DECONSTRUCTING ESG EXPOSURES – A FACTOR-BASED APPROACH

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Abstract

The paper analyzes the exposure of companies' stock prices in the utility and energy sector in the US market to Environmental, Social and Governance (ESG) factors. The paper first uses public ESG indices to quantify the ESG risk using the Fama/French (FF) strategy. Then, the linear and quantile regression including size, value, and market risk factors of FF along with the ESG risk factor are conducted to quantify the ESG exposure of stock returns at different quantiles of the conditional distribution of the company returns. The paper finds that high ESG score companies (utility sector) exposure is weaker than the exposure of low ESG score companies (energy sector). While the former has a small negative impact on the cumulative returns, the contribution of ESG performance to the cumulative returns of the later is positive. Furthermore, a panel correlation analysis is conducted to test if ESG exposures depend on company characteristics. Through the correlation analysis, for the utility sector, ESG performance, firm size, financial performance (measured by net income and EBITDA) and pollution level all are negatively correlated with ESG exposures. For the energy sector, the correlation coefficient is insignificant for most of the company characteristics.

Keywords: CFP, ESG, ESG Risk Factor, ESG Exposure, Factor Model, Fama/French Risk Factor, Linear Regression, Quantile Regression,VaR, CoVaR

Contents

1 Introduction

Does it payoff to be good? The answer is mixed. Ever since the beginning of the discussion in 1970s, when Friedman (1970) made his famous statement questioning the social responsibility of a company[1], there has always been debates about the impact of Environmental, Social and Governance (ESG) performance on the corporate financial performance (CFP). According to the meta-analysis conducted by Clark et al. (2015) and a recent meta-analysis by Stuart L. Gillan and Starks (2021), most researches in the literature have found that ESG performance of companies have weak positive impacts on CFP. Some, however, find insignificant and even negative impact of ESG performance to CFP. The CFP here includes operational financial return performance (e.g. ROA, ROE) and stock return performance.

The support for positive ESG-CFP relationship could be from several perspectives. Rajna Gibson and Mitali (2020) find that the positive return comes from strong investor preferences for sustainability, which caused institutional investors to place larger bets and exercise price pressure on high sustainability investments. Krueger (2015) thinks that the ESG impact comes from investor's reaction to ESG-related news and events. He found that investors do react strongly to "offsetting ESG": positive ESG news concerning firms with a history of poor ESG performances. Other explanations take form the corporate finance angle. Giese et al. (2019a) explain the positive ESG impact through three corporate finance transmission channels: cash-flow channel, the idiosyncratic risk channel, and the valuation channel. The cash-flow channel has the following logic: strong ESG performance means that the company is more competitive, thus with higher profitability and finally produces higher dividends. The idiosyncratic risk channel says that strong ESG performance means better risk management, and thus lower risk of severe incidents and finally with lower tail risk. And the valuation channel means that strong ESG performance brings lower systematic risk and thus lower cost of capital, resulting in higher valuation.

However, there are scholars challenging the existence of a relationship between ESG and CFP. Rost and Ehrmann (2015) study whether there are reporting bias in the current literature towards a positive relationship between ESG and CFP. They find that currently the research field expects a positive relationship between ESG and financial performance and findings meet that expectation, that is, on the one hand, editors of those "sustainability journals" are prone to accept papers with significant positive results; on the other hand, authors will not publish

[1] https://www.nytimes.com/1970/09/13/archives/a-friedman-doctrine-the-social-responsibility-of-business-is-to.html

results without significant positive results or with negative results. Krueger (2015) criticizes that "the mere observation of a positive correlation between some low-frequency ESG measure and value is consistent with at least two different interpretations: either more responsible firms tend to be more profitable or, alternatively, more profitable firms tend to channel more resources into projects that increase the well-being of stakeholders".

Apart from those empirical analysis, the work by Benabou and Tirole (2010) may give us a deeper look at the relationship between ESG and CFP. They provide with three possible understandings of ESG activities. First, ESG activities are the adoption of a long-term perspective by a company. For example, instead of cutting salary and increasing working hours to reduce cost for short-term benefit, firms may choose to invest in cultivating corporate culture and maintaining a competitive salary, such that more motivated workers may be attracted in the future. Second, ESG activities can be a result of the delegated exercise of philanthropy on behalf of stakeholders (NGOs, governments, consumers, etc.), that is, firms take ESG activities to respond to the demand from customers and governments, so as to gain advantages over competitors. For instance, firms invests in new technology to produce "eco-products", so as to reduce the future green taxation by governments, as well as to gain shares from customers who want to protect the environment. Third, ESG activities can be an insider-initiated corporate philanthropy. In other words, corporate ESG activities are the results of management's or the board members' own desires to engage in philanthropy. The first and second explanation indicates a positive ESG-CFP relationship. The last one may indicate a negative ESG-CFP relationship. In real situations, the motivation behind those ESG activities are heterogeneous – that is why we have observed mixed results.

Benabou and Tirole (2010) 's second explanation (the stakeholder demand) and Friedman's argument, together with the 50-year-long debate over the ESG-CFP relationship, may give us some new thoughts. According to the stakeholder theory proposed by Freeman in late 1980s, companies in the mordern business environment are faced with complicated stakeholder relationships. Failure in dealing with the stakeholder relationship may result in business failure. As a result, instead of studying the may-not-exist causality relationship between ESG and CFP, we may take from the risk perspective, that is, we can at least confirm that each company has exposures to the *ESG risk*, or the *stakeholder risk*. Becchetti et al. (2015) define the stakeholder risk as "risk of conflicts with stakeholders". In other words, a higher ESG score, especially E score and S score, means less conflicts with outside stakeholders like governments, NGOs and consumers, and a lower ESG score means more conflicts with stakeholders. More conflicts with stakeholders will lead to higher stakeholder risk: negative effects such as fines, punishments, etc. As a result, if a company is exposed to high shareholder risks, then the company's financial performance is likely to be affected. From this perspective, the ESG risk provides us with another angle to check the relationship between ESG and CFP.

The ESG risk has been priced by investors as a factor in recent years (de Haan et al. 2012, Becchetti et al., 2015, Becchetti et al., 2017). Currently, there are multiple strategies used by fund mangers in terms of sustainable investing, including but not limited to ESG integration, best-in-class/positive screening, sustainability themed/thematic investing, etc. In particular, the ESG integration method, as is defined by Global Sustainable Investment Alliance (GSIA)[2], means "the systematic and explicit inclusion by investment managers of environmental, social and governance factors into financial analysis". The ESG integration is largest sustainable investment strategy globally, covering more than 70% of total sustainable investment (25.2 trillion vs. 35.3 trillion). In the US market, the ESG integration strategy covers 62% of total sustainable investment. As a result, investors are faced with high exposures to ESG risk in their portfolios (*the ESG exposure*), thus managing the ESG exposure in portfolios becomes increasingly important.

To study the ESG exposure, we may first quantify the ESG risk. Starting from de Haan et al. (2012), scholars have been capturing the ESG risk factor as Fama/French risk factors. The Fama/French risk factors are calculated as the return difference between two groups of portfolios with opposite characteristics. For example, the SMB (Small minus Big) risk factor is calculated as return of a portfolio consisted of small market value stocks minus the return of a portfolio consisted of big market value stocks. Correspondingly, the ESG risk factor is usually calculated as the return difference between portfolios consisted of low-ESG stocks and portfolios with high-ESG stocks. After calculating ESG risk factors, researchers will use them in a regression analysis to explain stock returns. The corresponding factor loading (beta) in the regression measures the ESG exposure of a company. A large beta size, be it positive or negative, means the a company is more exposed to ESG risk and has higher idiosyncratic risk from ESG risk factors.

Apart from studying the return exposure, we also want to interpret and compare the exposure of downside risk of a company to ESG risk factor. Unlike the ESG-CFP relationship, the negative relationship between ESG and the downside risk has been observed and confirmed in the literature. For example, Loof and Stephan (2019) run a regression between ESG scores and estimated VaR to study the effect of ESG on downside risk. And they found a negative rela-

[2] http://www.gsi-alliance.org/

tionship between ESG score and downside risk. Hoepner et al. (2021) study the relationship by comparing the corporate ESG engagement data and portfolio's VaR, and find that engagement on ESG issues can reduce downside risk. Although ESG activities are evidenced in the literature to decrease downside risk of a company, if we follow the stakeholder risk logic mentioned above, the answer is still not clear: will the downside risk of a company be exposed to ESG risk factors? To which extent?

Once we have calculated the ESG exposure, we want to check if there are firm characteristics that can explain such exposure. So, we will analyze how the exposure depends on firm characteristics such as ESG performance, firm size, operational financial performance (such as EBITDA. ROA, etc.) and pollution level. In concrete, a panel correlation will be conducted between the ESG exposure and those firm characteristics.

We will use energy and utility sectors in US for analysis, because previous studies found a stronger ESG impact in the energy and utility industry than other sectors (Loof and Stephan, 2019, Torre et al., 2020). In addition, energy and utility sector has the highest exposure to key ESG issues like carbon emission and water stress (Giesea et al., 2020). Energy sector receives specific attention from the public and policymakers in therms of ESG issues (Streimikiene et al., 2009).

This paper contributes to the literature by providing a comparison of ESG exposures between utility and energy sectors. In addition, the paper tries to test if company characteristics will affect the ESG exposure. For investors who are implementing ESG investing strategy, our study offers additional information as of to which extent the ESG exposure will be affected by financial and ESG characteristics of a company. From the risk management perspective, by studying the ESG exposure to the downside risk, our study provides investors who use factor-based investing strategy (the ESG Integration) with another factor to manage the portfolio risk. In addition, the paper also offers a new method of using public ESG index to construct ESG risk factors.

In terms of the ESG exposure of stock return, companies in the utility sector have negative ESG exposure to ESG risk factors, and firms in the energy sector have positive ESG exposure to ESG risk factors. A positive ESG exposure means the stock return will receive a positive return contribution from ESG risk factors. Among ESG/E/S/G risk factors, the social risk factor has the highest level of return contribution to both sectors (in the long-run), with a cumulative return contribution of -7% to the utility sector and 8% to the energy sector by social risk factor (from 2009 to 2020).

In terms of the ESG exposure of downside risk, we find that for the utility sector, the ESG tail exposure, which is the exposure of downside risk of companies to ESG risk (measured by quantile beta), is more negative than ESG exposure. For energy sector, the ESG tail exposure is larger (more positive) than the ESG exposure. That means for companies in the utility sector, the downside risk will be increased by ESG risk factors. For the energy sector, the downside risk is decreased. The cumulative risk contribution by social risk factor for utility sector is -18% and 5% for energy sector (from 2009 to 2020).

Through correlation analysis between the ESG exposure/tail exposure and other indicators, we found that, in utility and energy sectors, companies with higher ESG scores have lower ESG exposure to ESG risk factors. Companies with better financial performance (EBITDA, net income) have lower ESG exposure. For utility sector, the higher emission and energy use level, the lower the ESG exposure. For energy sector, the higher the emission and energy use level, the higher ESG exposure. The correlation of the above indicators with ESG tail exposure does not change the sign but with a decreased correlation size.

This paper will be arranged as follows: Section 2 depicts in detail the methodology. Section 3 describes the data we are going to use. Section 4 presents the results we have gotten and Section 5 is the conclusion for this paper.

2 Methodology

In this section, we first describe the way to capture ESG risk factors by using public ESG indices. Then we will use the linear regression to calculate the exposure of company returns to ESG risk factors (the ESG exposure) under rolling window scheme. We also demonstrate how to calculate the exposure of downside risk to ESG risk factors (the ESG tail exposure) using the method of quantile regression. We then deeepen our analysis by calculating the contribution of ESG risk factors to the downside risk of the company using $\Delta Co - ESGVaR$ (the ESG risk exposure). We finish the section by defining the correlation analysis that we are going to implement.

