Risk Analysis of ESG (Environment, Social, and Governance), Healthcare and Financial Sectors

Sajid M. Chaudhry
Department of Economics, Finance & Entrepreneurship, Aston Business School,
University of Aston, Birmingham, UK
Email: s.m.chaudhry@outlook.com

Xihui Haviour Chen
Edinburgh Business School, The Centre for Social and Economic Data Analytics (CSEDA),
Heriot-Watt University, Edinburgh, UK
Email: Xihui.chen@hw.ac.uk

Rizwan Ahmed
Kent Business School, University of Kent, UK
Email: r.ahmed@kent.ac.uk

Muhammad Ali Nasir

Department of Economics, University of Leeds, UK
Department of Land Economy, University of Cambridge, UK
Email: M.A.Nasir@leeds.ac.uk

Abstract

Climate change poses enormous ecological, socio-economic, health, and financial challenges. A novel extreme value theory is employed in this study to model the risk to ESG, healthcare, and financial sectors, and assess their downside risk, extreme systemic risk, and spillover risk. We use a rich set of global daily data from 1st July 1999 to 30th June 2022 in the case of healthcare and financial ETFs and from 1st July 2007 to 30th June 2022 in the case of ESG ETFs. We find that the financial sector is the riskiest when we consider the tail index, tail quantile, and tail expected shortfall. However, the ESG sector exhibits the highest tail risk in the extreme environment when we consider a shock in the form of ETF drop of 25% or 50%. We also find that the ESG sector poses the highest extreme systemic risk when a shock comes from the Chinese financial market. Finally, we find that ESG and healthcare sectors have lower extreme spillover risk (contagion risk) compared to the financial sector. Our study provides great insights into making sustainable economic, business, and financial strategies as it includes a detailed risk assessment of ESG, healthcare and financial sectors, as well as a new approach to risk analysis.

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1. Introduction

Ecological challenges pose existential risks to human civilisation and to address these risks many countries have embarked on the road to carbon neutrality or net zero (Gil and Bernardo, 2020; Shubbar et. al, 2021 and Too et. al 2022). As the progress to achieve net zero remains slow, the Intergovernmental Panel on Climate Change (IPCC) in the final draft of the synthesis report to the sixth assessment report reiterates the importance of an increase in the pace of taking effective actions in the following words: "With climate change fast bearing down on humanity, the Synthesis Report will underscore the urgency of taking more ambitious action,"[1]. Climate change induces a number of risks (e.g., death and illness from extreme weather events, and mental health issues), yet most of the attention has been only focused on financial risks (see Kron et al. 2019; Mirza, 2003; Moore, 2015; Fankhauser and McDermott 2014). However, for a sustainable and feasible strategy, we also need to understand the risks posed by the environment, socio-economic, corporate governance and health underpinning climate change. In this paper, we fill this gap in the literature and provide a comprehensive risk assessment and analysis from ecological, socio-economic, governance, health and financial perspectives. To this aim, drawing on extreme value theory, we analyse and model ecological risks to ESG (Environment, Social and Governance), financial, and healthcare ETFs (Exchange Traded Funds) employing rich data from each category.

There is a strong motivation and nexus between ESG (environmental, social, and governance) risks, the healthcare industry, and the financial sector. For instance, the healthcare industry is sensitive to ESG risks associated with environmental factors such as air and water pollution, which can result in health problems for individuals and communities. Furthermore, social factors such as income inequality, lack of access to healthcare, and discrimination can have an effect on the healthcare industry. For example, a community with limited access to health care may experience higher rates of preventable diseases or poor health outcomes.

[1]https://www.ipcc.ch/2022/11/25/ipcc-circulates-final-draft-ar6-synthesis-report/#:~:text=The%20IPCC%20is%20currently%20working,be%20released%20in%20March%202023.

These ESG risks can also have an impact on the financial sector, as they can have an effect on the profitability and long-term viability of healthcare companies. Companies in the healthcare industry that do not prioritise ESG factors may encounter reputational risks, regulatory risks, and financial risks, which can have an impact on their ability to attract and retain investors. Similar to this, financial institutions that engage in healthcare organisations could run into ESG risks. For instance, a financial company may run the risk of damaging its image by investing in a healthcare company that has a poor track record when it comes to social or environmental issues. Financial risks associated with regulatory changes or market shifts may also apply to financial companies that invest in healthcare organisations.

Overall, ESG risks can have an influence on both the financial and healthcare sectors, so businesses in these industries need to be conscious of them and take action to address them in order to prevent any negative effects on their operations and financial performance.

The overarching research on the subject focuses on the environmental costs and social imbalances caused by economic activity as a result of climate change and growing societal concerns. Financial markets have an important role to play in reducing social and environmental injustices and environmental externalities because ecological risks can have different levels of relevance to ETFs depending on the specific investments within each of these categories. Investors interested in managing ecological risks in their investment portfolio may consider examining the underlying holdings of the ETFs they are considering and evaluating the environmental impact of those holdings (Asefi-Najafabady et al., 2021). Additionally, investors can look for ETFs that prioritize sustainability and environmental responsibility, such as those that track socially responsible or ESG indexes. ESG ETFs, which invest in companies that meet certain environmental, social, and governance criteria, are often designed to minimize ecological risks (Steffen et al., 2018). These ETFs may avoid companies that have a negative impact on the environment or focus on companies that have strong sustainability practices. For example, ESG ETFs that invest in companies with environmentally responsible practices and policies may offer opportunities for investors to promote sustainability and benefit from the growing demand for sustainable products and services. These ETFs may also invest in companies that are leaders in areas such as renewable energy, waste reduction, and sustainable agriculture (Asefi-Najafabady et al., 2021; Hansen et al., 2017). Therefore, ecological risks are typically taken into account in the investment selection process of ESG ETFs.

The financial industry estimates that the effects of climate change put US$693 billion at risk, and the majority of those risks are expected to materialise by 2024 (Carbon Disclosure Project, 2019). According to Dietz et al. (2016), the projected "climate Value-at-Risk" for global financial assets under their business-as-usual scenario is US$2.5 trillion. Financial ETFs may have limited relevance to ecological risks, as they are typically focused on investments in the financial industry, such as banks and insurance companies. However, ecological risks may be relevant in some cases where financial institutions are exposed to environmental risks or invest in companies that are involved in environmentally harmful activities (Ilhan et al., 2020a, Moore, 2015). Battiston et al. (2017) also stress the link between financial portfolio exposure and climate policy. For example, a financial ETF that invests in the oil and gas industry may be exposed to ecological risks associated with the exploration, production, and transportation of fossil fuels, such as oil spills, air pollution, and greenhouse gas emissions (Hansen et al., 2017; Ripple et al., 2020). Similarly, an ETF that invests in mining companies may be exposed to risks associated with the extraction of minerals, including water pollution and habitat destruction.

Healthcare ETFs, on the other hand, may indirectly involve themselves in environmentally damaging activities, such as in cases where healthcare companies use hazardous chemicals in their manufacturing processes or contribute to pollution through their operations (Ripple et al., 2020). Thus, healthcare companies are subject to several constraints and shifting regulations which pose significant risks to their performance. Healthcare funds are actively managed mutual funds that make equity investments in companies engaged in the production of medical equipment, pharmaceuticals, hospital management, and biotech research (Kaushik et al., 2014 and Chen et al., 2018). These healthcare ETFs are far more specialised in their investment strategies than their mutual fund equivalents because they typically follow the performance of an index made up of the healthcare sector that also manifests healthcare risks.

In terms of contribution to the risk analysis literature, this is the first study to provide comprehensive risk analysis and risk assessment of ESG, healthcare and financial sectors. Our approach to modelling risks is based on a novel extreme value theory (EVT). More specifically, our study contributes to the literature in several ways: First, we determine the tail risk of extreme incidents (e.g., the financial crisis and the COVID-19 pandemic crisis) as they can cause high volatility in ESG, healthcare, and financial ETFs.[2] We select the top 10 ESG, healthcare and financial ETFs with the highest net asset value (NAV) and are the most liquid. These ETFs are widely used as risk hedges in portfolios, as demonstrated in our study. Earlier studies only focus on stock, bond or foreign exchange markets (Hartmann et al., 2004; Straetmans and Chaudhry, 2015). Second, we estimate the extreme quantiles for p-values of 0.2% or 0.1%. This means that the tail-VaRs are estimated to be triggered every 500 days or 1,000 days, respectively. This is the hallmark of extreme value theory and has never been applied to the evaluation of the risk associated with ESG and healthcare ETFs. Third, we use multivariate EVT to calculate the extreme systemic risk (tail-β). We consider 10 different ETF investment markets as conditioning factors. These 10 conditioning factors are the whole world, Europe, Eurozone, China, S&P 500, US total market, US tech, traditional energy, green energy and even bond ETFs. There is no other paper that has used these comprehensive conditional factors in calculating extreme systemic risk except one study by Straetmans and Chaudhry (2015) which use bank index, stock market index, bond and real estate market index for the US and Europe. We use green energy, traditional energy, high-tech, and bond ETFs as conditioning factors as their impact on ESG, healthcare and financial ETFs could potentially be different. Finally, we measure the extent to which a shock in expected joint crashes and multi-variant spills over risk within the ESG, healthcare and financial ETFs.

Our risk modelling and analysis reveal the following findings: first, the financial sector is the riskiest when we consider the tail index, tail quantile, and tail expected shortfall. However, the ESG sector exhibits the highest tail risk in the extreme environment when we consider a shock in the form of an ETF drop of 25% or 50%. The global financial crisis of 2007-2008 and the COVID-19 crisis are examples of such shocks in financial markets. Second, for extreme systemic risk (tail-β), we find that the ESG ETFs are most exposed to all 10 shocks while the shock that originates from China presents the highest risk. The healthcare and financial ETFs exhibit similar risks for all shocks for traditional energy and green energy. This shows that both the healthcare and financial ETFs are sensitive to a shock from the energy sectors and particularly from the green energy sectors. Finally, we find that ESG and healthcare ETFs have lower extreme spillover risk (contagion risk) compared to financial ETFs. We use the number of expected joint crashes and the probability of a crash in the ETFs given there is a crash in one of the other ETFs for extreme spillover risk. Our risk analyses provide valuable insights for making sustainable economic, health, business, and financial strategies as they offer detailed

[2] In this study we use ESG, healthcare and financial ETFs as proxies for ESG, healthcare and financial sectors.

risk modelling and assessment of the risks associated with where ESG, healthcare and financial sectors.

The remainder of the paper is organized as follows. Section 2 provides relevant literature reviews on ESG, financial, and healthcare risk management, as well as extreme value theory. Section 3 presents data and methodology. Section 4 reports empirical findings and discussions. Section 5 provides the main conclusion and policy implications.

