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Does ESG Investing Pay off? Comparing the Performance of ESG and Traditional ETFs Across European and US Markets

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ABSTRACT

Investors have long recognized the importance of firms in promoting sustainability, leading to the rise of socially responsible investment (SRI). Specifically, there is a growing preference for exchange-traded funds (ETFs) that prioritize environmental, social, and governance (ESG) principles. However, the performance of ESG ETFs has not been extensively studied, and existing findings remain inconclusive. This research addresses this gap by comparing ESG ETFs with traditional ETFs in Europe and the United States, analyzing the period 2014–2024, along with subperiods of pre-crisis (2014–2019) and crisis (2020–2024). The results show that ESG ETFs can offer diversification benefits, hedging capabilities, and safe-haven properties. However, performance outcomes vary across regions, investment strategies, and market conditions. In Europe, ESG ETFs improve risk-adjusted performance in utility-maximizing strategies. In the United States, ESG ETFs also enhance returns adjusted for risk in utility-maximizing portfolios during periods of market stress, though this advantage is less evident in more stable market conditions.

JEL Classification: G11, G15, G17, C32

1 | Introduction

Socially responsible investment (SRI) is an investment approach that incorporates environmental, social, and governance (ESG) ratings (Widyawati 2020). Recently, SRI has increased in significance, with the United Nations playing a pivotal role in its promotion. The commitment of this organization to sustainability can be traced back to 1992 when Agenda 21 was adopted at the Earth Summit in Rio de Janeiro. Subsequent efforts have led to various initiatives, with a significant milestone occurring in 2015 through the establishment of the 2030 Agenda for Sustainable Development. This agenda gave rise to the 17 Sustainable Development Goals (SDGs), serving as a guiding framework for SRI and significantly amplifying these investment practices (United Nations, n.d.). In recent years, regulations on disclosing sustainability actions have advanced significantly to meet investor needs and ensure market transparency. Europe and the United States lead in these efforts (Pietrancosta and Marraud des Grottes 2022). Endeavors have been particularly relevant in Europe. In this region, various regulations concerning non-financial reporting have been introduced, with the most recent being launched in 2022, the Corporate Sustainability Reporting

Directive (CSRD). These regulations include the European Financial Reporting Standards (EFRS), requiring a growing number of firms to disclose nonfinancial information used to calculate ESG ratings. In the United States, the regulatory framework is also important, but comparatively less extensive, and imposes certain requirements on companies that are clearly inferior to those in Europe. For example, the Securities and Exchange Commission (SEC) recently implemented new rules requiring public companies to disclose detailed climate-related information in their filings. However, the new administration under Donald Trump began rolling back these regulations in 2025 (Green Central Banking 2025). These regulatory changes also had consequences in Europe, where, on April 3, 2025, the European Parliament voted to delay the application of new corporate sustainability and due diligence rules, citing the need to reduce administrative burdens and enhance competitiveness—particularly amid concerns over the unequal global regulatory landscape (European Parliament 2025). Despite all these recent regulatory shifts, sustainability remains an essential component of corporate vision and strategy, and it is firmly embedded in the collective consciousness of the investment community.

The academic literature has acknowledged the growing importance and interest in sustainability, and previous research in the finance field can be categorized into two main lines of work. The first line adopts a firm-level perspective and analyzes how, and to what extent, corporate sustainability practices influence firms' performance—focusing on variables such as profitability, market value, and default risk, among others. In general, this research shows that corporate sustainability has a significant impact on profitability and risk (Busch and Friede 2018; Friede et al. 2015; Huang 2021; Khan 2022; Prashar 2023). The second line of research adopts an investor-oriented perspective and analyzes the financial performance of SRI, focusing on the effectiveness of sustainable stocks and funds as investment vehicles. This is particularly relevant today, as more investors are choosing mutual funds and ETFs that emphasize ESG principles (SEC 2023). As a result, evidence showing that SRI does not compromise—and may even enhance—financial returns could encourage more firms to improve their sustainability ratings, thereby contributing to the achievement of the SDGs. In this context, ESG metrics have revealed highly valuable, serving as a proxy for sustainability performance and, at the same time, as an enabler of the SRI market (Widyawati 2020). However, this line of research focused on the investor is still recent and offers inconclusive results. Some authors conclude that the financial performance of SRI does not significantly differ from that of conventional investments or benchmark indices (Hornuf and Yüksel 2024; Widyawati 2020). Nevertheless, the literature also includes some studies finding outperformance (Martí-Ballester 2015; Pirgaip et al. 2021) and others reporting underperformance (Azmi et al. 2020; Gangi and Varrone 2018). This heterogeneity has been attributed to various factors, including contextual differences, thematic focus, investment horizon, and methodological choices (Revelli and Viviani 2015; Widyawati 2020). In addition, it has been noted that the predominance of studies focused on the US market limits the generalizability of findings to other contexts, such as Europe, underscoring the importance of expanding research to different countries and using diverse analytical approaches (Rathner 2013; Stellner et al. 2015).

In this context, the main objective of this paper is to compare the performance of ESG ETFs with traditional ETFs, focusing on those with the highest total net assets under management in Europe and the United States over the period 2014–2024. In particular, this research identifies two specific objectives in its empirical study: (1) to evaluate the diversification, hedge, and safe-haven properties of ESG equity and bond ETFs within portfolios that include conventional equity and bond ETFs and (2) to analyze the risk-reducing potential of portfolios incorporating these sustainable investments. The analysis distinguishes between periods of market stability and crisis, allowing for an assessment of whether the benefits of sustainable investments vary with market conditions.

In this way, the paper will make three main contributions. Firstly, as indicated, sustainability is a topic of growing interest not only in international financial markets but also for society in general. Over the past years, institutions have promoted the publication of nonfinancial information related to sustainability, imposing greater transparency requirements on companies. Although recent regulatory rollbacks—particularly in the United States—may appear to slow down the push for transparency, this only highlights the tension between institutional inertia and growing societal demand for sustainable practices. In fact, investors are increasingly turning to sustainable financial products. At the same time, consumers are demanding more responsible practices from companies, and firms themselves are becoming increasingly aware of their potential to drive social and environmental change. Therefore, on a general level, this paper contributes to advancing the study of sustainability, which is a relevant topic and a key player not only in the economic but also in the social sphere. To achieve this objective, the paper adopts the investor's perspective in the analysis of SRI. Previous research has examined this perspective without reaching conclusive results, as noted above. This highlights the need for further empirical analysis of the performance of this type of investment, given its current relevance and expected continued prominence in financial markets. Therefore, a second contribution of this paper is that it provides empirical evidence on the performance of SRI through an analysis that considers three relevant factors that have not been explored simultaneously to date: ESG ETFs, the European and US markets, and, from a methodological perspective, the integration of EGARCH and GJR-GARCH specifications with copula approaches.

Focusing particularly on ESG ETFs, they are one of the least explored vehicles in the SRI literature, which has traditionally centered on mutual funds and equity portfolios. Specifically, ESG ETFs have gained popularity among investors as they combine the benefits of ETFs with a focus on sustainability. ETFs are tradable financial instruments that track the performance of an index, commodity, bond, or a collection of assets, similar to index funds. Unlike mutual funds, ETFs are traded on stock exchanges like individual stocks (Miralles-Quirós et al. 2019). Their rapid growth is attributed to two main factors (Madhavan 2016): (1) They offer diversification benefits similar to traditional funds while providing the convenience of stock trading on an exchange; and (2) they are typically designed to track an underlying index, aligning with the growing preference for passive investments. These characteristics create a diverse range of investment opportunities. Investors are attracted to these assets due to a combination of personal values and the belief that ESG investing offers a favorable trade-off between return and risk (Kanuri 2020). As a result, ESG funds are now viewed not only as contributors to global SDGs but also as vehicles for achieving consistent financial returns (Kanamura 2021). As anticipated, in this study, the analysis of ESG ETFs' performance is carried out through two novel and relevant dimensions: the simultaneous and comparative evaluation of different markets and the application of a methodological approach that has not been previously used in this context.

Regarding the markets, this research considers European and US ESG ETFs. This is relevant because both the US and Europe are leaders in ESG regulation and promotion. Furthermore, the differences in regulatory frameworks and cultural contexts between these two markets provide a unique opportunity to explore how these factors shape ESG investment performance. By incorporating European ESG ETFs, this study broadens the scope and helps to address the anticipated market bias toward the United States, offering a more comprehensive understanding of ESG strategy performance across distinct regulatory and market environments. In fact, previous research has noted that European investors exhibit greater ESG awareness compared to their US counterparts (Amel-Zadeh and Serafeim 2018), whereas US portfolio managers tend to be more skeptical about the benefits of responsible investing (Van Duuren et al. 2016). Furthermore, US managers typically assign low weights to environmental and social factors but share a high regard for corporate governance with Europeans (Van Duuren et al. 2016). Regarding consumer preferences, research indicates that European consumers are more inclined than their US counterparts to support responsible businesses, driven by concerns about adherence to legal and ethical standards. Conversely, US consumers tend to place greater value on the economic performance of the firm (Maignan 2001). These cultural and regulatory differences, along with the rich historical data available for both equity-based and bond-based ESG ETFs in Europe and the United States, make the comparative analysis of ESG ETF performance between the two regions particularly valuable.

The literature addressing the dynamics of ESG ETFs is relatively recent and has primarily focused on a global scope or the United States, yielding mixed results. In contrast, research specifically examining the European market—despite its leading role in promoting sustainability—remains notably limited. To the best of our knowledge, only Landi et al. (2024) have exclusively analyzed both the United States and Europe in the context of ESG ETFs. However, their focus is on how ESG risk metrics influence ETF performance, treating geography merely as a control variable rather than exploring its role as a potential moderator. As a result, no comparative insights into how ESG investments perform across these two markets are provided. Additionally, the research of Landi et al. (2024) spans only the 2020–2023 period, capturing short-term effects largely shaped by the COVID-19 context. In contrast, Chakrabarty et al. (2017) offer relevant insights through a multi-country study that includes—but is not limited to—the United States and Europe. However, their analysis is restricted to data until 2015, limiting its relevance for more recent trends. These authors found that European ETFs significantly outperformed their respective indices, whereas no significant differences were observed for US ETFs. Moreover, they noted that during bear markets, neither region showed performance advantages. However, these authors did not construct portfolios, which limits the understanding of ESG-based diversification strategies. Together, these studies underscore a key gap in the literature: the lack of comparative, recent, and long-term analyses of ESG ETF performance across regions—particularly between the United States and Europe—which this study seeks to address.

Focusing on the methodology, this research employs EGARCH and GJR-GARCH specifications to model ETF return dynamics, alongside the copula methodology to capture correlations in the non-deterministic component of returns. Although alternative methods exist for simulating multivariate data—such as multivariate regression, time series models (e.g., VAR, DCC-GARCH), parametric joint distributions, empirical simulation techniques, and machine learning approaches—copulas offer a significant advantage by decoupling dependence structures from marginal distributions. This decoupling allows for more accurate modeling of non-linear relationships and tail dependencies, especially in the context of ETF returns, where such dependencies play a crucial role in assessing their potential as diversifiers, hedges, and/or safe havens during periods of market volatility. In comparison to other methodologies, such as DCC-GARCH models or multivariate regression techniques, copulas provide a flexible framework by modeling both the degree and structure of correlations across all ETFs in the portfolio simultaneously. This makes the analysis more robust and improves risk management and portfolio optimization, particularly by capturing tail dependencies that are often overlooked by traditional methods. Whereas some studies have applied copula methodology to ESG-related investments (Bax et al. 2023; Górka and Kuziak 2022; He et al. 2021; Liu and Hamori 2020), no prior research has specifically used copulas to assess the performance of ESG ETFs or simulated data derived from them. Most studies on ESG ETF performance typically rely on standard asset pricing models—such as CAPM, the Fama–French three- and five-factor models, and the Carhart four-factor model—and commonly apply multiple regression techniques. A limited number of studies—such as Asih et al. (2024), Huang (2024), Meehan and Corbet (2025), and Sabbaghi (2011)—use GARCH models to account for time-varying volatility. However, these approaches do not incorporate copula methodologies to model tail dependencies, which are critical for accurately understanding ETF behavior during extreme market conditions. In this context, the methodological innovation of our study lies not in the use of GARCH models, which are common in financial econometrics, but rather in the integration of copulas to capture the complex, nonlinear relationships and tail dependencies between ETFs—elements that are crucial for comprehensive risk assessment and portfolio construction. This combination of methodologies provides a deeper understanding of the interactions between assets in extreme market scenarios, a key consideration for risk management.

Finally, a third contribution of the paper lies in the time frame covered. The analysis considers a broad and recent time period, 2014–2024, which is characterized by different economic environments, including a pandemic period. This contributes to assessing the robustness of our results in different market environments. Importantly, 2014 marks the adoption of the Non-Financial Reporting Directive (NFRD) in the European Union

(EU), a regulatory milestone that significantly enhanced corporate sustainability disclosures and likely influenced investor behavior. The chosen time frame also captures the transition from a relatively stable economic phase (2014–2019) to a crisis-driven environment (2020–2024), shaped by the COVID-19 pandemic and subsequent geopolitical tensions such as the Russia–Ukraine war and the Israel–Palestine conflict. As noted, Chakrabarty et al. (2017) and Landi et al. (2024) are among the few studies that consider the European market in their analysis of ESG ETFs' performance, but they differ significantly from our research. Chakrabarty et al. (2017) focus on a period ending in 2015, when sustainability regulations in Europe were less developed, which may limit the applicability of their findings to the current European market. In contrast, Landi et al. (2024) analyze a more recent period, 2020–2023, but they acknowledge that the relatively short time frame of their study limits their ability to capture long-term trends, particularly in the context of ongoing global challenges. In recent years, there has been an increase in studies analyzing ESG ETF performance during times of crisis. However, most of them focus on relatively short periods, typically no longer than 6 years. Nofsinger and Varma (2014) and Huang (2024) are an exception in this regard, as these studies consider longer time frames despite their focus on periods of crisis; however, they do not address Europe but rather examine the United States. This highlights a significant gap in the literature on European ETFs, particularly in terms of a sufficiently long and recent study period that takes into account the impact of the most recent crises. This research aims to fill this gap by providing a more comprehensive and up-to-date analysis of ESG ETFs performance in Europe.

The remainder of this article is structured as follows: Section 2 reviews pertinent literature and offers an in-depth examination of the theoretical foundations of the subject. Following this, Section 3 presents the data and sample used in this research. Section 4 outlines the methodology employed, and Section 5 presents and discusses the results obtained through copula and portfolio analyses. Finally, Section 6 encapsulates the key findings and conclusions of the study.

2 | Theoretical Background

The literature on sustainability in business and finance has followed two main research lines. The first line explores the effect of sustainability practices on corporate performance, measured by various indicators such as return (ROA and ROE, among others) or firm value (Tobin's Q), and default risk (Z-score). Meta-analyses consistently highlight a significant effect of sustainability, as measured through ESG metrics, on corporate performance (Busch and Friede 2018; Friede et al. 2015; Huang 2021; Khan 2022; Prashar 2023) and firm survival (Vivel-Búa et al. 2024). A second and more recent line of research focuses on the impact of SRI on investors' outcomes. It investigates whether there is a trade-off between financial performance and sustainability—whether investing in sustainable stocks comes at a cost or, conversely, underperforms conventional investments due to its alignment with contemporary societal values. The results of this research line remain inconclusive. Whereas some studies suggest that ESG integration enhances returns, others find neutral or even negative effects. Several economic theories help explain these varying outcomes, offering perspectives on both the potential benefits and limitations of ESG investing.

Theories supporting outperformance can be explained through four key frameworks: *modern portfolio theory*, *stakeholder theory*, *resource-based view theory*, and *risk management theory* (Landi et al. 2024). The *modern portfolio theory* (Markowitz 1952) emphasizes diversification as a key to reducing risk and improving risk-adjusted returns. Integrating ESG factors introduces additional dimensions to portfolio construction, which may help spread risk more effectively and lead to more stable returns. This perspective is complemented by the *stakeholder theory* (Freeman 1984), according to which firms that meet the expectations of various stakeholders—such as employees, customers, and communities—tend to benefit from enhanced reputational capital, reduced legal and compliance costs, and stronger relationships. These advantages can result in lower cash flow volatility, better access to financing, and improved resilience and market performance in times of crisis (Atif and Ali 2021; Landi et al. 2024). In addition, the *resource-based view theory* (McWilliams and Siegel 2011) reinforces the outperformance premise. According to this theory, companies that build internal capabilities and develop strategic ESG-related resources—such as sustainability expertise or stakeholder management systems—are better positioned to manage risks and respond to environmental and social challenges (McWilliams and Siegel 2011). As suggested by recent research (Tsang et al. 2023), such capabilities helped firms navigate uncertainties brought by the COVID-19 pandemic, helping preserve their financial performance. Finally, the *risk management theory* (Bouslah et al. 2018) provides further insights. This perspective emphasizes the proactive identification, assessment, and management of risks. ESG strategies can serve as early-warning tools for operational, reputational, or regulatory risks. By addressing these factors, companies can reduce uncertainty and financial volatility (Bouslah et al. 2013; Demers et al. 2021). Godfrey et al. (2009) further argue that strong ESG practices build "moral capital," which can act as a form of insurance, protecting firms during crises and helping protect shareholder value.

In contrast, *agency theory* (Jensen and Meckling 1976) offers a countervailing explanation that supports the possibility of underperformance (Landi et al. 2024). It argues that managers may pursue ESG strategies not to maximize shareholder value, but to advance personal or reputational goals—potentially leading to inefficient capital allocation. This idea is elaborated in the *theory of managerial opportunism*, which suggests that executives might overinvest in ESG or CSR initiatives not to enhance the firm's performance but to improve their own reputations as responsible social citizens (Barnea and Rubin 2010; Bouslah et al. 2013; Preston and O'Bannon 1997). Additionally, the *window dressing phenomenon* (Palazzo and Richter 2005) refers to the strategic use of ESG as a symbolic gesture, intended to appease stakeholders without substantive impact. When investors perceive ESG actions as insincere, confidence erodes and underperformance may follow (Broadstock et al. 2021; DesJardine et al. 2023).

Based on the theoretical perspectives outlined above, the following hypotheses are proposed:

Hypothesis 1. *Portfolios that include ESG ETFs outperform traditional portfolios composed exclusively of non-ESG ETFs under normal market conditions.*

This hypothesis is grounded in *modern portfolio theory* and *stakeholder theory*, which emphasize diversification and stakeholder engagement as drivers of financial performance.

Hypothesis 2. *Portfolios that include ESG ETFs outperform traditional portfolios composed exclusively of non-ESG ETFs during periods of market crisis, such as the COVID-*19 *pandemic.*

This hypothesis is supported by *risk management theory* and the *resource-based view*, which highlight how ESG capabilities enhance resilience in volatile contexts.

Hypothesis 3. *Portfolios that include ESG ETFs underperform traditional portfolios composed exclusively of non-ESG when ESG actions are perceived as symbolic or insincere.*

This hypothesis is based on *agency theory* and its extensions, which suggest that ESG can reduce firm value when driven by managerial self-interest or window dressing practices.