2.1 Capturing ESG Risk Premium Factor using ESG Indices

We use public ESG indices to capture the ESG risk premium factor. The ESG index is an index like S&P 500. Major ESG data providers in the market (MSCI, Thomson, S&P...) all have their own ESG index family, which ranges from regional to country-level and to global level[3]. In our paper, the ESG index (in the US market) to be used is constructed by choosing the top 50% stocks with the highest ESG score in every sector from the parent index (best-in-class selection method). The weights in both parent index and ESG index are float-adjusted and contain companies in all sectors, making it able to isolate ESG risk. Such selecting process can also be regard as implementing an ESG investment policy of tilting towards high ESG/E/S/G companies. As a result, the return difference is the risk premium between ESG index and its parent index. The the following formula depicts how we are going to use ESG index to construct ESG risk premium factor (details of ESG indices will be introduced in Section 3):

$$ESG_t = R_{Parent,t} - R_{ESG,t} \tag{1}$$

where $R_{ESG,t}$ is the daily return of the chosen ESG Index (with high ESG score). The $R_{Parent,t}$ is the daily return of the parent index of the chosen ESG index (with lower ESG score than ESG index). Similarly, we will calculate the environmental risk factor (ENV), social risk factor (SOC) and governance risk factor (GOV) using respective ESG indices and their parent indices as below:

$$ENV_t = R_{Parent,t} - R_{E,t} \tag{2}$$

$$SOC_t = R_{Parent,t} - R_{S,t} \tag{3}$$

$$GOV_t = R_{Parent,t} - R_{G,t} \tag{4}$$

where $R_{ESG,t}$,$R_{E,t}$,$R_{S,t}$ and $R_{G,t}$ are corresponding daily return of selected ESG index.

The ESG risk premium factor calculated above is similar to the risk factor in the Fama/French (FF) research factors[4]. In FF factor model, take SMB risk factor for example, the SMB risk factor is set to capture the additional return for investors by investing in companies with small market capitalization, the so-called "size premium". Similarly, the ESG risk premium factor measures the additional return for investors by investing in companies with lower ESG scores ("ESG premium"). Both ESG risk premium factor and FF factor share the same mission of capturing risk premium.

[3]for example, https://www.refinitiv.com/en/financial-data/indices/esg-index

[4]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

However, the method used here to calculate ESG risk premium factor is different from the method used by many in the literature (Becchetti et al., 2017, Becchetti et al., 2015, Hubel and Scholz, 2019, Bolton and Kacperczyk, 2021), though the idea behind is the same. For example, Becchetti et al. (2017) used two self-constructed portfolios: one with companies that have high ESG scores (top portfolio) and the other with low ESG scores (bottom portfolio). Then, the ESG risk factor is calculated as the return difference between the two portfolios (bottom minus top). However, the way of self-constructed portfolio, though it has been widely used, has a practical issue that makes it hard to apply– it lacks replicability. Currently in the literature, different authors use different methods and stocks to construct the ESG risk factor. Some re-balance the portfolio annually and some semi-annually. Some uses monthly return and some weekly. The set of companies chosen to construct bottom/top portfolio is also different. As a result, the calculated risk factor could be different. However, if investors want to replicate and implement similar investing strategy, it could be hard for them to follow the literature. Here, we use the public ESG index to construct risk factor and the ESG risk factor measures the return difference between market index (with lower ESG score) and high ESG index (with higher ESG score).

The risk-return trade-off theory says that higher risk is associated with greater probability (but not necessarily) of higher return and lower risk with a greater probability of smaller return. Having said that, we would expect the ESG risk premium factor (later on we call it "ESG risk factor") to be positive. Most recent literature (Becchetti et al., 2017, Verheyden et al., 2016, Giese et al., 2019b, Bolton and Kacperczyk, 2021, etc.) found that portfolios with low ESG score stocks, given other characteristics similar, have higher return than high ESG score portfolios. Becchetti et al. (2017) found that portfolios with higher ESG score demonstrate lower return, a phenomenon they classified as "responsibility effect", which says that ESG risk factors have negative contribution to stock return of high ESG companies. In addition, empirical results by Hubel and Scholz (2019), who constructed ESG risk factors using FF approach in European market, also shows a positive cumulative return of ESG risk factors. In our case, we do find daily negative ESG risk factors ($ESG_t < 0$), but in the long run, as is shown in Figure 1, the cumulative return of ESG risk factor is positive.

2.2 Calculating ESG Exposures

After getting the risk factor series, we will conduct a linear regression between the ESG risk factor and the return of each company to calculate the ESG exposures:

$$R_{i,t} = a_i + b_i R_M + c_i SMB_t + d_i HML_t + \beta_i^{ESG} ESG_t + \epsilon_{i,t} \tag{5}$$

where R_M is the return on the market, value-weight return of all Center for Research in Security Prices (CRSP) firms incorporated in the US and listed on the NYSE[5]. ESG_t is the risk factor series that we have just calculated. SMB_t and HML_t are Fama/French risk factors capturing the size and value risk. Similarly, ENV_t, SOC_t and GOV_t are used to estimate β_i^E, $\beta_i^S$and β_i^G. We have avoided putting all ESG/E/S/G risk factors into Eq. (5) because component companies of selected ESG/E/S/G indices are quite similar (because many big companies with good practice in one ESG aspect usually have good scores in other aspects), thus there are high correlation among ESG/E/S/G risk factors[6]. We add ESG risk factor as a risk premium because ESG does not have a systematic effect, either positive or negative, on market-based financial performance (i.e. ESG risk are not part of the R_M) (Humphrey et al., 2012).

To better catch the time changing characteristic in the market, we will use a rolling window approach. Each window has a four-year period and there is only one-day difference between adjacent windows. The total number of window is 2086. The first window starts from 2009.01.02 to 2013.01.02. The last window ends at 2020.12.31. Thus, the estimated results will be a beta series for each company i :$\left\{\beta_{i,k}^{ESG}\right\}_{k=1}^{2086}, i = 1, 2...N$. N is the number of companies in each group and K denotes the number of windows.

β_i^{ESG}, β_i^E,$\beta_i^S$and β_i^G are *the ESG/E/S/G exposure*. They are the exposure of the company return to the ESG risk factor. So, $\beta_i^{ESG} > 0$ means the company has positive exposure to the ESG risk factor. $\beta_i^{ESG} < 0$ means that the company has negative exposure to the ESG risk factor. Becchetti et al. (2017) found that company with high ESG score will have lower and even negative β_i^{ESG} because high ESG companies should have its return reduced by having less stakeholder risk, thus having less return.

It should be noted that in the original setting of Fama/French 3-factor model (Fama and French, 1993), the risk premium of the company $(R_{i,t} - R_F)$ and the risk premium of the market $(R_M - R_F)$ were used. However, in our case, because we are going to study the exposure of the company return and will focus on the estimated beta instead of asset-pricing, we will use directly the company return and market return. Mathematically, adding R_F by both side in Eq.(5) won't change our estimation for β_i^{ESG}.

[5]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

[6]The high correlation between parent index and the ESG index(screened) is in-line with the finding of Verheyden et al. (2016), who applied an ESG-screening strategy to a well-diversified global portfolio and found that the portfolio after screening has a very high correlation of 0.99 with the original portfolio.

2.3 ESG Tail Exposure and ESG Risk Exposure

To study the relationship between ESG performance and the downside risk of a company, various methods have been used in the literature. Some use regression analysis between downside risk measures and the ESG score, or compare the downside risk of portfolios with different levels of ESG performance. Others try to build macro-economic models to study the mechanism of ESG impact to risk (Albuquerque et al., 2019). However, in terms of the exposure of downside risk to ESG risk factor, we haven't found previous studies for a reference. In our paper, we try to quantify such exposure through the quantile regression.

We first run quantile regressions at the level of $\tau = 5\%, 50\%$. The quantile regressions will be estimated as:

$$F^{-1}[\tau \mid R_{i,t}] = a_i^\tau + b_i^\tau R_M + c_i^\tau SMB_t + d_i^\tau HML_t + \beta_i^{ESG,\tau} ESG_t, \tag{6}$$

And the result of the estimation is the quantile beta series $\left\{\beta_{i,k}^{\tau}\right\}_{k=1}^{2086}, i = 1,2...N$. Similarly, ENV_t ,SOC_t and GOV_t are used to estimate $\beta_i^{E,\tau}$, $\beta_i^{S,\tau}$ and $\beta_i^{G,\tau}$. They are the *ESG tail exposures* .

After getting ESG tail exposures, we borrow concept of Conditional Value at Risk (CoVaR), raised by Adrian and Brunnermeier (2016) and also by Caporin et al. (2021). Originally, the CoVaR and delta CoVaR is used to capture the co-movement of tail risk between company returns and the market return. In our case, we are going to use it as a measure to capture ESG risk exposure. We develop the idea of *conditional ESG risk (Co-ESGVaR)*, which is the VaR of a company conditioned that ESG risk factor being at a particular state. In particular, $Co-ESGVaR^{95\%}$ is the VaR of a company conditioned that the ESG risk factor being at its 95% quantile ($VaR_{ESG,t}^{95\%}$). $VaR_{ESG,t}^{95\%}$ means that in the market, the return of low-ESG companies is well above the high-ESG companies. On the contrary, $Co-ESGVaR^{5\%}$ is the VaR of a company conditioned that the ESG risk factor being at its 5% quantile ($VaR_{ESG,t}^{5\%}$). $VaR_{ESG,t}^{5\%}$ means that in the market, the return of low-ESG companies is well below the high-ESG companies. Then we define the change of conditional ESG risk as *delta conditional ESG risk or ESG risk exposure* :

$$\Delta Co-ESGVaR_{i,k} \equiv \left\{Co-ESGVaR_{i,k}^{95\%} - Co-ESGVaR_{i,k}^{50\%}\right\}_{k=1}^{2086} \tag{7}$$

for company i in each window k (under rolling window scheme). Eq. (7) measures contribution of ESG risk factor to the downside risk of company i when in different quantile levels.

We use the $\Delta Co - ESGVaR$ to evaluate the ESG exposure to downside risk (*the ESG risk exposure*). In other words, $\Delta Co - ESGVaR$ will provide the impact of a sharp change in the ESG risk factor to the downside risk of a company.

The reason for us choosing $\Delta Co - ESGVaR$ is quite practical. Though ESG risk factor is supposed to be positive, it can sometimes be negative or sometimes be too large. The extreme change of ESG risk factor indicates the drastic change of market sentiment towards ESG investing. Such drastic change of sentiment will happen during the financial crisis, when investors are craving for high ESG companies for safety and as a result, ESG risk factor becomes very low and negative. Through this indicator, we want to answer the following question: to which extent the downside risk of a company would change when ESG risk changes from normal state to stressed state? The interpretation of $\Delta Co - ESGVaR$ are shown below in Table 1. If $\Delta Co - ESGVaR^{95\%} > 0$, mathmatically, it means that $Co - ESGVaR^{95\%}$ is larger than $Co - ESGVaR^{50\%}$. Economically, the VaR of a company is reduced (become more positive) when the ESG risk factor changes from normal state ($VaR_{ESG}^{50\%}$) to very large state ($VaR_{ESG}^{95\%}$) , that is, a positive contribution to the downside risk of a company. Similarly, if $\Delta Co - ESGVaR^{95\%} < 0$, we have a negative contribution.

Table 1: Interpretation of $\Delta Co-ESGVaR$

Indicator	Meaning
$Co-ESGVaR^{95\%}$	$VaR_i^{5\%}$of Company i when ESG risk factor is equal to $VaR_{ESG}^{95\%}$;
$Co-ESGVaR^{5\%}$	$VaR_i^{5\%}$of Company i when ESG risk factor is equal to $VaR_{ESG}^{5\%}$;
$\Delta Co-ESGVaR^{95\%}>0$	1. $Co-ESGVaR^{95\%}>Co-ESGVaR^{50\%}$; 2. A **positive** contribution to the downside risk of a company when the ESG risk factor is changing from normal state to $VaR_{ESG}^{95\%}$;
$\Delta Co-ESGVaR^{95\%}<0$	1. $Co-ESGVaR^{95\%}<Co-ESGVaR^{50\%}$; 2. A **negative** contribution to the downside risk of a company when the ESG risk factor is changing from normal state to $VaR_{ESG}^{95\%}$;
$\Delta Co-ESGVaR^{5\%}>0$	1. $Co-ESGVaR^{5\%}>Co-ESGVaR^{50\%}$; 2. A **positive** contribution to the downside risk of a company when the ESG risk factor is changing from normal state to $VaR_{ESG}^{5\%}$;
$\Delta Co-ESGVaR^{5\%}<0$	1. $Co-ESGVaR^{5\%}<Co-ESGVaR^{50\%}$; 2. A **negative** contribution to the downside risk of a company when the ESG risk factor is changing from normal state to $VaR_{ESG}^{5\%}$;

For calculation, there are several ways in the literature to calculate CoVaR, including but not limited to copulas, GARCH multivariate, quantile regression and Bayesian methods. We use the method of quantile regression brought by Adrian and Brunnermeier (2016) because it is numerically efficient and easy to explain. In addition, as we have already set up a framework of quantile regression when calculating the ESG tail exposure, we deepen our analysis by using such framework.