2. Literature Review

2.1 Risk to Environmental Activities

Recognizing the dynamics of environmental activities as they are perceived by businesses is crucial because it enables management to better construct the company's environmental risk management strategy (Kirkland and Thompson 1999). Numerous environmental activities are documented in existing studies, though the risks to them are rarely analysed. For instance, few studies demonstrate the integration of corporate social responsibility into environmental activities (Hainmueller and Hiscox, 2015), compliance with environmental regulations (Barber et al., 2019; Cumperayot et al., 2000), effective cost-cutting measures (Albarrak et al., 2019), gaining a distinct competitive advantage over rivals (Lábaj et al., 2018), improving brand image, forming connections with indigenous groups, increasing the effectiveness of insurance policies (Liu, 2013), providing access to loans, and ethical motivations (Popesko et al., 2015). However, some of these environmental activities are more influenced by corporate enterprises than others, and it is feasible that the same environmental actions and associated risks will have similar relevance in various circumstances. Furthermore, there are numerous studies (e.g., Bui et al., 2019; Czerwińska and Kaźmierkiewicz, 2015; Gil and Bernardo, 2020; Renn et al., 2022) in the literature that focus on environmental activities and risks corporate firms face that are based on environmental regulation. On the other hand, corporate firms hardly ever mention ethical considerations and upholding international agreements when it comes to environmental risks.

Moreover, two major issues the world is currently confronting are climate change and ecological degradation. The average surface temperature of the planet could increase by more than 1.5°C above pre-industrial levels in the coming decades, the Intergovernmental Panel on Climate Change (IPCC) has warned, having an irreversible effect on ecosystems, societies, and economies.

Many governments, businesses, and organisations have made the commitment to achieve net-zero emissions of greenhouse gases by 2050 or sooner in order to address this issue. In order to achieve net zero, greenhouse gas emissions and removals from the environment must be equal. This calls for drastic cuts in emissions, especially those resulting from the burning of fossil fuels, as well as the use of technologies to collect and store carbon dioxide from the atmosphere.

In order to mitigate the effects of climate change and safeguard ecosystems and species, net-zero emissions must be achieved. However, on its own, it is insufficient. To treat the underlying causes of the issue, additional steps are required. These include safeguarding and restoring ecosystems, lowering consumption and waste, and switching to more sustainable food and energy systems. Overall, urgent action is needed at all levels, from people to governments and international organizations, to address the problems caused by ecological degradation and climate change. A key component of this action is achieving net-zero emissions, but it must be accompanied by wider initiatives to advance sustainability and resilience.

2.2 Debate on ESG Benefits and Risks

Recent literature (Asefi-Najafabady et al., 2021; Chen et al., 2022; Galletta and Mazzù, 2023; Steffen et al., 2018) on ecological risks has highlighted the significance of the ongoing ESG debate, which has gained considerable attention from researchers and is having a significant impact on businesses and investors. Investors are increasingly interested in firm-level ESG disclosures and their quality to make informed investment decisions regarding environmental risks (e.g., Ilhan et al. 2021). To address the gap between supply and demand for ESG information, many countries have proposed mandatory ESG disclosure legislation to govern corporations in an effort to provide adequate information on ESG concerns alongside conventional financial disclosures or in separate focused reports (such as sustainability reports or environmental impact reports). The goal of such legislation is to improve the source of ESG information and reduce environmental risks. For example, large publicly listed firms in the UK, EU, and New Zealand are mandated to report on their ESG performance, which is a significant development in the field of ecological risk management. However, assessing the effectiveness of these policies in improving the environment and reducing ecological risks is challenging. For example, several countries (e.g., China) issued legislation with lenient standards and principles, allowing businesses to comply with straightforward disclosure obligations (Chen et al., 2022; Leuz et al., 2003; Burgstahler, Hail, and Leuz 2006; Christensen, et al., 2019). This raises questions about the potential risks associated with mandatory ESG disclosure, which is a critical issue in the ecological risk literature. Additionally, some businesses voluntarily share ESG data event before the implementation of rules, suggesting that further disclosure obligations may not significantly impact their business operations. Hence, it is essential to strike the balance between the benefits and risks associated with ESG disclosure to make informed decisions regarding ecological risk management.

The existing literature on ecological risks has demonstrated that major carbon disclosures could reduce the cost of equity by holding firms accountable for their poor carbon performance. Many researchers (e.g., Albarrak et al., 2019; Bui et al., 2019) have documented the impacts of carbon disclosure on risk management. Czerwinska and Kazmierkiewicz (2015) find that lower risks to stock returns were a result of more transparency in the disclosure of ESG data. He (2011) asserts that there is a correlation between the effectiveness of capital allocation in organisational facing failure risks and the transparency with which governance issues are disclosed. Leuz et al., (2009) find that corporations with lax governance norms and inadequate disclosure of non-financial (ESG) information may face the risks of attracting fewer investments from overseas owners. Furthermore, Serafeim and Grewal (2017) suggest using ESG data to predict a company's financial performance. On the other hand, some evidence suggests that increased ESG disclosure by businesses may risk large disclosure costs, as highlighted by Mattoo et al. (2009, Aggarwal and Dow (2011), and Hainmueller and Hiscox (2015). These studies find that some companies attempt to embrace less onerous climate change laws standards to lower the risks associated with ESG disclosure.

Currently, world is presently facing a climate emergency, which is the rapid deterioration of the Earth's climate due to human activities such as the burning of fossil fuels and deforestation. Rising temperatures, sea level rise, more frequent and severe natural disasters, a loss of biodiversity, and dangers to human health and well-being are just a few of the devastating effects that have come from this.

Ecological breakdown issues, which relate to the ongoing loss of species and ecosystems as a result of human activity, are also widely acknowledged. This involves, among other things, habitat destruction, pollution, overfishing, and deforestation. For human societies, the loss of biodiversity and ecosystems has serious repercussions, including effects on food security, water accessibility, and cultural legacy.

Therefore, Governments, corporations, and people all over the world will need to take immediate action to reduce greenhouse gas emissions, switch to renewable energy sources, safeguard and restore ecosystems, and move towards more sustainable and equitable economic systems in order to address these issues.

2.3 Healthcare and Risk Management

Investments in healthcare have historically been seen as costly but necessary to prevent significant social losses and risks to public health. Over the past 40 years, all stakeholders and the general public have been increasingly interested in the financial performance of the healthcare sector (Cleverly, 1978; Popesko et al., 2015; IBM, 2022; Barber, 2019; Jeurissen, 2010; Batrancea and Nichita 2015; Romaniuk et al., 2020). Regardless of the company's size or the area in which it operates, a healthcare company's economic viability and risks associated with it are vital in this context. However, factors such as the ageing population, the rapid advancement in new diagnosis and treatment technologies, and the rising number of chronically ill patients have significantly increased costs and pose risks to the healthcare sector, particularly in the United States of America and many European nations. These factors and risks have also contributed to the development of medical tourism. On the opposite end of the scale, Asian healthcare institutions have adopted low-cost tactics that have enabled them to improve their performance levels over their European and North American counterparts (Health Management, 2022).

Assuming that rural healthcare providers face greater risks and lower returns, Siedlecki et al. (2016) conduct an evaluation and comparison of rural and urban hospitals in Poland. They use various metrics including hospital indebtedness rate, labour costs, net income margin, operational margin ratio, and return on assets to analyse the risks to healthcare. Their empirical findings show that despite being smaller, rural hospitals have significantly lower financial risks and are financially healthier in terms of liquidity and performance. A similar study by Guimares and Nossa (2010) focuses on how much the capital structure influences healthcare profitability and financial risks and finds that businesses with the following working capital structures achieved greater levels of performance and lower risks. Creixans-Tenas and Arimany-Serrat (2018) examine the financial and non-financial performance levels of Spanish healthcare firms based on liquidity, indebtedness, firm size, legal structure, national income level, population density, and measures of corporate social responsibility. Their results show that with the exception of firms' size and legal structure, all factors significantly affect healthcare sector performance. Their results imply that these factors could have implications for the risks faced by healthcare. In a later study, Lim and Rokhim's (2021) analysis of Indonesia shows that the Lerner index, liquidity, sustainable growth ratio, and total sales have a substantial impact on the health sector company's performance. Most recently, King (2022) concludes that performance levels during COVID-19 were mostly impacted by the global health crisis after taking into account data from prominent hospital chains in the USA. On the other hand, due to narrower profit margins, smaller healthcare facilities experience severe risks during the health crisis.

2.4 Related literature on Extreme Value Theory and Risk Analysis

Several studies ranging from social science to engineering have made extensive use of extreme value theory (EVT) (see Giesecke and Goldberg, 2005; Liu, 2013). It has also been used to analyse financial market risks in relation to the global financial crisis. The tails of financial data series have been studied by McNeil and Frey (2000), Danielsson and De Vries (2000), Neftci (2000), Hartmann et al. (2004), Gilli and Kellezi (2006), Straetmans et al. (2008) and Onour (2010). Extreme value theory is one of the best methods, according to Zhao (2020), for analysing the financial markets' tail risks. For example, employing stock and government bond data from G-5 industrial nations, Hartmann et al. (2004) extreme-value analysis suggests that during market turbulence, there are modest but not insignificant cross-asset market links. Extreme losses often occur far less frequently in government bond indices than in stock indices.

Straetmans et al. (2008) use multivariate extreme value estimators to evaluate sectoral returns and sectoral system risk in the US financial market. Measurements fall into two categories: those that quantify sectoral vulnerability to extreme systematic risk or shocks (known as tail-s) and those that measure the extreme spillovers among economic sectors (sectoral co-exceedance probabilities). The tail index alone cannot provide a reliable indication of sectoral tail risk due to its cross-sectional uniformity. Also, tail behaviour is affected by structural modifications. Furthermore, for both the pre-9/11 and post-9/11 periods, the right tail indicates a greater upward potential than a negative risk. When 9/11 is used as the sample midpoint, the bivariate results imply that tail-s frequently rise statistically and economically. In another remarkable study, Allen et al. (2013) examine extreme market risk for various stock and volatility indices by applying univariate extreme value theory. The results show that the univariate EVT can be used to model extreme market conditions, but that implies volatility indices are not fully incorporated into the model.

Among the other noteworthy example of using EVT in risk modelling, Straetmans and Chaudhry (2015) use statistical extreme value analysis to evaluate the possibility of financial distress for certain institutions as well as exposure for specific banks. They discover that systemic risk and tail risk are both lower in the Eurozone than in the US. Their finding is consistent with an earlier study by Hartmann et al. (2006) using multivariate extreme value theory to analyse the systemic and contagion risks for US and European banks. It is argued that the risk in the Eurozone is slowly rising because of European integration. Furthermore, the biggest financial institutions in the US appear to have the sharpest rises in excessive systemic risk. Gkillas and Katsiampa (2018) also use EVT to analyse risk in the crypto market and to study the tail risk behaviour. The results show that Bitcoin Cash is the most volatile asset due to its potential for both positive and negative returns, as well as its high Expected Shortfall (ES). On the other hand, the Value-at-Risk (VaR) and Expected Shock (ES) outcomes of the extreme returns of Litecoin in the left tail and Bitcoin in the right tail are the lowest among the cryptocurrencies considered, indicating that they are the least risky cryptocurrencies. In further examples, the extreme value theory is also used by Osterrieder and Lorenz (2017) and Osterrieder et al. (2017) to analyse risk in the crypto markets.

In light of the studies that we discussed in this section, it is prima facie evident that extreme value theory (EVT) has been widely applied in financial markets to model and evaluate spillover risk, systemic risk, and tail risk. Despite its advantages, extreme value theory has not been applied to the analysis of spillover risk, systemic risk, and tail risk in ESG, healthcare and financial investing. Concomitantly, in this study, we draw on the EVT to model and analyse the risks in these sectors.