Despite the theoretical support for these hypotheses, the empirical evidence on ESG ETFs remains fragmented. Most research has focused on broader SRI vehicles like mutual funds and equity portfolios, with relatively limited attention paid specifically to ESG ETFs. These financial products are gaining popularity among investors (SEC 2023) and, as noted in the Introduction, deserve closer examination because they combine the benefits of ETFs—such as diversification and stock-like trading—with a focus on sustainability. Their rapid growth is driven by their ability to track indices and provide exposure to ESG assets, creating a favorable trade-off between risk and return for investors. However, the few studies that have specifically addressed ESG ETFs' performance have not yielded conclusive results. Therefore, we now review the existing literature on ESG investing, highlighting the current understanding of ESG ETFs' financial performance and identifying gaps that this study aims to address. Table 1 presents a summary of previous literature on this topic. As shown in this table, the literature within this research branch can be broadly categorized according to the period analyzed. On the one hand, some studies adopt a long-term perspective that extends beyond periods of financial turmoil (Chakrabarty et al. 2017; Dumitrescu et al. 2023; Fiordelisi et al. 2023; Kanuri 2020; Lobato et al. 2021; Miralles-Quirós et al. 2019; Plagge and Grim 2020; Sabbaghi 2011). On the other hand, a more recent and distinct line of research has emerged, focusing primarily—or exclusively—on the performance of ESG ETFs during crisis periods, such as the COVID-19 pandemic (Asih et al. 2024; Folger-Laronde et al. 2022; Huang 2024; Kanamura 2021; Landi et al. 2024; Meehan and Corbet 2025; Mirza et al. 2025; Naffa and Fain 2020; Nofsinger and Varma 2014; Omura et al. 2021; Pavlova and de Boyrie 2022; Valadkhani and O'Mahony 2024). Most of these studies focusing on crisis periods concentrate on short-term horizons. Nofsinger and Varma (2014) and Huang (2024) are exceptions, covering a decade-long period. Nevertheless, these authors are classified within crisis-focused literature due to its primary emphasis on crises.

Among the studies that take a long-term perspective beyond periods of financial turmoil, Sabbaghi (2011) stands out as one of the earliest contributions. Adopting a global perspective, this author concludes that green ETFs are not protected from market volatility, as evidenced by return declines during the 2008–2009 financial crisis. Building on such evidence, a number of subsequent studies have also adopted a global scope, comparing the performance of sustainable ETFs with their conventional counterparts—although many retain a primary focus on US investments. In fact, to the best of our knowledge, no studies within this branch have explored markets beyond the global or US scope. Overall, the findings of these studies reveal that ESG ETF performance varies significantly depending on the market, asset class, and methodology employed. For instance, Chakrabarty et al. (2017) find that CSR-oriented ETFs generally perform in line with their benchmark indexes, with some outperforming based on Jensen's alpha. However, these ETFs fail to act as safe havens during downturns, as they do not consistently outperform in bear markets. Similarly, Kanuri (2020) shows that ESG equity ETFs tend to underperform relative to global and US benchmarks, although occasional outperformance is observed during bear and bull markets. Lobato et al. (2021) find no significant performance difference between SRI and conventional ETFs. Meanwhile, Fiordelisi et al. (2023) highlight that ESG ETFs outperform non-ESG counterparts primarily during periods of heightened climate change awareness—such as after the 2015 Paris Agreement—but this advantage diminishes during economic downturns, when investors appear to revert to traditional investment strategies. Collectively, these findings suggest that ESG ETFs do not consistently outperform non-ESG ETFs across all market conditions.

Focusing more specifically on the US market, Miralles-Quirós et al. (2019) demonstrate that integrating SDG-aligned equity and bond ETFs into a traditional stock–bond portfolio enhances overall performance. In contrast, Plagge and Grim (2020), using a broad dataset of ESG index and actively managed mutual funds and ETFs, report considerable heterogeneity in performance. After adjusting for risk factors, most funds show neither significant outperformance nor underperformance, with industry allocations playing only a minor role. Expanding on this line of inquiry, Dumitrescu et al. (2023) compare the alpha of passive SRI ESG ETFs to non-SRI benchmark ETFs. Over the full sample period, the equally weighted SRI portfolio underperforms its benchmark; however, no significant differences are observed in the second half of the period, and some outperformance is recorded in the final two years. Taken together, these findings indicate that even within the US market—despite being the most frequently studied—the performance of ESG ETFs remains inconclusive.

Previous investigations that specifically examine periods of crisis have also predominantly adopted either a global or US perspective. Among those with a global scope, Pavlova and de Boyrie (2022), Mirza et al. (2025), and Naffa and Fain (2020) provide key insights. Pavlova and de Boyrie (2022) observe that, although ESG equity ETFs are not immune to losses, they tend to perform in line with the broader market during downturns. Notably, they find that ESG ETFs with lower sustainability ratings outperformed both the market and higher-rated peers in the

TABLE 1 | References on ESG ETFs and performance evaluation.

Authors	Market	Methodology	Period	Main results: Outperformance	Main results: Underperformance	Main results: No difference
Research exploring periods beyond crisis moments						
Sabbaghi (2011)	Global	t-GARCH (1,1); value-at-risk forecasts; autocorrelation analysis	2005–2009			
Chakrabarty et al. (2017)	Global	Sharpe ratios; Jensen's alpha	ETFs' inception date to 2015	✓		✓
Miralles-Quirós et al. (2019)	USA	Rolling portfolio optimization; Sharpe and Sortino ratios	2008–2013	✓		
Plagge and Grim (2020)	USA	Style factor controls; industry-adjusted alpha	2004–2018			✓
Kanuri (2020)	Global	CAPM; Carhart's four-factor; Fama–French five-factor; Sharpe, Sortino, and Omega ratios	2005–2019	✓	✓	
Lobato et al. (2021)	Global	Single-factor and Fama–French five-factor models; Sharpe, Treynor, and Information ratios	2005–2019			✓
Dumitrescu et al. (2023)	USA	Carhart's four-factor; CAPM; Fama–French models; alpha	2010–2020	✓	✓	✓
Fiordelisi et al. (2023)	Global	Sharpe style analysis; rolling window; adjusted returns (market, strategy, country)	2009–2018	✓		✓
Research specifically exploring periods of crisis						
Nofsinger and Varma (2014)	USA	CAPM; Fama–French three-factor; Carhart's four-factor; alpha; Newey–West errors	2000–2011	✓	✓	
Naffa and Fain (2020)	Global	Factor portfolio method; constrained weighted least squares regressions; GMM with robust distance instruments (GMM-IVd); CAPM; Fama–French three-factor, five-factor, and five-factor plus liquidity models; alpha; Sharpe ratio	2015–2019	✓		✓
Kanamura (2021)	USA	Price correlation and volatility model; maximum likelihood estimation	2018–2020	✓		
Omura et al. (2021)	USA (for ETFs)	Asset pricing models; Sharpe ratio; abnormal returns; Fama–French five-factor	2018–2020			✓

(Continues)

TABLE 1 | (Continued)

Authors	Market	Methodology	Period	Main results: Outperformance	Main results: Underperformance	Main results: No difference
Folger-Laronde et al. (2022)	Canada	ANOVA; Tukey test; multivariate regression	2019–2020		✓	
Pavlova and de Boyrie (2022)	Global	CAPM; Fama–French three-factor and five-factor model; Carhart's four-factor; momentum factor; ESG rating portfolios; alpha	2019–2020		✓	✓
Asih et al. (2024)	Indonesia	DCC-GARCH; PELT algorithm; quadratic programming optimization; Sharpe ratio; portfolio rebalancing	2018–2023	✓		
Huang (2024)	USA	GARCH family (GARCH, IGARCH, GJR-GARCH); FHS-GARCH; neural networks; Markov switching GARCH; value at risk; modified Sharpe ratio; expected shortfall	2012–2022	✓		✓
Landi et al. (2024)	USA and Europe	OLS; LOGIT; Sharpe ratio; ESG risk metrics (E, S, G scores; dESGRisk); out-of-sample testing	2020–2023	✓		
Valadkhani and O'Mahony (2024)	USA	Sharpe, Sortino, Omega, and Calmar ratios	2018–2023	✓	✓	✓
Meehan and Corbet (2025)	USA	EGARCH (1,1); dummy variables for COVID-19 events	2018–2023	✓	✓	
Mirza et al. (2025)	Global	Mean–variance optimization; quadratic programming optimization; rolling, dynamic, and static strategies; Sharpe ratio	2019–2024			✓

Note: The tick in the last three columns denotes significant empirical evidence.

lead-up to the COVID-19 crash—a counterintuitive result that invites further investigation. Adding another dimension, Mirza et al. (2025) examine the combined role of Sharia-compliant and ESG investments in global portfolio optimization. Their findings highlight the stabilizing influence of Sharia-compliant assets during periods of volatility, although ESG ETFs appeared to play a more opportunistic role. Furthermore, they report no consistent outperformance of ESG assets during the pandemic, despite selective periods of increased allocation. Naffa and Fain (2020) extend this discussion by focusing on ESG-themed megatrend portfolios. Their results show strong performance in areas such as energy efficiency, food security, water scarcity, and governance-related innovation. Yet, once risk factors are accounted for, the statistical significance of this outperformance diminishes. Still, they conclude that ESG investing does not entail a sacrifice in returns, even when accounting for high transaction costs.

In contrast, and within the body of previous research focused on analyzing periods of crisis, studies with a US focus are more abundant and often highlight the resilience of ESG investments during market downturns. For instance, Nofsinger and Varma (2014) demonstrate that SRI equity mutual funds, including some ETFs, outperformed during crisis periods, though this outperformance was generally counterbalanced by underperformance during non-crisis periods. Building on this, Kanamura (2021) specifically examines ESG high-yield bond ETFs, which he finds to have outperformed their conventional counterparts during market downturns, further emphasizing the defensive role of ESG investments in times of stress. When looking at broader indices, Omura et al. (2021) find that MSCI SRI indices, which span global, the United States, and other regions, consistently outperformed conventional indices both before and during the pandemic, with some regions showing statistically significant excess returns. Despite this, they note that US-focused ESG ETFs did not demonstrate superior performance, highlighting a more mixed picture in the US market. Similarly, Huang (2024) compares ESG ETFs with oil and gas ETFs during the COVID-19 period and finds that the former provided better downside protection. However, he notes that ESG ETFs did not show superior risk-adjusted returns. Over the longer term (2012–2022), his analysis indicates that ESG ETFs did not outperform oil and gas ETFs, producing neutral returns on average. This aligns with findings from Valadkhani and O'Mahony (2024), who observe that whereas some ESG ETFs performed well under extreme market conditions, others did not, indicating that the financial success of these funds often depends on fund selection rather than a clear-cut advantage of ESG strategies. Further contributing to the discussion, Meehan and Corbet (2025) explore the performance of SRI ESG ETFs during the COVID-19 pandemic and show that they outperformed SIN ETFs, demonstrating greater resilience, higher returns, and lower volatility in response to pandemic-related market shocks. Whereas SIN ETFs experienced greater declines and volatility during significant COVID-19 events, SRI ETFs exhibited more stable and positive returns. However, in a brief reversal, they note that during the announcement of the Omicron variant, SIN ETFs temporarily outperformed SRI ETFs, reflecting the unpredictable nature of market reactions even within ESG-focused investments.

Beyond studies focused on the US or global markets, research examining periods of crisis in other regions remains limited. For example, Folger-Laronde et al. (2022) examine Canada and show that ETFs with Eco-fund ratings failed to prevent losses during the COVID-19 pandemic. In contrast, Asih et al. (2024), studying the Indonesian market, find that ESG equities offered diversification benefits, particularly during the pandemic. Similarly, Landi et al. (2024), focusing on both the United States and Europe, observe a positive correlation between higher ESG standards and the financial performance of ETFs, especially during the pandemic.

Regarding the methodology applied in earlier studies, Table 1 shows that research on the performance of ESG ETFs has predominantly used multivariate regressions to calculate risk-adjusted metrics, employing the CAPM model and its extensions, such as Carhart's four-factor model and the Fama–French three-factor and five-factor models (Chakrabarty et al. 2017; Dumitrescu et al. 2023; Kanuri 2020; Lobato et al. 2021; Naffa and Fain 2020; Nofsinger and Varma 2014; Omura et al. 2021; Pavlova and de Boyrie 2022). The methodology extends beyond OLS regressions, with some studies incorporating additional techniques like ANOVA and Tukey tests (Folger-Laronde et al. 2022), LOGIT models (Landi et al. 2024), price correlation and volatility models, and GMM (Naffa and Fain 2020). More recently, some studies have employed GARCH models to account for time-varying volatility (Asih et al. 2024; Huang 2024; Meehan and Corbet 2025; Sabbaghi 2011). However, none of these investigations have specifically employed copulas in the context of ESG ETFs, although they have been used in related ESG research. In particular, Górka and Kuziak (2022) compare return volatility between selected ESG and conventional indices, employing copulas to analyze tail dependence. Their findings indicate that diversification benefits fluctuate over time, highlighting the need for separate analyses during crisis and stabilization periods. Similarly, Bax et al. (2023) focus on evaluating the informativeness of ESG scores, especially in assessing tail risk. Their analysis of return data and ESG metrics identifies significant positive ESG risks, notably during the 2008 financial crisis. This indicates that, during the crisis, ESG indicators provided important signals about financial risks. Additionally, Liu and Hamori (2020) and He et al. (2021) use copula analysis to investigate extreme dependencies between investments in top-rated ESG companies and renewable energy firms. Their results suggest that ESG stocks effectively enhance risk-adjusted returns and mitigate downside risk in renewable energy portfolios. Collectively, these analyses offer valuable insights into the potential of ESG investments and their impact on risk and return dynamics, particularly concerning tail risk and extreme dependencies during various market conditions. Given these findings, it is plausible that similarly favorable outcomes may apply to ESG ETFs—an assumption this study seeks to investigate.

3 | Data and Sample

As previously introduced, this paper presents an empirical analysis of the diversification, hedge, and safe-haven properties of ESG equity and bond ETFs in comparison to traditional ETFs, along with an examination of their implications for risk management. The study uses weekly price data of the selected ETFs, covering the period from January 3, 2014, to November 29, 2024. Weekly data are preferred over daily data because they reduce disruptions and noise that can make it harder to identify underlying patterns and complicate the modeling process. In fact, daily data can be affected by unpredictable changes, varying variances, and long-term trends, as noted by Reboredo (2013). The choice of this time frame (2014–2024) is based on data availability, particularly for bond funds, which constitute a relatively recent and less frequently studied facet within the two typologies explored in this research. Notably, ESG bond ETFs with launch data prior to 2014 are not listed in the Refinitiv Eikon database for the United States, making 2014 the earliest feasible starting point for a comprehensive analysis.

The chosen period is particularly relevant to this study's objectives for several reasons. First, 2014 marked the adoption of the NFRD in the European Union, a regulatory milestone that significantly influenced corporate sustainability disclosures and, consequently, investor behavior. This regulatory shift provides a critical context for examining the evolution and impact of ESG investments. Furthermore, this time frame allows for the assessment of ESG investing under two distinct market scenarios: a phase of relative stability (2014–2019) and a phase of pronounced crisis (2020–2024). The latter includes significant global disruptions, beginning with the initial shockwaves of the COVID-19 pandemic, followed by the pandemic's broader economic impacts, and further exacerbated by geopolitical conflicts, such as the Russia–Ukraine war and the Israel–Palestine conflict. These contrasting periods provide a unique opportunity to evaluate the resilience and performance of sustainable investments under varying market conditions.

The present analysis focuses on ETFs holding stocks and bonds. These asset categories are among the most common assets found in investment portfolios and have traditionally served as reliable instruments for institutional asset managers and individual investors seeking stability during turbulent market conditions. Their effectiveness in this regard is primarily attributed to their low correlation, offering investors who hold both asset classes valuable diversification advantages, as detailed by Miralles-Quirós et al. (2019).

Specifically, the most relevant ETFs for each market—Europe and the United States—were selected based on their total net assets under management. Additional criteria included (1) active funds launched on or before 2014, (2) asset type (bonds and equities), and (3) geographical focus (Europe and the United States). The main goal of this research is to evaluate the risk management benefits of including ESG ETFs in a portfolio that consists solely of traditional stock and bond ETFs. To ensure a thorough comparison, conventional European and US ETFs were also filtered using the same criteria applied to ESG ETFs. Table 2 provides an overview of the selected ETFs for each market and asset type, highlighting their key characteristics. It is relevant to note that conventional and ESG equity-based ETFs within each market have similar industry weights. For more details, Table A1 presents a dataset codebook with ETF identifiers and data sources.

Weekly price data for the selected ETFs were obtained from the Thomson Reuters Eikon database. The calculation of continuously compounded weekly returns involved computing the natural logarithm difference between two consecutive prices within the time series. This methodology was employed to ensure precision in return calculations and maintain data consistency. To facilitate visual representation, Figure 1 displays the time paths of weekly returns for each of the ETFs under examination throughout the sample period. This graphical illustration serves to convey the dynamics and trends in returns for the ETFs in question, offering a visual perspective on their performance over the specified time frame. Clear trends in the data are not readily discernible; however, certain facets of ETF dynamics merit attention. Firstly, it is apparent that the volatility of bond-based ETFs is notably lower than that of equity-based ETFs. Secondly, both categories of ETFs, encompassing those with a geographical focus on Europe and the United States, as well as those based on bonds and equities, exhibit significant shifts coinciding with the onset of the pandemic. This period witnessed a marked and abrupt decline, followed by a substantial resurgence.

Table 3 provides a thorough overview of the descriptive statistics and stochastic properties of weekly returns. It is worth noting that

TABLE 2 | Characteristics of the selected ETFs.

