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ORIGINAL ARTICLE

Risk modelling of ESG (environmental, social, and governance), healthcare, and financial sectors

Sajid M. Chaudhry[1] | **Xihui Haviour Chen**[2] | **Rizwan Ahmed**[3] | **Muhammad Ali Nasir**[4,5]

[1]Economics, Finance & Entrepreneurship Department, Aston Business School, Aston University, Birmingham, UK

[2]Edinburgh Business School, The Centre for Social and Economic Data Analytics (CSEDA), Heriot-Watt University, Edinburgh, UK

[3]Kent Business School, University of Kent, Canterbury, UK

[4]Department of Economics, University of Leeds, Leeds, UK

[5]Department of Land Economy, University of Cambridge, Cambridge, UK

Correspondence
Muhammad Ali Nasir, Department of Economics, University of Leeds, Leeds, 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 environmental, social, and governance (ESG), healthcare, and financial sectors and assess their downside risk, extreme systemic risk, and extreme spillover risk. We use a rich set of global daily data of exchange-traded funds (ETFs) from 1 July 1999 to 30 June 2022 in the case of healthcare and financial sectors and from 1 July 2007 to 30 June 2022 in the case of ESG sector. 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 an ETF drop of 25% or 50%. The ESG sector poses the highest extreme systemic risk when a shock comes from China. Finally, we find that ESG and healthcare sectors have lower extreme spillover risk (contagion risk) compared to the financial sector. Our study seeks to provide valuable insights for developing sustainable economic, business, and financial strategies. To achieve this, we conduct a comprehensive risk assessment of the ESG, healthcare, and financial sectors, employing an innovative approach to risk modelling in response to ecological challenges.

KEYWORDS

ecological risk modeling, ESG, extreme value theory, financial risks, healthcare risks, risk analysis, risk assessment

1 | INTRODUCTION

Ecological challenges pose existential risks to human civilization, and to address these risks, many countries have embarked on the road to carbon neutrality or net zero (Gil & Bernardo, 2020; Hallegatte & Rentschler, 2015; 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 several 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, e.g., Fankhauser & McDermott, 2014; Kron et al., 2019; Mirza, 2003; Moore, 2015). However, for a sustainable and feasible strategy, we also need to understand the risks posed by the environment, socio-economic, governance, and healthcare sectors (de Goër de Herve et al., 2023;

[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

Wu et al., 2022). In this article, we fill this gap in the literature and provide a comprehensive risk assessment and analysis from ecological, socio-economic, governance, healthcare, and financial perspectives. To this aim, drawing on extreme value theory (EVT), we analyze and model ecological risks to environmental, social, and governance (ESG), financial, and healthcare exchange-traded funds (ETFs)[2] employing rich data from each category.

We focus on the ESG sector because of the climate change crisis that humanity is facing now and will continue to face for some time in the future until we achieve the transition to net zero.[3] Our risk analysis and risk assessment of this sector help us mitigate the ecological risk posed to our economic and financial systems in particular and to other ecosystems in general. We focus on the healthcare sector because we have observed an unprecedented crisis in the form of the COVID-19 crisis in 2020. Our risk measurement of healthcare educates us on the risks this sector poses and the need to keep the sector within reasonable risk so that any future pandemic crisis can easily be dealt with. Finally, the financial sector is in the business of providing resources not only to ESG and healthcare sectors but also to other sectors that are important for the sustainability of all the socio-economic sectors. The risk analysis and risk measurement of this sector provides us with an idea of where we stand with respect to financing resources so that we do not run into a problem in the case of financing needs. Because the financial sector is in the business of risk-taking, this sector also provides us with an opportunity to do a comparative analysis.

Ecology-related risk analyses are instrumental in evaluating the probability of future climate hazards and their potential impacts on cities and communities (de Goër de Herve et al., 2023). Furthermore, these analyses contribute to the prevention and preparedness for different risk contexts enabling proactive measures to mitigate risks and ensure the well-being of populations. This information is essential for guiding the prioritization of climate action and making informed decisions regarding investments in adaptation measures (Wu et al., 2022). 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. Ecological risks and environmental costs are both relevant factors to consider when analyzing the risks in the ESG, financial, and healthcare sectors (Asefi-Najafabady et al., 2021; Gholami et al., 2022). Ecological risks refer to the potential harm or damage caused to ecosystems and the environment by human activities, which could ultimately lead to environmental costs, such as the costs of pollution control and remediation (Donou-Adonsou, 2022). In the context of ETFs, ecological risks and environmental costs can arise from the companies included in the ETFs' portfolios and their business practices. The assessment of these risks and costs can be useful in evaluating the overall sustainability and social responsibility of ETFs. Therefore, incorporating ESG factors into ETF analysis is essential for investors who prioritize sustainability in their investment strategies. More specifically, 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 (for context, see 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 (for context, see 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.

According to some estimates, the effects of climate change put US$693 billion at risk, and the majority of those risks are expected to materialize by 2024 (Carbon Disclosure Project, 2019). According to Dietz et al. (2016), the projected "climate Value-at-Risk" under the business-as-usual scenario is US$2.5 trillion. Ecological risks are relevant in cases where businesses are exposed to environmental risks or invest in companies that are involved in environmentally harmful activities (Ilhan et al., 2022; Moore, 2015). Battiston et al. (2017) also stressed the link between investment 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

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

[3] ESG sector is not a sector analogous to healthcare and financial sector, but to be consistent, we use ESG sector in this article.

shifting regulations that 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 (Chen et al., 2018). Investing in the effective treatment of diseases is crucial to minimize the impact on the population within the network (Huang et al., 2022). Healthcare ETFs, which exhibit a greater degree of specialization in their investment strategies compared to their mutual fund counterparts, often track an index comprising the healthcare sector that encompasses various healthcare risks.

In terms of contribution to the risk analysis literature, this is the firfst study to provide comprehensive risk analysis and risk assessment of ESG, healthcare, and financial sectors. Our approach to modeling risks is based on a novel EVT. More specifically, our study contributes to the literature in the following 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. 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 EVT-based studies only focus on stock, bond, or foreign exchange markets (Hartmann et al., 2004; Straetmans & Chaudhry, 2015). Second, we estimate the extreme quantiles for p-values of 0.2% or 0.1%. This means that the tail-value-at-risks (VaRs) are estimated to be triggered every 500 or 1000 days, respectively. This is the hallmark of EVT and has never been applied to the evaluation of the risk associated with ESG and healthcare sectors. Most of the literature on systemic risk measurement does not go beyond p-values of 1% as they draw upon quantile regression (Adrian & Brunnermeier, 2016), dynamic conditional correlation (Brownlees & Engle, 2017), and CoRisk (Chan-Lau, 2010). The EVT methodology allows us to go further into the tail of the distribution. Third, the tail risk and systemic risk measurements are estimated using semi-parametric estimation procedures to avoid misspecification of parametric probability distributions. It is because tail risk and systemic risk estimates are likely to be heavily distorted by incorrect distribution assumptions. Fourth, we use multivariate EVT to calculate the extreme systemic risk (tail-β) by considering 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 factor. There is no other article that has used these comprehensive conditional factors in calculating extreme systemic risk except one study by Straetmans and Chaudhry (2015), which uses only the bank index, stock market index, bond, and real estate market index for the United States and Europe. We use green energy, traditional energy, high-tech, and bond ETFs as conditioning factors as their impact on ESG, healthcare, and financial sectors could potentially be different. Finally, we measure the extent to which a shock in expected joint crashes and multivariant spills over risk within the ESG, healthcare, and financial ETFs.