3. Data and Methodology

Data from our sample includes ETFs investing in ESG, healthcare, and financial stocks. We compare all three groups of ETFs using systemic risk and tail risk evaluations. Based on the data available on the Bloomberg database, we obtain healthcare and financial ETFs' daily equity returns from 1st July 1999 to 30th June 2022. Additionally, we obtain ESG ETF's daily returns from 1st July 2007 to 30th June 2022. Our selection criteria are the top ten ESG, healthcare, and financial ETFs by net asset value (NAV) and we use all the data that are available. These three groups are limited to the top ten ETFs because their sizes diminish after the top ten. Among our selected ETFs, some focus on global markets, but most are based in the US. For tail-β or extreme systemic risk estimation, we also use the Bloomberg database to calculate ESG, healthcare, and financial ETFs across certain worldwide markets (e.g., China, EU zone, UK, and US), and certain ETF categories (e.g., green energy, traditional energy, high-tech, and bonds). We calculate tail risk using a 6-year rolling data source for healthcare and financial ETFs, and a 6-year rolling data source for ESG ETFs.

3.1 Measurement of tail risk

Because extreme incidents (e.g., the financial crisis and the COVID-19 pandemic crisis) can cause high volatility in ESG, healthcare, and financial ETFs, the univariate extreme value theory (EVT) is used to assess equity tail risk. A univariate EVT is derived from Generalized Extreme Value (GEV) distributions and consideration of limit laws for maxima of stationary methods. Peaks-Over-Threshold (POT) is used to measure GEV distribution parameters. Using Chaudhry et al. (2022) as a guide, we matched the distribution of excess losses over a high threshold using the semi-parametric method to achieve the Generalised Pareto Distribution (GPD).

As in Equation (1), we examine the quantile χ for extremely low values of $P = p\{X > \chi\}$ using the semi-parametric estimator developed by De Hanan et al. (1994):

$$\hat{x}_p = X_{n-m,n} \left(\frac{m}{np}\right)^{1/a} \tag{1}$$

where a sample size is n, $X_{n-m,n}$ is the tail cut-off point for $(n-m)^{th}$ ascending order statistics.

We used the Hill (1975) estimator to derive α in equation (1), which becomes Equation (2):

$$\hat{a} = \left(\frac{1}{m}\sum_{j=0}^{m-1} ln\left(\frac{X_{n-j,n}}{X_{n-m,n}}\right)\right)^{-1} \tag{2}$$

where m representing the number of extreme returns is evaluated in the estimation. In our study, we adopt $m = 300$ as our main investigation for ESG, healthcare and financial ETFs (see Table 1). As a measure of m values, we adopt Hill's (1975) estimator.

By substituting Hill's (1975) estimator in Equation (2) and the tail quantile estimator in Equation (1), the expected shortfall estimator is obtained in Equation (3):

$$\hat{E}\left(X - \widehat{x_p} | X > \widehat{x_p}\right) = \frac{\widehat{x_p}}{\widehat{a-1}} \tag{3}$$

The tail quantiles are calculated for probability values from 0.1% to 0.2% (see Table 1), which means that the tail quantiles are expected to be violated every 500 and 1,000 days, respectively. Moreover, we examine the expected shortfall (ES) estimated based on the $p(\%)$ tail-VaRs and crisis barriers $x = 25\%$ and $x = 50\%$ Lastly, expected shortfall measurements are reported with varying thresholds x which is used to determine the extreme expected shortfall measurements when the extreme quantile estimates $\left(\widehat{x_p}\right)$ are lower than x. Statistically, the underlying framework entails calculating extreme values using the median of the probability deviations, which are investigated in a time-dependent sequence.

3.2 Measurement of systemic risk

The systemic risk measurements are estimated using semi-parametric estimation procedures to avoid misspecification of parametric probability distributions. It is because systemic risk estimates are likely to be heavily distorted by incorrect distribution assumptions.

The following Equation (4) is used to derive multivariate spillover risk:

$$\hat{P}_{N|1} = \frac{\hat{P}_q}{p} = \frac{m}{n}\left(C_{n-m,n}\right)^a q^{1-a} \tag{4}$$

From the cross-sectional minimum series, $C_{n-m,n}$ represents the cut-off point for tail cut-off ascending order statistic. The nuisance parameter is m. According to Hill (1975), n represents the total number of observations, and m represents the number of extreme returns used in estimation. When $\alpha > 1$, the original return vector shows tail independence, the systemic risk estimator decreases with threshold q and eventually reaches zero if $q \rightarrow \infty$. Nevertheless, when $\alpha = 1$ as we assumed throughout our analyses, changes in q no longer affect systemic risk.

Equation (5) is used as another systemic risk measure.

$$\hat{E}[\theta|\theta \geq 1] \approx \frac{N}{\frac{n}{kn}\frac{1}{}\sum_{i=1}^{N} U_{i=1}^{N} X_i > X_{i,n-k}} \quad (5)$$

As shown in Equation (5), an estimator of the stable tail dependence function $l(.)$ is used as the denominator (Straetmans and Chaudhry, 2015). Quantile $Q_i\left(\frac{k}{n}\right)$ is estimated by the upper-order statistic $X_{i,n-k}$. The indicator function is $l\{.\}$ and the nuisance parameter is k. For the Hill (1975) estimator, k refers to the number of extremes in the calculation of risk measures.

The theoretical framework of systemic risk given in Equations (4) and (5) is measured by tail- β. The estimate captures the exposure to large adverse movements in aggregate shocks in ESG, healthcare, and financial ETFs. Generally, aggregate shocks represent a macroeconomic (non-diversifiable) shock and are used to identify extreme systematic risk (or tail-β) associated with different candidate-risk factors.

4. Empirical findings and discussions

4.1 The downside risk estimates of ESG, healthcare, and financial ETFs

The results presented in Table 1 show estimates of the tail index $\hat{\alpha}$ and corresponding values of tail-VaR, tail quantiles, and the tail expected shortfall for the top 10 ESG (Panel I), healthcare (Panel II), and financial ETFs (Panel III), respectively. In all three panels, we use the nuisance parameter $m = 300$ as our main investigation. We calculate extreme quantiles for p-values of 0.2% or 0.1%. This means that the tail-VaRs are estimated to be triggered every 500 days or 1000 days, respectively. We also calculate the expected shortfall conditional upon crisis barriers of s = 25% or 50% in addition to the p-values of 0.2% or 0.1%.

In healthcare ETFs, the tail indices have fluctuated around three standard deviations ($\alpha = 2.40$). The average value for financial ETFs is the lowest ($\alpha = 2.05$), and ESG ETFs are second ($\alpha = 2.14$), indicating fat tails. Our results are similar to previous studies (e.g., Nguyen et al., 2020). In contrast, healthcare ETFs ($\alpha = 2.40$) have thinner tails than the other two ETF categories. This could be due to the exponential growth of demand for ESG and financial ETFs over the past few years. We concur with Papanikolaou and Wolff (2014), who state that market demands, regulatory changes, and technological advancements are potential sources of high risk for healthcare companies. A further possibility is that healthcare ETFs are much more likely to actively manage their risk as a result of stricter regulations and public scrutiny as opposed to ESG and finance ETFs. Healthcare firms with better risk management are less exposed to tail risks, according to Ellul and Yerramilli (2013). Although studies suggest that healthcare companies may not be fully managing all their risks (e.g., medical waste) well (Kelland, 2020; Manupati et al., 2021), they are still less prone to extreme shocks compared to other ETFs in our sample. On the other hand, the advancement of financial technologies has significantly increased turnover rates for financial-related products and services to satisfy consumer and societal needs. Similarly, more green or renewable technologies are needed to combat social and environmental issues. Thus, inventing and testing new products requires substantial investment (Goble and Bier, 2013). Especially during COVID-19, ESG and financial ETFs have grown much faster due to market demand. In turn, they come with higher risk. As a result, ESG and financial ETFs in our sample have a higher tail risk than healthcare ETFs.

When looking at specific ETFs in Table 1, such as SPYX SPDR S&P 500 Fossil Fuel Reserves Free ETF ($\alpha = 1.5083$) in Panel I, FHLC Fidelity MSCI Health Care ($\alpha = 1.832$) in Panel II, and FNCL Fidelity MSCI Financials Index ($\alpha = 1.708241$) in Panel III are the highest tails exhibited in the three panels. It is important to note that the top holdings of all these three ETFs are primarily invested in information technology, biotech, health care, and financial companies, e.g., the four tech giants, Johnson & Johnson, Pfizer, Berkshire Hathaway, and JP Morgan. As advanced technologies have grown rapidly over the past few decades, an investment portfolio may have an inherent risk that can be captured by tail risk. Furthermore, SPYX SPDR S&P 500 Fossil Fuel Reserves Free ETF and FNCL Fidelity MSCI Financials Index have frequently suffered from climate change debates, geopolitical risks, the recent Ukrainian-Russian war, and inflation debates, which negatively affect the stock price (Nasir et al., 2020; Wang et al., 2022). Thus, investment portfolios that include ESG and financial ETFs are always exposed to geopolitical risks, economic recessions, and financial regulations. They may experience sharp decreases in return on investment as a result. From another perspective, although the SPYX SPDR S&P 500 Fossil Fuel Reserves Free ETF excludes companies that own fossil fuel reserves from the S&P 500, it is top 10 largest positions are with high-tech companies, e.g., Apple, Microsoft, Amazon, Alphabet, Tesla, and NVIDIA. High-tech firms may cause market instability as equity markets' recalibration for higher interest rates (Roychowdhury and Srinivasan, 2019), even when supporting responsible corporate behaviour may bring lower volatility and, therefore, lower risk (Renn et al., 2022). Thus, ETFs with high concentrations of tech stocks are more exposed to risk. While Iyer et al., (2020) find that specialised education among board of directors can reduce risks for high-tech companies, our findings suggest that investors should always check the composition of ETF portfolios before investing, especially given the potential for tail risk. Regulation is another perspective from which we can observe and understand ETF differences. According to existing studies (e.g., Lábaj et al., 2018), healthcare ETFs are more strictly regulated than ESG and finance ETFs, and they pose more of a threat to firms that are not regulated.