Geographical focus	ESG/conventional	Asset type	Asset name	Abbreviation
Europe	ESG	Equity	iShares MSCI Europe SRI UCITS ETF EUR (Acc)	IUSK.AS
		Bonds	iShares € Corp Bond Interest Rate Hedged ESG UCITS ETF	IRCP.L
	Conventional	Equity	Vanguard European Stock Index Fund ETF	VGK
		Bonds	iShares € High Yield Corp Bond UCITS ETF EUR D	IHYG.L
USA	ESG	Equity	iShares MSCI KLD 400 Social ETF	DSI
		Bonds	SPDR Bloomberg SASB US HY Corp ESG UCITS ETF Dis	SJNK.L
	Conventional	Equity	SPDR S&P 500 ETF Trust	SPY
		Bonds	Vanguard Total Bond Market Index Fund ETF	BND.O

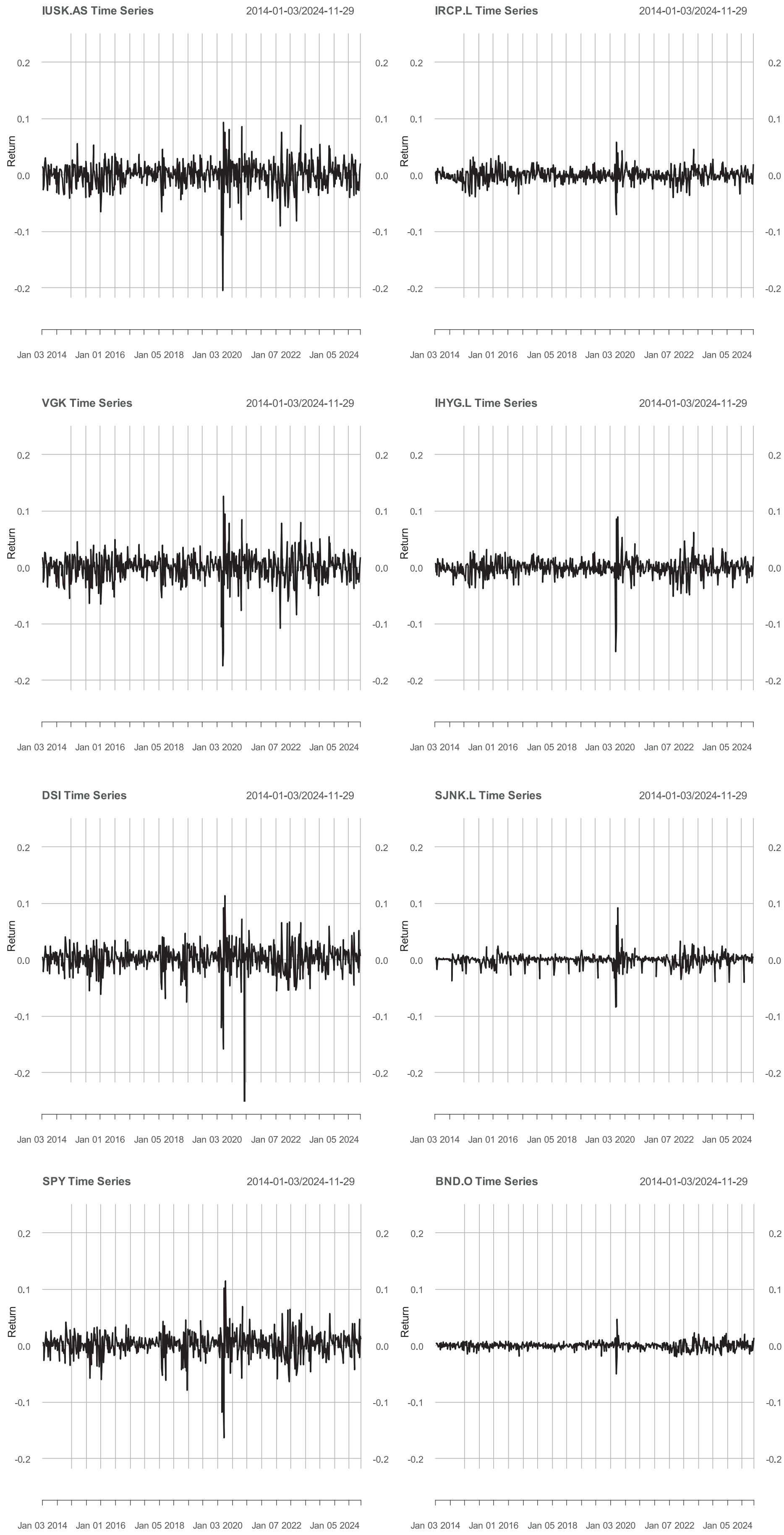


FIGURE 1 | Weekly returns time paths.

TABLE 3 | Descriptive statistics and stochastic properties of weekly returns for the entire period.

	IUSK.AS	IRCP.L	VGK	IHYG.L	DSI	SJNK.L	SPY	BND.O
Observations	569	569	569	569	569	569	569	569
Mean	0.0010	−0.0005	0.0002	−0.0007	0.0009	−0.0004	0.0021	−0.0001
SD	0.0246	0.0126	0.0257	0.0169	0.0378	0.0116	0.0230	0.0069
Skewness	−1.1073	−0.2451	−0.8629	−1.1130	−11.4984	−0.6564	−0.9190	−0.2125
Kurtosis	9.8605	3.2939	7.4507	15.2786	209.7360	17.4736	7.8355	8.1664
JB	2421.4***	262.92***	1386.7***	5651.8***	1055449***	7279.6***	1535.7***	1585.4***
LJ(10)/(20)	7.37/14.05	15.86/21.7	5.73/11.10	17.00*//25.56	9.36//14.42	29.14***/39.77***	10.81/14.45	3.88/11.34
LJ SQ (10)/(20)	91.90***/102.86***	180.27***/199.24***	256.53***/267.31***	180.16***/186.63***	0.05/0.10	269.28***/272.33***	288.45***/292.64***	169.14***/170.71***
ARCH-LM (10)/(20)	80.076***/86.267***	121.96***/129.64***	163.02***/167.44***	143.87***/147.57***	0.05/0.10	163.45***/163.27***	204.41***/205.56***	173.8***/177.11***

Note: The Jarque–Bera (JB) test is a test for normality in the data, assessing whether the sample's skewness and kurtosis match those of a normal distribution under the null hypothesis that the data follow a normal distribution. The test statistic is asymptotically distributed as χ^2 with two degrees of freedom. A significant result indicates a departure from normality. The Ljung–Box test for LJ(10) and LJ(20) is a test of autocorrelation of orders up to 10 and 20, respectively, under the null hypothesis that the returns are uncorrelated. Similarly, the Ljung–Box test for squared returns, LJ SQ(10) and LJ SQ(20), examines whether there is autocorrelation in the variance of the returns under the same null hypothesis. In both cases, the test statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the lag count. The ARCH LM test for ARCH LM(10) and ARCH LM(20) is a test for autoregressive conditional heteroskedasticity (ARCH) of orders up to 10 and 20, respectively, under the null hypothesis that there is no ARCH effect in the returns (i.e., the variance of the residuals is constant). The test statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the lag count.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.
***Statistical significance at the 1% level.

those based on equity manifest a positive mean value over the entire sampling period, whereas those based on bonds show a negative mean. Furthermore, these mean values are proximate to zero, signifying a balanced distribution of returns. In terms of volatility, the standard deviation consistently surpasses the mean for all the ETFs, suggesting notable fluctuations in returns. Generally, ETFs focusing on Europe exhibit higher standard deviations when compared to their US counterparts, though IUSK.AS represents an exception in this regard.

Skewness values uniformly exhibit negativity, ranging from −11.4984 to −0.2125, indicating a leftward skew in the distribution. This asymmetry implies a proclivity for lower returns, thus underscoring an increased susceptibility to downside risk. US ETFs, on average, tend to display more negative skewness, with a few exceptions such as BND.O, which exhibits less negative skewness than its European counterpart. All ETFs exhibit excess kurtosis, with values ranging from 3.2939 to 209.7360, signifying an elevated probability of extreme values when compared to a standard normal distribution. In general, US ETFs tend to display higher excess kurtosis when contrasted with those with a focus on Europe, again with the exception of BND.O, which demonstrates lower excess kurtosis than its European counterpart.

In the context of evaluating the stochastic properties of the data, a series of tests has been employed. Firstly, the Jarque–Bera (JB) test is applied to assess the normality assumption of the dataset. Remarkably, for all examined ETFs, the null hypothesis, which posits normality, is rejected at a significance level of 1%. Subsequently, the Ljung–Box test is administered to explore the presence of serial correlation within the returns and squared returns, utilizing lag values of 10 and 20. Regarding returns, we fail to reject the null hypothesis of absence of autocorrelation at a 1% significance level in all cases, except for SJNK.L. However, concerning squared returns, it is rejected for all ETFs, except for DSI. Lastly, the ARCH-LM test is conducted to scrutinize the presence of autoregressive conditional heteroskedasticity, employing lag values of 10 and 20. The null hypothesis of homoskedasticity is rejected at a 1% significance level for all analyzed ETFs, with the exception of DSI. In summary, the results of these comprehensive tests collectively affirm the departure from several fundamental statistical assumptions, including normality, autocorrelation, and homoskedasticity, underpinning the complex nature of the financial data under investigation.

Figures 2 and 3 present the Pearson correlation matrices for the returns of ETFs with a geographical focus on Europe and the United States, respectively. Remarkably, all computed correlations exhibit a positive sign and hold statistical significance at the 1% level of confidence. In the case of the European-focused ETFs, the coefficients vary between 0.582 and 0.943. Meanwhile, for the US-focused ETFs, Pearson correlation coefficients span a

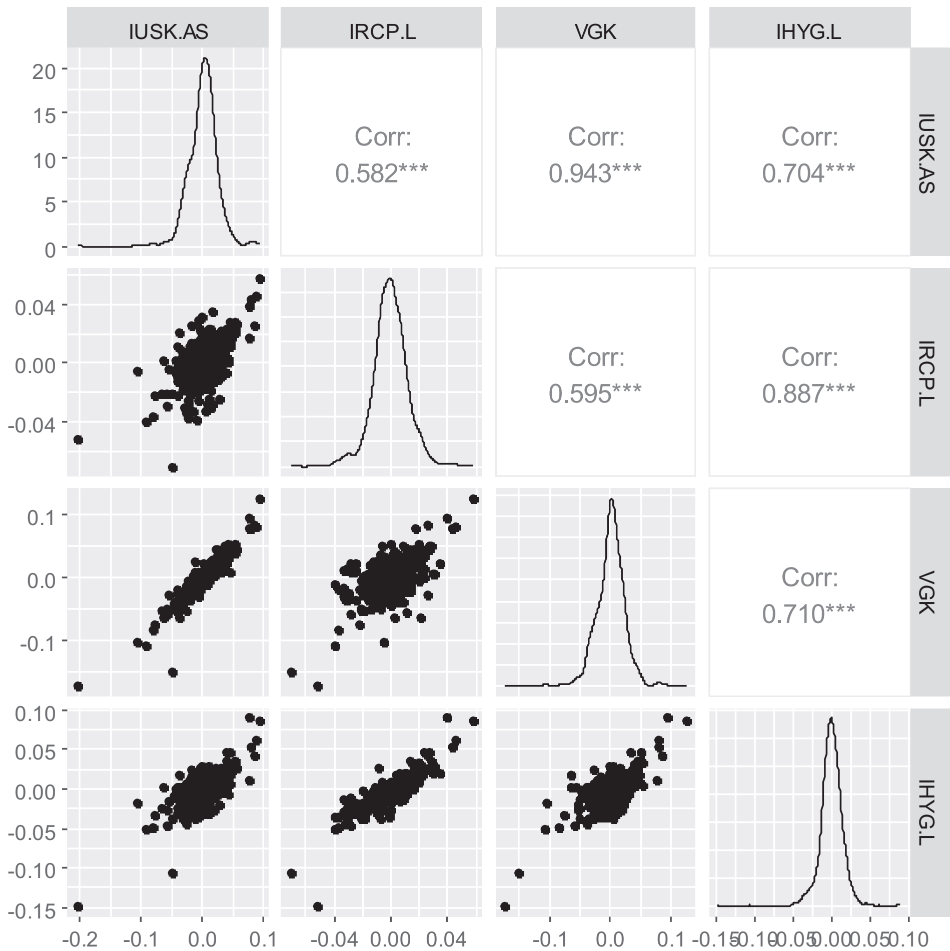


FIGURE 2 | Pearson correlation matrix for European ETFs' weekly returns. *Note:* * denotes statistical significance at the 10% level; ** denotes statistical significance at the 5% level; *** denotes statistical significance at the 1% level.

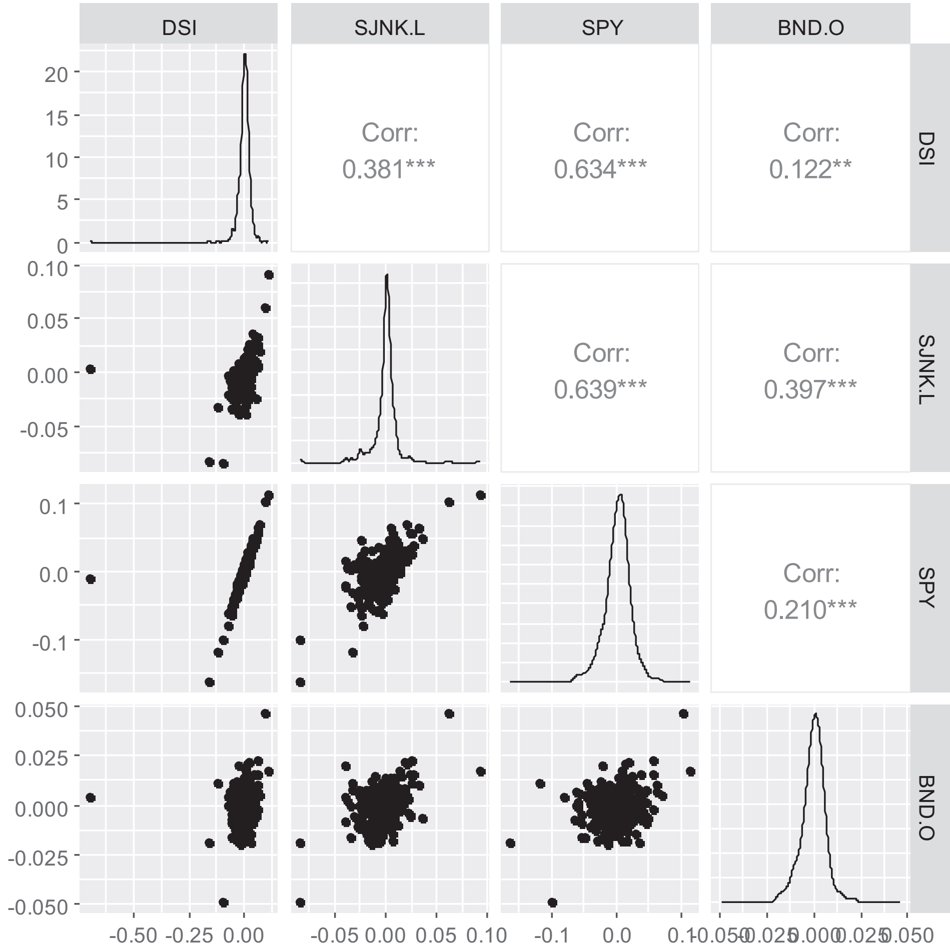


FIGURE 3 | Pearson correlation matrix for US ETFs' weekly returns. *Note:* * denotes statistical significance at the 10% level; ** denotes statistical significance at the 5% level; *** denotes statistical significance at the 1% level.

range from 0.122 to 0.639 for the pairwise combinations. These findings underscore the presence of substantial and statistically significant linear relationships among the returns of these ETFs, both within the European and US contexts.

4 | Methodology

4.1 | Analysis of the Diversification, Hedge, and Safe-Haven Properties of the ETFs

Following Mensi et al. (2015) and Reboredo (2013), this research uses ARMA(p,q) models to characterize weekly ETFs' return dynamics. This specification is chosen for its ability to capture inherent characteristics of returns, including fat tails, asymmetries, and leverage.

The ARMA(p,q) model is represented by the equation:

$$r_t = \mu + \sum_{j=1}^{p} \Phi_j r_{t-j} + \sum_{h=1}^{q} \theta_h \varepsilon_{t-h} + \varepsilon_t \tag{1}$$

where μ is the constant term, Φ_j are autoregressive coefficients reflecting the influence of past values on the current value, θ_h denote moving average coefficients representing the impact of past error terms, and p and q are the lags. The error term, denoted ε_t, is modeled as $\varepsilon_t = \sigma_t z_t$, where the innovation z_t follows a skew Student-t distribution and σ^2 represents the conditional variance.

The dynamics of the conditional variance are modeled using either GJR-GARCH or EGARCH specifications. As reported in previous literature, both are well suited for modeling asymmetries in volatility, particularly when conditional variance increases more sharply after negative shocks than positive shocks of the same magnitude. The choice between these two models is made by comparing their Akaike Information Criterion (AIC) values, with the model exhibiting the lowest AIC selected as the best fitting and most parsimonious representation of the data. Before this selection, candidate models are required to pass a series of diagnostic tests to ensure their statistical adequacy.

A GJR-GARCH model is specified as follows:

$$\sigma_t^2 = \omega + \sum_{k=1}^{r} \beta_k \sigma_{t-k}^2 + \sum_{h=1}^{m} \alpha_h \varepsilon_{t-h}^2 + \sum_{h=1}^{m} \gamma_h \varepsilon_{t-h}^2 I_{t-h} \tag{2}$$

where ω is the constant term, $\beta_k, \alpha_h, \gamma_h$ are coefficients determining the contribution of past error terms to the conditional variance, and r and m denote the lags. The term ε_{t-h} represents the error term at time $t-h$, and I_{t-h} is an indicator function taking the value of 1 if $\varepsilon_{t-h} < 0$ and 0 otherwise. Therefore, the components $\beta_k \sigma^2_{t-k}$, $\alpha_h \varepsilon^2_{t-h}$, and $\lambda_h \varepsilon^2_{t-h} I_{t-h}$, respectively, capture the effects of past conditional variance and squared past error terms and introduce asymmetry by considering additional impact on conditional variance when ε_{t-h} is negative, representing the leverage effect.

Similarly, an EGARCH specification takes the form of

$$\log\left(\sigma_t^2\right) = \omega + \sum_{k=1}^{r} \beta_k \log\left(\sigma^2_{t-k}\right) + \sum_{h=1}^{m} \alpha_h \left| \frac{\varepsilon_{t-h}}{\sigma_{t-h}} \right| + \sum_{h=1}^{m} \gamma_h \frac{\varepsilon_{t-h}}{\sigma_{t-h}} \tag{3}$$

where ω is the constant term, β_k measures the persistence of past logarithmic conditional variances, and α_h captures the effect of standardized past shocks ($|\varepsilon_{t-h} / \sigma_{t-h}|$) on the current log-variance. Finally, γ_h introduces asymmetry in the variance dynamics, capturing the leverage effect, where negative shocks can have a disproportionately larger impact on the conditional variance than positive shocks. This logarithmic specification ensures that the conditional variance is always positive, avoiding the need for explicit non-negativity constraints on the parameters.

Once these models are estimated, copulas are applied to the standardized residuals of the ETFs of each market (Europe and the United States). Introduced by Sklar (Sklar 1959), copulas serve as a valuable tool for comprehending the relationships among multivariate outcomes. They establish a connection between univariate marginals and the multivariate distribution, facilitating a nuanced exploration of the relationships between different variables (Frees and Valdez 1998). According to Sklar's theorem, the copula can be formally defined as a multivariate distribution with its univariate margins following a uniform distribution U(0,1) (Joe 2014). Thus, it satisfies

$$F\left(x_1, \ldots, x_d\right) = C\left(F_1\left(x_1\right), \ldots, F_d\left(x_d\right)\right) \tag{4}$$

where F is a d-variate distribution such that $F \in F\left(F_1, \ldots, F_d\right)$ and C is the copula associated with F.

Concretely, this paper employs vine copulas, which are increasingly applied to address high-dimensional probabilistic modeling problems in recent ESG-related literature (e.g., Bax et al. 2023; Górka and Kuziak 2022). To avoid the direct use of an N-dimensional copula, vine copulas decompose the joint distribution into conditional probabilities, which are then decomposed into bivariate copulas (du Toit 2023). Vine copulas enable the modeling of complex dependency relationships among multiple variables, including nonlinear and asymmetric dependencies. This approach overcomes the limitations of traditional multivariate copulas, such as Gaussian or Student-t copulas, which impose rigid, symmetric dependency structures and often fail to capture tail asymmetries or localized dependence. Specifically, this research examines R-vine copulas (regular vine copulas), which include both D-vine (dynamic vine) and C-vine (canonical vine) structures. Regular vine copulas offer a more interpretable and computationally tractable alternative to nested vine copulas, as they require fewer parameters and are less prone to overfitting. Depending on the dependence structure of the data, we select the best-fitting subclass between the C-vine and D-vine. As described in Afifah et al. (2018), a regular vine is classified as a C-vine when each tree T_i contains a node of maximum degree, forming a star structure, although it is considered a D-vine when nodes in the first tree T_1 have a maximum degree of two, forming a path structure. C-vine copulas are suitable for hierarchical dependence with a central dominant variable, whereas D-vines accommodate more flexible, sequential dependencies without a central node. In this study, the choice between D-vine and C-vine copula constructions is guided by AIC, which is also the default model selection criterion in the statistical software employed. The AIC allows for a consistent and data-driven comparison between different vine structures by balancing model fit and complexity.