Our risk modeling and analysis reveal the following key findings: First, the financial sector is the riskiest when we consider the tail index, tail quantile, and tail expected shortfall (ES). 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 and the COVID-19 crisis are examples of such shocks. Second, for extreme systemic risk (tail-β), we find that the ESG sector is most exposed to all 10 shocks while the shock that originates from China presents the highest risk. The healthcare and financial sectors exhibit similar risks for all shocks for traditional energy and green energy. This shows that both the healthcare and financial sectors are sensitive to a shock from the energy sectors and particularly from the green energy sectors. Finally, we find that ESG and healthcare sectors have lower extreme spillover risk (contagion risk) compared to the financial sectors. 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 risk modeling and assessment of the risks associated with ESG, healthcare, and financial sectors.

The remainder of the article is organized as follows: Section 2 provides relevant literature reviews on ESG, financial, and healthcare risk management, as well as EVT; 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 & Thompson, 1999). Numerous environmental activities are documented in existing studies, though the risks to them are rarely analyzed. For instance, few studies demonstrate the integration of corporate social responsibility into environmental activities (Hainmueller & 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 & Kaźmierkiewicz, 2015; Gil & 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 IPCC has warned, having an irreversible effect on ecosystems, societies, and economies. Many governments, businesses, and organizations have committed to achieving net-zero emissions of greenhouse gases by 2050 or sooner to address this issue. 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 & 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 United Kingdom, 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). 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 even before the implementation of rules, suggesting that further disclosure obligations may not significantly impact their business operations. Hence, it is essential to strike a 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. Leuz et al. (2009) found that corporations with lax governance norms and inadequate disclosure of nonfinancial (ESG) information may face the risks of attracting fewer investments from overseas owners. Furthermore, Serafeim and Grewal (2017) suggested 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) 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.

The increasing degradation of the climate on earth brought on by human actions like the combustion of fossil fuels and deforestation puts the globe in the midst of a climate emergency. Among the terrible consequences of this are increasing temperatures, sea level rise, more frequent and severe natural catastrophes, a loss of biodiversity, and risks to human health and well-being.

Environmental problems, such as the continual extinction of species and the destruction of ecosystems due to human activities, are also well known. This encompasses, among other things, deforestation, pollution, habitat damage, and overfishing. The decline of ecosystems and biodiversity has negative implications on human society, including those on food security, access to water, and cultural legacies.

In order to solve these concerns, governments, businesses, and individuals throughout the globe will need to act right away to cut greenhouse gas emissions, convert to renewable energy sources, protect and restore ecosystems, and move toward more sustainable and fair economic systems.

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 (Barber et al., 2019; Batrancea & Nichita, 2015; Cleverly, 1978; IBM, 2022; Jeurissen, 2010; Popesko et al., 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 aging 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 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, 2016).

Assuming that rural healthcare providers face greater risks and lower returns, Siedlecki et al. (2016) conducted an evaluation and comparison of rural and urban hospitals in Poland. They use various metrics, including hospital indebtedness rate, labor costs, net income margin, operational margin ratio, and return on assets, to analyze 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 Guimaraes and Nossa (2010) focused 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) examined the financial and nonfinancial 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 except for 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) concluded 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 EVT (e.g., see Liu, 2013). It has also been used to analyze 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), and Straetmans et al. (2008). EVT is one of the best methods, according to Zhao (2020), for analyzing 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 suggested 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) used 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. Moreover, tail behavior 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) examined extreme market risk for various stock and volatility indices by applying univariate EVT. 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 worth noting example of using EVT in risk modeling, Straetmans and Chaudhry (2015) used this methodology to evaluate the possibility of financial distress for certain institutions as well as exposure for specific banks. They discovered that systemic risk and tail risk are both lower in the Eurozone than in the United States. Their finding is consistent with an earlier study by Hartmann et al. (2004) using multivariate EVT to analyze the systemic and contagion risks for the United States 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 United States appear to have the sharpest rises in excessive systemic risk. Gkillas and Katsiampa (2018) also used EVT to analyze risk in the crypto market and to study the tail risk behavior. 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 ES. On the other hand, the 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 EVT is also used by Osterrieder and Lorenz (2017) to analyze risk in the crypto markets.

In light of the studies that we discussed in this section, it is prima facie evident that EVT has been widely applied in financial markets to model and evaluate tail risk, systemic risk, and spillover risk. Despite its advantages, EVT has not been applied to the analyses of tail risk, systemic risk, and spillover risk in ESG, healthcare, and financial sectors as these sectors pose extreme challenges to the global economic and financial system as we have seen in the form of the global financial crisis of 2007–08 and COVID-19 crisis. Concomitantly, in this study, we draw on the EVT to model and analyze 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 tail risk, systemic risk, and spillover risk evaluations. Based on the data available on the Bloomberg database, we obtain healthcare and financial ETFs' daily equity returns from 1 July 1999 to 30 June 2022. Additionally, we obtain ESG ETF's daily returns from 1 July 2007 to 30 June 2022. Our selection criteria are the top 10 ESG, healthcare, and financial ETFs by NAV, and we use all the data that are available. These 3 groups are limited to the top 10 ETFs because their sizes diminish after the top 10. Among our selected ETFs, some focus on global markets, but most are based in the United States. For tail-β or extreme systemic risk estimation, we also use the ETF data from the Bloomberg database to calculate the extreme systemic risk of ESG, healthcare, and financial sectors across certain worldwide markets (e.g., China, Europe, Eurozone, United Kingdom, and United States), and certain ETF categories (e.g., green energy, traditional energy, high-tech, and bonds). We also perform tail risk, extreme systemic risk, and extreme spillover temporal analyses using the 7-year rolling windows for all the ESG, healthcare, and financial sectors to identify the time series risk exposure of these sectors.

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 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 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 generalized Pareto distribution.