As a result of comparing the tail quantiles and expected shortfalls among three panels in Table 1, it is worth noting that TAN Invesco Solar ETF (in ESG ETFs, tail-VaR = 21.377%) and KBE SPDR S&P Bank (in financial ETFs, tail-VaR = 19.2717%) have the highest 0.1% tail-VaR among the top-10 ETFs in both panels. TAN Invesco Solar ETF, for example, is expected to experience daily erosion of 21.377% or more in equity capital once every 1,000 days (approximately 3.8 years). Among the full sample of financial ETFs, the FNCL Fidelity MSCI Financials Index represents the highest expected shortfall (ES(x(p)) = 0.1%). The expected shortfall value of 70.5975% of FNCL Fidelity MSCI Financials Index represents the additional expected loss when the tail-VaR exceeds 10.6297% (when p = 0.1%). Further, the tail quantile and expected shortfall of financial ETFs have increased significantly during the economic recession, which indicates extreme losses. As we examine the ETFs at the three panels, ESGE iShares ESG Aware MSCI EM (8.2504% among ESG ETFs), XLV Health Care Select Sector (7.3304% among healthcare ETFs), and FNCL Fidelity MSCI Financials Index (10.6297% among finance ETFs) display the lowest tail quantiles. In contrast, XSOE WisdomTree Emerging Markets ex-State-Owned Enterprises Fund (7.4512% among ESG ETFs), IBB iShares Nasdaq Biotechnology (25.0324% among healthcare ETFs), and XLF Financial Select Sector (39.9366% among Financial ETFs) have the lowest expected shortfall (ESx(p)). Our findings contradict Cornell's (2020) findings that highly rated ESG companies have lower risks and lower expected investment returns for investors. However, several studies (e.g., Tong, 2015) suggest that under-regulation and competition could be reasons for the higher risk observed in ESG and financial ETFs, particularly those with a focus on ecological risks. Furthermore, the rapidly growing development of advanced technologies has led to new synergies between financial and non-financial activities that may cause systemic risks in the market for ESG and financial ETFs (Zhu and Hua, 2020). Therefore, investors should be cautious and carefully evaluate the composition and potential risks of ETF portfolio before investing.

Table 1 Full samples estimates of tail risk indicators for ESG, healthcare, and financial sectors

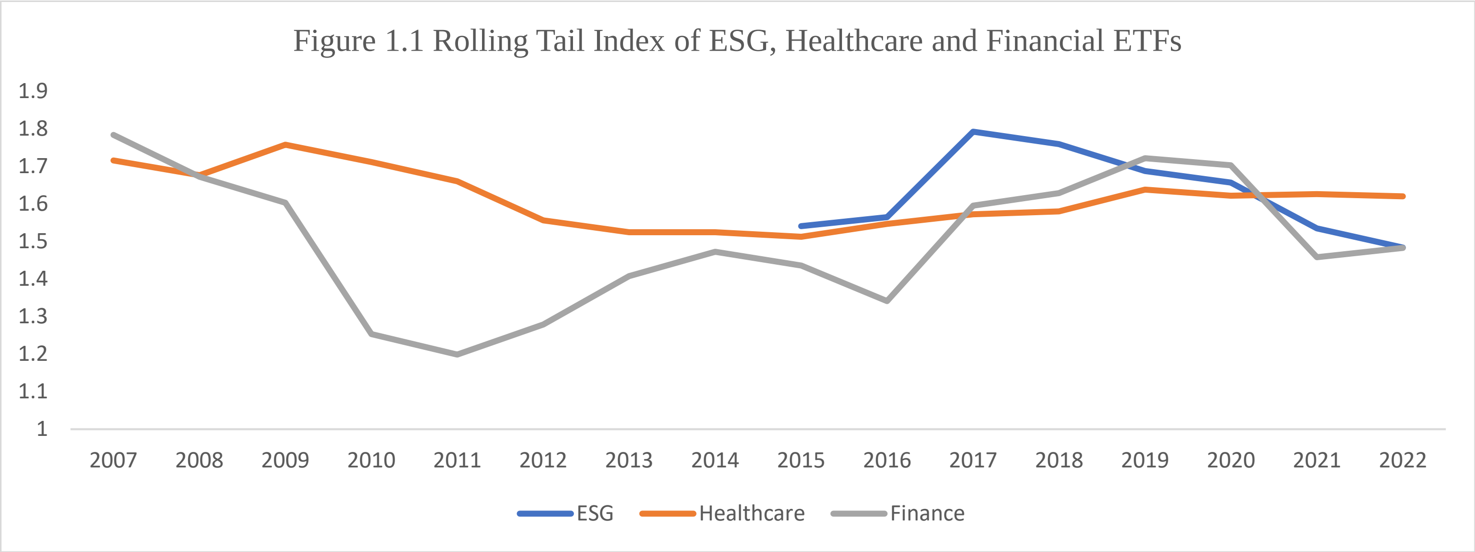
	α	**x(p)**		**ES(x(p))**		**ES(X>s)**	
		p=0.1%	**p=0.2%**	**p=0.1%**	**p=0.2%**	**s=25%**	**s=50%**
Panel I: ESG ETFs, m = 300							
DSI iShares MSCI KLD 400 Social ETF	2.186282	0.11353	0.082684	0.095702	0.0697	0.210742	0.421485
ESGD iShares ESG Aware MSCI EAFE ETF	1.700649	0.088202	0.058678	0.125887	0.083747	0.356812	0.713624
ESGE iShares ESG Aware MSCI EM ETF	2.068559	0.082504	0.059013	0.07721	0.055227	0.23396	0.46792
SUSA iShares MSCI USA ESG Select ETF	2.297722	0.103797	0.076767	0.079984	0.059155	0.192645	0.38529
ICLN iShares Global Clean Energy ETF	2.348718	0.165078	0.122891	0.122396	0.091117	0.185361	0.370722
TAN Invesco Solar ETF	2.465353	0.21377	0.161377	0.145883	0.110129	0.170607	0.341215
XSOE WisdomTree Emerging Markets ex-State-Owned Enterprises Fund	2.156921	0.086204	0.062512	0.074512	0.054033	0.216091	0.432182
SPYX SPDR S&P 500 Fossil Fuel Reserves Free ETF	1.508298	0.123293	0.077867	0.24256	0.153192	0.491838	0.983676
iShares ESG MSCI USA Leaders ETF	2.067329	0.083734	0.060243	0.07844	0.056457	0.23519	0.46915
PBW Invesco WilderHill Clean Energy ETF	2.60434	0.165849	0.127094	0.103375	0.079219	0.155827	0.311655
Average	**2.14042**	**0.122596**	**0.088913**	**0.114595**	**0.081198**	**0.244907**	**0.489692**
Panel II: Healthcare ETFs, m = 300							
XLV Health Care Select Sector SPDR Fund	2.775961	0.073304	0.057106	0.281538	0.281538	0.032155	0.140769
ARKG ARK Genomic Revolution ETF	1.936917	0.153389	0.107245	0.533665	0.533665	0.114466	0.266833
FHLC Fidelity MSCI Health Care Index ETF	1.832797	0.080156	0.054915	0.600386	0.600386	0.065941	0.300193
IBB iShares Nasdaq Biotechnology ETF	2.997413	0.099007	0.078566	0.250324	0.250324	0.039334	0.125162
IHF iShares US Healthcare Providers ETF	2.335671	0.094083	0.069924	0.374344	0.374344	0.052351	0.187172
IHI iShares US Medical Device ETF	2.118144	0.102672	0.074017	0.447169	0.447169	0.066196	0.223585
IXJ iShares Global Healthcare ETF	2.412976	0.07869	0.059042	0.353863	0.353863	0.041786	0.176931
IYH iShares US Healthcare ETF	2.425083	0.084923	0.063811	0.350857	0.350857	0.044777	0.175428
VHT Vanguard Health Care Index Fund ETF	2.379642	0.076875	0.057449	0.362413	0.362413	0.04164	0.181206
XBI SPDR S&P Biotech ETF	2.806671	0.110082	0.085993	0.276752	0.276752	0.047597	0.138376
Average	**2.402128**	**0.095318**	**0.070807**	**0.383131**	**0.383131**	**0.054624**	**0.191566**
Panel III: Financial ETFs, m = 300							
XLF Financial Select Sector SPDR Fund	2.251983	0.150329	0.110502	0.399366	0.399366	0.088262	0.199683
EUFN iShares MSCI Europe Financials ETF	2.089593	0.122443	0.087877	0.458887	0.458887	0.080651	0.229444
FNCL Fidelity MSCI Financials Index ETF	1.708241	0.106297	0.070843	0.705975	0.705975	0.100027	0.352987
FXO First Trust Financials AlphaDEX Fund	1.907707	0.1479	0.102842	0.550839	0.550839	0.113299	0.275419
IYF iShares US Financials ETF	2.185142	0.141963	0.103374	0.42189	0.42189	0.087225	0.210945
IYG iShares US Financial Services ETF	2.238574	0.151452	0.111122	0.40369	0.40369	0.089718	0.201845
KBE SPDR S&P Bank ETF	1.959207	0.192717	0.135292	0.521264	0.521264	0.141046	0.260632
KBWB Invesco KBW Bank ETF	1.962541	0.118598	0.083308	0.519458	0.519458	0.08655	0.259729
KRE SPDR S&P Regional Banking ETF	2.200882	0.157065	0.114631	0.416361	0.416361	0.095456	0.20818
VFH-Vanguard Financials ETF	2.034429	0.149069	0.106028	0.483358	0.483358	0.102499	0.241679
Average	**2.05383**	**0.143783**	**0.102582**	**0.488109**	**0.488109**	**0.098473**	**0.244054**

In order to look at the temporal changes in the tail risk of ESG, healthcare and financial firms, we demonstrate the eight-year average rolling tail risk for ESG, healthcare, and financial ETFs. The results are provided in Figure 1. Figure 1.1 provides a rolling tail index of ESG, healthcare and Financial ETFs. Because the data for the ESG ETFs goes back only until July 2007, the start date of the ESG ETF is from 2014. We also resent the rolling tail quantile (Figure 1.2), rolling expected shortfall (Figure 1.3), and rolling expected shortfall conditional upon 25% (Figure 1.4). In Figure 1.1, the time-varying effect indicates a sudden drop in the tail index (increased tail risk) for financial ETFs after the financial crisis between 2007 and 2011, followed by a gradual economic recovery (decreased tail risk). Among the time-varying tail indexes of financial ETFs, 2011 (1.1987) has the lowest value. The tail-risk of healthcare ETFs is similar to that of financial ETFs, but the level of increased tail-risk is lower. Comparatively, healthcare ETFs steadily rise and fall while financial ETFs fall quickly. After a sharp decline in 2009, the tail index of financial ETFs quickly rebounded in 2011 and 2012. These ETFs have a fat tail in their return distribution based on their lower tail index values. In terms of ESG ETFs, there was an increase between 2016 and 2017, followed by a rapid decline. ESG ETFs have a sudden downward trend in 2020, similar to Financial ETFs. Overall, the rolling tail risk for healthcare ETFs seems to have remained stable and consistent throughout the COVID-19 crisis. It is possible that investors avoid risky assets when times are turbulent (Cornell, 2021). Healthcare ETFs are perceived by investors as a tool for preventing loss of return or diversifying portfolio risks. Understandably, investors use healthcare ETFs to hedge the downward risk over the course of the COVID-19 pandemic, given its infectious nature that requires high demands of healthcare-related products and services (Kaushik et al., 2014).