We first estimate the dynamic VaR series at 95% and 5% for the ESG risk factor using the parametric approach:

$$VaR_{ESG,t}^{95\%}=\mu+\hat{\sigma}_{ESG,t}\sqrt{\frac{\upsilon-2}{\upsilon}}t_{\upsilon}^{-1}(95\%) \tag{8}$$

$$VaR_{ESG,t}^{5\%}=\mu-\hat{\sigma}_{ESG,t}\sqrt{\frac{\upsilon-2}{\upsilon}}t_{\upsilon}^{-1}(95\%) \tag{9}$$

Where μ is the historical average of daily return from 2009 to 2020. We assume the risk factor to follow a t-student distribution, and $t_v^{-1}(95\%)$ is the 95% quantile of a standard t-student distribution with a mean of 0 and a standard deviation of 1 (t(0,1,v)). The degree of freedom ν is estimated using the Maximum Likelihood Estimation(MLE) by fitting the standardized return distribution of ESG risk factor to t-student distribution. $\hat{\sigma}_t$ is estimated using GJR-GARCH model proposed by Glosten et al. (1993) as:

$$a_t = R_{ESG,t} - \mu = \sigma_{ESG,t}\varepsilon_t, \varepsilon_t \sim t(0,1,\nu) \tag{10}$$

$$\hat{\sigma}^2_{ESG,t+1} = \alpha_0 + \alpha_1 a_t^2 + \gamma I_{\{\varepsilon_t<0\}} a_t^2 + \alpha_2 \sigma^2_{ESG,t} \tag{11}$$

After getting the dynamic VaR series of ESG risk factor, under the rolling window scheme, we will use the quantile regression Eq.(6) at $\tau = 5\%$, to calculate the conditional ESG risk as:

$$Co - ESGVaR^{95\%}_{i,k} = VaR_{5\%}^{i,k|ESG_t=VaR^{95\%}_{ESG,t}} = a_i^{5\%} + b_i^{5\%} R_M + c_i^{5\%} SMB_t + d_i^{5\%} HML_t + \beta^{5\%}_{i,k} VaR^{95\%}_{ESG,t} \tag{12}$$

for company i in each window k (the rolling window approach still applies in the quantile regression). Eq.(12) means the VaR of company i conditioned that the ESG risk factor is at its risk.

In addition, we will calculate $Co - ESGVaR^{\tau}_{i,k}$ for $\tau = 50\%$ and the $VaR^{50\%}_{ESG,t}$ (median) will be used. That is, we will calculate $Co - ESGVaR^{50\%}_{i,k}$ as below:

$$Co - ESGVaR^{50\%}_{i,k} = VaR_{5\%}^{i,k|ESG_t=VaR^{50\%}_{ESG,t}} = a_i^{5\%} + b_i^{5\%} R_M + c_i^{5\%} SMB_t + d_i^{5\%} HML_t + \beta^{5\%}_{i,k} VaR^{50\%}_{ESG,t} \tag{13}$$

For the calculation of $VaR^{50\%}_{ESG,t}$, if we are going to use the method of parametric VaR, the estimation of $VaR^{50\%}_{ESG,t}$ will always be the average μ because $t_v^{-1}(50\%) = 0$. To solve the issue, we are going to use a method proposed by Eengle and Manganelli (2004) called *conditional auto-regressive value at risk(CAViaR)*, where the VaR is estimated by modeling directly the distribution of the quantile. Such idea is based on the observation that there is high auto-correlation in the variance of returns. We are going to use the *Asymmetric CAViaR*, with the setting as:

$$VaR_t^{50\%} = \beta_0 + \beta_1 VaR_{t-1}^{50\%} + \beta_2 (r_{t-1})^+ + \beta_3 (r_{t-1})^- \tag{14}$$

where the initial value $VaR_0^{50\%}$ is given by the median of the whole sample period. $(r_{t-1})^+ = max(r_{t-1}, 0)$ and $(r_{t-1})^- = -min(r_{t-1}, 0)$. And the parameter estimation for Eq. (14) is based on quantile regression:

$$\hat{\beta}(50\%) = \underset{\beta}{argmin} \left\{ \sum_{\{t: r_t \geq VaR_t^{50\%}\}} 0.5 \mid r_t + VaR_t^{50\%} \mid + \sum_{\{t: r_t \leq VaR_t^{50\%}\}} 0.5 \mid r_t + VaR_t^{50\%} \mid \right\} \tag{15}$$

Finally, the $\Delta Co - ESGVaR$ is then calculated as:

$$\Delta Co - ESGVaR_{i,k}^{95\%} = \beta_{i,k}^{5\%} (VaR_{ESG,t}^{95\%} - VaR_{ESG,t}^{50\%}) \tag{16}$$

$$\Delta Co - ESGVaR_{i,k}^{5\%} = \beta_{i,k}^{5\%} (VaR_{ESG,t}^{5\%} - VaR_{ESG,t}^{50\%}) \tag{17}$$

for company i in window k. As can be seen from Eq.(16) and Eq.(17), under the quantile regression method, the sign of $\beta_{i,k}^{5\%}$ will determine the sign of $\Delta Co - ESGVaR$, that is, when a company has a positive ESG tail exposure ($\beta_{i,k}^{5\%} > 0$), the downside risk of the company will be decreased when the return of low-ESG companies is well above high-ESG companies ($VaR_{ESG,t}^{95\%}$), and the downside risk of the company will be increased when the return of low-ESG companies is well below high-ESG companies ($VaR_{ESG,t}^{5\%}$).

2.4 Correlation Analysis

To be able to interpret the calculated ESG exposure, we will look from three aspects using the correlation analysis. First, the correlation with ESG performance (represented by ESG score). Second, we will check the relationship between financial indicators (firm size, performance) and ESG exposure. Englich and Gedda (2020) studied the financial characteristics of high ESG companies, they found that higher profitability leads to higher ESG rating and larger firm size does not necessarily have higher ESG score. Finally, because we study the energy and utility sectors, we will check if the environmental practice such as emission and resource use have correlation with the observed ESG exposure.

We use the ESG data from 2013 to 2019 and omit the year 2020 for the sake of not having enough ESG data in 2020. Pearson correlation coefficient among panel data will be used. We will calculate average correlation coefficient for each sector among all companies in each year from 2013 to 2020 as below:

$$Corr_{s,t}^{ESG} = Average_t[Corr(\beta_{i,t}, ESG_{i,t})] \tag{18}$$

Where $t = 2013, 2014...2019$ and $i = 1, 2...n$. n is the number of company in sector s.

3 Data Description

3.1 The Index & Company Data

We are using the database of Thomson Eikon Datastram. The number of companies with available prices from 2009 to 2020 for energy and utility sector is 134, with 57 utility companies and 77 firms in the energy sector. The daily return for each company will be used in our analysis and is calculated in a logarithm manner as:

$$R_{i,t} = Ln(P_{i,t+1} - P_{i,t}) \tag{19}$$

for each company i and time t. The type of companies in the two sectors are shown below in Table 2. Oil & Gas companies take up the major part of companies in the energy sector. In the utility sector, many companies also produce powers.

Table 2: Company Types in Two Sectors

Sector	Company Type	No. of Companies
Utility	Electrical Utilities & IPPs*	30
	Multiline Utilities	10
	Water & Related Utilities	8
	Natural Gas Utilities	9
Energy	Oil & Gas	40
	Oil & Gas Related Equipment and Services	30
	Renewable Energy	6
	Coal	1
	Total	134

*IPP means independent power producer.

The ESG index to be used is Thomson Reuters US Large Cap ESG Index (TRESGUS). The TRESGUS is derived from selecting component companies in S-Network US Large Cap Index (SNUSL), the parent index. It identifies the 500 largest capitalization companies in the USA, representing 70–80 percent of US market capitalization. TRESGUS currently has 245 component companies. Similarly, for the calculation of Environmental, Social and Governance risk factors, we will use Thomson Reuters/S-Network US Large-Cap Environmental Best Practices Index (TRENVUS), Thomson Reuters US Large-Cap Social Best Practices Index (TRSCUS) and Thomson Reuters US Large-Cap Governance Best Practices Index (TRCGVUS). All four indices have the same parent index: SNUSL.

The selection process and criteria from the parent index to construct the ESG index are as below:

- Minimum Trading Volume: each stock must have certain daily trading volumes higher than their floating market capitalization;
- ESG Rating: In each sector, half of stocks with the highest applicable ratings as of the last trading day are selected for inclusion;
- Weighting: All stocks selected are weighted on a hybrid basis: 50 percent of the weight assigned to each stock is based on market capitalization, and 50 percent of the weight assigned to each stock within a sector is based on ESG rating;

We will use the index daily return from 2009.01.01-2020.12.31. The definition of utility and energy sector in our paper is from TRBC Sector Classification of Refinitiv[7] .

[7] https://www.refinitiv.com/en/financial-data/indices/trbc-business-classification

3.2 The ESG Score

We will use the ESG score as a representation of the ESG performance for each company. The ESG score is from Thomson Eikon Datastream, and is updated on a real-time basis. Appendix A summarizes some characteristics of those ESG scores. We have downloaded monthly ESG Score data form 2013.01.01 to 2020.12.31. However, the monthly data within each year seldom changes (often we would observe 12 monthly scores of the same value within a year). So, we have calculated the ESG score of compay i for each year using the average of monthly data: $ESG_{year,i} = Avg\{ESG_{month,i}\}, i = 1, 2...n$.

The range for ESG scores is from 0-100. A higher score means a better performance in such category. For computational convenience, each score will be divided by 100 to form a range from 0 - 1. We will conduct our analysis for each year from 2013 to 2020. So, the final ESG indicator used in our analysis will be:

$$ESG_i = ESG_{year,i}/100 \tag{20}$$

for each company i and i = 1,2..n.

A general review of the calculated ESG indicator for the the two sectors is as below in Table 3. Although we will only analyze the utility and energy sector, for better comparison, the first table in Table 3 is calculated using all sectors in the market. The ESG performance varies among companies (standard deviation is high relative to the average). In general, governance pillar score is the highest among E/S/G pillar scores. In terms of sub-indicators, community score is the highest, followed by management and shareholder score. Environmental pillar score is the lowest. Actually, the utility sector has the highest ESG score and governance score in the market (rank 1^{st} among 10 sectors) and energy sector rank 9^{th}. The "weight" column in Table 3 shows the weight of each ESG sub-score used to calculate the final ESG whole score. Each pillar score takes up around one-third of the total score. Sub-scores like human rights and innovation have high diversity of performance among companies as there is huge gap between average and the median value.