We examine the quantile χ for extremely low values of $P = p\{X > \chi\}$ using the semi-parametric estimator developed by De Haan et al. (1994):

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

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

We use the Hill (1975) estimator to derive α in Equation (1), from which the following equation is derived:

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

where m represents the number of extreme returns evaluated in the estimation. In our study, we adopt $m = 300$ as our main investigation for ESG, healthcare, and financial ETFs (see Table 1).[4] 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 ES estimator is obtained, as shown in the following equation:

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

The tail quantiles are calculated for probability values from 0.2% to 0.1% (see Table 1), which means that the tail quantiles are expected to be violated every 500 and 1000 days, respectively. Moreover, we examine the ES estimated based on the $p(\%)$ tail-VaRs and crisis barriers $x = 25\%$ and $x = 50\%$. Lastly, ES measurements are reported with varying thresholds x, which are used to determine the extreme ES measurements when the extreme quantile estimates $(\widehat{x_p})$ 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 the misspecification of parametric probability distributions. It is because systemic risk estimates are likely to be heavily distorted by incorrect distribution assumptions.

[4] As a robustness test, we also use $m = 200$, but our results generally remain the same.

The following equation 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 the 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, and the systemic risk estimator decreases with threshold q and eventually reaches zero if $q \to \infty$. Nevertheless, when $\alpha = 1$ as we assumed throughout our analyses, changes in q no longer affect systemic risk.

The following equation is used as another systemic risk measure:

$$\hat{E}\left[\theta|\theta \geq 1\right] \approx \frac{N}{\frac{n}{k}\frac{1}{n}\sum_{i=1}^{N} U_{i=1}^{N} X_i > X_{i,n-k}}. \tag{5}$$

As shown in Equation (5), an estimator of the stable tail dependence function $l(.)$ is used as the denominator (Straetmans & Chaudhry, 2015). Quantile $Q_i(\frac{k}{n})$ 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 sectors. 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 sectors

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 ES for the top 10 ESG (Panel I), healthcare (Panel II), and financial sectors (Panel III), respectively. In all three panels, we use the nuisance parameter $m = 300$ as our main investigation.[5] 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 or 1000 days, respectively. We also calculate the ES conditional upon crisis barriers of $s = 25\%$ or 50% in addition to the p-values of 0.2% or 0.1%.

In the healthcare sector, 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. 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 stated 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. Indeed, Djalante et al. (2020) called for the integration of disaster resilience strategies, and utilization of the health-emergency disaster risk management framework to complement the response to COVID-19 and similar phenomena in the future. Although studies suggest that healthcare companies may not be fully managing all their risks (e.g., medical waste) well (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 finance-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 conducting risk analyses to test new products requires substantial investment (Goble & 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, healthcare, and financial companies, for example, 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, in the context of ecology-related risk analysis, it is important to consider the broader implications of an investment strategy that focuses on building resilience by addressing the underlying causes of negative events (de Goër de Herve et al., 2023; Wu et al., 2022). For example, 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

[5] As robustness test, we have also used nuisance parameter $m = 200$, in addition to $m = 300$ in the revised version of the article and our results remain the same generally. We do not report these results in the article for the sake of brevity.

TABLE 1 Full samples estimates of tail risk indicators for environment, social, and governance (ESG), healthcare, and financial sectors.

		$x(p)$		ES($x(p)$)		ES($X > s$)	
	α	$p = 0.1\%$	$p = 0.2\%$	$p = 0.1\%$	$p = 0.2\%$	$s = 25\%$	$s = 50\%$
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

(Continues)

TABLE 1 (Continued)

	α	$x(p)$		ES($x(p)$)		ES($X > s$)	
		$p = 0.1\%$	$p = 0.2\%$	$p = 0.1\%$	$p = 0.2\%$	$s = 25\%$	$s = 50\%$
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**

Abbreviation: ETF, exchange-traded fund.

debates (Nasir et al., 2020; Wang et al., 2022). Such events carry substantial ecological and social ramifications, leading to setbacks in prevention and recovery efforts aimed at mitigating these detrimental risks and causes of climate change. Investment portfolios incorporating ESG and financial ETFs are thus exposed to risks beyond purely financial considerations. 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, for example, Apple, Microsoft, Amazon, Alphabet, Tesla, and NVIDIA. Investments by companies in innovative technologies aimed at mitigating the risks associated with future epidemics can have significant implications in the realm of social science and ecological risk (Huang et al., 2022). The recalibration of equity markets in response to higher interest rates, as highlighted by Roychowdhury and Srinivasan (2019), may introduce market instability. However, prioritizing responsible corporate behavior has the potential to reduce volatility and subsequently lower risk, as noted by Renn et al. (2022). Consequently, ETFs with substantial allocations to technology stocks face heightened exposure to risk in this context. Although Iyer et al. (2020) found that the specialized education of the board of directors can reduce governance risks for high-tech companies, our findings suggest that investors should always check the investment strategies of ETFs 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 ESs 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 1000 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 ES value of 70.5975% of the 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 ES 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 ES (ES$x(p)$). Our findings contradict Cornell's (2021) findings that highly rated ESG companies have lower risks and lower expected investment returns for investors. However, the higher risk observed in ESG and financial ETFs, especially those with a specific focus on investment in mitigating ecological risks, could be attributed to factors such as under-regulation and competition. Furthermore, the rapidly growing development of advanced technologies has led to new synergies between financial and nonfinancial activities that may cause systemic risks in the market for ESG and financial ETFs. Therefore, investors should be cautious and carefully evaluate the composition and potential risks of ETF portfolios before investing.

In order to look at the temporal changes in the tail risk of ESG, healthcare, and financial sectors, we demonstrate the 7-year average rolling tail risk for ESG, healthcare, and financial ETFs. The results are provided in Figure 1. Figure 1(1.1) provides a rolling tail index of ESG, healthcare, and financial sectors. Because the data for the ESG ETFs goes back