The rolling tail quantile and expected shortfall metrics (Figures 1.2 to 1.4) also demonstrate similar results. The healthcare ETFs in these three figures show a stable trend throughout our sample period, indicating moderate tail risk. On the other hand, during the global financial crisis since 2009, the average rolling tail quantile of finance ETFs (see Figure 1.2) shows more variation over time. After 2011, the average tail quantile decreased gradually until it reached its pre-crisis level in 2017. A possible reason could be that in the post-crisis period, financial firms have been subjected to stricter regulations. COVID-19 has caused an upward trend in 2020. Moreover, once we introduce the ESG data since 2015, we observe a similar trend for ESG ETFs compared to Financial ETFs. Our result shows that in comparison to healthcare ETFs, both financial and ESG ETFs carry a high level of risk. While studies (Kaushik et al., 2014; Lábaj et al., 2018; Popesko et al., 2015) find that healthcare companies may face reputation risks when involved in controversies (e.g., drug recalls, patient safety issues and unethical practices), ESG and financial ETFs may be riskier due to their exposure to a wider range of industries. Companies in industries such as oil and gas or mining are particularly susceptible to regulatory changes or reputational risks (Klinke and Renn, 2021; Renn et al., 2022).

According to Figure 1.3, the average rolling expected shortfall for financial ETFs is very similar to the average rolling tail quantile. Prior to the financial crisis (pre-2009), financial ETFs were moderately stable but increased substantially between 2009 and 2011, before dropping sharply post-crisis (post-2011) to pre-crisis levels in 2018. Once again, the level of risk increased in 2020 due to the COVID-19 crisis. Healthcare ETFs, however, maintain a stable average rolling expected shortfall, with a slight increase between 2011 and 2015. Despite a slight drop in 2015, recent data shows an upward trend (between 2019 and 2022). Nevertheless, the rolling tail expected shortfall conditional upon the tail quantile of financial ETFs is much higher than healthcare ETFs throughout our sample period. A similar trend is observed in ESG ETFs, but the level of increased tail-risk is lower than in Financial ETFs. This again reaffirms the need for regulation of financial and ESG-related activities (Klinke and Renn, 2021). The rolling tail expected shortfall situation conditional upon the tail quantile of ESG, healthcare, and financial ETFs (see Figure 1.) shows very similar patterns if the 25% threshold is used (see Figure 1.4).

Figure 1 The rolling tail risk of ESG, healthcare, and financial ETFs



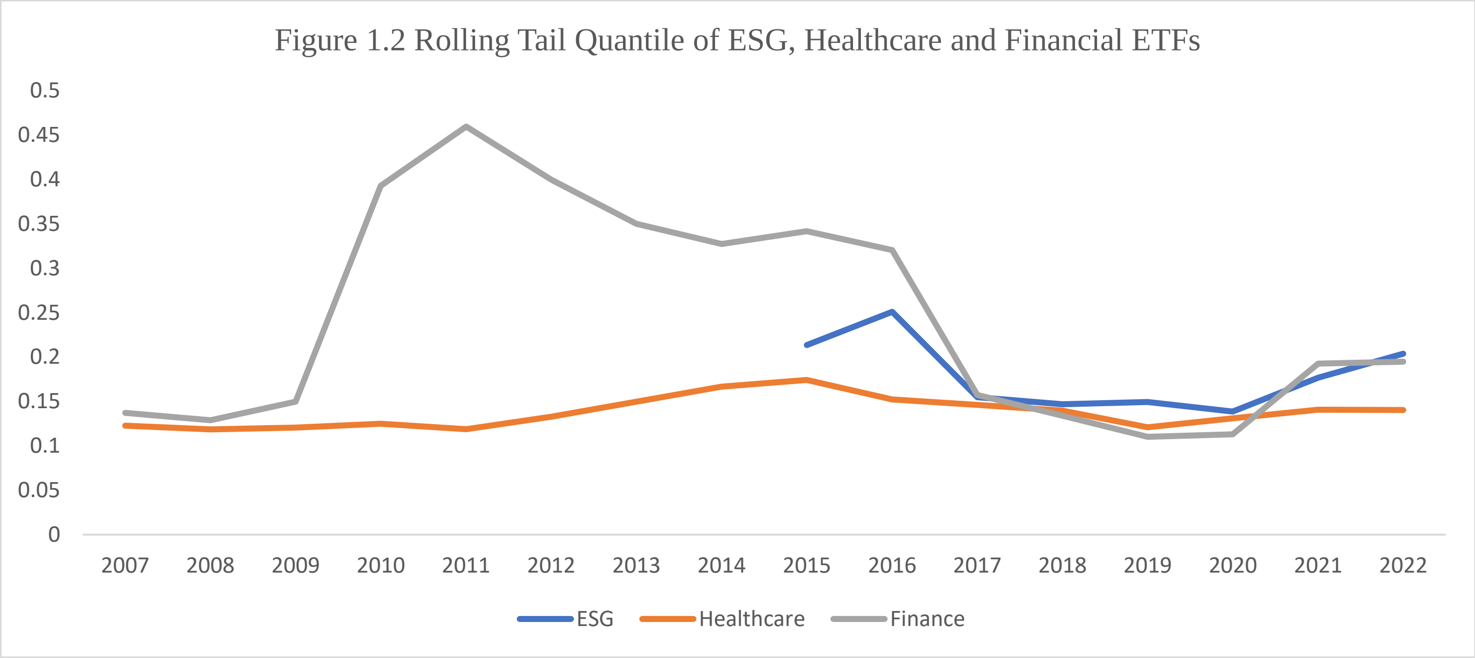


Figure 1.3 Rolling Expected Shortfall of ESG, Healthcare and Financial ETFs

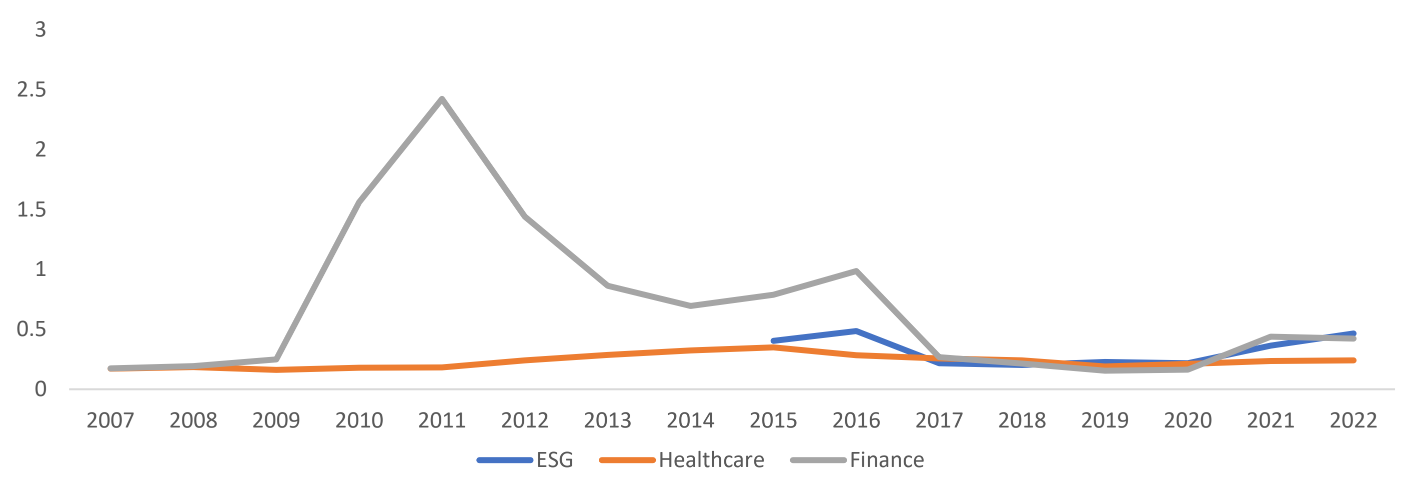
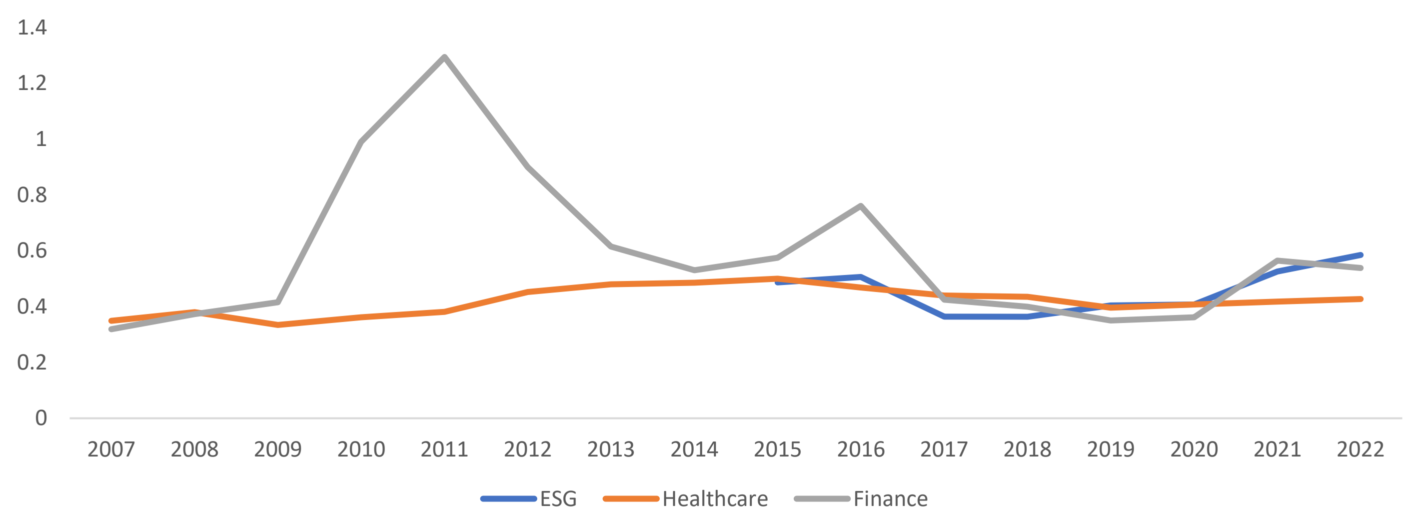


Figure 1.4 Rolling Expected Shortfall Conditional Upon 25% threshold of ESG, Healthcare and Financial ETFs



4.2 Extreme systematic risk of ESG, healthcare, and financial ETFs

In this section, we estimate the exposure of the top-10 ETFs in ESG, healthcare, and financial investing, respectively, to large adverse movements in aggregate shocks. We employ 10 different conditioning factors, which are FTSE All-World ETF, Vanguard FTSE Europe ETF, EZU iShares MSCI Eurozone ETF, MCHI iShares MSCI China ETF, VOO Vanguard S&P 500 ETF, VTI Vanguard Total Stock Market ETF, QQQ Invesco QQQ Trust, Energy Select Sector SPDR Fund, Green Energy First Trust NASDAQ, and iShares Core US Aggregate Bond. These ETFs cover ETFs of the major countries and economic regions. Because of the importance of energy for a sector or an economy, we also include traditional and green energy ETFs. Finally, we also include another important asset class of bonds as a conditioning factor. Table 2 presents the extreme systematic risk (tail-βs) for ESG, healthcare, and financial EFTs in Panel I, II, and III, respectively. The 10 indices are compared with nuisance parameters ($m = 300$). Overall, the MCHI iShares MSCI China ETF index shows high extreme systematic risk in ESG (βs = 0.32147). Among both the healthcare (βs = 0.455846902) and financial (βs = 0.483737585) panels, the Green Energy First Trust NASDAQ index has a higher extreme systematic risk (tail- βs). These results are used to interpret economic intuition. For example, the tail-βs = 0.3022 for DSI iShares MSCI KLD 400 Social under the FTSE All-World ETF index column indicates that a large downturn in the DSI iShares MSCI KLD 400 Social return index. According to our results, a daily stock price decline of comparable magnitude is 30.22% likely for DSI iShares MSCI KLD 400 Social. Thus, nearly three out of ten times, a sharp drop in the FTSE All-World ETF index is expected to be matched by a similarly large drop in DSI iShares MSCI KLD 400 Social.

