	84.64%	86.93%
$\tau = 10\%$	81.37%	79.74%	84.64%	85.95%	83.66%
$\tau = 5\%$	87.25%	82.03%	81.05%	85.95%	87.25%

$\triangle CoESGRisk_{\tau}^{5\%}$	High-ESG	80-60	60-40	40-20	Low-ESG
OLS	87.25%	81.70%	83.33%	85.95%	86.60%
$\tau = 50\%$	84.31%	78.43%	83.99%	83.99%	85.95%
$\tau = 20\%$	83.33%	79.74%	83.01%	84.31%	86.93%
$\tau = 10\%$	81.37%	80.07%	84.64%	85.62%	83.66%
$\tau = 5\%$	87.58%	82.03%	81.05%	85.62%	87.25%

Panel B: Percentage of companies with p-value <1% in the KS test for $\triangle QL - CoESGRisk_{\tau}^{\theta}$

$\triangle QL - CoESGRisk_{\tau}^{95\%}$	High-ESG	80-60	60-40	40-20	Low-ESG
OLS	83.01%	84.97%	87.25%	88.89%	87.25%
$\tau = 50\%$	83.99%	84.31%	87.58%	86.27%	88.56%
$\tau = 20\%$	76.14%	84.31%	92.81%	94.44%	95.75%
$\tau = 10\%$	82.35%	87.25%	94.44%	97.06%	97.71%
$\tau = 5\%$	91.18%	92.81%	97.39%	97.71%	97.39%

$\triangle QL - CoESGRisk_{\tau}^{5\%}$	High-ESG	80-60	60-40	40-20	Low-ESG
OLS	88.24%	85.95%	86.93%	87.58%	84.97%
$\tau = 50\%$	84.64%	79.41%	87.58%	88.56%	88.56%
$\tau = 20\%$	93.79%	83.66%	89.22%	88.89%	88.24%
$\tau = 10\%$	96.41%	90.52%	90.20%	87.91%	91.50%
$\tau = 5\%$	98.04%	96.41%	93.14%	91.18%	93.46%

Note: The table presents the the percentage of companies in each ESG group with p-value <1% in the KS test. p-value <1% means the ESG risk contribution is significantly different from zero. Panel A shows the results for $\triangle CoESGRisk_{\tau}^{\theta}$ and panel B presents the results for $\triangle QL - CoESGRisk_{\tau}^{\theta}$.

Table 14: **Average $\triangle CoESGRisk$ for Different ESG Databases**

Panel A: $\triangle CoESGRisk_{\tau}^{95\%}$ (basis points)

Eikon	High	80-60	60-40	40-20	Low	**Bloom**	High	80-60	60-40	40-20	Low
OLS	23.43	6.15	-12.54	-23.59	-26.39	OLS	18.15	-0.85	-30.59	-40.09	-40.35
50%	19.42	2.75	-12.89	-23.31	-24.46	50%	13.96	-2.46	-30.45	-38.47	-35.79
20%	21.13	3.47	-13.26	-24.19	-27.01	20%	14.74	-4.10	-33.00	-41.54	-39.97
10%	22.43	3.99	-13.55	-25.07	-28.01	10%	15.64	-6.45	-34.04	-44.03	-42.61
5%	26.14	5.52	-11.88	-24.69	-28.18	5%	17.15	-5.74	-32.57	-44.38	-46.67

Panel B: $\triangle CoESGRisk_{\tau}^{5\%}$ (basis points)

Eikon	High	80-60	60-40	40-20	Low	**Bloom**	High	80-60	60-40	40-20	Low
OLS	-24.48	-6.43	13.11	24.66	27.58	OLS	-17.45	0.82	29.41	38.55	38.79
50%	-20.30	-2.87	13.47	24.36	25.57	50%	-13.42	2.36	29.28	36.99	34.41
20%	-22.08	-3.62	13.86	25.29	28.23	20%	-14.17	3.94	31.72	39.94	38.43
10%	-23.44	-4.17	14.16	26.20	29.28	10%	-15.04	6.20	32.73	42.33	40.97
5%	-27.32	-5.77	12.42	25.80	29.45	5%	-16.49	5.52	31.31	42.67	44.87

Note: The table presents the average $\triangle CoESGRisk$ using ESG scores from different data providers. The sample period for the Bloomberg is from 2015 to 2020.