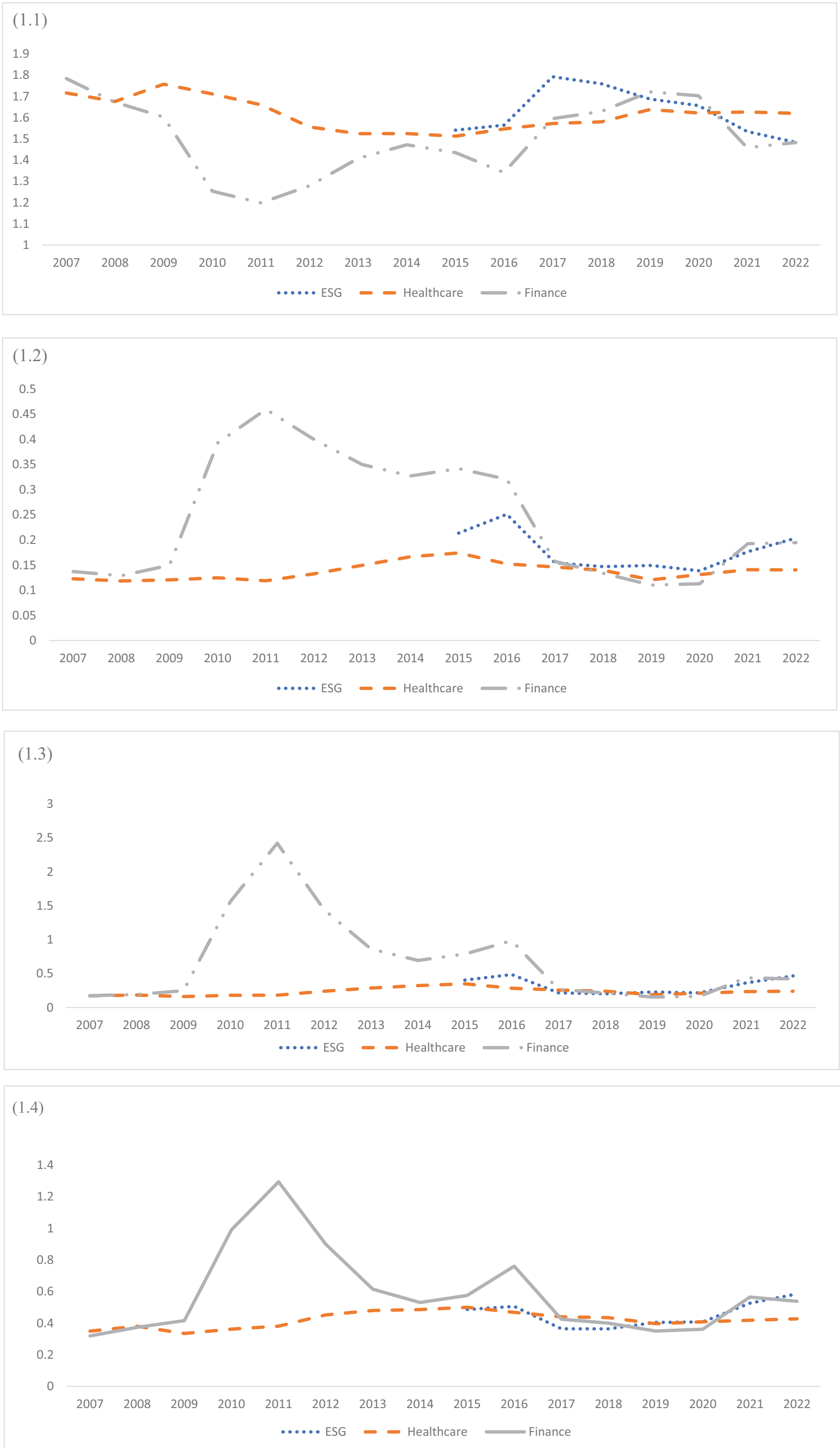

FIGURE 1 The rolling tail risk of environmental, social, and governance (ESG), healthcare, and financial exchange-traded funds (ETFs): (1.1) rolling tail index of ESG, healthcare and financial ETFs; (1.2) rolling tail quantile of ESG, healthcare, and financial ETFs; (1.3) rolling expected shortfall of ESG, healthcare, and financial ETFs; (1.4) rolling expected shortfall conditional upon 25% threshold of ESG, healthcare, and financial ETFs.

only until July 2007, the start date of the ESG ETF in Figure 1(1.1) is from 2014 due to the 7-year rolling window. We also present the rolling tail quantile (Figure 1(1.2)), rolling ES (Figure 1(1.3)), and rolling ES conditional upon 25% (Figure 1(1.4)). In Figure 1(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, whereas 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 regarded by investors as a means to mitigate the potential loss of returns and diversify portfolio risks in response to climate change risks and their associated adverse effects. 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-quality healthcare services and a significant demand for healthcare-related products (Deng et al., 2023).

The rolling tail quantile and ES metrics (Figure 1(1.2–1.4)) 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(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. Although studies (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 & Renn, 2021; Renn et al., 2022).

According to Figure 1(1.3), the average rolling ES 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 ES, 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 ES 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 the regulation of financial and ESG-related activities (Klinke & Renn, 2021). The rolling tail ES 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(1.4)).

4.2 | Extreme systematic risk of ESG, healthcare, and financial sectors

In this section, we estimate the exposure of the top 10 ETFs in ESG, healthcare, and financial sectors, 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 ETFs in Panels 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 ($\beta s = 0.32147$). Among both the healthcare ($\beta s = 0.455846902$) and financial ($\beta s = 0.483737585$) 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-$\beta s = 0.3022$ 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 3 out of 10 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 Panel III in Table 2, these financial ETFs are more exposed to extreme systematic risk

TABLE 2 Extreme systematic risk (tail-βs) for environmental, social, and governance (ESG), healthcare, and financial sectors.

	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**

(Continues)

TABLE 2 (Continued)

	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 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**

Abbreviation: ETF, exchange-traded fund.

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 holding companies in the healthcare ETFs are headquartered in the United States, 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 United States, 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 10 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.

Similar to the tail risk temporal plots, we also explore the temporal changes in the extreme systemic risk of ESG, healthcare and financial sectors. We use 7-year average rolling windows to calculate the extreme systemic risk. The results are provided in Figure 2. As shown in Figure 2(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 United Kingdom, EU, China, and the USA). As for the types of ETFs, we cover technology, energy, green energy, and aggregate bonds (see Figure 2(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