Furthermore, as shown in the Penal III in Table 2, these financial ETFs are more exposed to extreme systematic risk in the green energy First Trust NASDAQ index. Our results show that compared to the other nine indices, the individual financial ETFs are more likely to be affected by a shock from a green energy First Trust NASDAQ index. In fact, the iShares Core US Aggregate Bond index has the least impact on financial ETFs. As with the Green Energy First Trust NASDAQ index, healthcare ETFs show the highest extreme systematic risk (tail-s). It may be because most of the top holdings companies in the healthcare ETFs are headquartered in the US, so US indices (e.g., the NASDAQ index in our case) better reflect the performance of the healthcare ETFs. Individual financial ETFs are more affected by shocks from the Green Energy First Trust NASDAQ index. Next to the US, the other big index in our sample is the MCHI iShares MSCI China ETF index based in China. ESG ETFs show the highest extreme systematic risk compared to the MCHI iShares MSCI China ETF index, meaning this index has a greater impact on individual ESG ETFs than the other nine global indices. Additionally, our findings indicate that financial ETFs, and especially ESG ETFs, require not only local but also global regulation to mitigate the effects of extreme systematic risk. According to Battiston and Martinez-Jaramillo (2018), if ETFs invest in the same group of companies as another ETF, tail risk connections are more likely to happen. For example, Johnson & Johnson is popular in the ESG and healthcare ETFs, and Berkshire Hathaway is popular in the ESG and financial ETFs in our sample. Compared with healthcare ETFs, the extreme systemic risks of financial ETFs are not much different based on the ten indices in our data sample. As a result, financial and healthcare firms tend to have a broader range of investors than ESG ETFs. Consequently, these indices in the healthcare and finance panels have high co-movement in tail-βs.

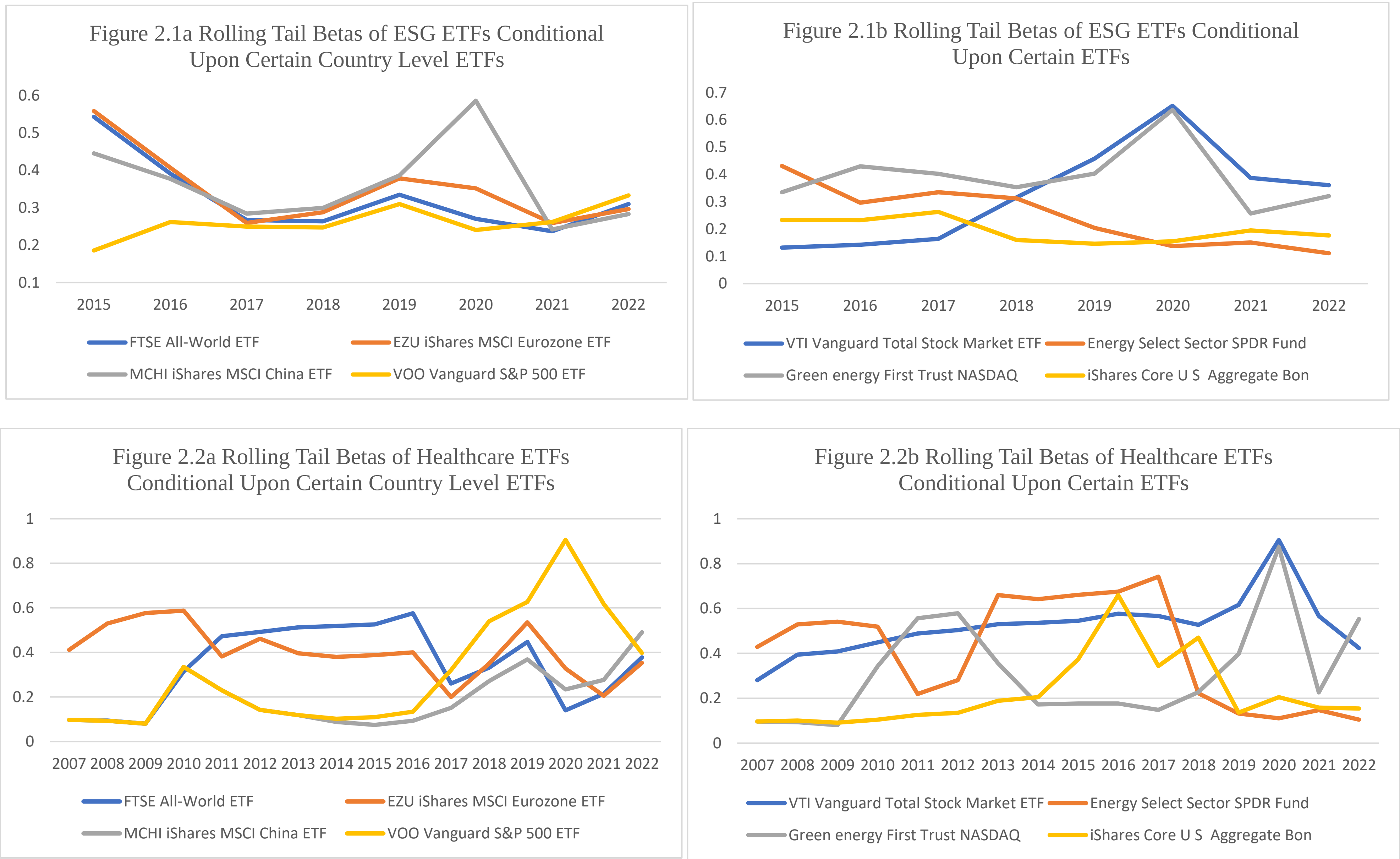
Table 2 Extreme systematic risk (tail-βs) for ESG, healthcare, financial sectors ETFs

	FTSE All-World ETF	Vanguard FTSE Europe ETF	EZU iShares MSCI Eurozone ETF	MCHI iShares MSCI China ETF	VOO Vanguard S&P 500 ETF	VTI Vanguard Total Stock Market ETF	QQQ Invesco QQQ Trust	Energy Select Sector SPDR Fund	Green energy First Trust NASDAQ	iShares Core US Aggregate Bond
	m = 300	**m = 300**	**m = 300**	**m = 300**	**m = 300**	**m = 300**	**m = 300**	**m = 300**	**m = 300**	**m = 300**
Panel I: ESG ETFs										
DSI iShares MSCI KLD 400 Social ETF	0.3022	0.3025	0.3001	0.2842	0.28256102	0.30038019	0.30068117	0.2928	0.3001	0.2863
ESGD iShares ESG Aware MSCI EAFE ETF	0.2614	0.2609	0.2596	0.3223	0.31323571	0.26864799	0.26937146	0.2815	0.2675	0.2807
ESGE iShares ESG Aware MSCI EM ETF	0.2594	0.2574	0.2587	0.3186	0.31620633	0.26768939	0.27606238	0.2863	0.2667	0.2756
SUSA iShares MSCI USA ESG Select ETF	0.2682	0.2679	0.2679	0.3368	0.32231988	0.27530258	0.28389764	0.2842	0.2743	0.2779
ICLN iShares Global Clean Energy ETF	0.3031	0.3034	0.2995	0.2919	0.30098276	0.30526939	0.29978003	0.2802	0.2894	0.2922
TAN Invesco Solar ETF	0.2776	0.2753	0.2738	0.3364	0.32903488	0.28309416	0.28993218	0.2983	0.2858	0.2789
XSOE WisdomTree Emerging Markets ex-State-Owned Enterprises Fund	0.2776	0.2753	0.2738	0.3368	0.32511355	0.28336148	0.28993218	0.2962	0.2858	0.2789
SPYX SPDR S&P 500 Fossil Fuel Reserves Free ETF	0.2784	0.2751	0.2766	0.3368	0.3315799	0.2863357	0.29077501	0.2908	0.2839	0.2786
iShares ESG MSCI USA Leaders ETF	0.2606	0.2584	0.2599	0.3198	0.3174363	0.2689194	0.27729238	0.2875	0.2679	0.2768
PBW Invesco WilderHill Clean Energy ETF	0.2699	0.2696	0.2706	0.3323	0.32511355	0.27759464	0.28389764	0.2842	0.2766	0.2804
Average	**0.27584**	**0.27460**	**0.27405**	**0.32159**	**0.316358391**	**0.281659491**	**0.28616220**	**0.28820**	**0.2798**	**0.2806**
Panel II: Healthcare ETFs										
XLV Health Care Select Sector SPDR Fund	0.21727154	0.21401711	0.2299249	0.21356014	0.20982657	0.21602015	0.23063182	0.43422864	0.40547567	0.20287491
ARKG ARK Genomic Revolution ETF	0.26091478	0.24695637	0.21295386	0.3219442	0.30869547	0.22526426	0.20191924	0.25799827	0.35678002	0.24100562
FHLC Fidelity MSCI Health Care Index ETF	0.2604618	0.24119935	0.21509103	0.32368068	0.31255416	0.22209622	0.1991055	0.27252679	0.37742389	0.23757086
IBB iShares Nasdaq Biotechnology ETF	0.23259844	0.22679667	0.23700789	0.23223838	0.22904732	0.23515046	0.22696822	0.39273821	0.42201405	0.21220084
IHF iShares US Healthcare Providers ETF	0.27203263	0.26482965	0.2315216	0.26251268	0.25866551	0.2345989	0.21190113	0.43110919	0.51203412	0.22957306
IHI iShares US Medical Device ETF	0.26910493	0.2615972	0.23187944	0.27203263	0.26742602	0.23441562	0.20693241	0.40879018	0.55055412	0.23626141
IXJ iShares Global Healthcare ETF	0.24276051	0.24374654	0.24004159	0.23832565	0.2345989	0.24004159	0.22226074	0.42380225	0.44917963	0.22492653
IYH iShares US Healthcare ETF	0.2224255	0.22095139	0.23700789	0.22835007	0.21901605	0.22939755	0.23134309	0.4386725	0.42987392	0.21145313
VHT Vanguard Health Care Index Fund ETF	0.25645469	0.2557988	0.2315216	0.25558091	0.25492948	0.23794766	0.21539985	0.42201405	0.51644061	0.2435487
XBI SPDR S&P Biotech ETF	0.26862309	0.26343459	0.22887261	0.27911813	0.26958849	0.23478247	0.21085874	0.37366375	0.53869299	0.2345989
Average	**0.250264791**	**0.243932767**	**0.229582241**	**0.262734347**	**0.256434797**	**0.230971488**	**0.215732074**	**0.385554383**	**0.455846902**	**0.227401396**