Moreover, the choice of vine copulas is also motivated by their superior flexibility in modeling heterogeneous dependence structures compared to alternative approaches such as multivariate elliptical copulas (e.g., Gaussian or t-copulas) or copula-GARCH hybrids (Engle 2002; Andersen et al. 2006; Halbleib and Voev 2016). As noted in Wang et al. (2017), vine copulas outperform these models in capturing complex, localized, and asymmetric tail dependencies frequently observed in financial data. Therefore, the methodological framework adopted here is not only theoretically robust but also consistent with recent advances in empirical research.

This study implements a diverse range of bivariate copula families, including Gaussian, Student-t, Clayton, Gumbel, Frank, Joe, BB1, BB6, BB7, and BB8, along with their respective rotated versions (90°, 180°, and 270°), which are widely available in standard statistical software for pair-copula construction. The selection of the appropriate copula family for each pair of variables is performed based on AIC, which is the default model selection criterion implemented in the statistical package used. The AIC is favored in this context as it tends to balance model fit and complexity without being as conservative as the Bayesian Information Criterion (BIC), which penalizes model complexity more heavily. This makes AIC particularly suitable when the goal is to capture the dependence structure accurately without risking underfitting. Among the candidate copulas, the one with the lowest AIC is chosen, ensuring a statistically sound fit to the dependence structure of the data. Based on the selected copulas, we derive insights into the diversification, hedge, and safe-haven properties of ETFs. According to Baur and Lucey (2010), Baur and McDermott (2010), and Kaul and Sapp (2006), these properties can be defined as follows:

- A diversifier is characterized as an asset that, on average, exhibits a positive correlation (albeit not perfect) with another asset or portfolio.
- A hedge is delineated as an asset that, on average, maintains an uncorrelated or negatively correlated relationship with another asset or portfolio.
- A safe haven is characterized as an asset that, during periods of turmoil, exhibits an uncorrelated or negatively correlated relationship with another asset or portfolio.

TABLE 4 | Copula families and diversification, hedge, and safe-haven properties.

Copula family	Average dependence	Potential based on average dependence	Tail dependence	Potential based on tail dependence
Gaussian	Positive/negative	Positive (non-perfect): diversifier Negative: hedge	$\lambda_L = \lambda_U = 0$	Safe haven in bear and bull markets
Student-t	Positive/negative	Positive (non-perfect): diversifier Negative: hedge	$\lambda_L = \lambda_U > 0$	
Clayton	Positive	Positive (non-perfect): diversifier	$\lambda_L > 0, \quad \lambda_U = 0$	Safe haven in bull market
Gumbel	Positive	Positive (non-perfect): diversifier	$\lambda_L = 0, \quad \lambda_U > 0$	Safe haven in bear market
Frank	Positive/negative	Positive (non-perfect): diversifier Negative: hedge	$\lambda_L = \lambda_U = 0$	Safe haven in bear and bull markets
Joe	Positive	Positive (non-perfect): diversifier	$\lambda_L = 0, \quad \lambda_U > 0$	Safe haven in bear market
BB1	Positive	Positive (non-perfect): diversifier	$\lambda_L \geq 0, \quad \lambda_U \geq 0, \lambda_L \neq \lambda_U$ $\left(if\ \lambda_L \neq 0\ or\ \ \lambda_u \neq 0\right)$	It can be a safe haven in bear and/or bull markets
BB6	Positive	Positive (non-perfect): diversifier	$\lambda_L \geq 0, \quad \lambda_U \geq 0, \lambda_L \neq \lambda_U$ $\left(if\ \lambda_L \neq 0\ or\ \ \lambda_u \neq 0\right)$	It can be a safe haven in bear and/or bull markets
BB7	Positive	Positive (non-perfect): diversifier	$\lambda_L \geq 0, \quad \lambda_U \geq 0, \lambda_L \neq \lambda_U$ $\left(if\ \lambda_L \neq 0\ or\ \ \lambda_u \neq 0\right)$	It can be a safe haven in bear and/or bull markets
BB8	Positive	Positive (non-perfect): diversifier	$\lambda_L \geq 0, \quad \lambda_U \geq 0, \lambda_L \neq \lambda_U$ $\left(if\ \lambda_L \neq 0\ or\ \ \lambda_u \neq 0\right)$	It can be a safe haven in bear and/or bull markets
Survival Clayton	Positive	Positive (non-perfect): diversifier	$\lambda_L = 0, \quad \lambda_U > 0$	Safe haven in bear market
Survival Gumbel	Positive	Positive (non-perfect): diversifier	$\lambda_L > 0, \quad \lambda_U = 0$	Safe haven in bull market
Survival Joe	Positive	Positive (non-perfect): diversifier	$\lambda_L > 0, \quad \lambda_U = 0$	Safe haven in bull market
Survival BB1	Positive	Positive (non-perfect): diversifier	$\lambda_L \geq 0, \quad \lambda_U \geq 0, \lambda_L \neq \lambda_U$ $\left(if\ \lambda_L \neq 0\ or\ \ \lambda_u \neq 0\right)$	It can be a safe haven in bear and/or bull markets
Survival BB6	Positive	Positive (non-perfect): diversifier	$\lambda_L \geq 0, \quad \lambda_U \geq 0, \lambda_L \neq \lambda_U$ $\left(if\ \lambda_L \neq 0\ or\ \ \lambda_u \neq 0\right)$	It can be a safe haven in bear and/or bull markets
Survival BB7	Positive	Positive (non-perfect): diversifier	$\lambda_L \geq 0, \quad \lambda_U \geq 0, \lambda_L \neq \lambda_U$ $\left(if\ \lambda_L \neq 0\ or\ \ \lambda_u \neq 0\right)$	It can be a safe haven in bear and/or bull markets
Survival BB8	Positive	Positive (non-perfect): diversifier	$\lambda_L \geq 0, \quad \lambda_U \geq 0, \lambda_L \neq \lambda_U$ $\left(if\ \lambda_L \neq 0\ or\ \ \lambda_u \neq 0\right)$	It can be a safe haven in bear and/or bull markets

(Continues)

TABLE 4 | (Continued)

Copula family	Average dependence	Potential based on average dependence	Tail dependence	Potential based on tail dependence
Rotated Clayton (90°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated Gumbel (90°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated Joe (90°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated BB1 (90°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated BB6 (90°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated BB7 (90°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated BB8 (90°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated Clayton (270°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated Gumbel (270°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated Joe (270°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated BB1 (270°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated BB6 (270°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated BB7 (270°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets
Rotated BB8 (270°)	Negative	Hedge	$\lambda_L = 0, \ \lambda_U = 0$	Safe haven in bear and bull markets

Note: λ_L and λ_U denote lower and upper tail dependence, respectively.

In accordance with these definitions, this article adopts the view that an asset serves as a diversifier when exhibiting positive and non-perfect average dependence. Conversely, it is considered a hedge when average dependence is negative or does not exceed 0.05. Additionally, the concept of a safe haven is applied when tail dependence is zero or does not exceed 0.05, offering protection against extreme bearish market conditions when lower tail dependence is zero and safeguarding against extreme bullish market conditions when upper tail dependence is zero. Table 4 presents the copula families examined in this study, providing an overview of their diversification, hedge, and safe-haven properties based on their average and tail dependence.

Figure 4 summarizes the procedure applied in the examination of the potential diversification, hedge, and safe-haven properties of the ETFs.

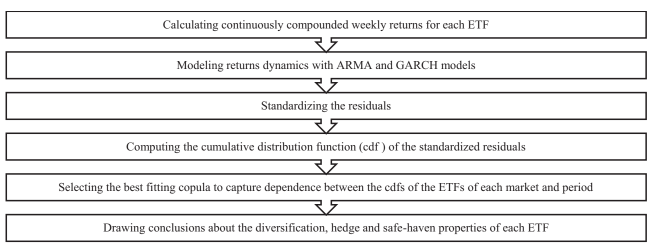


FIGURE 4 | Steps followed to assess the ETFs' diversification, hedge, and safe-haven properties.

4.2 | Portfolio Analysis

Two portfolios are designed for each market and period under consideration: (1) consisting of both conventional and ESG ETFs and (2) comprised solely of conventional ETFs. The purpose of this analysis is to evaluate and compare the risk exposure associated with each portfolio. Should the portfolio incorporating ESG ETFs demonstrate lower risk, it implies that ESG investments may not only be motivated by ethical considerations but also by risk-related factors. In this assessment, the research proceeds through a series of steps:

1. Simulation: the procedure commences with simulating 1000 paths of the skew Student-t cumulative distribution function (cdf) for the standardized residuals of each ETF, based on the copula selected for each market and period.
2. Conversion to standardized residuals: The simulated values are subsequently transformed into standardized residuals using the quantile function of the skew Student-t distribution.
3. Transformation to residuals: The standardized residuals are further transformed into residuals by taking the product of the standardized residuals and the sigma of the chosen ARMA-GARCH model, following the expression:

$$\varepsilon_t = \sigma_t z_t$$

4. Addition to fitted values: Finally, these residuals are added to the fitted values of the selected ARMA-GARCH model for each ETF.
5. Transformation to simple returns: Converting log returns into simple returns.

This comprehensive process aids in the modeling of market dynamics for the given ETFs and serves as the foundation for a forward-looking evaluation of the models' practical performance.

The simulation procedure described above enables the evaluation of ETF behavior and portfolio performance under a broad range of hypothetical scenarios, based on the dependence structure and marginal distributions estimated from historical data. This forward-looking approach offers a flexible alternative to conventional pseudo out-of-sample validation by generating synthetic but plausible market conditions consistent with the estimated models. Thus, it allows us to assess the stability and practical relevance of the copula-GARCH framework beyond the estimation period.

From the simulated data, two different portfolios are designed under two constraints: the sum of the weights is set to be equal to the unit and short selling is not allowed:

1. Minimum standard deviation portfolio: The optimizer tries to find the portfolio that minimizes risk.
2. Maximum quadratic utility portfolio: The optimizer seeks to identify the portfolio that maximizes expected returns while accounting for the associated risk. Specifically, quadratic utility maximizes expected returns while imposing a quadratic penalty on risk. A risk aversion value of 1 is used, signifying moderate risk aversion, where the investor reasonably penalizes risk (variance) but remains willing to accept some level of risk in pursuit of higher returns.

For the portfolio analysis, the continuously compounded returns are transformed into simple returns. According to Dorfleitner (2003), the choice between simple returns and log returns depends on the focus of the analysis, particularly when addressing portfolio aspects within the realm of classical capital market theory. The simplicity and convenient portfolio additivity property associated with simple returns make them well suited for discussions within this framework. However, caution is advised when attempting to approximate this additivity property with log returns unless there is compelling evidence to support such a transition. On the other hand, due to its advantageous time additivity property, the log return finds its suitability in time series models, such as GARCH models. Consequently, in the initial section of this article, where GARCH models are employed to facilitate the application of copulas, log returns are utilized. However, in this specific segment of the study, dedicated to determining the asset weights in the investment portfolio, the use of simple returns is deemed more appropriate. This deliberate choice reflects a thoughtful consideration of the analytical requirements of each modeling approach within the broader context of the research.

In alignment with Miralles-Quirós et al. (2019), the methodology employed in this study to compute portfolio weights adopts a rolling window approach. Let M denote the length of the estimation window for the parameters, set at M = 26 weeks in this research, which is equivalent to approximately 6 months. At each week t, commencing from $t = \mathrm{M} + 1$, the estimation of portfolio weights is conducted by utilizing return observations from the preceding M trading weeks. This process is iteratively applied, advancing the sample period by 1 week at a time, to consistently compute weights for subsequent weeks. Hence, the time frame selected for assessing the risk mitigation potential spans from July 11, 2014, to November 29, 2024. The portfolio analysis is divided into the following subperiods: the pre-crisis period, from July 11, 2014, to December 27, 2019; the COVID-19 transition phase, from January 3, 2020, to June 26, 2020; and the crisis period, from July 3, 2020, to November 29, 2024. It is crucial to separate the transition phase from the crisis period in the portfolio analysis, as the initial 6 months of COVID-19 were marked by unprecedented volatility driven by the pandemic's onset. The crisis period also involved additional factors, such as geopolitical conflicts. This distinction allows for a more accurate assessment of market reactions during these distinct phases of turmoil.

Once portfolio weights are estimated, the return and risk-reducing potential of each portfolio is analyzed through different measures, reported in annualized terms:

- Mean return
- Standard deviation (SD)
- Semi-deviation:

$$Semi - deviation = \sqrt{\frac{1}{n} x \sum_{r_t < \bar{r}}^{n} \left(\bar{r} - r_t\right)^2} \tag{5}$$

where n is the total number of observations below the mean, r_t denotes the observed return value in week t, and $\bar{r}$ is the mean return.

- Downside deviation (DD):

$$DD = \sqrt{\frac{1}{n} x \sum_{r_t < T}^{n} \left(T - r_t\right)^2} \tag{6}$$

where n is the total number of observations below T, r_t denotes the observed return value in week t, and T is the threshold. In this paper, the target is set at a value of 0.

- Historical VaR

$$\Pr\left(r_t \leq VaR_t | \psi_{t-1}\right) = p \tag{7}$$

where r_t denotes the observed return value in week t, $(1-\text{p})$ is the confidence interval, set at the 95%, and ψ_{t-1} represents the past information available at time $\text{t}-1$.

- Historical ES

$$\text{E}\left[r_t | \, r_t < VaR_t(p)\right] \tag{8}$$

where r_t denotes the observed return value in week t and $VaR_t(p)$ is the value at risk at the confidence level p.

- Return–risk ratio

$$Return - risk\ ratio = \frac{\bar{r}}{SD} \tag{9}$$

where $\bar{r}$ is the mean return and SD denotes the standard deviation of returns.

- Return–DD ratio

$$Return - DD\ ratio = \frac{\bar{r}}{DD} \tag{10}$$

where $\bar{r}$ is the mean return and DD denotes the downside deviation.

For each ETF, 1000 simulated paths are generated. Within each path, portfolios are constructed, and the relevant measures are calculated. Subsequently, the average of each measure across all simulated paths is determined. These computed averages are then compiled and presented for each of the markets under consideration for further analysis and interpretation in Section 5.3.

Figure 5 details the steps followed to assess portfolio performance, as examined by the mean return, risk, and downside risk measures introduced above.

5 | Results and Discussion

This section presents and discusses the empirical results, with each component of the analysis organized into a dedicated section. Section 5.1 describes the estimation of the marginal models—specifically, the ARMA-GJR-GARCH and ARMA-EGARCH specifications—used to capture the conditional volatility of ETF return series. Section 5.2 focuses on the copula selection process, which is essential to understanding how the returns of ESG and non-ESG ETFs move in relation to each other—particularly during turbulent periods, when tail dependence becomes especially relevant. Accurately modeling this dependence structure allows for a more precise evaluation of joint risk behavior. Finally, Section 5.3 evaluates the performance of the constructed portfolios across both regions and periods, focusing on return, volatility, and downside risk measures.

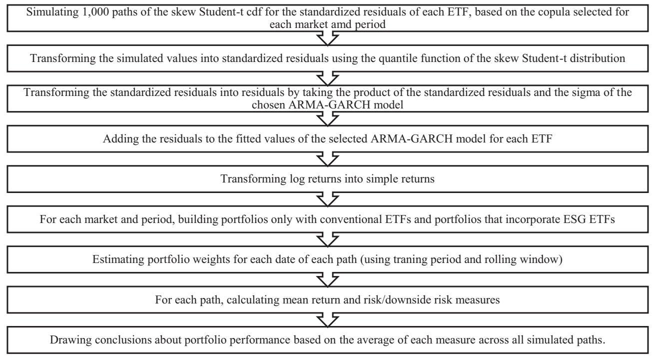


FIGURE 5 | Steps followed to assess portfolio performance.

5.1 | Marginal Model Estimation

The parameters of the marginal distribution models are estimated using the maximum likelihood method, exploring various combinations of p, q, r, and m with lag values from 0 to 4. To deem a model valid, it must successfully pass several tests: (1) the Ljung–Box test for autocorrelation in the residuals and squared residuals (up to lags 10 and 20); (2) the ARCH LM test for autoregressive conditional heteroskedasticity (ARCH) in the residuals (up to lags 10 and 20); (3) the Nyblom stability test (both joint and individual) to assess parameter stability over time; (4) the sign bias tests (including sign bias, negative sign bias, positive sign bias, and joint effect) to evaluate the appropriateness of an asymmetric GARCH model in capturing volatility dynamics; and (5) the adjusted Pearson goodness-of-fit test (for groups 20, 30, 40, and 50) to compare observed and expected frequencies in predefined groups. Once valid models are identified for both ARMA-GJR-GARCH and ARMA-EGARCH specifications, the best model is selected based on the AIC.

Estimation results, as presented in Table 5 (entire period), Table 6 (pre-crisis subperiod), and Table 7 (COVID-19 transition phase and crisis subperiod), generally indicate mean models with significant autoregressive and moving average components, emphasizing the role of past returns and residuals in explaining current returns. The constants in both the mean and variance models are significant in most cases, further highlighting their importance in capturing underlying trends. Notably, differences across indices and subperiods emerge. For example, whereas simpler ARMA(0,1) models dominate in some series, others, such as IHYG.L, require more complex ARMA(4,3) specifications, reflecting a more intricate return-generating process. These variations underscore the heterogeneity of financial markets and the need for tailored modeling approaches.

TABLE 5 | Estimates of the marginal distribution models for the entire period.