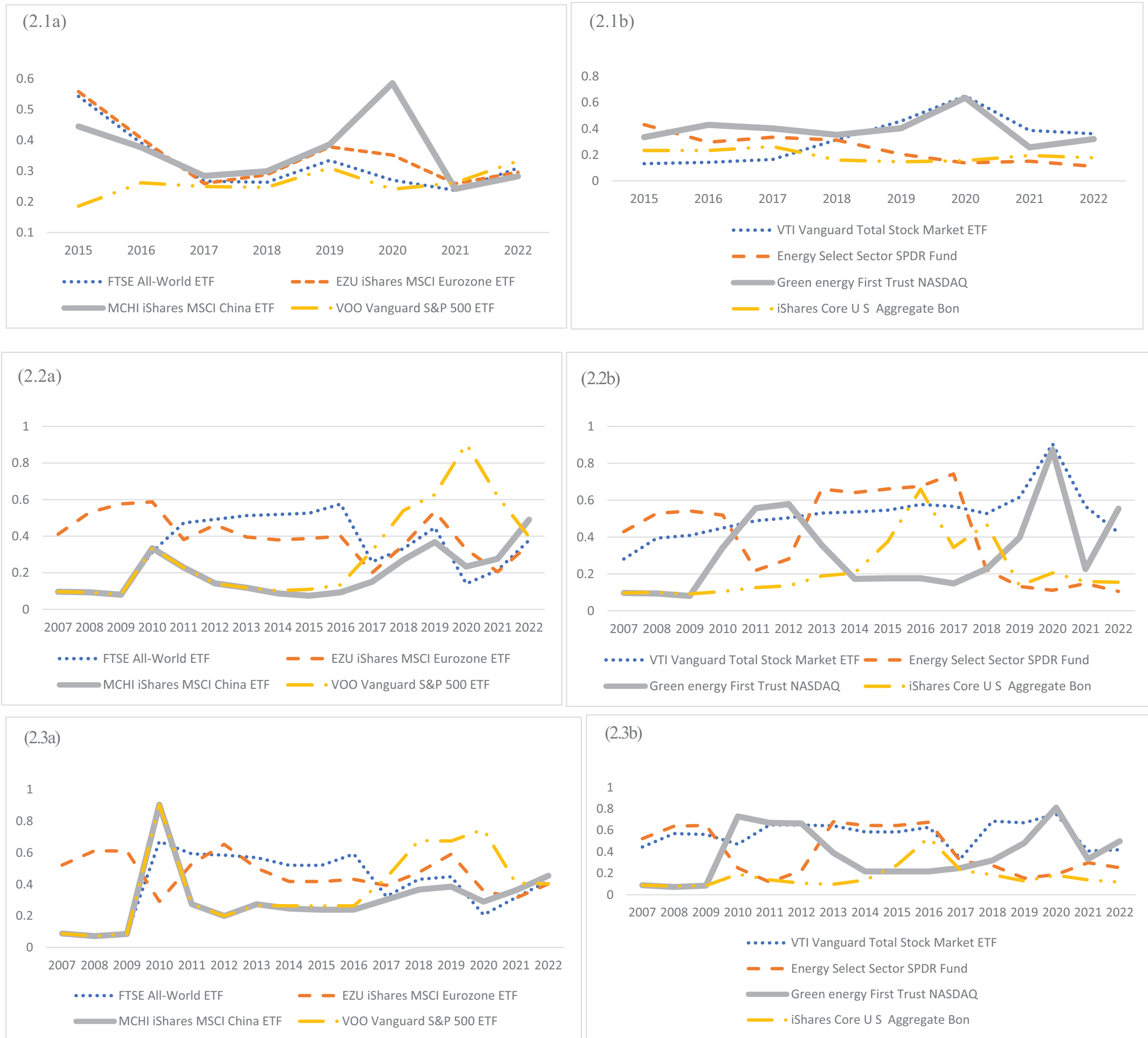

FIGURE 2 Rolling tail-betas of environmental, social, and governance (ESG), healthcare, and finance exchange-traded funds (ETFs) conditional upon certaint country level ETFs and certain types of ETFs: (2.1a) rolling tail-betas of ESG ETFs conditional upon certain country level ETFs; (2.1b) rolling tail-betas of ESG ETFs conditional upon certain ETFs; (2.2a) rolling tail-betas of healthcare ETFs conditional upon certain country level ETFs; (2.2b) rolling tail-betas of healthcare ETFs conditional upon certain ETFs; (2.3a) rolling tail-betas of finance exchange-traded funds (ETFs) conditional upon certain country level ETFs; (2.3b) rolling tail-betas of finance exchange-traded funds (ETFs) conditional upon certain ETFs.

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 Figure 2(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 1 year of the pandemic, suggesting that some brokers may want to invest in these markets to hedge against the financial crisis (Lean & 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(2.1a)), but lower in the United States (VOO Vanguard S&P 500 ETF, see Figure 2(2.2a and 2.3a)) for healthcare and financial ETFs.

4.3 | Spillover risk of ESG, healthcare, and financial sectors

Table 3 illustrates the multivariate spillover risk for ESG, healthcare, and financial sectors 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 eco-

TABLE 3 Spillover risk of environmental, social, and governance (ESG), healthcare, and financial sectors.

	Parameters	ESG	Healthcare	Finance
Expected joint crashes ($1 < E < 10$)	$m = 200$	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.

nomic 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 & Serafeim, 2021). Therefore, ESG ETFs may also be an attractive option for investors seeking to minimize their exposure to ecological risks in their portfolios.

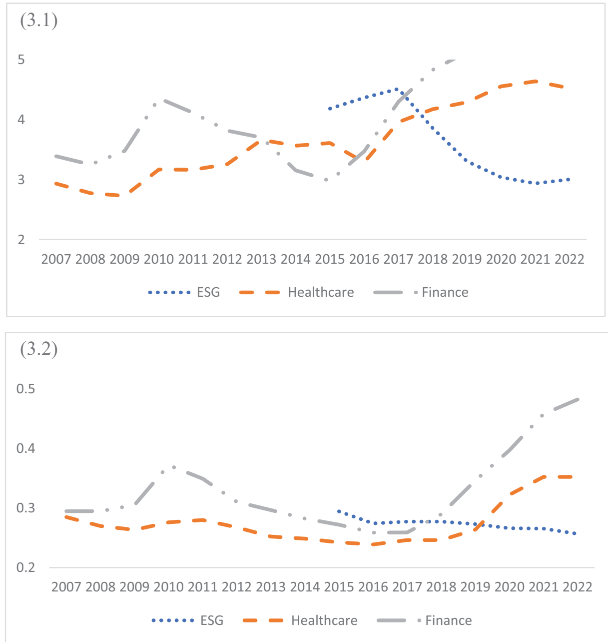

FIGURE 3 Time-varying spillover risk: (rolling) expected co-crash indicators and co-crash probabilities for environmental, social, and governance (ESG), healthcare, and finance exchange-traded funds (ETFs): (3.1 and 3.2) expected joint crashes ($1 < E < 10$).

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 7-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 a 7-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(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 the 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 three 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(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 although ESG investing can be a useful tool to encourage companies to prioritize environmental and social issues, it is also important to recognize 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 emphasizes 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 is crucial for investors to consider not only the ecological risks but also the social risks when evaluating their investment options.