Panel III: Financial ETFs										
XLF Financial Select Sector SPDR Fund	0.23205877	0.23063182	0.24454115	0.20808044	0.20938729	0.225603	0.23663406	0.46883124	0.4630432	0.18295853
EUFN iShares MSCI Europe Financials ETF	0.26886378	0.25866551	0.22748445	0.31617702	0.30369635	0.22835007	0.20083801	0.35300234	0.43297546	0.21175158
FNCL Fidelity MSCI Financials Index ETF	0.26023589	0.24394471	0.2147831	0.31886503	0.3058634	0.22046436	0.19990139	0.30125702	0.35635629	0.21160225
FXO First Trust Financials AlphaDEX Fund	0.28387132	0.27031711	0.23738291	0.27680073	0.27227949	0.23441562	0.2105628	0.46519689	0.57371318	0.21175158
IYF iShares US Financials ETF	0.24178242	0.24197741	0.25214453	0.21648773	0.21416987	0.23570463	0.23080923	0.48085255	0.50770219	0.19534635
IYG iShares US Financial Services ETF	0.24675328	0.24454115	0.25755536	0.22046436	0.2185375	0.23626141	0.23205877	0.4770302	0.51466894	0.19209475
KBE SPDR S&P Bank ETF	0.27885872	0.27178623	0.23700789	0.25956055	0.25711396	0.23626141	0.21265201	0.44717138	0.51644061	0.20495355
KBWB Invesco KBW Bank ETF	0.26205413	0.24756765	0.21790268	0.31988485	0.30965118	0.22425411	0.1991055	0.32403023	0.40767934	0.20056951
KRE SPDR S&P Regional Banking ETF	0.28226903	0.27277454	0.23775911	0.26389797	0.2632035	0.23719525	0.21401711	0.43297546	0.49108346	0.19884161
VFH-Vanguard Financials ETF	0.27104967	0.2700738	0.23908525	0.24197741	0.24100562	0.23794766	0.21280283	0.49431959	0.57371318	0.20967994
Average	**0.262779701**	**0.255227993**	**0.236564643**	**0.264219609**	**0.259490816**	**0.231645752**	**0.214938171**	**0.42446669**	**0.483737585**	**0.201954965**

Similar to the tail risk temporal plots, we also explore the temporal changes in the extreme systemic risk of ESG, healthcare and financial firms. We use eight-year average rolling windows to calculate the extreme systemic risk. The results are provided in Figure 2. As shown in Figures 2.1a, 2.2a, and 2.3a, we also examine the rolling tail betas of ESG, healthcare, and financial ETFs based on their trading markets (i.e., the UK, EU, China, and USA). As for the types of ETFs, we cover technology, energy, green energy, and aggregate bonds (see Figures 2.1b, 2.2b, and 2.3b). The figures of Vanguard FTSE Europe ETF VTI Vanguard Total Stock Market ETF and QQQ Invesco QQQ Trust are not reported for the sake of brevity. We observe that in turbulent times, such as the 2008 global financial crisis, the 2015 oil price crisis, and the 2019 COVID-19 pandemic crisis, tail betas are significantly low for the majority of the selected ETF markets. Interestingly, before the COVID-19 pandemic started, the systemic risk measures were already rising. A similar pattern has also been observed by (Chaudhry et al., 2022). The upward trend of betas is particularly evident in VTI Vanguard Total Stock Market ETF and Green Energy First Trust NASDAQ (see Figures 2.1b, 2.2b, and 2.3b), indicating these two markets are more sensitive to systematic risk, which can result in more volatile price swings in the investment portfolio. On the other hand, a significant drop in betas is observed after one year of the pandemic, suggesting that some brokers may want to invest in these markets to hedge against the financial crisis (Lean and Pizzutilo, 2021). Similar beta indications are found in country-level ETFs. ESG ETF betas are especially high in China (MCHI iShares MSCI China ETF, see Figure 2.1a), but lower in the US (VOO Vanguard S&P 500 ETF, see Figures 2.2a and 2.3a) for healthcare and financial ETFs.

Figure 2 Rolling Tail Betas of ESG, healthcare, and finance ETFs conditional upon certainty country level ETFs and certain types of ETFs



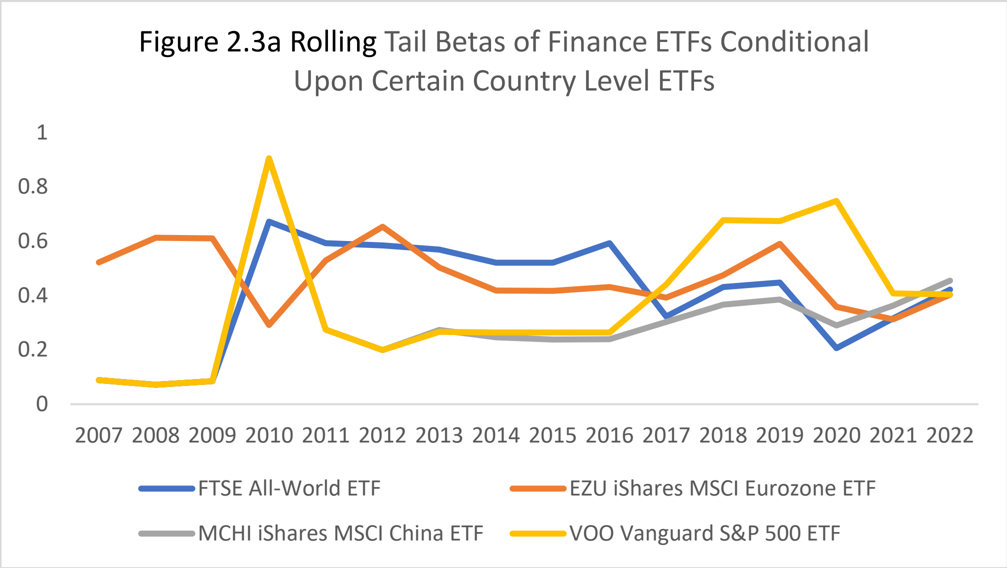


Figure 2.3a Rolling Tail Betas of Finance ETFs Conditional Upon Certain Country Level ETFs
1
0.8
0.6
0.4
0.2
0
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
FTSE All-World ETF
EZU iShares MSCI Eurozone ETF
MCHI iShares MSCI China ETF
VOO Vanguard S&P 500 ETF

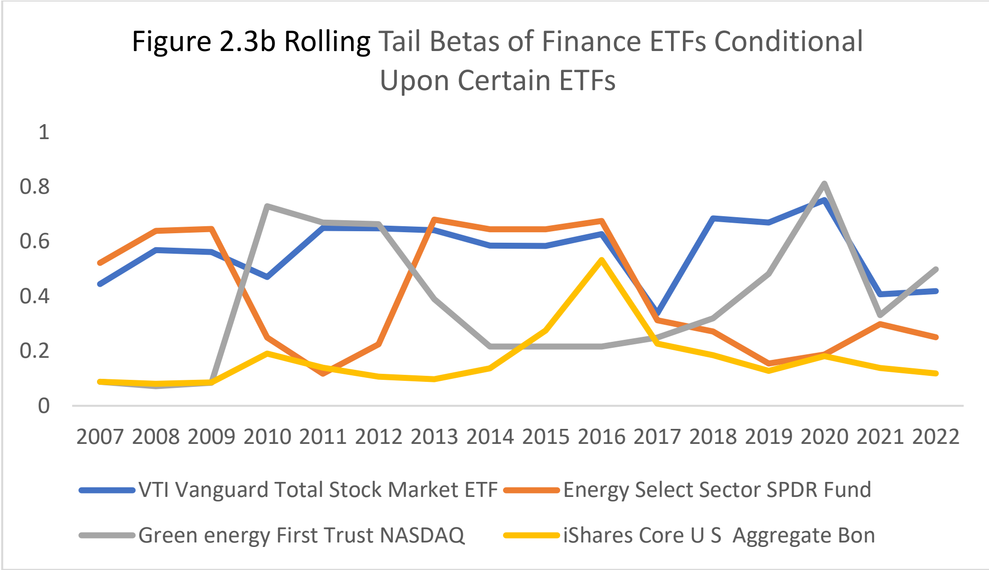


Figure 2.3b Rolling Tail Betas of Finance ETFs Conditional Upon Certain ETFs
1
0.8
0.6
0.4
0.2
0
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 2021 2022
VTI Vanguard Total Stock Market ETF
Energy Select Sector SPDR Fund
Green energy First Trust NASDAQ
iShares Core U S Aggregate Bon

4.3 Spillover risk of ESG, healthcare, and financial sectors

Table 3 illustrates the multivariate spillover risk for ESG, healthcare, and financial ETFs with two nuisance parameters ($m = 200$, and $m = 300$). For example, when the nuisance parameter $m = 200$, if one ESG ETF goes into distress, there is a 17.7195% probability that all 10 ESG ETFs will go into distress, according to the economic interpretation of the multivariate spillover risk of 0.177195. This number is 16.4097% in healthcare ETFs and 20.5797% in financial ETFs. Similar patterns have also been observed that $EFinancial$ (22.714%) $>$ $EESG$ (22.1135%) $>$ $EHealthcare$ (17.6605%) with $m = 300$. One possible reason could be that the systemic risk may be higher in a more integrated financial system because financial ETFs are more interdependent (Renn et al., 2022). Therefore, financial ETFs have a higher multivariate spillover risk than ESG and healthcare ETFs. Our study assesses the multivariate spillover risk across three ETF categories to provide a broad understanding of systemic risk. Our findings indicate that healthcare ETFs have the lowest level of systematic risk. This is consistent with previous research (e.g., Chen et al., 2018), which suggests that the more diversified the portfolio composition, the lower the systematic risk for healthcare ETFs. However, investors looking to minimize their exposure to ecological risks may find ESG ETFs a promising avenue. The recent IPCC AR6 Synthesis Report 2023 warns that global warming is accelerating faster than previously anticipated and that urgent and large-scale actions are needed to mitigate the risks of climate change (Ripple et al., 2020). Furthermore, firms with higher ESG ratings tend to have better environmental management practices, which can help mitigate ecological risks (Hansen et al., 2017; Ioannou and Serafeim, 2021). Therefore, ESG ETFs may also be an attractive option for investors seeking to minimize their exposure to ecological risks in their portfolios.