	IUSK.AS	IRCP.L	VGK	IHYG.L	DSI	SJNK.L	SPY	BND.O
GARCH model	EGARCH (4,1).	GJR-GARCH (2,1)	EGARCH (1,2)	EGARCH (2,3)	GJR-GARCH (4,1)	EGARCH (3,4)	EGARCH (4,3)	EGARCH(1,4)
Mean model	ARMA (0,0)	ARMA (3,2)	ARMA (4,4)	ARMA (4,3)	ARMA (4,2)	ARMA (2,2)	ARMA (0,2)	ARMA (4,4)
mu	0.0004 (0.00072)	−0.0008* (0.00048)	−0.0002 (0.00086)	−0.0008*** (0.00003)	0.0112 (0.00006)	−0.0008*** (0.00000)	0.0030*** (0.00000)	−0.0001*** (0.00000)
ar1		−0.3568*** (0.08493)	0.8930*** (0.01293)	−2.1238*** (0.00585)	1.5873 (0.00101)	−0.2449*** (0.00128)		−1.6846*** (0.00472)
ar2		−0.9613*** (0.05502)	−0.5274*** (0.00838)	−2.0489*** (0.00408)	−0.5185 (0.00010)	−0.9748*** (0.00009)		−1.9011*** (0.01107)
ar3		−0.0685 (0.04440)	0.9052*** (0.00600)	−0.8287*** (0.00194)	−0.1516 (0.00024)			−1.4180*** (0.00554)
ar4			−0.9983*** (0.00365)	0.0415*** (0.00024)	0.0826 (0.00014)			−0.3444*** (0.00138)
ma1		0.3124*** (0.06995)	−0.8916*** (0.00200)	2.1215*** (0.00000)	−1.7339 (0.00017)	0.2657*** (0.01822)	−0.1141*** (0.00002)	1.5964*** (0.00234)
ma2		0.9102*** (0.06833)	0.5197*** (0.00118)	2.1138*** (0.00000)	0.7338 (0.00007)	0.9689*** (0.00010)	−0.1200*** (0.00026)	1.7956*** (0.00301)
ma3			−0.9102*** (0.00144)	0.8994*** (0.00009)				1.2913*** (0.01052)
ma4			1.0152*** (0.00070)					0.2580*** (0.00084)
omega	−0.3137*** (0.01009)	0.0000*** (0.00000)	−0.5308*** (0.11490)	−0.9876*** (0.09662)	0.0001 (0.00004)	−0.1848*** (0.00016)	−3.2338*** (0.00040)	−0.4710 (2.93306)
alpha1	−0.3208*** (0.08608)	0.0000 (0.36606)	−0.2125*** (0.04689)	−0.1375*** (0.03186)	0.0000 (0.17432)	−0.6049*** (0.00280)	−0.2935*** (0.00008)	0.0087 (0.89040)
alpha2	0.1751* (0.10073)	0.0039 (0.35445)		−0.1187*** (0.03089)	0.0000 (0.20811)	−0.0008 (0.00810)	−0.3305*** (0.00009)	
alpha3	−0.0367 (0.08688)				0.2369 (0.18656)	−0.8736*** (0.01955)	−0.0241*** (0.00000)	
alpha4	0.0636 (0.05130)				0.2680 (0.17020)		0.1925*** (0.00005)	
beta1	0.9587*** (0.00000)	0.9236*** (0.01276)	0.8989*** (0.00225)	−0.8026*** (0.01266)	0.3561 (0.19879)	0.7144*** (0.00007)	−0.7130*** (0.00039)	0.9987*** (0.03033)
beta2			0.0313** (0.01464)	0.8437*** (0.01222)		−0.6891*** (0.00131)	0.4834*** (0.00027)	−0.6740*** (0.02533)

(Continues)

TABLE 5 | (Continued)

	IUSK.AS	IRCP.L	VGK	IHYG.L	DSI	SJNK.L	SPY	BND.O
beta3				0.8436*** (0.00947)		0.7914*** (0.00005)	0.8395*** (0.00021)	0.8827*** (0.02005)
beta4						0.1592*** (0.00008)		−0.2532 (0.26138)
gamma1	0.0553 (0.14347)	0.2189 (0.28364)	0.1709*** (0.04234)	0.1360*** (0.02881)	0.5490 (0.14173)	−0.4076*** (0.00420)	0.2875*** (0.00006)	0.3469 (0.54224)
gamma2	0.2130 (0.17020)	−0.1235 (0.24509)		0.2331*** (0.04403)	0.0173 (0.32432)	0.2806*** (0.01350)	0.5063*** (0.00004)	
gamma3	−0.2136*** (0.00246)				−0.2681 (0.14778)	−0.3261*** (0.00712)	0.4261*** (0.00008)	
gamma4	0.0838 (0.07620)				−0.1488 (0.14894)		0.3223*** (0.00005)	
Skew	0.7866*** (0.05488)	0.9579*** (0.06395)	0.7763*** (0.05585)	0.9160*** (0.05025)	0.6775 (0.05899)	0.6503*** (0.01523)	0.6820*** (0.00166)	0.7791*** (0.11039)
Shape	6.5999*** (2.05057)	7.0465*** (2.20414)	6.6688*** (1.87901)	4.9597*** (1.38095)	6.0788 (2.28377)	2.0875*** (0.00089)	35.2005*** (0.16455)	9.6107 (13.03298)
Log Lik.	1398.84	1741.69	1388.52	1655.07	1425.20	2019.55	1504.52	2137.06
LJ(10)/(20)	3.33/12.04	7.77/14.79	10.14/15.88	6.72/15.44	7.42/16.65	8.24/14.22	13.89/22.45	6.21/11.37
LJ SQ(10)/(20)	11.31/22.50	11.29/16.58	10.70/15.99	1.58/2.66	0.10/0.16	2.14/3.55	8.467/23.13	7.02/12.13
ARCH LM(10)/(20)	10.64/22.12	10.46/15.95	10.14/15.88	1.52/2.52	0.10/0.16	2.05/3.26	8.36/20.75	6.57/10.90
Nyblom (joint)/ (individual)	2.62/all stable	2.34/all stable	2.06/all stable	1.65/all stable	2.11/all stable	2.45/all stable	1.11/all stable	2.66/all stable
Sign bias/negative/ positive/joint	1.35/1.04/ 0.39/2.07	1.05/0.90/ 0.56/2.90	1.38/1.15/ 0.51/3.98	1.48/0.56/ 0.91/2.22	0.47/0.09/ 0.18/0.70	0.49/0.31/0.86/0.84	0.86/0.17/ 0.36/2.65	0.46/0.08/ 0.79/1.93
Pearson GOF group 20/30/40/50	20.77/33.16/ 41.26/64.83*	15.22/21.25/ 34.51/41.28	17.96/27.36/ 33.53/45.32	17.82/25.46/ 36.62/46.55	22.04/20.72/ 37.75/44.80	10.02/34.01/ 31.70/44.62	21.47/20.30/ 44.22/47.96	22.18/33.79/ 52.37*/47.26

Note: This table presents the maximum likelihood (ML) estimates and associated standard errors (in brackets) for the parameters of the marginal distribution model defined in Equations (1) and (2). LogLik represents the log-likelihood value. The Ljung–Box test for LJ(10) and LJ(20) is a test of autocorrelation of orders up to 10 and 20, respectively, under the null hypothesis that the residuals are uncorrelated. Similarly, the Ljung–Box test for squared residuals, LJ SQ(10) and LJ SQ(20), examines whether there is autocorrelation in the variance of the residuals (indicative of volatility clustering) under the same null hypothesis. In both cases, the test statistic is asymptotically distributed as χ_2 with degrees of freedom equal to the lag count. The ARCH LM test for ARCH LM(10) and ARCH LM(20) is a test for autoregressive conditional heteroskedasticity (ARCH) of orders up to 10 and 20, respectively, under the null hypothesis that there is no ARCH effect in the residuals (i.e., the variance of the residuals is constant). The test statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the lag count. The Nyblom stability test (joint and individual) evaluates whether the parameters of a time series model are constant over time. The null hypothesis assumes parameter stability (i.e., no time-varying behavior), and the test statistic is compared to asymptotic critical values. For the joint test, all parameters are assessed together, whereas the individual test examines each parameter separately. The sign bias tests (sign bias, negative sign bias, positive sign bias, and joint effect) assess the adequacy of an asymmetric GARCH model in capturing volatility dynamics. The null hypothesis assumes no sign bias effects in the residuals, meaning past positive or negative shocks do not asymmetrically affect volatility. Each test evaluates a specific type of bias, although the joint effect combines them. Test statistics are asymptotically distributed as *t* values under the null hypothesis. The adjusted Pearson goodness-of-fit test (groups 20, 30, 40, and 50) evaluates the adequacy of a fitted model by comparing observed and expected frequencies in predefined groups. The null hypothesis assumes the model fits the data well across all groups. The test statistic follows a χ^2 distribution with degrees of freedom determined by $g-1$, where g is the number of groups.

*Statistical significance at the 10% level.

**Statistical significance at the 5% level.

***Statistical significance at the 1% level.

TABLE 6 | Estimates of the marginal distribution models for the pre-crisis subperiod.

	IUSK.AS	IRCP.L	VGK	IHYG.L	DSI	SJNK.L	SPY	BND.O
GARCH model	EGARCH (2,3)	EGARCH (3,3)	EGARCH (1,1)	EGARCH (2,4)	EGARCH (1,4)	EGARCH (4,4)	EGARCH (1,4)	EGARCH(1,2)
Mean model	ARMA (4,3)	ARMA (4,0)	ARMA (4,2)	ARMA (1,3)	ARMA (0,1)	ARMA (0,2)	ARMA (0,1)	ARMA (4,3)
mu	0.0017*** (0.00000)	−0.0025*** (0.00000)	0.0000 (0.00099)	−0.0012*** (0.00000)	0.0017** (0.00072)	0.0000*** (0.00000)	0.0016** (0.00070)	−0.0001*** (0.00000)
ar1	0.1059*** (0.00010)	−0.0021*** (0.00004)	−1.5813*** (0.05748)	−0.8815*** (0.00006)				−0.7094*** (0.00014)
ar2	−0.7465*** (0.00016)	−0.0482*** (0.00004)	−0.9168*** (0.07485)					−1.0220*** (0.00012)
ar3	−0.4232*** (0.00001)	−0.0261*** (0.00007)	−0.0809 (0.06225)					−0.7777*** (0.00009)
ar4	−0.0105*** (0.00001)	0.1777*** (0.00001)	−0.0376 (0.03338)					−0.1189*** (0.00003)
ma1	−0.2450*** (0.00018)		1.6124*** (0.04048)	0.9030*** (0.00015)	−0.1287*** (0.04613)	0.0365 (0.33758)	−0.1052* (0.05392)	0.4879*** (0.00007)
ma2	0.8374*** (0.00010)		0.9393*** (0.03374)	0.0031*** (0.00005)		−0.1177*** (0.00514)		1.0121*** (0.00007)
ma3	0.2920*** (0.00003)			−0.0977*** (0.00002)				0.6000*** (0.00013)
omega	−1.2854*** (0.00089)	−0.6842*** (0.00032)	−2.8433 (1.93168)	−1.1997*** (0.00005)	−1.7443 (1.27557)	−0.0243*** (0.00000)	−1.6037*** (0.58505)	−0.7829*** (0.01138)
alpha1	−0.5010*** (0.00009)	−0.0869*** (0.00000)	−0.2809*** (0.08223)	0.0650*** (0.00001)	−0.2600** (0.11581)	−0.1833*** (0.00097)	−0.2787*** (0.07109)	0.0994** (0.04907)
alpha2	−0.1694*** (0.00002)	0.1786*** (0.00002)		−0.0254*** (0.00001)		0.6468*** (0.00335)		
alpha3		−0.1036*** (0.00005)				−0.8736*** (0.00120)		
alpha4						−0.0863*** (0.00211)		
beta1	−0.2044*** (0.00007)	0.1006*** (0.00000)	0.6449*** (0.24490)	0.6462*** (0.00009)	0.5848*** (0.13074)	0.7338*** (0.00094)	0.6091*** (0.02394)	−0.0058*** (0.00133)
beta2	0.2701*** (0.00005)	−0.0323*** (0.00000)		−0.6964*** (0.00006)	−0.0510 (0.15160)	−0.4472*** (0.00069)	−0.0129 (0.05599)	0.9343** (0.00007)
beta3	0.7798*** (0.00035)	0.8548*** (0.00013)		0.7399*** (0.00008)	0.6244*** 0.04705	0.3615*** (0.00058)	0.5879*** (0.02282)	

(Continues)

TABLE 6 | (Continued)

	IUSK.AS	IRCP.L	VGK	IHYG.L	DSI	SJNK.L	SPY	BND.O
beta4				0.1798*** (0.00002)	−0.3699** (0.18389)	0.3517*** (0.00061)	−0.3773*** (0.02692)	
gamma1	−0.4081*** (0.00008)	0.3064*** (0.00004)	0.1386 (0.10440)	0.3154*** (0.00033)	0.3581*** (0.07529)	0.4106*** (0.00847)	0.3133*** (0.10720)	0.1922*** (0.00479)
gamma2	−0.1473*** (0.00020)	0.4160*** (0.00002)		0.1791*** (0.00006)		0.6004*** (0.00283)		
gamma3		−0.2671*** (0.00002)				−0.6458*** (0.00161)		
gamma4						−0.6686*** (0.00410)		
skew	0.7049*** (0.00503)	0.6973*** (0.00816)	0.7406*** (0.09122)	0.9447*** (0.14521)	0.5844*** (0.05548)	0.6432*** (0.00486)	0.6172*** (0.05260)	0.7026*** (0.09203)
shape	7.9311*** (0.00200)	22.2729*** (0.23466)	21.5448 (29.05958)	53.2341*** (1.77082)	12.4072 (10.16150)	2.2014*** (0.00493)	9.4756** (4.57460)	33.1442*** (10.03111)
Log Lik.	848.29	989.37	812.93	961.23	864.90	1200.15	879.62	1271.23
LJ(10)/(20)	10.46/17.46	4.03/23.59	1.91/9.58	9.30/18.06	7.45/16.72	3.07/7.61	6.47/18.71	8.16/16.27
LJ SQ(10)/LJ SQ(20)	12.87/24.21	6.35/16.05	4.16/11.61	8.33/19.20	14.64/25.19	2.31/4.32	10.04/19.72	7.40/10.30
ARCH LM(10)/(20)	12.30/22.76	5.93/12.90	4.56/11.78	7.92/16.85	13.46/23.10	2.72/6.72	9.06/16.01	7.10/9.83
Nyblom (joint)/ (individual)	3.77/all stable	0.10/all stable	1.99/all stable	0.30/all stable	1.58/all stable	3.81/all stable	1.79/all stable	0.05/all stable
Sign bias/negative/ positive/joint	0.35/1.63/ 0.36/4.14	1.25/1.54/ 0.15/2.70	1.00/1.06/ 0.52/2.51	0.38/0.19/ 0.78/1.99	1.04/1.30/ 0.15/2.32	0.08/0.73/ 0.67/1.00	0.56/0.86/ 0.10/0.83	0.68/0.04/ 0.79/0.74
Pearson GOF group 20/30/40/50	17.1/23.77/ 41.08/37.36	26.46/29.35/ 45.95/42.17	14.03/22.23/ 31.85/35.76	21.85/28.96/ 38.26/39.92	10.31/19.35/ 30.56/28.38	14.79/29.15/ 31.59/46.33	8.51/20.12/ 22.87/43.45	10.31/28.96/ 31.33/44.09

Note: This table presents the maximum likelihood (ML) estimates and associated standard errors (in brackets) for the parameters of the marginal distribution model defined in Equations (1) and (2). LogLik represents the log-likelihood value. The Ljung–Box test for LJ(10) and LJ(20) is a test of autocorrelation of orders up to 10 and 20, respectively, under the null hypothesis that the residuals are uncorrelated. Similarly, the Ljung–Box test for squared residuals, LJ SQ(10) and LJ SQ(20), examines whether there is autocorrelation in the variance of the residuals (indicative of volatility clustering) under the same null hypothesis. In both cases, the test statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the lag count. The ARCH LM test for ARCH LM(10) and ARCH LM(20) is a test for autoregressive conditional heteroskedasticity (ARCH) of orders up to 10 and 20, respectively, under the null hypothesis that there is no ARCH effect in the residuals (i.e., the variance of the residuals is constant). The test statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the lag count. The Nyblom stability test (joint and individual) evaluates whether the parameters of a time series model are constant over time. The null hypothesis assumes parameter stability (i.e., no time-varying behavior), and the test statistic is compared to asymptotic critical values. For the joint test, all parameters are assessed together, whereas the individual test examines each parameter separately. The sign bias tests (sign bias, negative sign bias, positive sign bias, and joint effect) assess the adequacy of an asymmetric GARCH model in capturing volatility dynamics. The null hypothesis assumes no sign bias effects in the residuals, meaning past positive or negative shocks do not asymmetrically affect volatility. Each test evaluates a specific type of bias, although the joint effect combines them. Test statistics are asymptotically distributed as t values under the null hypothesis. The adjusted Pearson goodness-of-fit test (groups 20, 30, 40, and 50) evaluates the adequacy of a fitted model by comparing observed and expected frequencies in predefined groups. The null hypothesis assumes the model fits the data well across all groups. The test statistic follows a χ^2 distribution with degrees of freedom determined by $g-1$, where g is the number of groups.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.
***Statistical significance at the 1% level.

TABLE 7 | Estimates of the marginal distribution models for the COVID-19 transition phase and crisis subperiod.