Table 3: Calculated ESG Indicators

Name	Average	Weight[8]	Median	Min.	Max	Std.
ESG Whole	0.4224	100%	0.3950	0.0203	0.9235	0.1893
Environmental Pillar	0.2731	**34%**	0.1746	0.0000	0.9768	0.2826
Resource Use	0.3085	11.0%	0.1758	0.0000	0.9973	0.3336
Emissions	0.2916	12.0%	0.1606	0.0000	0.9968	0.3218
Innovation	0.2013	11.0%	0.0160	0.0000	0.9948	0.2855
Social Pillar	0.4352	**35.5%**	0.3984	0.0155	0.9687	0.2091
Workforce	0.4233	16.0%	0.3834	0.0039	0.9974	0.2583
Human Rights	0.2254	4.5%	0.0131	0.0000	0.9878	0.3056
Community	0.6276	8.0%	0.6449	0.0164	0.9986	0.2264
Product Responsibility	0.4182	7.0%	0.3571	0.0000	0.9944	0.2634
Governance Pillar	0.5146	**30.5%**	0.5293	0.0071	0.9717	0.2136
Management	0.5645	19.0%	0.5868	0.0041	0.9995	0.2728
Shareholders	0.5340	7.0%	0.5461	0.0008	0.9991	0.2786
CSR Strategy	0.2351	4.5%	0.0246	0.0000	0.9937	0.3191

Sector	ESG Average	Envir. Average	Social Average	Gov. Average
Utility	0.4966	0.4510	0.4414	0.6482
Energy	0.3907	0.3122	0.3696	0.5326

Note: The upper table calculates the average of the whole market (including 10 sectors), the lower table shows the average pillar score among for utility and energy sectors.

The correlation between the pillar score (ie. E/S/G scores) and its corresponding sub-indicators is around 0.8. The correlation between environmental sub-factors (emission, resource use) and ESG scores the highest among other factors. One possible explanation could be that these two indicators, as is shown in Table 3, apart from having relatively high weight in the constitution, also have the highest change(standard deviation) among all indicators. The average correlation of the system is around 0.5, and some can be as low as 0.1.

3.3 ESG Risk Factors

As is shown below in Table 4, the correlation among ESG risk factors is quite high, and the reason, as mentioned above, is that the component of ESG indices are quite similar. The correlation between ESG factor and FF factors is low enough for us to avoid the multicollinearity issue in the regression.

[8] Extracted from Eikon Datastream as of 2020.12. Such weight is adjusted regularly

Table 4: Correlation among Factors

	ESG	E	S	G	HML	SMB	RM
ESG	1						
E	0.9112	1					
S	0.9303	0.8557	1				
G	0.8460	0.7877	0.8110	1			
HML	-0.6175	-0.5871	-0.5779	-0.4134	1		
SMB	-0.3968	-0.3847	-0.4434	-0.4249	0.2667	1	
RM	-0.2817	-0.2267	-0.3017	-0.2571	0.3087	0.3078	1

Table 5 shows the descriptive statistics of the constructed ESG risk factors as well as the ESG index. It is worth mentioning that the risk-return profile of ESG indices is worse than the parent index. The higher fluctuation for ESG index in our case can be explained by that the ESG index has it component tilting toward tech industry, which, during the last ten years, had the highest change among all sectors[9]. Our results of the ESG risk factor are also consistent with Naffa and Fain (2021), who constructed ESG risk factors using Fama/french cross-sectional model, and they found that the high ESG portfolios actually under-performed the low ESG portfolios. The cumulative results in Figure 1 is also consistent with empirical results by Hubel and Scholz (2019), who constructed ESG risk factors in European market using FF approach: their results also demonstrated a positive cumulative return of ESG risk factors.

Table 5: Return and Risk of Risk Factors

Index Return	Parent	ESG	E	S	G
Average	0.0471%	0.0443%	0.0446%	0.0444%	0.0465%
Std.	1.14%	1.19%	1.18%	1.20%	1.18%
Information Ratio($r_{benchmark}$ = 0%)	4.12%	3.71%	3.79%	3.69%	3.95%
Cumulative	147.43%	138.60%	139.66%	139.04%	145.43%

Factor Return	ESG	E	S	G	HML	SMB	RM
Average	0.0028%	0.0025%	0.0027%	0.0006%	-0.0183%	0.0029%	0.0623%
Std.	0.16%	0.13%	0.18%	0.12%	0.75%	0.59%	1.16%
Information Ratio	1.78%	1.86%	1.50%	0.52%	-2.45%	0.49%	5.35%
Cumulative	8.83%	7.76%	8.38%	2.00%	-57.23%	9.07%	147.43%

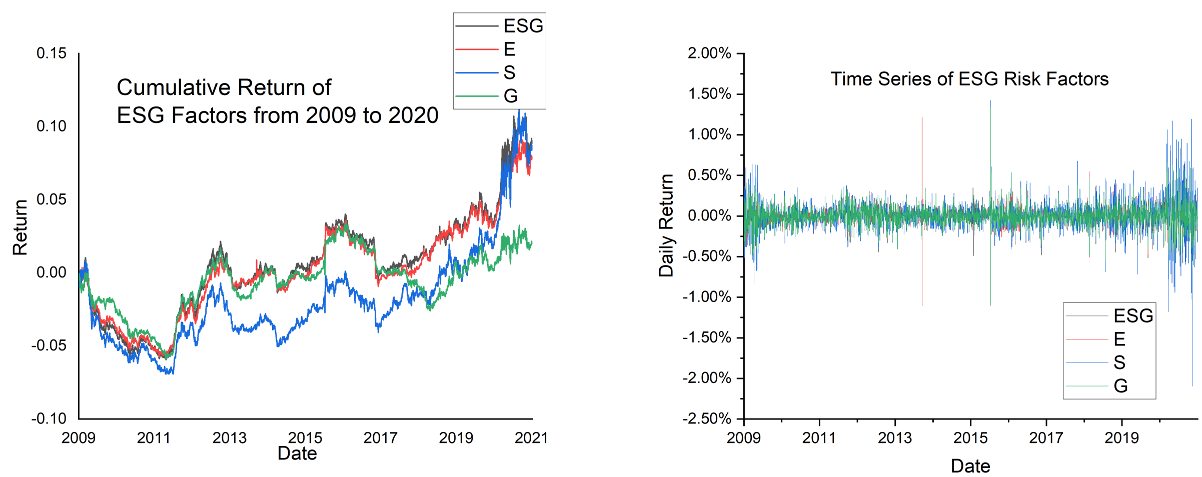
Note: The upper table shows the financial performance of ESG index and its parent index. The second shows the return of calculated ESG risk factors and FF risk factors. RM means the market risk factor in the FF library.

Figure 1 shows the performance of ESG risk factors. The cumulative return of governance risk factor is the lowest among all E/S/G risk factors, meaning that the G Index has the best performance ($R_{G,t}$ is higher, $GOV = (R_{Parent} - R_{G,t})$ is lower). One explanation could be that categories evaluated by G scores, such as corporate governance and board management, are di-

[9]https://eresearch.fidelity.com/eresearch/markets_sectors/sectors/si_performance.jhtml?tab=siperformance

rectly related to shareholder's interest instead of stakeholder's interest, and thus having higher G scores does not mean having less stakeholder conflicts. As a result, the G Index, which consists of companies with high G scores, have higher return than companies in other indices for having higher stakeholder risk premium. It should be noted that from 2009 to 2011 the ESG risk factor is negative for most of the time (Figure 1, left panel). This can be explained by the "slow pricing" effect proposed by Benabou and Tirole (2010), who says that environmental and social factors are gradually becoming recognized as relevant price factors for valuing a company; high-ESG firms experience high returns during this recognition period (in our case 2009 - 2011), but should experience lower ones once the repricing is complete (in recent years).

Figure 1: ESG Risk Factor Performance



Note: The first figure shows the cumulative return for ESG risk factors respectively, which is calculated as $\sum ESG_t$ from 2009 to 2020. The second figure plots the time series of ESG risk factors.

4 Results

4.1 ESG Exposure

4.1.1 Sector Comparison

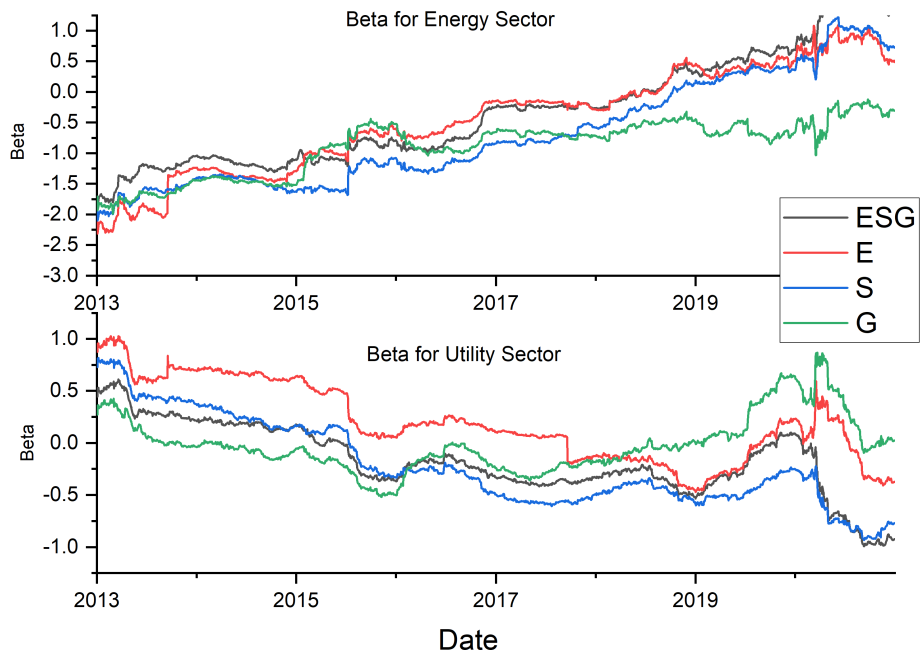
The average beta for each sector is shown below in Table 6. The R^2 of regression for all windows is around 0.4-0.5. Most estimated intercepts are not statistically significant. From 2009 to 2020, the ESG exposure of the utility sector has changed from positive to negative, meanwhile the ESG exposure of the energy sector has changed from negative to positive.

Table 6: The ESG Exposure

	β_i^{ESG}	2013	2014	2015	2016	2017	2018	2019	2020
ESG	Utility	0.3545	0.1763	-0.1261	-0.2172	-0.3690	-0.3417	-0.1743	-0.6538
	Energy	-1.3462	-1.1615	-0.9653	-0.7446	-0.2408	0.0565	0.5580	1.4221
E	Utility	0.7558	0.6605	0.3171	0.1781	0.0064	-0.2257	-0.1018	-0.0248
	Energy	-1.8077	-1.3547	-0.8534	-0.5367	-0.1862	0.0753	0.4095	0.7825
S	Utility	0.5305	0.2397	-0.0470	-0.3086	-0.5549	-0.4493	-0.4303	-0.6899
	Energy	-1.6822	-1.4604	-1.3864	-1.1401	-0.7412	-0.2182	0.3072	0.8576
G	Utility	0.1324	-0.0676	-0.2881	-0.1466	-0.2554	-0.0736	0.2914	0.3005
	Energy	-1.6949	-1.4638	-0.8008	-0.8707	-0.6856	-0.5477	-0.6543	-0.3779

Note: The table shows the average beta (β_i^{ESG}) for ESG/E/S/G risk factors(average of for every year).

Figure 2: ESG Exposure for Utility and Energy Sector



Note: The figure shows the beta average of all companies in the same sector for utility and energy sector, from window 1 to window 2068 (2013-2020).