5 | CONCLUSION

To tackle the ecological challenges and achieve environmental goals, it is important to understand the ecological, socio-economic, 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, governance, healthcare, and financial sectors. We model risk by employing statistical EVT to estimate indicators of tail risk, extreme systemic risk, and extreme spillover risk of ESG, healthcare, and financial ETFs. Tail risk refers to the downside risk in each sector (ESG, healthcare, or financial sector), and extreme systemic risk (tail-β) is the exposure to extreme systemic shock. We use 10 different conditioning factors as measures of extreme systemic shock. These factors are as broad as the whole world and also cover all the major economic regions, namely, the USA, China, and Europe. We also include unique macro shocks like traditional energy, green energy, and bonds. Finally, the extreme spillover risk is an expected number of co-crashes if there is a crash in one ETF or a multivariate probability of a joint drop of other ETFs if there is a drop in one. As our study makes stakeholders, including policymakers, investors, employees, and society, at large aware of the risks that these sectors pose, these stakeholders can make informed decisions to continue maintaining investments that will lead to solving the challenges to the environment, socio-economic, governance, and health underpinning climate change.

Our risk modeling 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, whereas the ESG sector reveals the lower risk in the tail ES. On the contrary, the financial sector exhibits the highest risk in both the tail quantile and the tail ES. 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 shocks 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.

Our article has implications for climate change risk management that could be useful for international and national organizations, governments, and corporations. The risk modeling 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 extreme 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.

The integration of the healthcare, financial, and ESG sectors also offers important insights that may guide policy in the areas of risk analysis, assessment, and management. First, it is clear that ESG risks may have a significant impact on the financial and healthcare industries. Therefore, it is essential that policymakers give ESG issues a top priority when developing frameworks for these sectors' risk analysis and evaluation. This might include integrating ESG considerations in financial reporting standards and urging healthcare businesses to do the same while formulating their strategic plans. Second, to address ESG concerns, the healthcare and finance industries need to work together and coordinate better. As an example, financial companies that invest in healthcare companies should take steps to communicate with these companies about ESG issues and encourage them to improve their ESG performance. To ensure that ESG risks are successfully handled in their operations, healthcare institutions should work closely with financial institutions. Third, policymakers need to assess how incentives and legislation may help the healthcare and finance industries promote ESG risk management. This may include establishing rules and guidelines requiring businesses to report on their ESG performance and offering rewards to those that give ESG considerations a high priority in their operations and investment choices. Therefore, the relationship among the financial, healthcare, and ESG sectors should be taken into consideration in a more integrated approach to risk analysis, appraisal, and management. By tackling ESG risks in a comprehensive and coordinated way, policymakers may promote robust, sustainable healthcare and financial systems that have a greater capacity to manage risk in the future.

Our results also have several significant implications for practitioners in ESG, healthcare, and finance sectors. First, by recognizing possible risks and their potential implications, businesses and governments may take steps to manage risks and reduce the likelihood of adverse results. This may assist to protect stakeholders in addition to maintaining the financial and healthcare sectors' sustainability and resilience. Second, risk analysis in the financial and healthcare sectors may also lead to more openness. By identifying possible risks and their potential repercussions, businesses and governments may inform stakeholders, such as investors, employees, patients, and the general public, more extensively and openly. This could encourage more accountability and trust-building. Third, the outcomes may also be utilized to direct policy in the healthcare and financial sectors. By identifying potential sources of these risks, regulators may take steps to lower systemic risk as well as other risks, improving financial stability and resilience. As a consequence, financial crises and other negative outcomes could be less probable.

In light of the importance of the Precautionary Principle highlighted in Article 3 of the United Nations Framework Convention on Climate Change (UNFCCC) (1992) and its wide interpretation in risk management, it is worth noting that the principle now seems to necessitate an emphasis on overweighting risk and frontloading responses. This approach is crucial to avoid irreversible effects and amplification problems. These problems can include the exacerbation of climate change impacts, the escalation of environmental degradation, the intensification of social and economic inequalities, and the compounding of adverse effects on ecosystems and human well-being. More specifically, Article 3 (3) of the UNFCCC (1992) emphasizes the critical role of precautionary measures in addressing climate change and minimizing its adverse effects. It emphasizes that the lack of complete scientific certainty should not serve as a justification for postponing necessary actions when there are threats of serious or irreversible damage. By embracing a precautionary approach, we can effectively reduce the potential amplification of these problems and strive toward sustainable and resilient solutions. Overall, the ESG, healthcare, and financial sectors are strongly influenced in terms of risk management, transparency, decision-making, and regulation. By implementing a thorough and integrated risk analysis approach, businesses and policymakers can help ensure the sustainability and resilience of these important sectors, protect the stakeholders, and promote more sustainable and resilient results.

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ORCID

Muhammad Ali Nasir https://orcid.org/0000-0003-2779-5854

REFERENCES

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *American Economic Review*, *106*(7), 1705–1741.

Albarrak, M. S., Elnahass, M., & Salama, A. (2019). The effect of carbon dissemination on cost of equity. *Business Strategy and the Environment*, *28*(6), 1179–1198.

Allen, D. E., Singh, A. K., & Powell, R. J. (2013). EVT and tail-risk modelling: Evidence from market indices and volatility series. *North American Journal of Economics and Finance*, *26*, 355–369.

Asefi-Najafabady, S., Villegas-Ortiz, L., & Morgan, J. (2021). The failure of Integrated Assessment Models as a response to 'climate emergency' and ecological breakdown: The Emperor has no clothes. *Globalizations*, *18*(7), 1178–1188.

Bătrâncea, L., & Nichita, A. (2015). Which is the best government? Colligating tax compliance and citizens' insights regarding authorities' actions. *Transylvanian Review of Administrative Sciences*, *11*(44), 5–22.

Barber, S. L., Lorenzoni, L., & Ong, P. (2019). Price setting and price regulation in health care: Lessons for advancing Universal Health Coverage [No. WHO/WKC-OECD/K18014]. World Health Organization.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, *7*(4), 283–288.

Battiston, S., & Martinez-Jaramillo, S. (2018). Financial networks and stress testing: Challenges and new research avenues for systemic risk analysis and financial stability implications. *Journal of Financial Stability*, *35*, 6–16.

Brownlees, C., & Engle, R. F. (2017). SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies*, *30*(1), 48–79.

Bui, A., Johnson, F., & Wasko, C. (2019). The relationship of atmospheric air temperature and dew point temperature to extreme rainfall. *Environmental Research Letters*, *14*(7), 074025.

Carbon Disclosure Project. (2019). *World's biggest companies face $1 trillion in climate change risks*. Carbon Disclosure Project. https://www.cdp.net/en/articles/media/worlds-biggest-companies-face-1-trillion-in-climate-change-risks

Chan-Lau, J. A. (2010). Regulatory capital charges for too-connected-to-fail institutions: A practical proposal. *Financial Markets, Institutions and Instruments*, *19*, 355–380.