	IUSK.AS	IRCP.L	VGK	IHYG.L	DSI	SJNK.L	SPY	BND.O
GARCH model	EGARCH (2,4)	EGARCH (3,1)	EGARCH (1,2)	EGARCH (1,2)	EGARCH (2,4)	EGARCH (2,4)	EGARCH (2,1)	EGARCH(4,4)
Mean model	ARMA (4,4)	ARMA (2,2)	ARMA (3,3)	ARMA (2,4)	ARMA (2,1)	ARMA (4,2)	ARMA (0,1)	ARMA (0,1)
Mu	0.0009 (0.00161)	−0.0015*** (0.00000)	−0.0001 (0.00132)	−0.0014*** (0.00019)	0.0029*** (0.00000)	−0.0010 (0.00460)	0.0025*** (0.00080)	−0.0010*** (0.00000)
ar1	0.5244*** (0.05681)	−1.8882*** (0.00006)	1.4760*** (0.00453)	−1.2273*** (0.00218)	−0.2704*** (0.01846)	−0.2398 (0.91045)		
ar2	0.1120 (0.10984)	−0.9903*** (0.00389)	−0.6774*** (0.00489)	−0.9894*** (0.00627)	−0.0158** (0.00718)	−0.8017*** (0.09790)		
ar3	0.3362*** (0.06564)		−0.1940*** (0.01214)			0.0616 (0.07655)		
ar4	−0.8929*** (0.01470)					0.1556 (0.09877)		
ma1	−0.6061*** (0.02450)	1.9167*** (0.00198)	−1.6082*** (0.00780)	1.2025*** (0.00109)	0.1796*** (0.04643)	0.2902 (0.29901)	−0.1358*** (0.05084)	−0.0046*** (0.00066)
ma2	0.0057 (0.02217)	1.0178*** (0.00146)	0.8903*** (0.00142)	1.0666*** (0.00048)		0.9603*** (0.00062)		
ma3	−0.4146*** (0.02269)		0.0782*** (0.01078)	0.0871*** (0.00477)				
ma4	0.8975*** (0.00372)			0.0822*** (0.00286)				
omega	−0.8741* (0.46126)	−0.1045*** (0.00004)	−0.1617 (0.19097)	−0.0029 (0.00253)	−0.5500*** (0.00014)	−0.1975*** (0.00910)	−0.3459*** (0.01537)	−5.5485*** (0.01703)
alpha1	−0.1941* (0.10845)	−0.0945*** (0.00130)	−0.1844* (0.10565)	−0.2613*** (0.03895)	−0.2672*** (0.00017)	−1.2301 (2.21848)	−0.5038*** (0.02599)	−0.1270*** (0.00308)
alpha2	−0.3585*** (0.08386)	0.2558*** (0.00011)			−0.2013*** (0.00010)	0.1528 (0.16453)	0.2574*** (0.02391)	−0.1892*** (0.00305)
alpha3		−0.2810*** (0.00030)						0.2238*** (0.00215)
alpha4								0.0313*** (0.00587)
beta1	0.0476 (0.13350)	0.9876*** (0.00097)	1.0000*** (0.00006)	0.3872*** (0.00000)	0.0533*** (0.00001)	0.7667*** (0.02664)	0.9551*** (0.00004)	−0.6380*** (0.00110)
beta2	0.2038 (0.12781)		−0.0220 (0.02521)	0.6128*** (0.00001)	0.1726*** (0.00003)	−0.2263*** (0.00061)		−0.1001*** (0.00098)

(Continues)

TABLE 7 | (Continued)

	IUSK.AS	IRCP.L	VGK	IHYG.L	DSI	SJNK.L	SPY	BND.O
beta3	0.7679*** (0.00003)				0.3639*** (0.00016)	1.0000*** (0.00694)		0.4946*** (0.00032)
beta4	−0.1368** (0.05675)				0.3390*** (0.00014)	−0.5655*** (0.01204)		0.6906*** (0.00237)
gamma1	0.0605 (0.05841)	0.4942*** (0.00045)	0.0037 (0.14354)	−0.0607*** (0.00339)	−0.1922*** (0.00008)	−0.6107** (0.24758)	−0.0289 (0.09235)	0.5423*** (0.00370)
gamma2	0.0268 (0.05260)	−0.2339*** (0.00020)			−0.2509*** (0.00010)	0.2889 (1.5436)	0.1355 (0.08950)	1.3257*** (0.00500)
gamma3		−0.3585*** (0.00008)						0.6425*** (0.00511)
gamma4								0.3148*** (0.00249)
skew	0.7941*** (0.06732)	0.8244*** (0.01621)	0.8281*** (0.23777)	0.8804*** (0.06543)	0.7458*** (0.01183)	0.7131 (0.94053)	0.5348*** (0.06164)	0.8178*** (0.00246)
shape	10.1452 (7.38909)	11.2065*** (0.04499)	5.9316 (11.50354)	5.0616*** (1.33068)	4.7883*** (0.00183)	2.1103*** (0.00048)	59.3915 (135.49312)	17.2551*** (0.44531)
Log Lik.	592.8982	779.5636	586.4303	707.5965	577.6462	828.6808	625.8735	909.3096
LJ(10)/(20)	4.42/12.39	9.0974/19.14	5.21/14.40	5.48/15.09	2.03/3.95	3.77/10.77	4.85/14.29	6.14/10.10
LJ SQ(10)/(20)	13.62/20.34	6.61/13.89	12.81/23.04	5.11/7.59	0.04/0.09	1.16/1.63	6.81/13.66	4.81/10.42
ARCH LM(10)/(20)	4.27/20.27	7.20/16.77	6.28/16.20	13.59/13.13	0.04/0.10	1.03/1.34	11.33/23.03	5.15/12.71
Nyblom (joint)/(individual)	3.44/stable	2.92/stable	2.37/stable	2.83/stable	1.81/stable	2.56/stable	1.97/stable	−4.30[a]/stable
Sign bias/negative/positive/joint	0.24/0.42/1.05/1.98	0.13/0.01/0.43/0.41	0.20/1.06/0.09/1.98	1.51/1.59/0.44/3.47	1.11/0.00/0.0.66/1.30	0.70/0.45/0.57/0.65	0.68/0.10/0.12/1.01	0.02/0.10/0.08/0.02
Pearson GOF group 20/30/40/50	16.81/17.28/31.81/47.91	13.06/23.38/36.5/45.56	16.19/24.78/29.62/36.19	24.78/29.7/35.88/50.64	24.62/31.81/44.31/51.42	7.91/23.38/30.25/38.92	11.81/12.36/29.94/22.12	9.94/19.63/33.06/51.03

Note: This table presents the maximum likelihood (ML) estimates and associated standard errors (in brackets) for the parameters of the marginal distribution model defined in Equations (1) and (2). LogLik represents the log-likelihood value. The Ljung–Box test for LJ(10) and LJ(20) is a test of autocorrelation of orders up to 10 and 20, respectively, under the null hypothesis that the residuals are uncorrelated. Similarly, the Ljung–Box test for squared residuals, LJ SQ(10) and LJ SQ(20), examines whether there is autocorrelation in the variance of the residuals (indicative of volatility clustering) under the same null hypothesis. In both cases, the test statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the lag count. The ARCH LM test for ARCH LM(10) and ARCH LM(20) is a test for autoregressive conditional heteroskedasticity (ARCH) of orders up to 10 and 20, respectively, under the null hypothesis that there is no ARCH effect in the residuals (i.e., the variance of the residuals is constant). The test statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the lag count. The Nyblom stability test (joint and individual) evaluates whether the parameters of a time series model are constant over time. The null hypothesis assumes parameter stability (i.e., no time-varying behavior), and the test statistic is compared to asymptotic critical values. For the joint test, all parameters are assessed together, whereas the individual test examines each parameter separately. The sign bias tests (sign bias, negative sign bias, positive sign bias, and joint effect) assess the adequacy of an asymmetric GARCH model in capturing volatility dynamics. The null hypothesis assumes no sign bias effects in the residuals, meaning past positive or negative shocks do not asymmetrically affect volatility. Each test evaluates a specific type of bias, although the joint effect combines them. Test statistics are asymptotically distributed as t values under the null hypothesis. The adjusted Pearson goodness-of-fit test (groups 20, 30, 40, and 50) evaluates the adequacy of a fitted model by comparing observed and expected frequencies in predefined groups. The null hypothesis assumes the model fits the data well across all groups. The test statistic follows a χ^2 distribution with degrees of freedom determined by $g-1$, where g is the number of groups.

[a]As the statistic of the Nyblom joint test was negative, which is implausible, the stability of the model was further confirmed using the CUSUM (cumulative sum) test. With a statistic value of 0.54624, the null hypothesis that the model is stable—meaning that the model's parameters have not changed significantly over time—could not be rejected.

*Statistical significance at the 10% level.

**Statistical significance at the 5% level.

***Statistical significance at the 1% level.

Regarding variance models, the ARCH, GARCH, and leverage terms are frequently significant, underscoring the persistence of volatility and the asymmetric responses to shocks in explaining conditional variance. The widespread selection of EGARCH across most return series likely reflects its flexibility in modeling a range of asymmetric responses, including situations where the impact of shocks is not distinctly skewed. However, for indices such as IRCP.L and DSI, the GJR-GARCH model seems more appropriate for the entire period, possibly reflecting more pronounced or differently structured leverage effects in these series. In line with this, the significance of both skewness and shape parameters in the models further reinforces the presence of asymmetry and heavy tails in the distribution of returns. These results point to two key insights, namely, (1) the presence of potential tail dependence in the joint distribution and (2) the suitability of the standardized t-student distribution over the normal distribution for modeling innovations, as it better captures extreme events and tail risks.

Finally, the subperiod analysis reveals changes in the best-fitting model structures and parameters, pointing to evolving dynamics in returns and volatility. For instance, whereas SPY consistently fits best with EGARCH models, the specific ARMA and volatility terms differ across subperiods. Similarly, the transition from GJR-GARCH to EGARCH for IRCP.L and DSI in specific periods reflects shifts in the nature of volatility asymmetries.

5.2 | Vine Copulas

After accurately specifying and modeling the return series and obtaining the standardized residuals, the next crucial step is selecting the most appropriate copula to effectively capture the dependence structure of both European and US ETFs. As anticipated, in this study, the choice between D-vine and C-vine copula constructions is guided by AIC. Table 8 summarizes the results. Notably, the analysis demonstrates that the D-vine copula generally provides a strong fit for both markets, performing well across multiple periods by effectively capturing the dependence structures in the financial time series of European and US ETFs. However, during the pre-crisis subperiod and the COVID-19 transition phase and crisis subperiod for Europe, the C-vine copula is preferred, reflecting its suitability in these specific contexts.

Ultimately, the copula-based analysis presented in this section enables a clearer understanding of how ESG ETFs behave in relation to traditional ETFs. This, in turn, lays the groundwork for evaluating their role in portfolio construction—particularly in terms of their potential as diversifiers, hedging instruments, and safe-haven assets under varying market conditions.

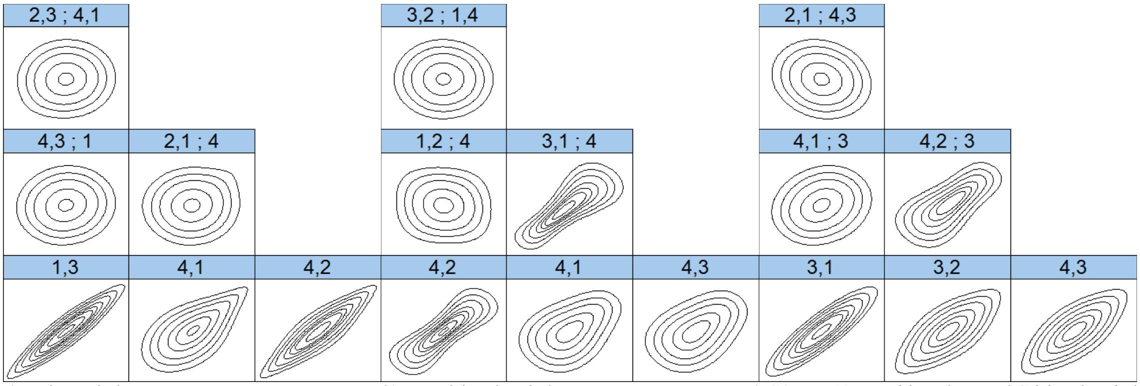
5.2.1 | Analysis for the European ETFs

Figures 6 and 7 exhibit the hierarchical dependence structure inherent in the optimally fitting vine copula for European ETFs for (a) the entire period, (b) the pre-crisis subperiod, and (c) the COVID-19 transition phase and crisis subperiod. Specifically, Figure 6 illustrates the overall hierarchical structure, whereas Figure 7 zooms in on the bivariate copula family selected, along with the magnitude of dependence measured through Kendall's tau. A clear pattern emerges, showing heightened average dependence at the first level, which typically decreases progressively and may even become zero or negative in subsequent levels. This suggests the potential of European ETFs as diversifiers and hedges. Additionally, as shown in Figures 6 and 7, copulas without tail dependence are selected in most cases,

TABLE 8 | Copula selection outcomes.

Entire period				
	Europe		**USA**	
Copula	**D-vine**	C-vine	**D-vine**	C-vine
Log. likelihood	**1078.235**	1074.054	**727.8084**	720.6307
AIC	**−2140.47**	−2128.108	**−1439.617**	−1425.261
Pre-crisis subperiod				
	Europe		**USA**	
Copula	D-vine	**C-vine**	**D-vine**	C-vine
Log. likelihood	462.3082	**467.0096**	**532.9415**	532.7937
AIC	−906.6165	**−914.0192**	**−1049.883**	−1047.587
COVID-19 transition phase and crisis subperiod				
	Europe		**USA**	
Copula	D-vine	**C-vine**	**D-vine**	C-vine
Log. likelihood	466.7499	**470.0256**	**364.7933**	360.0655
AIC	−917.4999	**−922.0512**	**−715.5866**	−706.131

Note: The selected copulas are highlighted in bold.



a) Entire period b) Pre-crisis subperiod c) COVID-19 Transition Phase and Crisis subperiod

FIGURE 6 | Contour plot of the D- and C-vine copulas for European ETFs. *Note:* 1: IUSK.AS; 2: IRCP.L; 3: VGK; 4: IHYG.L.

especially when considering subperiods. This detailed analysis emphasizes the risk-safe haven potential of an investment strategy that incorporates European ETFs.

The conclusions of this graphical analysis are further confirmed in Table 9, which presents the copula families identified by the best-fitting vine copula and provides insight into Kendall's tau and lower and upper tail dependence values. This analysis is conducted to assess the diversification, hedge, and safe-haven properties of the European ESG-based ETFs. Hence, ESG ETFs are allocated in the columns of the table. The threshold values used to assess the strength of the rank-based correlation statistic (negligible, weak, moderate, strong, and very strong) are derived from Schober et al. (2018). In this study, an asset is classified as a hedge when its correlation with other assets is either negative or does not exceed 0.05. The same threshold is used to classify an asset as a safe haven, based on tail dependence.

5.2.1.1 | Entire Period. The ESG ETF IUSK.AS demonstrates a dual role in portfolio construction. It acts as a diversifier with VGK, showing a strong—though not perfect—positive dependence (Kendall's Tau = 0.75), captured by the Student-t copula, which is well suited for modeling symmetric tail dependence. Additionally, IUSK.AS provides both diversification and safe-haven benefits during market downturns when paired with IHYG.L, as evidenced by a moderate dependence (Tau = 0.40) modeled by the Gumbel copula and by the absence of lower tail dependence—indicating that IUSK.AS does not decline simultaneously with IHYG.L during periods of market stress, a key feature of safe-haven assets.

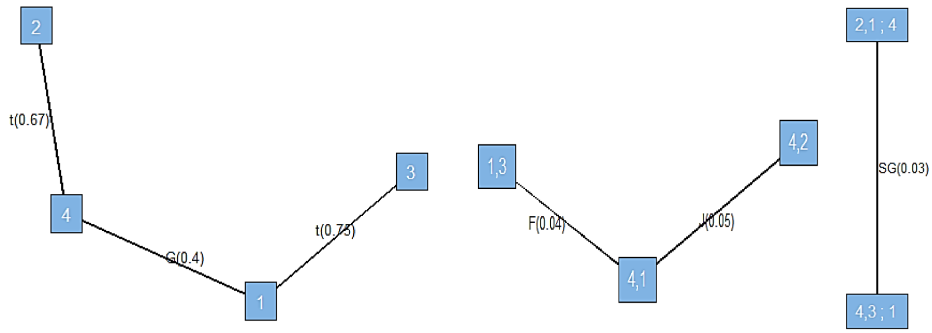
Similarly, the ESG ETF IRCP.L functions as a diversifier with IHYG.L (Tau = 0.67, Student-t copula), and more importantly, as a hedging instrument with safe-haven characteristics in both bullish and bearish market conditions relative to VGK. This is reflected in a negligible overall dependence (Tau = 0.03), captured by the survival Gumbel copula, and the absence of both lower and upper tail dependence.

Lastly, the negligible dependence between both ESG ETFs, IUSK.AS, and IRCP.L, (Kendall's Tau = 0.05, modeled by a Joe copula) suggests that these two ESG ETFs may also serve as hedges for one another. Their lack of lower tail dependence indicates they are unlikely to experience simultaneous extreme losses, supporting their potential role as safe-haven assets during bear markets. This enhances their relevance in portfolio strategies aimed at reducing risk through diversification and improving resilience in periods of financial stress.

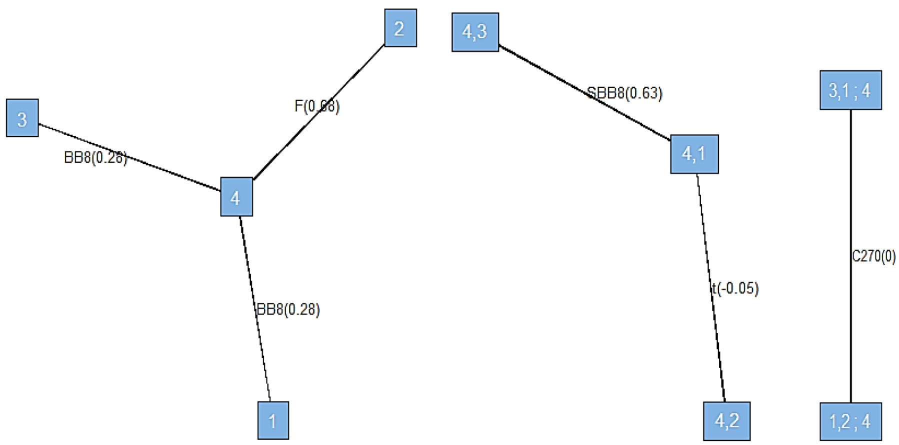
To conclude, the finding that ESG ETFs can act as diversifiers, hedges, and occasionally safe havens relative to traditional ETFs highlights their significant risk-mitigation potential—an aspect further explored in Section 5.3. This partially aligns with Chakrabarty et al. (2017), who documented the outperformance of European ESG ETFs but did not specifically examine their diversification or hedging capabilities. Contrary to their conclusion that neither region benefited during bear markets, our results indicate that ESG ETFs may provide safe-haven benefits at specific points throughout the full sample period, including phases of heightened market stress. These differences likely arise from our more recent dataset, which includes market shocks not covered in their study, as well as from evolving cultural and regulatory developments in Europe that have reinforced the importance of ESG investing.

5.2.1.2 | Pre-Crisis Subperiod. In the pre-crisis subperiod, the ESG ETF IUSK.AS continues to serve as a valuable diversifier, particularly in relation to VGK, with a moderate positive dependence (Kendall's Tau = 0.63), modeled by a survival BB8 copula. The absence of both lower and upper tail dependence suggests that IUSK.AS may provide protection against extreme market movements, enhancing its safe-haven potential during periods of financial stress. Additionally, its weak correlation with IHYG.L (Tau = 0.28, modeled by a BB8 copula) reinforces IUSK.AS's combined role as both a diversifier and a safe-haven asset, potentially reducing portfolio risk under varying market conditions.

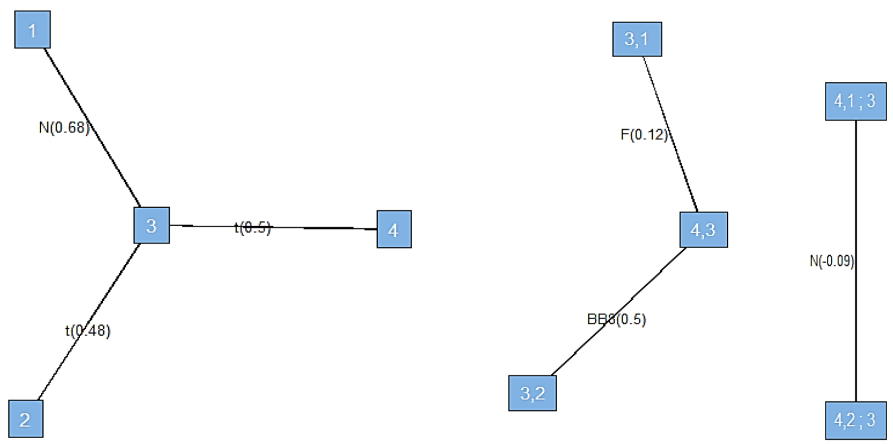
As in the entire period analysis, the ESG ETF IRCP.L functions primarily as a hedge and safe-haven asset with VGK. Its lack of dependence on this ETF (Kendall's Tau = 0), modeled using a 270° rotated Clayton copula, suggests that IRCP.L remains largely uncorrelated with broader market movements, even during periods of market stress, given the absence of both lower and upper tail dependence. Furthermore, its moderate association with IHYG.L (Tau = 0.68, modeled by a Frank copula) supports its role as a diversifier with potential safe-haven characteristics, as it lacks tail dependence.



a) Entire period



b) Pre-crisis subperiod



c) COVID-19 Transition Phase and Crisis subperiod

FIGURE 7 | D- and C-vine copula trees for European ETFs. *Note:* 1: IUSK.AS; 2: IRCP.L; 3: VGK; 4: IHYG.L.