Although we have observed a change of beta for both sectors from 2009 to 2020, the return contribution ($\beta_i^{ESG} ESG_t$) is constant over time. From 2009 to 2020, for utility sector, the return contribution in most times from ESG risk factor is negative ($\beta_i^{ESG} ESG_t < 0$) and for energy sector the return contribution in most times is positive ($\beta_i^{ESG} ESG_t > 0$) (as can be observed in Figure

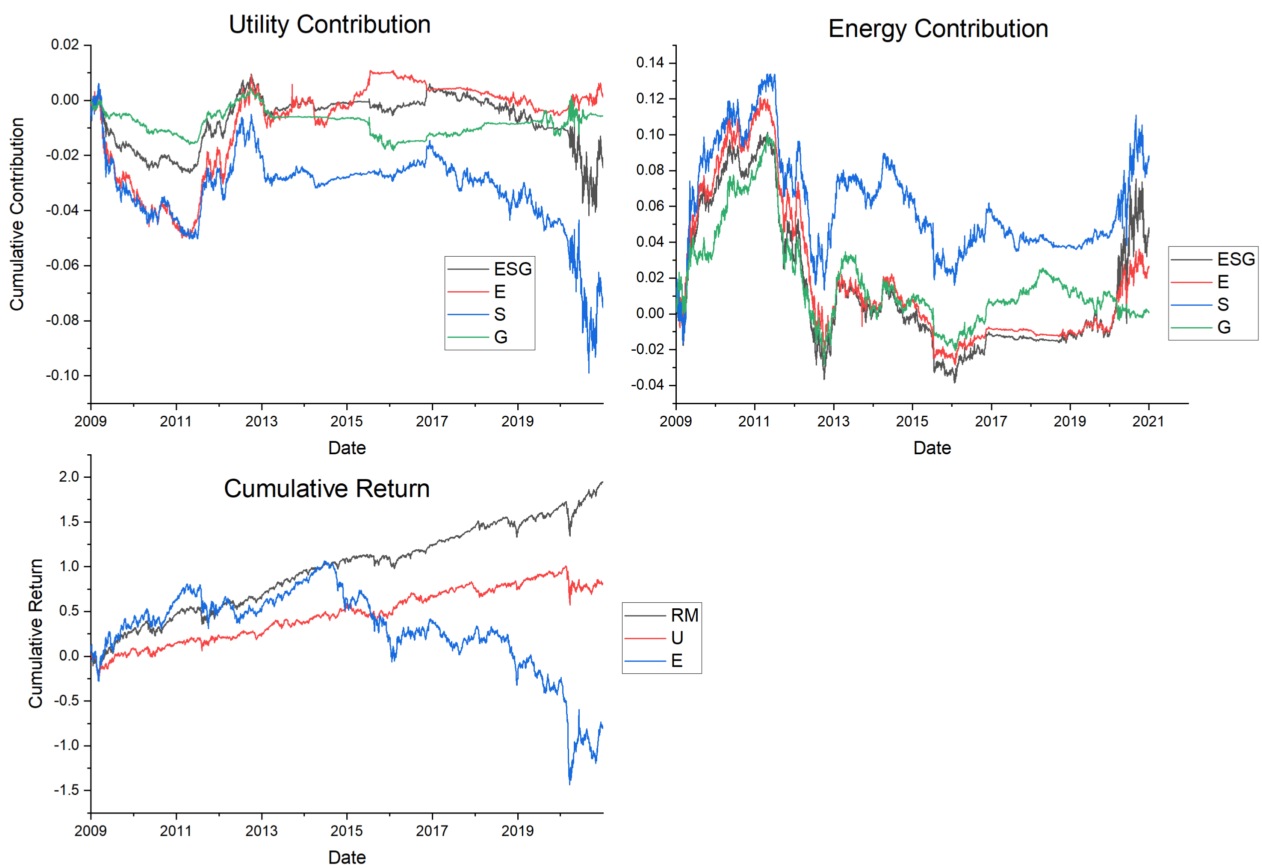
3).

The cumulative return contribution, calculated as the sum of ESG exposure multiplied by ESG risk factors ($\sum \beta_i^{ESG} ESG_t$), are shown below in Figure 3. We found that for the energy sector, the risk factors have positive cumulative return contribution up to 7% (Figure 3, upper right panel). For the utility sector, there are negative cumulative return contributions from ESG risk factors down to -8% from 2009 to 2020. However, the cumulative return performance from 2009 to 2020 for the utility sector (high-ESG) is +75% and for the energy sector (low-ESG) the number is -76%[10] (Figure 3, down left panel). In conclusion, we have observed that, without the return contribution from ESG risk factors, the cumulative return of the utility sector would have been higher and the cumulative return performance of the energy sector would have been lower.

The positive cumulative contribution of the ESG risk factor means the sector is having positive risk premium from the stakeholder risk. This results is in-line with our previous discussion that investors should ask for positive return compensation for low-ESG companies. The social risk factor has the highest cumulative contribution size for both utility and energy sectors, followed by ESG risk factor. The cumulative return contribution of governance and environmental factors is close to zero from 2009 to 2020.

[10] This is in line with many studies in the literature, who found that portfolios with high ESG scores perform better.

Figure 3: Cumulative Return and Cumulative Contribution



Note: The up-left panel and up-right panel shows the cumulative contribution for utility sector and energy sector respectively, which is calculated as $\sum \beta_i^{ESG} ESG_t$ from 2009 to 2020. The down-left panel shows the cumulative return of the market factor (R_M), the cumulative return of the average return of companies in the utility sector and energy sector.

4.1.2 Correlation with ESG Score

To find the relationship between ESG scores and ESG impact, we have conducted a correlation analysis between ESG exposure (β_i^{ESG}) and respective ESG scores. A brief summary of the correlation is listed in Table 7.

Table 7: Correlation between ESG Exposure and ESG Scores

Sector	**ESG**	**Envir.**	Resor.	Emis.	Innov.	**Social**	Workf.	Hum R.	Comm.	Prod. R	**Gov.**	Mgmt.	Share.	CSR
							ESG							
Utility	**-0.4252**	**-0.4200**	-0.3585	-0.4890	-0.1869	**-0.3966**	-0.4003	-0.2134	-0.3514	-0.2511	**-0.1589**	-0.0055	-0.1487	-0.5384
Energy	**-0.1647**	**-0.1232**	-0.1248	-0.0864	-0.0534	**-0.1937**	-0.1402	-0.1563	-0.1119	-0.2352	**-0.0779**	-0.0674	0.0060	-0.1020
							E							
Utility	**-0.3367**	**-0.3277**	-0.2533	-0.3821	-0.1726	**-0.3070**	-0.3013	-0.1813	-0.2442	-0.2005	**-0.1270**	0.0069	-0.1331	-0.4375
Energy	**-0.1353**	**-0.0847**	-0.0755	-0.0275	-0.0780	**-0.1826**	-0.0906	-0.1670	-0.0589	-0.2544	**-0.0449**	-0.0561	0.0471	-0.0346
							S							
Utility	**-0.3769**	**-0.3630**	-0.3112	-0.4435	-0.1355	**-0.3509**	-0.3387	-0.2178	-0.2962	-0.2460	**-0.1628**	-0.0260	-0.1256	-0.4945
Energy	**-0.0991**	**-0.0430**	-0.0859	-0.0067	0.0633	**-0.1170**	-0.1113	-0.0639	-0.1132	-0.1630	**-0.0981**	-0.1041	-0.0013	-0.0434
							G							
Utility	**-0.4203**	**-0.4036**	-0.3580	-0.4846	-0.1464	**-0.3963**	-0.3847	-0.2339	-0.3544	-0.2628	**-0.1768**	-0.0190	-0.1622	-0.5481
Energy	**-0.0804**	**-0.0385**	-0.0741	-0.0394	0.0868	**-0.0864**	-0.1109	-0.0457	-0.0707	-0.1079	**-0.0933**	-0.0800	-0.0554	-0.0592

Note: The table below demonstrated the average of yearly correlation from 2013 to 2019. We do not observe drastic change of yearly correlation, so we put in here the average level of correlation from 2013 to 2019.

All observed correlations are negative, i.e. for companies in utility and energy industry, the higher ESG score, the lower ESG exposure. This is in-line with our discussion in Section 2 as well as the findings by Becchetti et al. (2017). Among E/S/G pillar scores, G score has the lowest correlation. In comparison, environmental and social score has a higher correlation on ESG exposure. Among all those sub-indicators, emission and CSR strategy scores have the highest correlation size than others.

4.1.3 Correlation with Corporate Finance Indicators

We will examine financial indicators that represent two aspects of a company: firm size and profitability. For firm size, we will use total assets (TA) and market value (MV), and for profitability, we will use return on equity (ROE), return on assets (ROA), net income (NI) and earnings before interest, taxes, depreciation, and amortization (EBITDA). The financial indicators are taken from Eikon Datastream. The historical financial indicators for the two sectors are shown in Table 18. We have found that the financial performance is on average better in utility sector than in energy sector.

Insert Table 18 here

The estimated correlation between ESG exposure and the financial indicator is as below in Table 8. As for NI and EBITDA, we have observed a negative correlation for utility sector, while for energy sector we observe a correlation close to zero. For ROE and ROA, we have observed low positive correlation.

The negative correlation with TA and MV for the utility sector tells us that the larger the company size, the lower the beta. That is, the larger the firm size, the less the company stock return will be affected by stakeholder risk or even being negatively affected. However, for energy sector, we observe a correlation close to zero. Drempetic et al. (2019) studied the relationship between firm size and ESG score using Eikon ESG Database, and found a positive correlation between the two. They explained from the angle of organizational legitimacy, i.e. larger firms gets higher ESG scores through more publicity and having more resources of information for rating agencies to calibrate higher ESG scores. In our case, combining our findings in Section 4.1.2, the negative correlation between firm size and ESG exposure can be explained by the following logic: Larger Firm Size$\Rightarrow$Higher ESG Score$\Rightarrow$Lower ESG Exposure.

Table 8: Correlation between ESG Exposure and Financial Indicators

Sector	ROE	ROA	NI	EBITDA	TA	MV
			ESG			
Utility	0.1620	0.1133	-0.2036	-0.4313	**-0.5117**	**-0.4276**
Energy	0.0309	-0.0087	0.0661	-0.0041	**-0.0372**	**-0.0224**
			E			
Utility	0.2152	0.0547	-0.1171	-0.3565	**-0.4532**	**-0.3594**
Energy	0.0781	0.0285	0.1025	0.0411	**0.0032**	**0.0170**
			S			
Utility	0.1311	0.0636	-0.1869	-0.3932	**-0.4632**	**-0.3979**
Energy	0.0658	0.0234	0.1149	0.0419	**0.0153**	**0.0229**
			G			
Utility	0.1826	0.1441	-0.1538	-0.3844	**-0.4818**	**-0.3969**
Energy	0.0952	0.0465	0.1432	0.0921	**0.0645**	**0.0830**

Note: The table shows the correlation coefficient of estimated ESG exposure (β_i^{ESG}, β_i^E,β_i^S,β_i^G) and the corresponding financial indicators. The correlation is calculated using panel data each year, i.e. across all companies in the same sector, and then averaged from 2013 to 2019.

We further check the relationship between earning volatility, calculated as the standard deviation of EBIDA for past five years, and the ESG exposure as below in Table 9. For the utility sector, the higher the earning volatility the lower the ESG exposure. It seems that the energy sector has a far more higher earning volatility than the utility sector and in the meantime having lower ESG scores– this is in line with the finding by Giese et al. (2019a), who found that companies with higher ESG score (in our case the utility sector) have lower earning volatility.

Table 9: Correlation between ESG Exposure and Earning Volatility

	Earning Vol.($Million)		**Corr_ESG**		**Corr_E**		**Corr_S**		**Corr_G**	
	Utility	Energy	Utility	Energy	Utility	Energy	Utility	Energy	Utility	Energy
2017	351.85	1,464.56	-0.5171	-0.0938	-0.5266	-0.0792	-0.4682	-0.0835	-0.5328	-0.0330
2018	446.51	1,332.51	-0.3422	-0.0897	-0.3348	-0.0822	-0.2615	-0.1315	-0.4079	-0.0472
2019	481.24	1,168.03	-0.5872	-0.1358	-0.5085	-0.1097	-0.5549	-0.2045	-0.6253	0.0580

Note: The correlation here is calculated using panel data in each year.

4.1.4 Correlation with Emission and Resource Indicators

In this section, we are going to use three indicators to measure the emission to the environment and the use of the energy. The *CO2 Emission* measures the CO2 equivalents emission and it is the estimated total CO2 and CO2 equivalents emission in tonnes. The *Energy Use* is calculated as total direct and indirect energy consumption in gigajoules divided by revenue. The *Water Use* is the total water withdrawal in cubic meters divided by revenue.

The current emission and energy use level of the two sectors is shown below in Table 19. The utility sector produces more CO2 and waste than energy sector (we have calculated the CO2/EBITDA and the value is still larger for utility sector than for energy sector). However, energy use in energy sector is higher.