The time-varying systemic risk of expected co-crash indicators and co-crash probabilities are depicted in Figure 3 for ESG, healthcare, and financial ETFs. Similar to tail-βs, the eight-year rolling spillover risk measurement in healthcare ETFs is much higher than the full sample. For example, when one healthcare ETF is in distress for an eight-year rolling period, 2.894356 healthcare ETFs are, on average, likely to be in distress, compared to only 0.164097 for the full sample (see Figure 3.1). We also find that all three ETF categories exhibit a similar pattern of time-varying spillover risk, but financial ETFs have a more pronounced effect. Considering the distress of one financial ETF in 2019, the crash likelihood for financial ETFs is the highest, with 4.83 likely to be in distress. Assuming that one financial ETF crashed in 2015, the lowest crash likelihood would indicate a 2.98 financial ETFs crash. The likelihood of financial ETFs collapsing has increased to almost the highest level compared with ESG and healthcare ETFs since 2017. Interestingly, since 2017, the crash likelihood for ESG ETFs has declined dramatically, indicating that social system (e.g., ESG) is becoming more popular on the stock market (Renn et al., 2022). Regarding the healthcare ETF category, given that one healthcare ETF was in distress during the peak of the 2008 dot-com bubble financial crisis, almost 3 healthcare ETFs are likely to be in distress. After 2009, the crash likelihood went down to 2.73, and then gradually increased. Multivariate spillover risk (see Figure 3.2) shows that the financial ETFs are consistently higher than ESG and healthcare ETFs. Our results are consistent with the findings of Chaudhry et al. (2022) and Teixeira et al. (2018). In the sample period, ESG ETFs have been slightly higher than healthcare and financial ETFs between 2015 and 2019. We argue that while ESG investing can be a useful tool to encourage companies to prioritise environmental and social issues, it is also important to recognise that the current ESG framework may not be enough to tackle the magnitude of the ecological risks we face (Asefi-Najafabady et al., 2021, Ripple et al., 2020). As IPCC AR6 Synthesis Report 2023 emphasises that reducing greenhouse gas emissions and transitioning to renewable energy sources are crucial to avoid catastrophic environmental impacts (Steffen et al., 2018). Additionally, we observe that the multivariate spillover risk of financial ETFs has increased sharply since 2017. With the highest point of 0.482, it indicates that there is a 48.2% probability that all financial ETFs would go into distress if one financial ETF goes into distress. Healthcare ETFs also exhibit a similar pattern. As of 2018, however, the multivariate spillover risk increased and was less aggressive compared to financial ETFs. The multivariate spillover risk for ESG ETFs, on the other hand, is steadily declining. Our results highlight the importance of considering the intersectionality of social and ecological risks (Moore, 2015). Environmental degradation and climate change disproportionately affect marginalized communities and exacerbate social inequalities (Hansen et al., 2017). Therefore, it's crucial for investors to consider not only the ecological risks but also the social risks when evaluating their investment options.

Table 3 Spillover risk

	Parameters	ESG	Healthcare	Finance
Expected Joint Crashes (1<E<20)	m = 200	2.70636	2.894356	3.571429
	m = 300	2.876318	3.003003	3.699137
E = Multivariate Gaussian	m = 200	0.177195	0.164097	0.205797
	m = 300	0.221135	0.176605	0.22714

Note: the nuisance parameter m represents the number of extremes used in estimation for three sectors.

Figure 3 Time varying systemic risk: (rolling) expected co-crash indicators and co-crash probabilities for ESG, healthcare, and finance ETFs

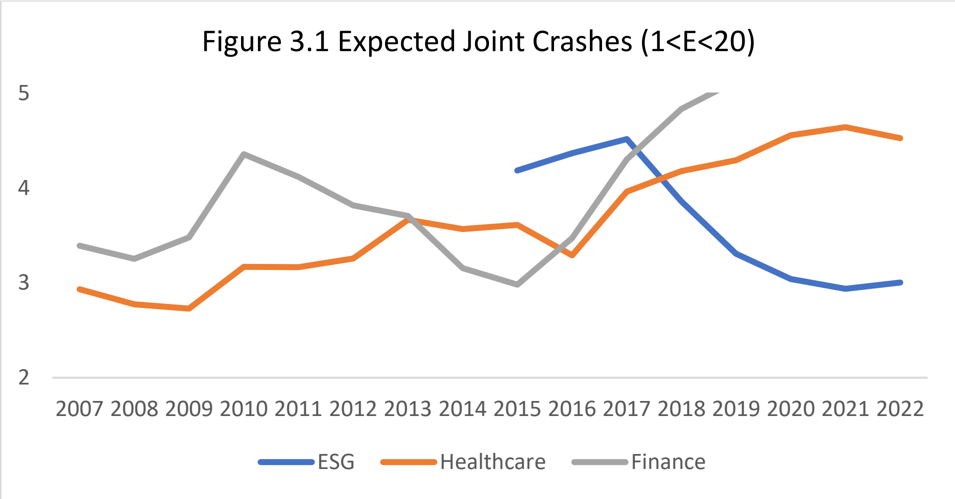


Figure 3.1 Expected Joint Crashes (1<E<20)

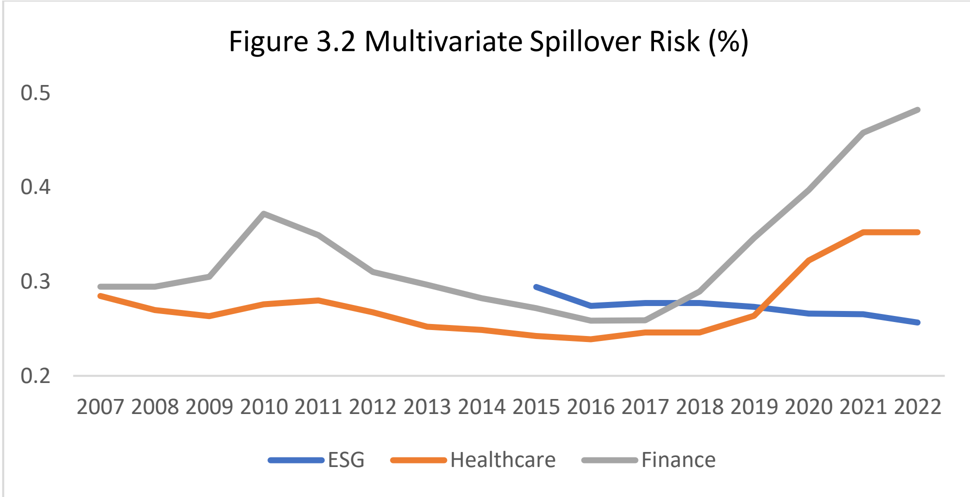


Figure 3.2 Multivariate Spillover Risk (%)

5. Conclusion

To tackle the ecological challenges and achieve environmental goals, it is important to understand the ecological, socioeconomic, health and financial risks posed by climate change. This study addresses this unexplored issue and provides a comprehensive risk analysis of the ecological, socio-economic, corporate governance, healthcare and financial sectors. We model risk by employing statistical extreme value theory to estimate indicators of tail risk, extreme systemic risk and extreme spillover risk of ESG (Environment, Social and Governance), healthcare and financial ETFs (Exchange Traded Funds). Since we use market price data to estimate these risks, the indicators are market-based. Tail risk refers to the downside risk in each ETF or each sector (ESG, healthcare or financial sector) and extreme systemic risk (tail-β.) is the exposure of an ETF or a sector to extreme systemic shock. We use 10 different conditioning factors as a measure of extreme systemic shock. These factors are as broad as the whole world and also cover all the major economic regions, namely, USA, China, and Europe. We also include unique macro shocks like traditional energy, green energy, and bonds. Finally, the spillover risk is an expected number of co-crashes in the returns of other ETFs if there is a crash in one ETF or a multivariate probability of a joint drop in the returns of other ETFs if there is a drop in one ETF.

Our risk modelling findings reveal that the ESG sector exhibits the highest tail risk in the extreme environment when we consider there is a shock of 25% or 50%. We observe such shocks in financial markets in situations like the global financial crisis of 2007-08 and the COVID-19 crisis. However, the healthcare sector shows the lowest risk on the tail quantile, while the ESG sector reveals the lower risk in the tail expected shortfall. On the contrary, the financial sector exhibits the highest risk in both the tail quantile and the tail expected shortfall. For extreme systemic risk, we find that the ESG sector is the riskiest with all of the 10 conditioning factors. The ESG sector shows the highest risk if the shock is coming from China. The healthcare and financial sectors exhibit similar risks for all the conditioning factors except for traditional energy and green energy. The healthcare (financial) sector's tail systemic risk is almost 50% (70%) higher in the case of traditional energy and almost 80% (90%) higher in the case of green energy. Our results show that both the healthcare and financial sectors are very sensitive to a shock from the energy sectors and particularly from the green energy sector. Additionally, we observe a similar pattern when we calculate the extreme spillover risk via the number of expected joint crashes and the probability of a crash in the ETFs of two other sectors given there is a crash in the ETFs in one other sector. We find that ESG and healthcare sectors have lower spillover risks compared to the financial sector. However, with the probability of a crash, the ESG sector is considered to be riskier than the healthcare and financial sectors.

There are essential lessons to be learned from the intersection of ESG, healthcare, and financial sectors, and these lessons can inform policy regarding risk analysis, assessment, and management. First, it is evident that ESG risks can have substantial effects on both the healthcare and financial sectors. Therefore, it is crucial that policymakers prioritise the integration of ESG considerations into risk analysis and assessment frameworks for these sectors. This may involve incorporating ESG factors into financial reporting requirements and encouraging healthcare organisations to consider ESG factors when making strategic decisions.

Second, better collaboration and coordination are required between the healthcare and financial sectors to address ESG risks. For instance, financial firms that invest in healthcare firms should take action to interact with these firms about ESG problems and motivate them to enhance their ESG performance. Similarly, healthcare organisations should collaborate closely with financial organisations to ensure that ESG risks are effectively managed in their operations. Thirdly, policymakers must evaluate the role of regulation and incentives in promoting ESG risk management in the healthcare and financial sectors. This can involve instituting regulations and standards that require companies to report on their ESG performance and providing incentives for companies that prioritise ESG factors in their operations and investment decisions.

Overall, there is a need for a more integrated approach to risk analysis, evaluation, and management that takes into account the interactions between the financial, healthcare, and ESG sectors. Policymakers can support resilient, sustainable healthcare and financial systems that are better equipped to handle risk in the future by addressing ESG risks in a comprehensive and coordinated manner.

Our paper has implications for climate change risk management that could be useful for international and national organisations, governments, and corporations. The risk modelling and risk assessment of ESG, healthcare and financial ETFs provide great insights for making sustainable economic, business, and financial strategies as we learn about the downside risk, extreme systemic risk and spillover risk. When formulating a policy, understanding downside risk can be helpful, as it shows how much risk each sector or each ETF investment has and how that risk can be incorporated into the policy. Similarly, the effects of macro shocks and the spillover from one sector to another are beneficial as policymakers are aware of how much risk these sectors pose to the system.

Our results also have several significant implications for practitioners in ESG, healthcare, and finance sectors. First, companies and policymakers can take action to mitigate risks and lessen the probability of negative effects by identifying potential risks and their potential impacts. In addition to ensuring the sustainability and resilience of the healthcare and financial sectors, this can help to safeguard stakeholders. Second, greater transparency can also be attained through risk analysis in the finance and healthcare industries. Companies and policymakers can educate stakeholders, such as investors, employees, patients, and the general public, more thoroughly and transparently by identifying potential risks and their potential effects. This may contribute to increased responsibility and trust-building. Third, results can also be used to guide legislation in the finance and healthcare industries. Regulators can take action to reduce systemic risk and other risks by locating possible sources of those risks, which will increase financial stability and resilience. Financial crises and other bad effects may be less likely as a result.

Overall, risk management, transparency, decision-making, and regulation are significantly impacted in the financial, healthcare, and ESG sectors. Companies and policymakers can contribute to ensuring the sustainability and resilience of these crucial sectors, safeguarding stakeholders, and promoting more sustainable and resilient outcomes by adopting a comprehensive and integrated strategy to risk analysis.

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