Chaudhry, S. M., Ahmed, R., Huynh, T. L. D., & Benjasak, C. (2022). Tail risk and systemic risk of finance and technology (FinTech) firms. *Technological Forecasting and Social Change*, *174*, 121191.

Chen, H., Estes, J., & Pratt, W. (2018). Investing in the healthcare sector: Mutual funds or ETFs. *Managerial Finance*, *44*, 495–508.

Chen, X., Chen, X., Xu, L., & Wen, F. (2022). Attention to climate change and downside risk: Evidence from China. *Risk Analysis*, *43*, 1011–1031.

Cleverley, W. O. (1978). Profitability analysis in the hospital industry. *Health Services Research*, *13*(1), 16–27.

Cornell, B. (2021). ESG preferences, risk and return. *European Financial Management*, *27*(1), 12–19.

Creixans Tenas, J., & Arimany-Serrat, N. (2018). Influential variables on the profitability of hospital companies. *Intangible Capital*, *14*(1), 171–185.

Cumperayot, P. J., Danielsson, J., Jorgensen, B. N., & de Vries, C. G. (2000). On the (Ir) relevancy of value-at-risk regulation. In *Measuring risk in complex stochastic systems* (pp. 99–117). Springer.

Czerwińska, T., & Kaźmierkiewicz, P. (2015). ESG rating in investment risk analysis of companies listed on the public market in Poland. *Economic Notes: Review of Banking, Finance and Monetary Economics*, *44*(2), 211–248.

Danielsson, J., & De Vries, C. G. (2000). Value-at-risk and extreme returns. *Annals of Economics and Statistics*, *60*, 239–270.

de Goër de Herve, M. G., Schinko, T., & Handmer, J. (2023). Risk justice: Boosting the contribution of risk management to sustainable development. *Risk Analysis*, 1–15. https://doi.org/10.1111/risa.14157

De Haan, L., Jansen, D. W., Koedijk, K., & de Vries, C. G. (1994). *Safety First Portfolio Selection, Extreme Value Theory And Long Run Asset Risks, Extreme Value Theory And Applications*, Springer, pp. 471–487.

Deng, Q., Xiao, X., Zhu, L., Cao, X., Liu, K., Zhang, H., Huang, L., Yu, F., Jiang, H., & Liu, Y. (2023). A national risk analysis model (NRAM) for the assessment of COVID-19 epidemic. *Risk Analysis*. https://doi.org/10.1111/risa14087

Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). 'Climate value at risk' of global financial assets. *Nature Climate Change*, *6*(7), 676–679.

Djalante, R., Shaw, R., & DeWit, A. (2020). Building resilience against biological hazards and pandemics: COVID-19 and its implications for the Sendai Framework. *Progress in Disaster Science*, *6*, 100080.

Donou-Adonsou, F. (2022). The effects of health conditions on financial sector development. *Economic Modelling*, *114*, 105947.

Fankhauser, S., & McDermott, T. K. (2014). Understanding the adaptation deficit: Why are poor countries more vulnerable to climate events than rich countries? *Global Environmental Change*, *27*, 9–18.

Galletta, S., & Mazzù, S. (2023). ESG controversies and bank risk taking. *Business Strategy and the Environment*, *32*(1), 274–288.

Gholami, A., Sands, J., & Rahman, H. U. (2022). Environmental, social and governance disclosure and value generation: Is the financial industry different? *Sustainability*, *14*(5), 2647.

Gil, L., & Bernardo, J. (2020). An approach to energy and climate issues aiming at carbon neutrality. *Renewable Energy Focus*, *33*, 37–42.

Gkillas, K., & Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters*, *164*, 109–111.

Goble, R., & Bier, V. M. (2013). Risk assessment can be a game-changing information technology-but too often it isn't. *Risk Analysis*, *33*(11), 1942–1951.

Guimaraes, A., & Nossa, V. (2010). Working capital, profitability, liquidity and solvency of healthcare insurance companies. *BBR—Brazilian Business Review*, *7*(2), 37–59.

Hainmueller, J., & Hiscox, M. J. (2015). *Buying green? Field experimental tests of consumer support for environmentalism* [Working Paper]. Harvard University.

Hallegatte, S., & Rentschler, J. (2015). Risk management for development—Assessing obstacles and prioritizing action. *Risk Analysis*, *35*, 193–210.

Hansen, J., Sato, M., Kharecha, P., Von Schuckmann, K., Beerling, D. J., Cao, J., Marcott, S., Masson-Delmotte, V., Prather, M. J., Rohling, E. J., & Shakun, J. (2017). Young people's burden: Requirement of negative CO_2 emissions. *Earth System Dynamics*, *8*(3), 577–616.

Hartmann, P., Straetmans, S., & Vries, C. D. (2004). Asset market linkages in crisis periods. *Review of Economics and Statistics*, *86*(1), 313–326.

Health Management (2016). A Closer Look at Financial Performance in Healthcare (Vol. 16) HealthManagement.org. https://healthmanagement.org/c/healthmanagement/issuearticle/a-closer-look-at-financial-performance-in-healthcare-1. (Access date: 17/12/2022)

Hill, B. M. (1975). A simple general approach to inference about the tail of a distribution. *The Annals of Statistics*, *3*(5), 1163–1174.

Huang, C. D., Baghersad, M., Behara, R. S., & Zobel, C. W. (2022). Optimal investment in prevention and recovery for mitigating epidemic risks. *Risk Analysis*, *42*(1), 206–220.

IBM. (2022). *Healthcare performance measurements*. IBM. https://www.ibm.com/watson-health/learn/healthcare-performance-measurements

Ilhan, E., Krueger, P., Sautner, Z., & Starks, L. T. (2022). *Climate risk disclosure and institutional investors* [Swiss Finance Institute Research Paper No. 19-66].

Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*, *34*(3), 1540–1571.

Ioannou, I., & Serafeim, G. (2021). *Corporate sustainability: A strategy?* [Harvard Business School Accounting & Management Unit Working Paper No. 19-065].

Iyer, S. R., Sankaran, H., & Walsh, S. T. (2020). Influence of director expertise on capital structure and cash holdings in high-tech firms. *Technological Forecasting and Social Change*, *158*, 120060.

Jeurissen, P. (2010). *For-profit hospitals: A comparative and longitudinal study of the for-profit hospital sector in four Western countries*. Erasmus University Repository.

King, R. (2022). *Large hospitals chains post profits in 2020 thanks to higher acuity and liquidity*. Fierce Healthcare. https://www.fiercehealthcare.com/hospitals/large-hospital-chains-post-profits-2020-thanks-to-higher-acuity-and-liquidity

Kirkland, L. H., & Thompson, D. (1999). Challenges in designing, implementing and operating an environmental management system. *Business Strategy and the Environment*, *8*(2), 128–143.