Insert Table 19 here

The correlation information is shown in Table 10. For energy sector, the correlation of CO2 emission changes from 0.3-0.4 in early years to -0.1 in 2020. The positive correlation of CO2 emission, water use and energy use indicates that: the more pollutant a company in the energy sector, the more stakeholder conflict they are facing, and thus they should take more stakeholder risk (higher beta). Hsu et al. (2018) studied the effects of environmental pollution on the cross-section of stock returns. They found that high emission firms are more exposed to the policy regime shift risk, and are therefore expected to earn a higher average return than low emission firms. Among all three indicators, water use has the highest correlation with the ESG exposure.

For utility sector, we have observed a negative correlation for all indicators between the level of pollution and the ESG exposure. One possible explanation could be that, as a highly regulated sector, having higher CO2 emission means more regulator's attention and will thus taking more measures to decrease stakeholder conflicts. As is shown in Table 17, the utility sector, despite having the highest CO2 emission, has the highest emission score among all sectors. As a result, companies with higher CO2 emission often have higher ESG scores.

Table 10: Correlation between ESG Exposure and Environmental Indicators

Sector	CO2 Emission	Energy Use	Water Use
	ESG		
Utility	-0.3391	**-0.0825**	**-0.2904**
Energy	0.0323	**0.0326**	**0.1632**
	E		
Utility	-0.3852	**-0.1261**	**-0.3043**
Energy	0.1216	**0.1360**	**0.1629**
	S		
Utility	-0.3665	**-0.1750**	**-0.2910**
Energy	0.1733	**0.0155**	**0.1534**
	G		
Utility	-0.4172	**-0.1143**	**-0.2794**
Energy	0.1906	**0.0252**	**0.0021**

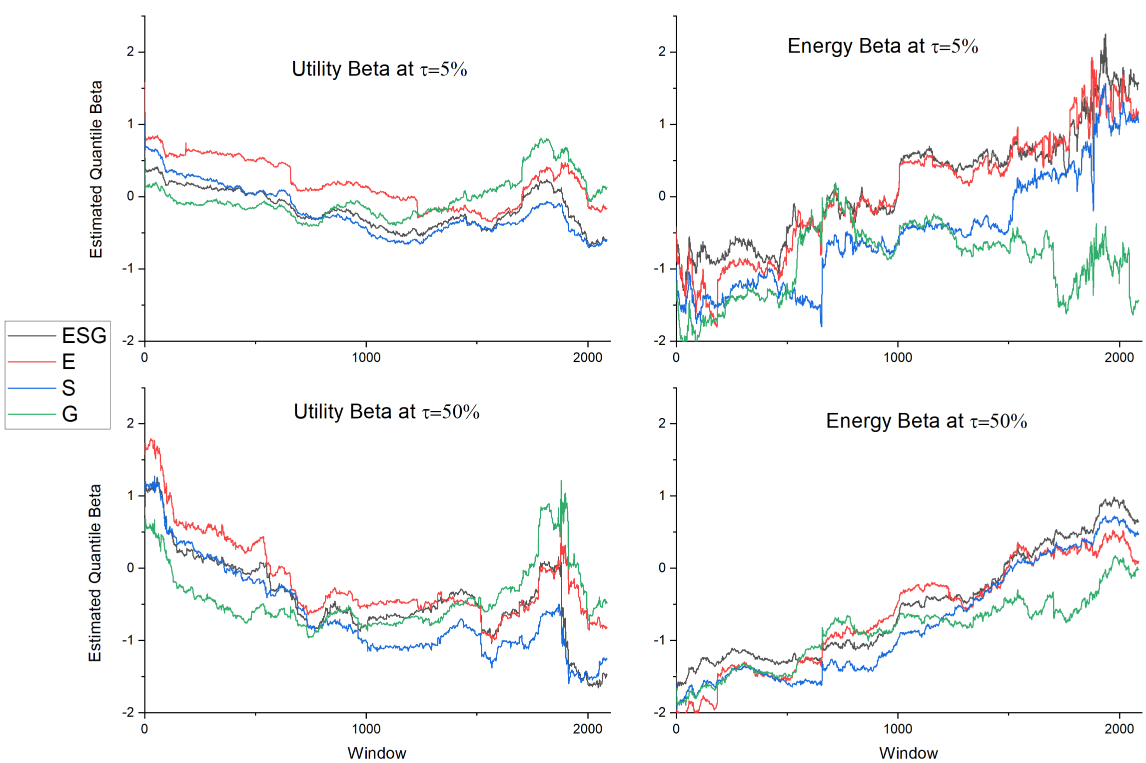
Note: The table shows the correlation coefficient of estimated ESG exposure (β_i^{ESG}, β_i^E,β_i^S,β_i^G) and the corresponding emission and energy use indicators. The correlation is calculated using panel data each year, i.e. across all companies in the same sector, and then averaged from 2013 to 2019.

4.2 ESG Tail Exposure and ESG Risk Exposure: $\beta_i^{ESG,\tau}$ & $\Delta Co-ESGVaR$

4.2.1 Sector Comparison

The estimated $\beta_i^{ESG,\tau}$ is shown in Table 11. $\beta_i^{ESG,5\%}$ measures the ESG exposure of the downside risk of each company to ESG risk factors (ESG tail exposure). From Figure 4, we have observed the same pattern of ESG tail exposure as the ESG exposure in the previous section. However, from Table 11, we found that, for utility sector, the ESG exposure has become more negative by changing from 50% to 5% ($\beta_i^{ESG,5\%} < \beta_i^{ESG,50\%}$) in more recent periods. For energy sector, the ESG exposure of ESG/E/S risk factors has become less negative(more positive) by changing from 50% to 5% ($\beta_i^{ESG,5\%} > \beta_i^{ESG,50\%}$).

Figure 4: ESG Tail Exposure -$\beta_i^{ESG,\tau}$



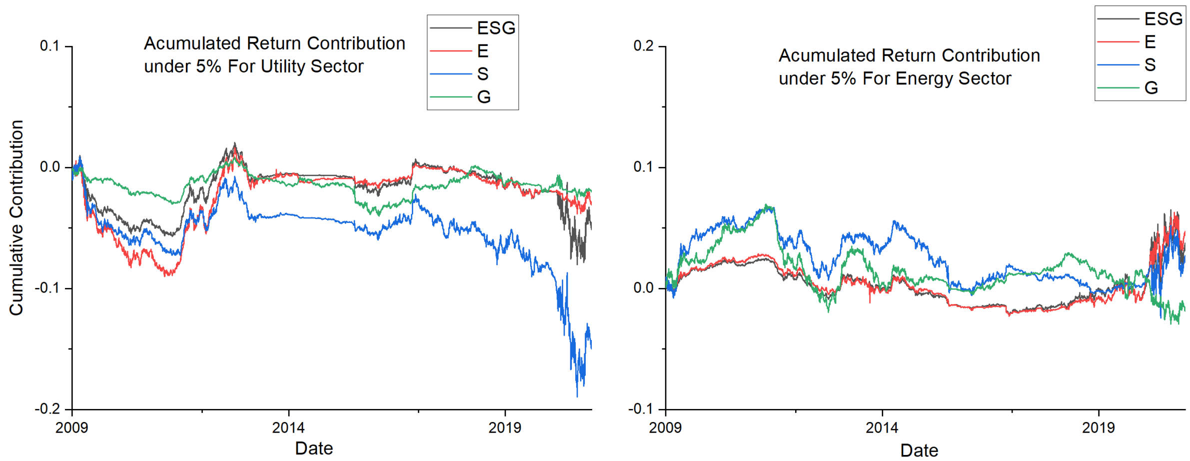
Note: The below figure shows the estimated $\beta_i^{ESG,\tau}$ for both sectors from window 1 to window 2068. The upper panel show $\beta_i^{ESG,5\%}$ for both sectors. The lower panel show $\beta_i^{ESG,50\%}$.

Table 11: ESG Tail Exposure-$\beta_i^{ESG,\tau}$

	β_i^{ESG}	τ	2013	2014	2015	2016	2017	2018	2019	2020
ESG	Utility	50%	0.2325	0.0873	-0.1554	-0.2641	-0.4813	-0.3648	-0.0699	-0.3429
		5%	0.5535	0.0350	-0.4341	-0.6703	-0.6338	-0.5083	-0.4493	-1.1329
	Energy	50%	-1.3486	-1.2380	-1.1619	-0.8966	-0.4405	-0.1209	0.3762	0.7568
		5%	-0.8591	-0.7218	-0.2626	-0.0304	0.5055	0.5478	0.6768	1.5278
E	Utility	50%	0.6634	0.5675	0.2895	0.1515	-0.0704	-0.2161	0.0300	0.1243
		5%	0.9858	0.4028	-0.2231	-0.4298	-0.4787	-0.5567	-0.5006	-0.3773
	Energy	50%	-1.7712	-1.4517	-1.1247	-0.7016	-0.3149	-0.1583	0.2156	0.3209
		5%	-1.2063	-0.9403	-0.2789	-0.0291	0.4144	0.4551	0.8186	1.3257
S	Utility	50%	0.4110	0.1353	-0.0894	-0.3573	-0.5998	-0.4042	-0.2740	-0.4670
		5%	0.6088	-0.0178	-0.4634	-0.8772	-1.0867	-0.9440	-0.9588	-1.2423
	Energy	50%	-1.6302	-1.4694	-1.4650	-1.2173	-0.7387	-0.2188	0.2210	0.5498
		5%	-1.4383	-1.1987	-1.0836	-0.6544	-0.4378	-0.3021	0.2950	0.9908
G	Utility	50%	-0.0013	-0.1098	-0.2473	-0.1677	-0.2808	-0.0426	0.4159	0.3238
		5%	0.0169	-0.5737	-0.7067	-0.6942	-0.7335	-0.5431	0.0176	0.0024
	Energy	50%	-1.6641	-1.4311	-0.9867	-0.8322	-0.7131	-0.5742	-0.5851	-0.1282
		5%	-1.7134	-1.3670	-0.3432	-0.5951	-0.4413	-0.6651	-1.0317	-0.9693

The cumulative risk contribution at $\tau = 5\%$ ($\sum \beta_i^{ESG,5\%} ESG_t$) is shown below in Figure 5. For utility sector, the social risk factor has the highest cumulative risk contribution to the downside risk of a company, the same observation as we have in Figure 3. However, the magnitude of contribution is much higher to downside risk (-18%) than to stock return (-8%). The governance risk factors have cumulative effect close to zero for both sectors.

Figure 5: Cumulative Risk Contribution



Note: The figure the cumulative risk contribution to the downside risk, which is calculated as $\sum \beta_i^{ESG,5\%} ESG_t$ from 2009 to 2020.

The calculated $\Delta Co - ESGVaR$ for the two sectors is shown below in Table 12 and Figure 6. By changing from $VaR_{ESG,t}^{50\%}$ to $VaR_{ESG,t}^{95\%}$ ($\Delta Co - ESGVaR^{95\%}$), we have observed a negative contribution of all ESG risk factors to the downside risk of companies in the utility sector. This can be explained by that, mathematically, because $\beta_i^{ESG,5\%}$ for utility sector is negative, so $\beta_i^{ESG,5\%}(VaR_{ESG,t}^{95\%} - VaR_{ESG,t}^{50\%})$ is negative. Economically speaking, that means the downside risk of utility sector is increased by the ESG risk factor when ESG risk factor changes to $VaR_{ESG,t}^{95\%}$.