Importantly, the very low and slightly negative correlation between both ESG ETFs, IUSK.AS, and IRCP.L, (Kendall's Tau = −0.05), modeled using a Student-t copula with negligible tail dependence, suggests that these two ESG ETFs may act as mutual hedges with safe-haven properties.

Overall, the pre-crisis findings reinforce the conclusions drawn for the entire period—namely, that ESG ETFs not only diversify but also offer hedge and safe-haven potential relative to traditional assets. Although Chakrabarty et al. (2017) found that European ETFs outperformed their benchmarks, their study did not explore whether these instruments offered diversification or hedging benefits. Our results complement and extend this perspective by showing that ESG ETFs may have served as risk-mitigating tools even before the crisis—through weak or asymmetric dependence with traditional ETFs—pointing to protective features that became more prominent during turbulent periods.

TABLE 9 | Copula families, correlation, tail dependence, and role of European ESG ETFs.

Entire period		
	IUSK.AS (1)	**IRCP.L (2)**
VGK (3)	Student-t (1,3)	Survival Gumbel (2,3;4,1)
	Tau = 0.75 (strong correlation)	Tau = 0.03 (negligible correlation)
	Lower = 0.49	Lower = 0.04
	Upper = 0.49	Upper = 0
	Diversifier	**Hedge**
	No safe haven	**Safe haven in bull market and bear markets**
IHYG.L (4)	Gumbel (4,1)	Student-t (4,2)
	Tau = 0.40 (moderate correlation)	Tau = 0.67 (moderate correlation)
	Lower = 0	Lower = 0.55
	Upper = 0.48	Upper = 0.55
	Diversifier	**Diversifier**
	Safe haven in bear markets	**No safe haven**
IRCP.L (2)	Joe (2,1;4)	
	Tau = 0.05 (negligible correlation)	
	Lower = 0	
	Upper = 0.11	
	Hedge	
	Safe haven in bear markets	
Pre-crisis subperiod		
	IUSK.AS (1)	**IRCP.L (2)**
VGK (3)	Survival BB8 (3,1;4)	Rotated Clayton 270° (3,2;1,4)
	Tau = 0.63 (moderate correlation)	Tau = 0 (negligible correlation)
	Lower = 0	Lower = 0
	Upper = 0	Upper = 0
	Diversifier	**Hedge**
	Safe haven in bull and bear markets	**Safe haven in bull and bear markets**
IHYG.L (4)	BB8 (4,1)	Frank (4,2)
	Tau = 0.28 (weak correlation)	Tau = 0.68 (moderate correlation)
	Lower = 0	Lower = 0
	Upper = 0	Upper = 0
	Diversifier	**Diversifier**
	Safe haven in bull and bear markets	**Safe haven in bull and bear markets**
IRCP.L (2)	Student-t (1,2;4)	
	Tau = −0.05 (negligible correlation)	
	Lower = 0.01	
	Upper = 0.01	
	Hedge	
	Safe haven in bull and bear markets	
COVID-19 transition phase and crisis subperiod		
	IUSK.AS (1)	**IRCP.L (2)**
VGK (3)	Gaussian (3,1)	Student-t (3,2)
	Tau = 0.68 (moderate correlation)	Tau = 0.48 (moderate correlation)
	Lower = 0	Lower = 0.21
	Upper = 0	Upper = 0.21
	Diversifier	**Diversifier**
	Safe haven in bull and bear markets	**Safe haven in bear markets**
IHYG.L (4)	Frank (4,1;3)	BB8 (4,2;3)
	Tau = 0.12 (weak correlation)	Tau = 0.5 (moderate correlation)
	Lower = 0	Lower = 0
	Upper = 0	Upper = 0
	Diversifier	**Diversifier**
	Safe haven in bull and bear markets	**No safe haven**
IRCP.L (2)	Gaussian (2,1;4,3)	
	Tau = −0.09 (negligible correlation)	
	Lower = 0	
	Upper = 0	
	Hedge	
	Safe haven in bull and bear markets	

Note: The diversification, hedging, or safe-haven properties are marked in bold.

5.2.1.3 | COVID-19 Transition Phase and Crisis Subperiod.

During the COVID-19 transition phase and crisis subperiod, the ESG ETF IUSK.AS continues to serve a dual role as both a diversifier and a safe-haven asset against traditional ETFs. Its moderate positive correlation with VGK (Tau = 0.68), captured by a Gaussian copula, indicates a balanced dependence without significant tail dependence—suggesting IUSK.AS may help mitigate risk in both rising and falling markets. Moreover, its weak correlation with IHYG.L (Tau = 0.12, modeled using a Frank copula), also lacking tail dependence, reinforces its versatility as a diversifier and safe-haven asset during turbulent periods.

In contrast, the ESG ETF IRCP.L primarily serves as a diversifier with VGK (Tau = 0.48, modeled by a Student-t copula), though it does not exhibit clear safe-haven properties. Its moderate correlation with IHYG.L (Tau = 0.5, modeled by a BB8 copula) suggests that IRCP.L offers diversification benefits and potential safe-haven qualities during market stress, as indicated by the absence of tail dependence.

Moreover, the slight negative correlation between IUSK.AS and IRCP.L (Tau = −0.09), modeled by a Gaussian copula, indicates that these two ESG ETFs continue to serve as mutual hedges, with their behavior complementing each other during the crisis period. Once again, the lack of significant tail dependence between them underscores their mutual capacity to act as safe-haven assets, providing crucial protection during the heightened market volatility characteristic of the COVID-19 crisis.

Taken together, the findings for this subperiod reinforce the observations from the entire and pre-crisis periods, where both ESG ETFs demonstrated strong risk-mitigating potential through diversification, hedging, and safe-haven qualities. Whereas Chakrabarty et al. (2017) found no performance advantages for Europe during bear markets, our analysis suggests that ESG ETFs may offer greater resilience under conditions of heightened market stress. These results are in line with Landi et al. (2024), who show that ESG standards positively affect risk-adjusted returns in Europe, further supporting the view that ESG investments can offer effective protection during times of crisis.

5.2.2 | Analysis for the US ETFs

Concerning the US market, Figures 8 and 9 display, respectively, the contour plot and the hierarchical structure of the vine copula that captures the dependence between the selected ETFs for this region in each of the periods considered. Similar to the European case, higher dependence is observed at the first hierarchical level, transitioning to lower and even negative values in subsequent levels. As with Europe, copulas with no tail dependence are preferred in most cases. This is further confirmed in Table 10, which shows the best-fitting vine copula, Kendall's tau, and tail dependence values for US ETFs. This allows for assessing the diversification, hedging, and safe-haven potential in each period.

5.2.2.1 | Entire Period. Over the entire period, the ESG ETF DSI shows strong positive dependence with SPY (Tau = 0.79, modeled by a Frank copula), indicating diversification benefits. The absence of tail dependence supports its role as a safe-haven asset during extreme market conditions. Additionally, DSI's negligible correlation with BND.O (Tau = 0.04, modeled by a survival Gumbel copula) reinforces its function as a hedge with safe-haven properties, especially during periods of market stress, as indicated by the lack of tail dependence.

On the other hand, the ESG ETF SJNK.L also functions as a diversifier and safe-haven asset with SPY (Tau = 0.41, modeled by a Frank copula), given its moderate correlation with SPY and the absence of tail dependence. However, its weak correlation with BND.O (Tau = 0.14, modeled by a Student-t copula) suggests that, although it provides diversification benefits, it does not fully exhibit safe-haven characteristics, as it shows some degree of tail dependence.

Furthermore, the negligible correlation between the two ESG ETFs, DSI and SJNK.L (Tau = 0.08, modeled by a Gaussian copula), indicates that these assets act as effective diversifiers against each other. Their lack of tail dependence suggests they both have safe-haven potential in various market conditions. The low correlation between them implies that, when held together, they can provide additional protective value, making them valuable tools for risk management during uncertain or volatile periods in the US market.

In conclusion, the ESG ETFs analyzed demonstrate significant potential as diversifiers, hedges, and safe-haven assets, providing protection in both bull and bear markets. Their ability to reduce risk and enhance portfolio value under various market conditions highlights their relevance for portfolio construction. When comparing our findings to previous studies on US ETFs over longer periods (beyond crisis episodes), our results are broadly consistent with Miralles-Quirós et al. (2019), who found evidence of outperformance, and Plagge and Grim (2020), who, while reporting no significant differences, still emphasize

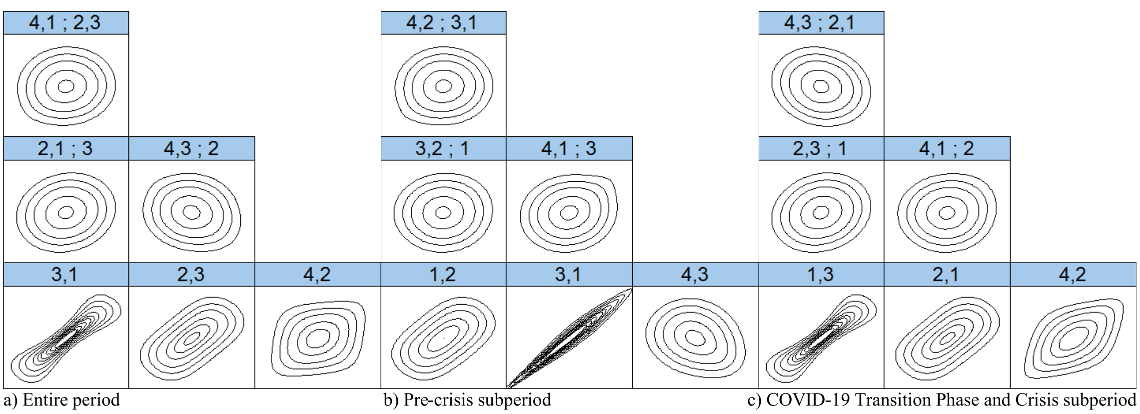
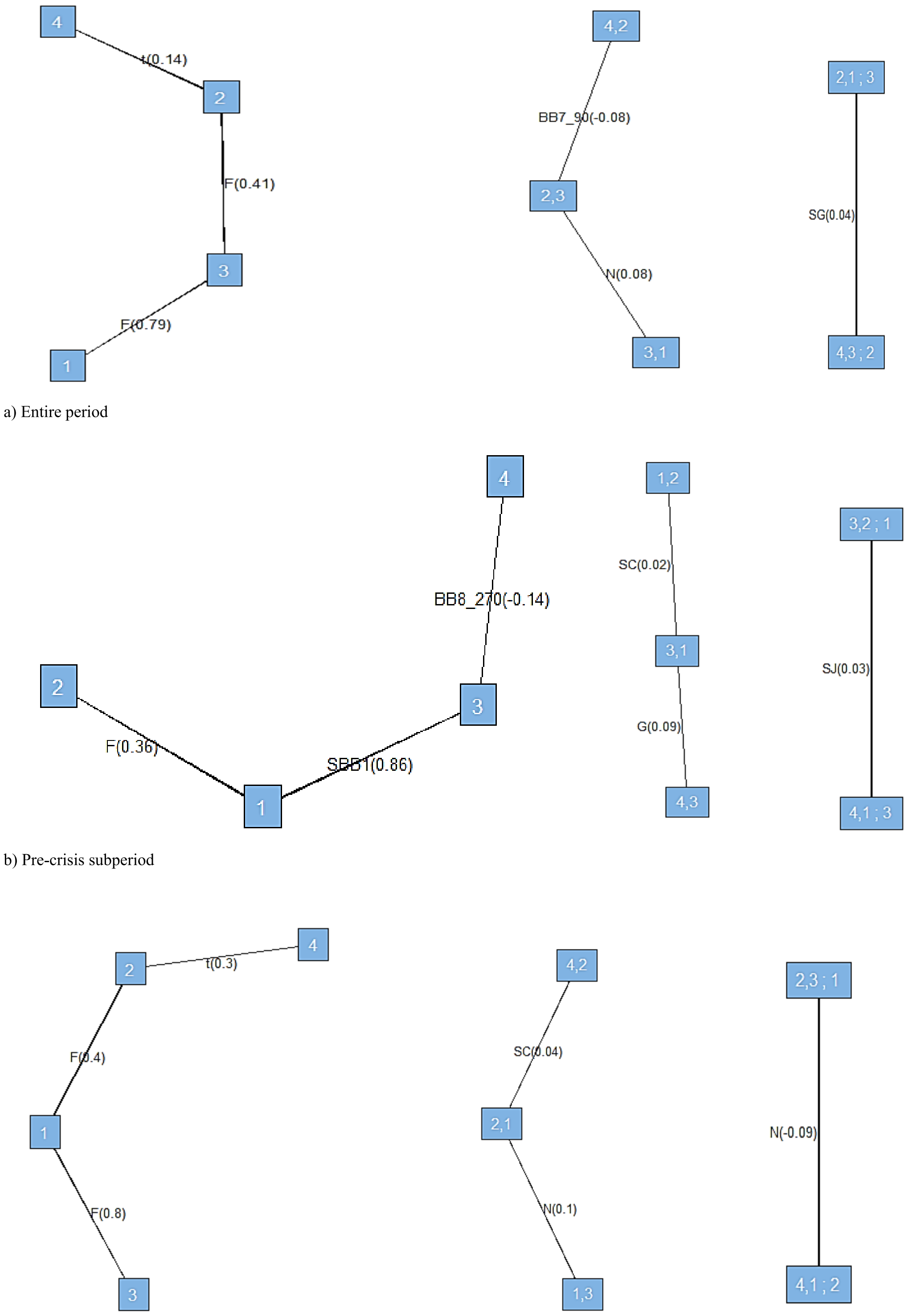


FIGURE 8 | Contour plot of the D-vine copula for US ETFs. *Note:* 1: DSI; 2: SJNK.L; 3: SPY; 4: BND.O.



c) COVID-19 Transition Phase and Crisis subperiod

FIGURE 9 | D-vine copula trees for US ETFs. *Note:* 1: DSI; 2: SJNK.L; 3: SPY; 4: BND.O.

the diversification and risk management roles of ESG ETFs. However, this research will further explore and formally test the extent of ESG ETFs outperformance or underperformance within a portfolio setting in Section 5.3. In contrast, Dumitrescu et al. (2023) report consistent underperformance throughout the period studied. These mixed findings contribute to the ongoing debate on the overall effectiveness of ESG ETFs, especially outside of crisis periods.

5.2.2.2 | **Pre-Crisis Subperiod.** During the pre-crisis subperiod, the ESG ETF DSI primarily serves as a diversifier with SPY (Tau = 0.86, modeled by a survival BB1 copula), but

TABLE 10 | Copula families, correlation, tail dependence, and role of US ESG ETFs.

Entire period	DSI (1)	SJNK.L (2)
SPY (3)	Frank (3,1)	Frank (2,3)
	Tau = 0.79 (strong correlation)	Tau = 0.41 (moderate correlation)
	Lower = 0	Lower = 0
	Upper = 0	Upper = 0
	Diversifier	**Diversifier**
	Safe haven in bull and bear markets	**Safe haven in bull and bear markets**
BND.O (4)	Survival Gumbel (4,1;2,3)	Student-t (4,2)
	Tau = 0.04 (negligible correlation)	Tau = 0.14 (weak correlation)
	Lower = 0.05	Lower = 0.11
	Upper = 0	Upper = 0.11
	Hedge	**Diversifier**
	Safe haven in bull and bear markets	**No safe haven**
SJNK.L (2)	Gaussian (2,1;3)	
	Tau = 0.08 (negligible correlation)	
	Lower = 0	
	Upper = 0	
	Diversifier	
	Safe haven in bull and bear markets	

Pre-crisis subperiod	DSI (1)	SJNK.L (2)
SPY (3)	Survival BB1 (3,1)	Survival Clayton (3,2;1)
	Tau = 0.86 (strong correlation)	Tau = 0.02 (negligible correlation)
	Lower = 0.88	Lower = 0
	Upper = 0.71	Upper = 0
	Diversifier	**Hedge**
	No safe haven	**Safe haven in bull and bear markets**
BND.O (4)	Gumbel (4,1;3)	Survival Joe (4,2;3,1)
	Tau = 0.09 (negligible correlation)	Tau = 0.03 (negligible correlation)
	Lower = 0	Lower = 0.08
	Upper = 0.12	Upper = 0
	Diversifier	**Hedge**
	Safe haven in bear markets	**Safe haven in bull markets**

(Continues)

TABLE 10 | (Continued)

Pre-crisis subperiod	DSI (1)	SJNK.L (2)
SJNK.L (2)	Frank (1,2)	
	Tau = 0.36 (weak correlation)	
	Lower = 0	
	Upper = 0	
	Diversifier	
	Safe haven in bull and bear markets	

COVID-19 transition phase and crisis subperiod	DSI (1)	SJNK.L (2)
SPY (3)	Frank (1,3)	Gaussian (2,3;1)
	Tau = 0.8 (strong correlation)	Tau = 0.1 (negligible correlation)
	Lower = 0	Lower = 0
	Upper = 0	Upper = 0
	Diversifier	**Diversifier**
	Safe haven in bull and bear markets	**Safe haven in bull and bear markets**
BND.O (4)	Survival Clayton (4,1;2)	Student-t (4,2)
	Tau = 0.04 (negligible correlation)	Tau = 0.3 (weak correlation)
	Lower = 0	Lower = 0.19
	Upper = 0	Upper = 0.19
	Hedge	**Diversifier**
	Safe haven in bull and bear markets	**No safe haven**
SJNK.L (2)	Frank (2,1)	
	Tau = 0.4 (moderate correlation)	
	Lower = 0	
	Upper = 0	
	Diversifier	
	Safe haven in bull and bear markets	

Note: For the survival Clayton, upper tail dependence is not exactly equal to zero. The diversification, hedging, or safe-haven properties are marked in bold.

it does not fully act as a safe-haven asset due to the presence of tail dependence. Although it offers diversification benefits, its performance during extreme market events may not provide complete protection. However, its negligible correlation with BND.O (Tau = 0.09, modeled by a Gumbel copula) suggests that DSI still functions as a solid diversifier, and the absence of lower tail dependence hints at some safe-haven qualities, particularly in bear markets, where it may offer a buffer against declines in traditional assets.

In contrast, the ESG ETF SJNK.L demonstrates a stronger hedging function and serves as a safe-haven asset in both bull and bear markets relative to SPY (Tau = 0.02, modeled by a survival Clayton copula). This indicates that SJNK.L is effective at reducing risk, holding up well during both market expansions and contractions, thanks to the lack of tail dependence. Its negligible correlation with BND.O (Tau = 0.03, modeled by a survival Joe copula) further underscores SJNK.L's role as a hedge with safe-haven properties. However, its safe-haven characteristics are more pronounced in bull markets than in bear markets, given the lack of upper tail dependence.

Additionally, the weak correlation between DSI and SJNK.L (Tau = 0.36, modeled by a Frank copula) highlights that these two ESG ETFs act as diversifiers and safe havens against each other. This suggests that investors can benefit from holding both assets in a portfolio, as they complement each other and offer valuable protection during periods of market stability.