Klinke, A., & Renn, O. (2021). The coming of age of risk governance. *Risk Analysis*, *41*(3), 544–557.

Kron, W., Löw, P., & Kundzewicz, Z. W. (2019). Changes in risk of extreme weather events in Europe. *Environmental Science & Policy*, *100*, 74–83.

Lábaj, M., Peter Silanič, P., Weiss, C., & Yontcheva, B. (2018). Market structure and competition in the healthcare industry. *The European Journal of Health Economics*, *19*(8), 1087–1110.

Lean, H. H., & Pizzutilo, F. (2020). Performances and risk of socially responsible investments across regions during crisis. *International Journal of Finance & Economics*, *26*(3), 3556–3568.

Leuz, C., Lins, K. V., & Warnock, F. E. (2009). Do foreigners invest less in poorly governed firms? *The Review of Financial Studies*, *22*(8), 3245–3285.

Leuz, C., Nanda, D., & Wysocki, P. D. (2003). Earnings management and investor protection: An international comparison. *Journal of Financial Economics*, *69*(3), 505–527.

Lim, H., & Rokhim, R. (2021). Factors affecting profitability of pharmaceutical company: An Indonesian evidence. *Journal of Economic Studies*, *48*(5), 981–995.

Liu, B. (2013). Extreme value theorems of uncertain process with application to insurance risk model. *Soft Computing*, *17*(4), 549–556.

Manupati, V. K., Ramkumar, M., Baba, V., & Agarwal, A. (2021). Selection of the best healthcare waste disposal techniques during and post COVID-19 pandemic era. *Journal of Cleaner Production*, *281*, 125175.

Mattoo, A., Subramanian, A., Van Der Mensbrugghe, D., & He, J. (2009). *Reconciling climate change and trade policy* [Center for Global Development Working Paper No. 189].

McNeil, A. J., & Frey, R. (2000). Estimation of tail-related risk measures for heteroscedastic financial time series: An extreme value approach. *Journal of Empirical Finance*, *7*(3–4), 271–300.

Mirza, M. M. Q. (2003). Climate change and extreme weather events: Can developing countries adapt? *Climate Policy*, *3*(3), 233–248.

Moore, J. (2015). *Capitalism in the web of life: Ecology and the accumulation of capital*. Verso Books.

Nasir, M. A., Balsalobre-Lorente, D., & Huynh, T. L. D. (2020). Anchoring inflation expectations in the face of oil shocks & in the proximity of ZLB: A tale of two targeters. *Energy Economics*, *86*, 104662.

Neftci, S. N. (2000). Value at risk calculations, extreme events, and tail estimation. *The Journal of Derivatives*, *7*(3), 23–37.

Osterrieder, J., & Lorenz, J. (2017). A statistical risk assessment of Bitcoin and its extreme tail behavior. *Annals of Financial Economics*, *12*(01), 1750003.

Popesko, B., Novák, P., & Papadaki, Š. (2015). Measuring diagnosis and patient profitability in healthcare: Economics vs ethics. *Economics and Sociology*, *8*(1), 234–245.

Papanikolaou, N. I., & Wolff, C. C. (2014). The role of on-and off-balance-sheet leverage of banks in the late 2000s crisis. *Journal of Financial Stability*, *14*, 3–22.

Renn, O., Laubichler, M., Lucas, K., Kröger, W., Schanze, J., Scholz, R. W., & Schweizer, P. (2022). Systemic risks from different perspectives. *Risk Analysis*, *42*(9), 1902–1920.

Ripple, W., Wolf, C., Newsome, T., Barnard, P., Moomaw, W., & Grandcolas, P. (2020). World scientists' warning of a climate emergency. *Bioscience*, *70*(1), 8–12.

Romaniuk, P., Poznańska, A., Brukało, K., & Holecki, T. (2020). Health system outcomes in BRICS countries and their association with the economic context. *Frontiers in Public Health*, *8*, 80.

Roychowdhury, S., & Srinivasan, S. (2019). The role of gatekeepers in capital markets. *SSRN Electronic Journal*, *57*(2), 295–322.

Serafeim, G., & Grewal, J. (2017). *The value relevance of corporate sustainability disclosures: An analysis of a dataset from one large asset owner*. Available at SSRN 2966767.

Siedlecki, R., Bem, A., Ucieklak-Jeż, P., & Prędkiewicz, P. (2016). Rural versus urban hospitals in Poland. Hospital's Financial Health Assessment. *Procedia – Social and Behavioral Sciences*, *220*, 444–451.

Steffen, W., Rockström, J., Richardson, K., Lenton, T. M., Folke, C., Liverman, D., Summerhayes, C. P., Barnosky, A. D., Cornell, S. E., Crucifix, M., & Donges, J. F. (2018). Trajectories of the earth system in the Anthropocene. *Proceedings of the National Academy of Sciences*, *115*(33), 8252–8259.

Straetmans, S., & Chaudhry, S. M. (2015). Tail risk and systemic risk of US and Eurozone financial institutions in the wake of the global financial crisis. *Journal of International Money and Finance*, *58*, 191–223.

Straetmans, S. T., Verschoor, W. F., & Wolff, C. C. (2008). Extreme US stock market fluctuations in the wake of 9/11. *Journal of Applied Econometrics*, *23*(1), 17–42.

Teixeira, J. C. A., Silva, F. J. F., Ferreira, M. B. S., & Cabral Vieira, J. A. (2018). Sovereign credit rating determinants under financial crises. *SSRN Electronic Journal*, *36*, 1–13.

Too, J., Ejohwomu, O. A., Hui, F. K., Duffield, C., Bukoye, O. T., & Edwards, D. J. (2022). Framework for standardising carbon neutrality in building projects. *Journal of Cleaner Production*, *373*, 133858.

United Nations Framework Convention on Climate Change (UNFCCC). (1992). United Nations Framework Convention on Climate Change, New York, United Nations FCCC/INFORMAL/84GE.05-62220 (E) 200705. https://unfccc.int/resource/docs/convkp/conveng.pdf (Access date: 15/12/2022)

Wang, Y., Bouri, E., Fareed, Z., & Dai, Y. (2022). Geopolitical risk and the systemic risk in the commodity markets under the war in Ukraine. *Finance Research Letters*, *49*, 103066.

Wu, D. D., Mitchell, J., & Lambert, J. H. (2022). Global systemic risk and resilience for novel coronavirus in postpandemic era. *Risk Analysis*, *42*(1), 1–4.

Zhao, Z. (2020). Dynamic bivariate peak over threshold model for joint tail risk dynamics of financial markets. *Journal of Business, Economics and Statistics*, *39*(4), 892–906.

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