Table 12: ESG Exposure for Downside Risk-$\Delta Co - ESGVaR$

$\Delta Co - ESGVaR^{95\%}$	Indicator	ESG	E	S	G
Utility	Avg.*	-0.1239%	-0.0375%	-0.1962%	-0.0905%
	Std,	0.1768%	0.1487%	0.1961%	0.0985%
Energy	Avg	0.0593%	0.0202%	-0.1529%	-0.2022%
	Std.	0.2415%	0.2145%	0.2409%	0.1126%

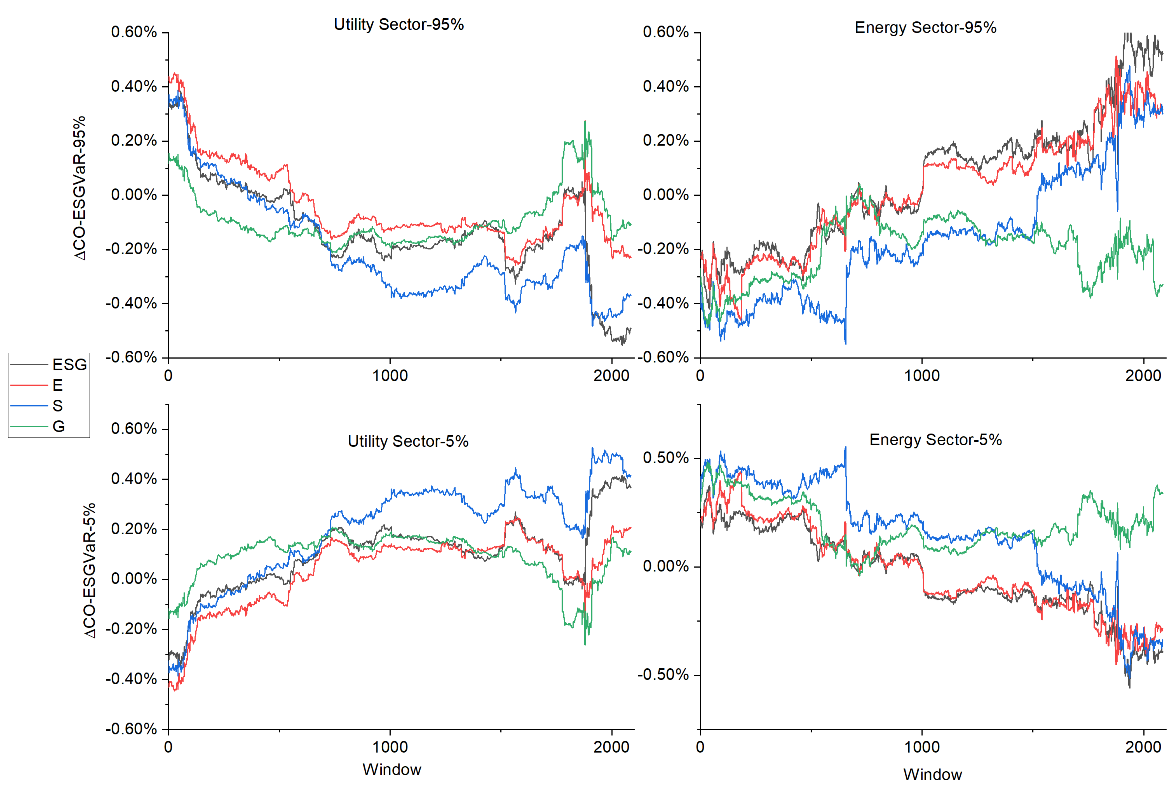
$\Delta Co - ESGVaR^{5\%}$	Indicator	ESG	E	S	G
Utility	Avg.	0.0999%	0.0384%	0.2013%	0.0886%
	Std,	0.1442%	0.1448%	0.2014%	0.0955%
Energy	Avg	-0.0395%	-0.0170%	0.1452%	0.1980%
	Std.	0.1974%	0.2018%	0.2468%	0.1134%

Note: For each window, we have calculated $\Delta Co - ESGVaR$ for each sector. Then we have calculated the average and standard deviation among window 1 to window 2086.

By changing from $VaR_{ESG,t}^{50\%}$ to $VaR_{ESG,t}^{5\%}$ ($\Delta Co - ESGVaR^{5\%}$), we have observed the opposite results to that of $\Delta Co - ESGVaR^{95\%}$. We have observed a positive contribution of all ESG risk factors to the downside risk of companies in the utility sector. That is, the downside risk of utility sector is increase by the ESG risk factor when ESG risk factor changes to $VaR^{5\%}_{ESG,t}$.

Similarly, for energy sector, the downside risk is decreased when ESG risk factors change to $VaR^{95\%}_{ESG,t}$. However, the G risk factor will increase downside risk of companies in the energy sector. The S risk factor, though having a negative average contribution , has positive contribution in recent years as is shown in Figure 6 upper-right panel.

Figure 6: $\Delta Co - ESGVaR$ for the Two Sectors



Note: The upper panel shows the 95% $\Delta Co - ESGVaR$ from window 1 to window 2086, calculated as the average of all companies in each sector. The lower panel shows 5% $\Delta Co - ESGVaR$ from window 1 to window 2086. As is discussed above in Table 1, positive $\Delta Co - ESGVaR$ means the ESG risk factor will decrease the downside risk.

4.2.2 Correlation with ESG Scores

The calculated correlation with ESG tail exposure under $\tau = 5\%, 50\%$ (correlation with $\beta_i^{ESG,\tau}$) is shown below in Table 20. The first observation is that under extreme return situation, the correlation is still negative for all sectors. In addition, under $\tau = 5\%$, ESG pillar scores still have the highest correlation with the ESG exposure than ESG sub-indicators. The governance score still has the minimum correlation among those ESG pillar scores.

Insert Table 20 Here

We do not observe drastic change in the correlation when changing to extreme return situation. However, the correlation size with ESG pillar scores has decreased for most ESG exposures when changing from $\tau = 50\%$ to $\tau = 5\%$.

4.2.3 Correlation with Financial Indicators

The calculated correlation with financial indicators is shown in Table 13. For utility sector, the correlation has decreased when changing from $\tau = 50\%$ to $\tau = 5\%$. The firm size indicator still has negative correlation with the ESG exposure.

In terms of the energy sector, the correlation is close to zero for almost all indicators.

Table 13: Correlation with Financial Indicators under QR

Sector	τ	ROE	ROA	NI	EBITDA	TA	MV
				ESG			
Utility	50%	0.1041	0.0964	-0.2055	-0.3811	**-0.4304**	**-0.3641**
	5%	0.1789	0.1071	-0.0912	-0.2423	**-0.2836**	**-0.2274**
Energy	50%	0.0096	0.0620	0.0748	-0.0070	**-0.0481**	**-0.0320**
	5%	-0.0459	-0.0648	0.0028	-0.0449	**-0.0694**	**-0.0740**
				E			
Utility	50%	0.1000	-0.0047	-0.1502	-0.3197	**-0.3679**	**-0.3086**
	5%	0.1621	0.0942	-0.1276	-0.2646	**-0.2947**	**-0.2578**
Energy	50%	0.0193	0.0753	0.1002	0.0308	**-0.0118**	**0.0040**
	5%	-0.0220	-0.0398	0.0307	-0.0047	**-0.0306**	**-0.0374**
				S			
Utility	50%	0.1082	0.0485	-0.1592	-0.3072	**-0.3459**	**-0.3009**
	5%	0.1391	0.0374	-0.1461	-0.2730	**-0.2732**	**-0.2416**
Energy	50%	-0.0006	0.0414	0.1140	0.0345	**0.0010**	**0.0097**
	5%	-0.0185	-0.0132	0.0585	0.0076	**-0.0172**	**-0.0193**
				G			
Utility	50%	0.1910	0.1532	-0.1318	-0.3324	**-0.4057**	**-0.3363**
	5%	0.1571	0.0965	-0.1201	-0.2936	**-0.3571**	**-0.2925**
Energy	50%	0.0480	0.0857	0.1426	0.0815	**0.0539**	**0.0671**
	5%	0.0023	0.0217	0.0659	0.0229	**-0.0020**	**0.0134**

4.2.4 Correlation with Emission and Resource Indicators

The calculated correlation is shown below in Table 14. For CO2 emission, we have seen a decreased correlation for both sectors, meaning the the emission level becomes less important in determining the ESG tail exposure under extreme return situation. Under $\tau = 5\%$, the correlation with CO2 emission is still negative for utility sector and positive for energy sector. For energy use and water use, we have observed the correlation changing from negative to positive for ESG and E risk factors in extreme situation. That is, when considering the downside risk, the more pollutant a company, the higher the ESG tail exposure for ESG/E risk factors.

Table 14: Correlation with Emission and Resource under τ = 5%&50%

Sector	τ	CO2 Emission	Energy Use	Water Use
		ESG		
Utility	50%	-0.3493	**-0.1469**	**-0.3038**
	5%	-0.2176	**-0.0573**	**-0.0473**
Energy	50%	0.0730	**-0.0646**	**0.0811**
	5%	0.0066	**0.0960**	**0.1427**
		E		
Utility	50%	-0.3211	**-0.2823**	**-0.2723**
	5%	-0.1758	**-0.0862**	**-0.0779**
Energy	50%	0.1013	**0.0248**	**0.0757**
	5%	0.0478	**0.1555**	**0.1371**
		S		
Utility	50%	-0.2850	**-0.2622**	**-0.2466**
	5%	-0.1812	**-0.1958**	**-0.1633**
Energy	50%	0.1560	**0.0382**	**0.0378**
	5%	0.0862	**0.0719**	**0.0780**
		G		
Utility	50%	-0.3341	**-0.2197**	**-0.2772**
	5%	-0.2738	**-0.1325**	**-0.0719**
Energy	50%	0.1817	**-0.0754**	**-0.0769**
	5%	0.0780	**0.1597**	**-0.0554**

5 Conclusion

This paper tries to quantify the ESG impact using factor model and then analyze it through correlation analysis. By constructing ESG risk factors, we found that while in short-term there will be negative cumulative return of those ESG risk factors (the slow pricing effect), in the long run, the cumulative return for all ESG risk factors are positive from 2009 to 2020. In other words, in the long run, low ESG score portfolios outperformed high ESG score portfolios.

Through linear regression, we found that, from 2009 to 2020, the ESG exposure of utility sector is changing from positive to negative and energy sector from negative to positive. But the cumulative return contribution for utility sector is always negative and the return contribution for energy sector is always positive during our sample period. We explain this by that high-ESG companies should have less exposure to ESG risk factors and thus less or even negative return contributions from ESG risk factors. The social risk factor have the highest level of accumulated return contribution in both sectors and contributed negatively to both sectors. By calculating the ESG tail exposure through quantile regression at τ = 5% and 50%, we find the ESG tail exposure has become more negative by changing from 50% to 5%. For energy sector, the ESG tail exposure has become less negative (more positive) by changing from 50% to 5%.

Under the quantile regression method, the ESG risk exposure ($\Delta Co - ESGVaR^{\tau}$) is calculated as $\beta_{i,k}^{5\%}(VaR_{ESG,t}^{\tau\%} - VaR_{ESG,t}^{50\%})$, thus the sign of the ESG tail exposure ($\beta_{i}^{ESG,5\%}$) determines the sign of the ESG risk exposure. We find that the utility sector has negative ESG tail exposure, so when low-ESG companies returns are well above high-ESG companies ($VaR_{ESG}^{95\%}$) in the market, the downside risk (daily VaR) of the utility sector (high-ESG) is increased by ESG and E factors by around 0.5%. Conversely, the ESG tail exposure is positive for the energy sector (low-ESG), and thus the downside risk (daily VaR) is decreased by ESG and E risk factors by around 0.5%. Therefore, an investor having a long position in high-ESG score companies will increase his/her tail risk from ESG risk factors when the market is favoring low-ESG companies. By calculating $\Delta Co - ESGVaR^{5\%}$, we have observed opposite results to $\Delta Co - ESGVaR^{95\%}$, but with a slightly smaller magnitude.

Table 15 summarizes what we have found in our correlation analysis (the correlation between ESG exposures and those indicators). "-" means we have observed negative correlation lower than -0.1, and "+" means we have observed positive correlation higher than 0.1, "close to 0" means the size of correlation is less than 0.1. The size of correlation is around 0.1-0.5 for most of the indicators. By switching from $\tau = 50\%$ to $\tau = 5\%$, we have seen a decrease of correlation size for most indicators. However, we do not observe drastic changes in the correlation.