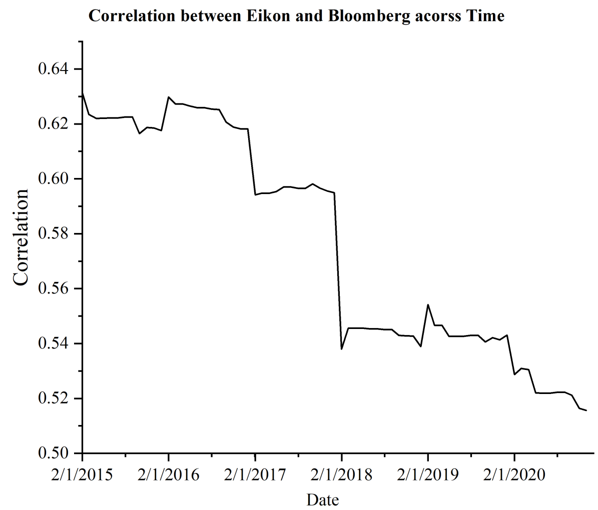
information and financial fundamentals data.[20] Bloomberg offers E, S and G score separately and we use the average of the three as the the ESG score for one company. The score ranges from 0 to 1 and combines a matrix of indicators of sustainability similar to that of Eikon. The ESG score used in our analysis dates back as early as 2015 and we have around 830 companies with ESG score.

We first provide in Figure 10 the cross-section correlation of ESG score between the two data providers in each month and the cumulative return of ESG risk factors. As can be seen, the overall correlation of ESG score is around 0.6 in early years and decreased to 0.5 in recent periods. In terms of the ESG risk factor, we observe a quite similar trends between the ESG risk factor calculated using common sets of companies (red line and blue line). In fact, the correlation between ESG risk factors is 0.67. In Table 14 – 15, we show the results for the whole period using the ESG risk factor calculated using common sets of companies. Though we still observe differences in the level of risk contribution, the pattern of the two is quite similar, indicating that our conclusion holds for different data providers.

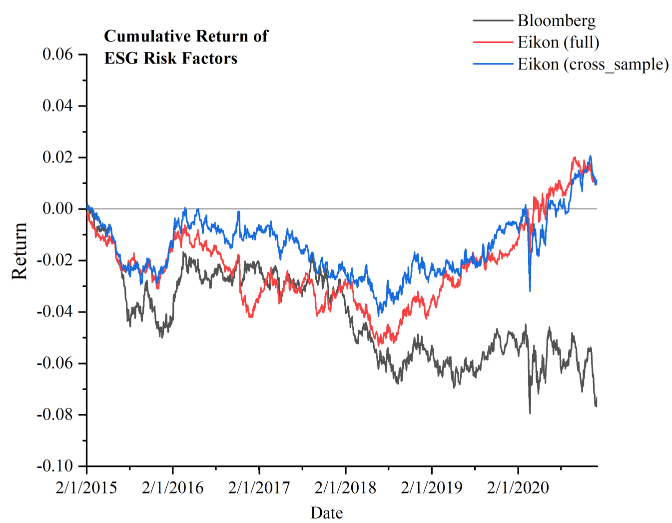
[20] https://data.bloomberglp.com/professional/sites/10/ESG_Environmental-Social-Scores.pdf

Figure 10: **Comparison of ESG Scores and ESG Factors**

Panel A: Cross-section correlation of ESG score over time



Panel B: Cumulative return of the ESG risk factor



Note: Panel A shows the cross-section correlation between ESG score of Eikon and Bloomberg. Panel B shows the the sum of daily factor return series from 2015 to 2020: $\sum_t f_{ESG,t}$.

Table 15: **Average $\triangle QL - CoESGRisk$ for Different ESG Databases**

Panel A: $\triangle QL - CoESGRisk_{\tau}^{95\%}$ (basis points)

Eikon	High	80-60	60-40	40-20	Low
OLS	19.97	7.65	-14.16	-23.08	-26.54
50%	19.27	4.26	-12.60	-22.02	-23.97
20%	2.29	-14.54	-32.89	-43.84	-49.77
10%	-13.35	-30.62	-49.00	-61.89	-68.98
5%	-27.35	-50.32	-67.55	-83.69	-89.22
Bloom	High	80-60	60-40	40-20	Low
OLS	14.32	-2.51	-29.35	-44.35	-35.93
50%	13.78	-2.33	-30.54	-38.99	-35.02
20%	-5.18	-25.98	-51.52	-63.24	-58.48
10%	-17.23	-43.56	-65.31	-79.98	-74.84
5%	-28.84	-59.34	-79.69	-99.24	-91.23

Panel B: $\triangle QL - CoESGRisk_{\tau}^{5\%}$ (basis points)

Eikon	High	80-60	60-40	40-20	Low
OLS	-29.40	-10.14	10.82	19.99	25.13
50%	-21.12	-2.69	12.93	24.39	25.13
20%	-40.47	-20.30	-4.80	6.40	8.14
10%	-57.21	-37.74	-19.53	-8.52	-5.84
5%	-81.74	-60.61	-37.80	-29.22	-26.10
Bloom	High	80-60	60-40	40-20	Low
OLS	-14.52	2.66	23.58	33.94	40.10
50%	-13.36	3.51	30.69	35.73	35.45
20%	-37.26	-19.21	11.52	16.98	21.47
10%	-58.50	-39.68	-6.04	0.34	6.20
5%	-80.76	-65.55	-33.00	-21.78	-9.69

Note: The table presents the average $\triangle QL - CoESGRisk$ using ESG scores from different data providers. The sample period for the Bloomberg is from 2015 to 2020.