Table 15: Summary of ESG Exposure(β_i^{ESG}) Correlation

Normal	RF	ESG Pillar Scores	ESG Sub-indicators	Performance	Firm Size	Earnings Vol.	Resource Use	Emission
Utility	ESG	-	-	-	-	-	-	-
	E	-	-	-	-	-	-	-
	S	-	-	-	-	-	-	-
	G	-	-	-	-	-	-	-
Energy	ESG	-	Close to 0	Close to 0	Close to 0	Close to 0	+	+
	E	-	Close to 0	Close to 0	Close to 0	Close to 0	+	+
	S	Close to 0	Close to 0	Close to 0	Close to 0	Close to 0	+	+
	G	Close to 0	Close to 0	Close to 0	Close to 0	Close to 0	+	+

τ = 5%	RF	ESG Pillar Scores	ESG Sub-indicators	Performance	Firm Size	Resource Use	Emission
Utility	ESG	-	-	-	-	-	-
	E	-	-	-	-	-	-
	S	-	-	-	-	-	-
	G	-	-	-	-	-	-
Energy	ESG	-	-	Close to 0	Close to 0	+	Close to 0
	E	-	Close to 0	Close to 0	Close to 0	+	Close to 0
	S	-	Close to 0	Close to 0	Close to 0	Close to 0	Close to 0
	G	-	Close to 0	Close to 0	Close to 0	Close to 0	Close to 0

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A ESG Index Description

Name	**Discription**
ESG Whole	Weighted average of the three pillar scores(weights around 30% each).
Environmental Pillar	Weighted average relative rating of environmental information and the resulting three environmental category scores.

Resource Use	Reflects performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management.
Emissions	Measures a company's commitment and effectiveness towards reducing environmental emission in the production and operational processes.
Innovation	Reflects a company's capacity to reduce the environmental costs and burdens for its customers, and thereby creating new market opportunities through new environmental technologies and processes or eco-designed products.
Social Pillar	Weighted average relative rating of a company based on the reported social information and the resulting four social category scores.
Workforce	Measures effectiveness towards job satisfaction, healthy and safe workplace, maintaining diversity and equal opportunities, and development opportunities for its workforce.
Human Rights	Measures a company's effectiveness towards respecting the fundamental human rights conventions.
Community	Measures commitment towards being a good citizen, protecting public health and respecting business ethics.
Product Reliability	Reflects capacity to produce quality goods and services integrating the customer's health and safety, integrity and data privacy.
Governance Pillar	Weighted average relative rating of a company based on the reported governance information and the resulting three governance category scores.
Management	Measures commitment and effectiveness towards following best practice corporate governance principles.
Shareholders	Measures effectiveness towards equal treatment of shareholders and the use of anti-takeover devices.
CSR Strategy	Reflects practices to communicate that it integrates the economic (financial), social and environmental dimensions into its day-to-day decision-making processes.

Table 17: ESG Score for Sectors

Sector	**ESG**	**Envir.**	Resor.	Emis.	Innov.	**Social**	Workr.	Hum R.	Comu.	Prod.	**Gov.**	Mgmt.	Sharh.	CSR
Utility	0.4966	0.4510	0.4439	0.5373	0.3589	0.4414	0.4204	0.1814	0.6938	0.4531	0.6482	0.6792	0.6406	0.4859
Telco	0.3043	0.1696	0.2074	0.1644	0.1321	0.2953	0.2793	0.2200	0.5266	0.2502	0.4257	0.4562	0.5053	0.1709
Tech	0.4442	0.3066	0.3694	0.3294	0.2560	0.4765	0.4669	0.3325	0.6130	0.4346	0.5008	0.5411	0.5437	0.2427
Industrial	0.4140	0.3005	0.3159	0.2941	0.2704	0.4161	0.3955	0.2596	0.6145	0.4118	0.5184	0.5698	0.5340	0.2288
Health	0.4181	0.2120	0.2665	0.2375	0.0709	0.4658	0.4951	0.2120	0.6143	0.4545	0.4852	0.5232	0.5588	0.1783
Financi	0.3982	0.1702	0.1975	0.2131	0.1249	0.4203	0.3992	0.0716	0.6213	0.3972	0.4953	0.5572	0.5148	0.1590
Energy	0.3907	0.3122	0.3405	0.3887	0.1410	0.3696	0.4473	0.1707	0.6186	0.3472	0.5326	0.5699	0.5652	0.3052
Con. NC	0.4698	0.3402	0.3972	0.3331	0.2425	0.4774	0.4308	0.3484	0.6597	0.4601	0.5497	0.6028	0.5372	0.3043
Con. Cy	0.4185	0.2945	0.3319	0.2754	0.2238	0.4332	0.4075	0.2856	0.6516	0.3971	0.4943	0.5538	0.4839	0.2071
BM	0.4374	0.3753	0.4043	0.3746	0.2962	0.4207	0.3958	0.3223	0.6257	0.4492	0.5617	0.6031	0.5403	0.3822

Rank	**ESG**	**Envir.**	Resr.	Emis.	Innov.	**Social**	Workr.	Hum Rig.	Comu.	Prod. Reli	**Gov.**	Mgmt.	Shareh.	CSR
Utility	1	1	1	1	1	4	5	8	1	3	1	1	1	1
Telco	10	10	9	10	8	10	10	6	10	10	10	10	9	9
Tech	3	5	4	5	4	2	2	2	9	5	6	8	4	5
Industrial	7	6	7	6	3	8	9	5	7	6	5	5	7	6
Health	6	8	8	8	10	3	1	7	8	2	9	9	3	8
Financial	8	9	10	9	9	7	7	10	5	7	7	6	8	10
Energy	9	4	5	2	7	9	3	9	6	9	4	4	2	3
Con. NC	2	3	3	4	5	1	4	1	2	1	3	3	6	4
Con. Cy	5	7	6	7	6	5	6	4	3	8	8	7	10	7
BM	4	2	2	3	2	6	8	3	4	4	2	2	5	2

B Statistics about the Firms

Table 18: Firm Size and Profitability Indicators for Utility and Energy Sector

Utility	ROE	ROA	NI($Million)	EBITDA($Million)	TA($Million)	MV($Million)
2013	9.1%	3.3%	462.52	1,687.73	20,239.12	8,867.53
2014	10.2%	3.4%	545.35	1,882.08	21,764.11	10,046.01
2015	5.6%	3.5%	369.82	1,774.70	22,349.32	10,233.28
2016	6.3%	3.4%	377.68	1,748.52	24,289.99	11,562.64
2017	4.1%	3.6%	563.22	1,995.91	25,131.37	12,851.87
2018	9.6%	3.9%	551.47	1,865.43	26,718.63	13,043.99
2019	44.8%	4.0%	678.39	2,040.96	29,206.97	15,682.40
Energy	ROE	ROA	NI($Million)	EBITDA($Million)	TA($Million)	MV($Million)
2013	8.4%	6.8%	1,389.75	3,160.86	19,775.59	19,439.82
2014	-83.1%	7.4%	1,298.90	3,053.71	20,699.89	21,445.30
2015	-22.2%	2.7%	-404.33	743.26	19,210.86	16,819.76
2016	-17.0%	0.0%	-452.85	837.52	18,759.70	16,237.15
2017	-7.1%	2.9%	358.27	1,537.17	19,191.12	16,736.30
2018	-3.4%	5.1%	875.61	2,477.13	19,531.91	17,709.94
2019	-5.5%	4.7%	157.90	1,847.40	20,318.22	15,218.22

Table 19: Energy Use and Emission for Utility and Energy Sector

	CO2 Emission(ton)		Energy Use(gigajoule/USD)		Water Use(cubic meter/USD)	
Sector	Utility	Energy	Utility	Energy	Utility	Energy
2013	26,902,844.15	8,757,783.25	1,178.62	2,801.94	362,531.24	1,397.92
2014	26,125,838.72	8,598,942.72	999.53	3,018.79	357,533.83	1,757.66
2015	18,513,294.18	6,597,471.04	1,102.17	4,614.09	317,843.76	3,968.23
2016	16,071,988.98	5,118,367.85	1,102.82	5,815.40	308,526.26	3,778.57
2017	15,140,261.02	4,983,725.45	1,217.95	14,398.96	288,749.76	3,751.77
2018	15,283,306.00	5,229,457.02	1,227.83	13,415.23	235,991.65	5,403.84
2019	14,653,778.15	5,136,869.77	1,112.52	15,324.68	216,713.23	6,169.75

C Correlation with ESG Scores under QR

Table 20: Correlation with ESG Scores under QR

Sector	τ	**ESG**	**Envir.**	Resor.	Emis.	Innov.	**Social**	Workf.	Hum R.	Comm.	Prod. R	**Gov.**	Mgmt.	Share.	CSR
							ESG								
Utility	50%	**-0.3482**	**-0.3448**	-0.2978	-0.4338	-0.1169	**-0.3360**	-0.3341	-0.1486	-0.3183	-0.2689	**-0.1244**	0.0080	-0.1189	-0.4781
	5%	**-0.1747**	**-0.1949**	-0.1913	-0.1973	-0.0880	**-0.1270**	-0.1348	-0.1332	-0.1515	0.0351	**-0.0473**	0.0267	-0.0554	-0.2521
Energy	50%	**-0.1665**	**-0.1168**	-0.1418	-0.0750	-0.0378	**-0.1900**	-0.1552	-0.1545	-0.1296	-0.2305	**-0.1052**	-0.0911	-0.0047	-0.1382
	5%	**-0.1422**	**-0.1445**	-0.1306	-0.0931	-0.1096	**-0.2117**	-0.1363	-0.1542	-0.0910	-0.2186	**0.0564**	0.0580	0.0638	-0.0295
							E								
Utility	50%	**-0.2969**	**-0.2844**	-0.2370	-0.3501	-0.1073	**-0.3022**	-0.2770	-0.1378	-0.2665	-0.2706	**-0.0986**	0.0181	-0.0852	-0.4318
	5%	**-0.1962**	**-0.1967**	-0.1770	-0.1954	-0.1105	**-0.1652**	-0.1628	-0.1588	-0.1605	-0.0089	**-0.0716**	-0.0071	-0.0392	-0.2283
Energy	50%	**-0.1511**	**-0.0995**	-0.1069	-0.0366	-0.0783	**-0.1785**	-0.1332	-0.1488	-0.0565	-0.2775	**-0.0815**	-0.0849	0.0215	-0.0737
	5%	**-0.0979**	**-0.1095**	-0.1061	-0.0419	-0.1022	**-0.1768**	-0.0676	-0.1610	-0.0702	-0.1783	**0.1038**	0.0854	0.1179	0.0284
							S								
Utility	50%	**-0.2740**	**-0.2691**	-0.2253	-0.3551	-0.0794	**-0.2509**	-0.2350	-0.1404	-0.2293	-0.2256	**-0.1249**	-0.0229	-0.0742	-0.3995
	5%	**-0.2045**	**-0.2186**	-0.2022	-0.2365	-0.0996	**-0.1452**	-0.1648	-0.1587	-0.1157	0.0114	**-0.1034**	-0.0327	-0.0533	-0.2485
Energy	50%	**-0.1207**	**-0.0800**	-0.1182	-0.0329	0.0086	**-0.1299**	-0.1153	-0.1037	-0.1107	-0.1760	**-0.1003**	-0.1150	0.0529	-0.0814
	5%	**-0.1071**	**-0.0934**	-0.0950	-0.0523	-0.0132	**-0.1704**	-0.1486	-0.0777	-0.0986	-0.2159	**0.0315**	0.0174	0.0628	0.0145
							G								
Utility	50%	**-0.3397**	**-0.3384**	-0.3078	-0.4294	-0.0929	**-0.3290**	-0.3059	-0.1798	-0.3015	-0.2741	**-0.1063**	0.0216	-0.0687	-0.4792
	5%	**-0.2152**	**-0.2186**	-0.2016	-0.2390	-0.0840	**-0.1593**	-0.1793	-0.1487	-0.1448	0.0068	**-0.1018**	0.0072	-0.1666	-0.3028
Energy	50%	**-0.0592**	**-0.0074**	-0.0775	0.0087	0.0943	**-0.0584**	-0.1061	-0.0253	-0.0556	-0.0940	**-0.1108**	-0.1052	-0.0311	-0.0911
	5%	**-0.0866**	**-0.0949**	-0.0779	-0.0952	0.0047	**-0.1359**	-0.1049	-0.0820	-0.0786	-0.1481	**0.0439**	0.0554	-0.0002	0.0007