In conclusion, the evidence from the pre-crisis period indicates that ESG ETFs can already play a relevant role in portfolio risk management, even in relatively calm market conditions. Although their safe-haven behavior is not fully developed at this stage—particularly in the case of DSI—they still exhibit clear diversification and hedging benefits, especially when combined. These findings suggest that the protective features of ESG ETFs are not confined to crisis episodes but may also be present in stable environments. As for the entire period, this perspective aligns more closely with studies such as Miralles-Quirós et al. (2019), which highlight the positive performance of ESG investments, and complements the more neutral stance of Plagge and Grim (2020), who find no significant performance gaps but recognize diversification potential. In contrast, the results diverge from Dumitrescu et al. (2023), who identify underperformance across broader periods. They also challenge the findings of Nofsinger and Varma (2014), who report that ESG investments tend to underperform specifically during non-crisis periods, suggesting instead that ESG ETFs may offer value even outside episodes of market turbulence. However, this hypothesis will be formally evaluated in Section 5.3 through a portfolio-based analysis.

5.2.2.3 | COVID-19 Transition Phase and Crisis Subperiod. During the COVID-19 transition and crisis subperiod, the ESG ETF DSI continues to function effectively as both a diversifier with SPY (Tau = 0.80, modeled by a Frank copula) and a safe-haven asset across bull and bear markets. Its negligible correlation with BND O (Tau = 0.04, modeled by a survival Clayton copula) and the absence of tail dependence reinforce DSI's role as a hedge with safe-haven characteristics, making it a suitable asset to hold during periods of market stress.

In contrast, the ESG ETF SJNK.L exhibits a negligible correlation with SPY (Tau = 0.1, modeled by a Gaussian copula), also without tail dependence, positioning it as a diversifier with safe-haven potential. However, its weak correlation with BND.O (Tau = 0.3, modeled by a Student-t copula) suggests that, although it provides diversification benefits, it may fall short as a full safe-haven asset due to the presence of tail dependence, which limits its effectiveness during extreme market events.

Additionally, the moderate correlation between DSI and SJNK.L (Tau = 0.4, modeled by a Frank copula), combined with the absence of tail dependence, indicates that these two ESG ETFs act as complementary diversifiers with safe-haven potential relative to one another. Although each demonstrates distinct safe-haven features under different market conditions, their joint behavior during the COVID-19 transition and crisis subperiod enhances their overall risk-mitigating capacity. This complementarity supports portfolio diversification and stability in both bull and bear markets.

Given these findings, it appears that the inclusion of ESG ETFs in investment portfolios may be beneficial or, at least, not detrimental to financial outcomes. This contributes to the ongoing debate on the performance of ESG instruments in the US market during crisis periods, where existing literature presents mixed results. Specifically, the results are consistent with the conclusions of Nofsinger and Varma (2014), Kanamura (2021), Huang (2024), and Landi et al. (2024), who report outperformance or positive effects of ESG standards on financial performance. In contrast, they diverge from Omura et al. (2021), who find no superior performance of ESG ETFs during the COVID-19 crisis, and partially from Valadkhani and O'Mahony (2024) and Meehan and Corbet (2025), who document context-dependent results. They also challenge the conclusions of Chakrabarty et al. (2017), who argue that US CSR ETFs do not serve as safe havens during economic downturns. However, it is important to note that this section evaluates ESG ETFs in terms of relative performance only—that is, how they perform compared to traditional ETFs during crisis periods. A more rigorous analysis of whether ESG ETFs deliver superior financial outcomes when integrated into actual investment portfolios, taking into account risk–return trade-offs, is conducted in Section 5.3.

5.3 | Risk Management and Portfolio Analysis

In Section 5.2, it was demonstrated that ESG ETFs have strong potential to enhance portfolio performance by mitigating risk in both Europe and the United States. This section provides a deeper evaluation, beginning with Europe, followed by the United States, and concluding with a comparative analysis. Tables 11 and 12 display the results of the portfolio analysis for Europe and the United States, respectively. The methodology used for the calculation of the mean return and the risk and downside risk measures was previously introduced in Section 4.2.

5.3.1 | Analysis for the European ETFs

In light of the findings of Table 11, it becomes evident that allocating resources to ESG ETFs in the European market varies according to the pursued investment strategy and period considered.

5.3.1.1 | Entire Period. Throughout the entire analyzed period, for Portfolio 1—focused on minimizing standard deviation—the ESG version exhibits marginally lower performance in terms of mean return (−0.034 vs. −0.031) and return–risk ratios. Although it consistently demonstrates significantly lower risk across multiple metrics, including standard

TABLE 11 | Performance of conventional versus ESG portfolios in Europe.

Entire period

	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Mean	−0.034	−0.031	−0.003	−5.59***	**0.032**	−0.035	0.067	8.00***
Standard deviation	**0.096**	0.121	−0.025	−93.78***	**0.140**	0.143	−0.003	−2.31**
Semi-deviation	**0.009**	0.012	−0.002	−86.94***	**0.014**	0.014	0.000	−2.32**
Downside deviation (DD)	**0.010**	0.012	−0.002	−79.09***	**0.014**	0.015	−0.001	−5.77***
Historical VaR	**−0.021**	−0.025	0.004	87.24***	**−0.030**	−0.033	0.002	6.25***
Historical ES	**−0.030**	−0.038	0.008	86.34***	**−0.044**	−0.047	0.003	4.63***
Return–risk ratio	−0.357	−0.258	−0.100	−21.07***	**0.265**	−0.253	0.518	3.68***
Reteurn-DD ratio	−3.411	−2.414	−0.997	−21.94***	**13.630**	8.509	5.121	−3.85***

Pre-crisis subperiod

	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Mean	−0.050	−0.044	−0.006	−11.24***	**0.088**	−0.028	0.116	7.43***
Standard deviation	**0.0843**	0.087	−0.003	−32.27***	0.129	0.122	0.007	6.99***
Semi-deviation	**0.008**	0.009	0.000	−11.93***	0.013	0.012	0.001	7.02***
Downside deviation (DD)	**0.009**	0.009	0.000	−5.49***	0.013	0.013	0.000	−0.98
Historical VaR	**−0.020**	−0.020	0.000	3.02***	−0.028	−0.028	0.000	−0.81
Historical ES	**−0.027**	−0.027	0.000	4.18***	−0.039	−0.037	−0.002	−4.42***
Return–risk ratio	−0.590	−0.504	−0.086	−14.23***	**0.555**	−0.341	0.897	3.69***
Return–DD ratio	−5.394	−4.692	−0.702	−12.77***	**39.430**	2.948	36.482	1.96*

COVID-19 transition phase

	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Mean	−0.034	−0.021	−0.013	−3.06***	**0.181**	0.106	0.075	2.16**
Standard deviation	**0.166**	0.201	−0.035	−27.51***	0.302	0.291	0.011	4.25***
Semi-deviation	**0.016**	0.020	−0.003	−22.05***	0.030	0.028	0.002	5.15***
Downside deviation (DD)	**0.017**	0.020	−0.003	−19.01***	0.029	0.028	0.001	3.31***
Historical VaR	**−0.035**	−0.041	0.006	16.02***	−0.061	−0.058	−0.003	−3.60***
Historical ES	**−0.046**	−0.055	0.009	16.96***	−0.085	−0.079	−0.006	−5.26***
Return–risk ratio	−0.171	−0.081	−0.090	−4.13***	**0.418**	0.186	0.231	2.0634**
Return–DD ratio	1.396	2.883	−1.486	−4.25***	13.766	16.660	−2.894	0.88

Crisis subperiod

	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Mean	−0.071	−0.061	−0.010	−10.72***	**0.022**	−0.040	0.062	5.99***
Standard deviation	**0.093**	0.121	−0.028	−76.72***	0.162	0.158	0.004	3.26***
Semi-deviation	**0.009**	0.012	−0.003	−59.69***	0.016	0.016	0.000	3.10***

(Continues)

TABLE 11 | (Continued)

Crisis subperiod								
	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Downside deviation (DD)	**0.010**	0.013	−0.003	−52.62***	0.0162	0.0162	0.000	0.02
Historical VaR	**−0.022**	−0.027	0.005	49.99***	−0.035	−0.035	0.000	−1.45
Historical ES	**−0.032**	−0.041	0.009	55.98***	−0.051	−0.050	0.000	−0.89
Return–risk ratio	−0.759	−0.499	−0.260	−34.78***	**0.105**	−0.310	0.414	2.96***
Return–DD ratio	−6.751	−4.462	−2.289	−34.13***	**3.937**	−0.903	4.839	4.19***

Note: Portfolio 1: minimum standard deviation portfolio; Portfolio 2: maximum quadratic utility portfolio. Portfolio 1 ESG and Portfolio 2 ESG are portfolios consisting of traditional and ESG ETFs. Portfolio 1 wo ESG and Portfolio 2 wo ESG are portfolios comprising solely conventional ETFs. Figures in bold show the cases where ESG portfolios outperform conventional portfolios.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.
***Statistical significance at the 1% level.

deviation, semi-deviation, downside deviation (DD), value at risk (VaR), and expected shortfall (ES), the decline in return–risk and return–DD ratios (by 0.100 and 0.997 points, respectively) suggests that the reduction in risk does not translate into improved risk-adjusted performance. These results indicate that although ESG inclusion reduces certain risk measures, it may come at the expense of return efficiency, leading to weaker risk–return trade-offs.

For Portfolio 2, which aims to maximize quadratic utility—a more realistic investment strategy that balances both return and risk objectives—ESG integration proves to be particularly advantageous. The ESG portfolio achieves a significantly higher mean return (0.032 vs.−0.035). This performance delta of 0.067 in mean return reflects a substantial performance improvement due to ESG integration. Additionally, the return–risk ratio increases by 0.518, indicating a marked enhancement in efficiency compared to the non-ESG version. These statistically significant results suggest that integrating ESG assets within this portfolio framework effectively enhances financial performance without substantially increasing risk. These results are consistent with Chakrabarty et al. (2017), who reported outperformance of European ESG ETFs in terms of risk-adjusted returns. However, the comparison should be interpreted with caution, as their analysis covers an earlier time period and may reflect different market dynamics. In addition, our results highlight the ability of European ESG ETFs to mitigate downside risk—an aspect not previously explored in the European context, as discussed in Section 5.2.1.

5.3.1.2 | Pre-Crisis Subperiod. Before the crisis, Portfolio 1 with ESG investments continues to show slightly lower returns (−0.050 vs. −0.044) and weaker return–risk ratios compared to its non-ESG counterpart, with these differences being statistically significant according to the t-test. However, it consistently maintains lower risk levels, particularly in terms of standard deviation and semi-deviation—differences that are also statistically significant. The delta in mean return is −0.006, whereas the return–risk and return–DD ratios decline by 0.086 and 0.702 points, respectively—suggesting that although ESG investments reduce risk, they fall short in delivering superior risk-adjusted performance in stable markets.

In contrast, Portfolio 2 with ESG investments significantly outperforms the non-ESG portfolio in terms of mean return (0.088 vs. −0.028). The observed delta of 0.116 in mean return suggests a meaningful financial advantage for ESG portfolios—the most notable among the periods considered. However, these gains are accompanied by a slight increase in risk during this period, with most differences being statistically significant according to the *t*-test—except for DD and VaR. Despite this, the return–DD ratio improves by 36.482 points, indicating a significant enhancement in downside-adjusted performance. Furthermore, the ESG portfolio exhibits a significantly higher return-to-risk ratio, with a delta value of 0.897, underscoring its superior overall risk-adjusted financial performance. As in the entire period analysis, these results are consistent with those of Chakrabarty et al. (2017).

5.3.1.3 | COVID-19 Transition Phase. During the COVID-19 transition phase, Portfolio 1 ESG continues to underperform in terms of returns (−0.034 vs. −0.021) and return–risk ratios but maintains significantly lower overall and downside risk exposure, showcasing its protective role in turbulent markets. This resilience was already anticipated based on the results discussed in Section 5.2.1. Specifically, the mean return delta is −0.013, and the return–risk ratio is −0.090, but Portfolio 1 ESG achieves a 0.006 and 0.009 improvement in VaR and ES, respectively—emphasizing its downside protection capacity despite performance sacrifices.

Meanwhile, Portfolio 2 with ESG investments significantly outperforms its non-ESG counterpart in terms of mean return (0.181 vs. 0.106), with the difference being statistically significant. This return delta of 0.075 highlights a notable improvement. Although the ESG portfolio exhibits slightly higher risk across all measures, it achieves a markedly superior return–risk ratio (0.418 vs. 0.186), reflecting an

TABLE 12 | Performance of conventional versus ESG portfolios in the United States.

Entire period	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Mean	0.002	0.014	−0.012	−24.52***	0.211	0.227	−0.016	−1.44
Standard deviation	0.063	0.048	0.015	1.61	0.111	0.100	0.010	7.52***
Semi-deviation	0.006	0.005	0.001	13.20***	0.010	0.009	0.001	7.82***
Downside deviation (DD)	0.006	0.005	0.001	21.85***	0.009	0.008	0.001	7.26***
Historical VaR	−0.011	−0.011	0.000	−15.31***	−0.021	−0.018	−0.002	−6.57***
Historical ES	−0.018	−0.016	−0.003	−37.34***	−0.029	−0.025	−0.004	−7.88***
Return–risk ratio	0.047	0.301	−0.254	−49.72***	**3.870**	3.297	0.573	0.40
Return–DD ratio	0.707	3.162	−2.454	−25.98***	37.943	60.038	−22.095	−1.71*

Pre-crisis subperiod	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Mean	0.001	0.004	−0.003	−9.04***	**0.122**	0.112	0.010	1.18
Standard deviation	0.035	0.032	0.002	11.22***	0.092	0.088	0.005	4.48***
Semi-deviation	0.004	0.003	0.000	16.03***	0.009	0.008	0.001	4.62***
Downside deviation (DD)	0.004	0.003	0.000	16.03***	0.008	0.008	0.001	3.83***
Historical VaR	**−0.007**	−0.008	0.000	11.04***	−0.018	−0.017	−0.001	−3.07***
Historical ES	−0.012	−0.010	−0.002	−24.47***	−0.026	−0.024	−0.002	−3.56***
Return–risk ratio	0.058	0.118	−0.060	−7.15***	**2.008**	1.555	0.452	0.87
Return–-DD ratio	0.743	1.301	−0.558	−6.71***	**38.534**	36.184	2.350	−0.14

COVID-19 transition phase	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Mean	−0.032	−0.017	−0.015	−4.62***	**1.380**	0.377	1.004	3.25***
Standard deviation	0.105	0.088	0.017	13.37***	0.280	0.250	0.030	7.38***
Semi-deviation	0.010	0.008	0.002	13.88***	0.026	0.023	0.003	7.47***
Downside deviation (DD)	0.011	0.009	0.002	13.08***	0.024	0.022	0.003	5.05***
Historical VaR	−0.020	−0.018	−0.002	−9.37***	−0.051	−0.047	−0.004	−4.22***
Historical ES	−0.031	−0.024	−0.007	−14.42***	−0.073	−0.065	−0.008	−4.79***
Return–risk ratio	−0.253	−0.173	−0.080	−2.98***	**6.003**	2.776	3.228	1.58
Return–DD ratio	2.044	2.200	−0.156	−0.33	**89.878**	59.059	30.819	2.78***

Crisis subperiod	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Mean	**−0.033**	−0.033	0.000	1.10	**0.201**	0.108	0.094	6.13***
Standard deviation	0.070	0.066	0.004	15.57***	0.165	0.137	0.028	12.77***

(Continues)

TABLE 12 | (Continued)

Crisis subperiod								
	Portfolio 1 ESG	Portfolio 1 wo ESG	Difference (Delta)	*t*-test	Portfolio 2 ESG	Portfolio 2 wo ESG	Difference (Delta)	*t*-test
Semi-deviation	0.007	0.007	0.001	16.32***	0.016	0.014	0.002	9.66***
Downside deviation (DD)	0.008	0.007	0.001	14.96***	0.015	0.013	0.001	5.71***
Historical VaR	−0.016	−0.015	−0.001	−13.90***	−0.030	−0.029	−0.001	−3.07***
Historical ES	−0.024	−0.022	−0.002	−21.62***	−0.047	−0.042	−0.005	−7.03***
Return–risk ratio	**−0.465**	−0.505	0.040	7.35***	**1.246**	0.749	0.496	4.57***
Return–DD ratio	**−4.074**	−4.533	0.459	9.30***	**29.440**	11.133	18.307	3.41***

Note: Portfolio 1: minimum standard deviation portfolio; Portfolio 2: maximum quadratic utility portfolio. Portfolio 1 ESG and Portfolio 2 ESG are portfolios consisting of traditional and ESG ETFs. Portfolio 1 wo ESG and Portfolio 2 wo ESG are portfolios comprising solely conventional ETFs. Figures in bold show the cases where ESG portfolios outperform conventional portfolios.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.
***Statistical significance at the 1% level.

improvement—or delta—of 0.231, which is also statistically significant. Additionally, it maintains a positive return–DD ratio. These results suggest that ESG investments contributed to a more resilient portfolio, enhancing performance while maintaining a favorable risk–return balance during a period of heightened uncertainty. This finding contrasts with Chakrabarty et al. (2017), who argue that CSR ETFs do not consistently outperform during bear markets. In contrast, our results align more closely with Landi et al. (2024), who report a general ESG premium during the pandemic. However, their study does not differentiate between European and US markets, as it treats geography merely as a control variable. This limits the ability to draw regional insights—an important distinction addressed in our study through a direct comparison of regional performance.

5.3.1.4 | **Crisis Subperiod.** During periods of market distress, Portfolio 1 with ESG investments follows its usual pattern of lower returns (−0.071 vs. −0.061) and weaker return–risk ratios while effectively reducing risk compared to the non-ESG portfolio. All differences are statistically significant. The delta in mean return is −0.010, and the return–risk and return–DD ratios are lower by 0.260 and 2.289 points, respectively. However, the ESG portfolio delivers notable improvements in standard deviation (−0.028) and downside metrics (e.g., ES increases by 0.009), highlighting its defensive attributes in volatile markets.

Portfolio 2 with ESG investments once again demonstrates superior financial performance, with a notably higher mean return (0.022 vs. −0.040). The delta of 0.062 in mean return further reinforces the strength of ESG inclusion in turbulent periods. However, whereas certain risk metrics, such as DD, VaR, and ES, show no statistically significant differences, others—such as standard deviation—are slightly higher for the ESG portfolio, with a delta value of 0.004. This suggests that, although ESG portfolios may offer some degree of downside protection, their effectiveness varies across different risk measures during crises. Specifically, the return–risk ratio improves by 0.414 and the return–DD ratio by 4.839 points, both statistically significant—underscoring their potential to enhance returns while mitigating risk in challenging market conditions. As for the COVID-19 transition phase, this is in line with the findings of Landi et al. (2024).

5.3.2 | Analysis for the US ETFs

Based on Table 12, it is clear that integrating ESG assets into US portfolios affects both risk and return dynamics, with varying outcomes across different market periods.

5.3.2.1 | **Entire Period.** Similar to the European case, over the entire period, Portfolio 1 with ESG investments underperforms the non-ESG portfolio in terms of mean return (0.002 vs. 0.014) and return–risk ratios. This corresponds to a return delta of −0.012, indicating sizable and statistically significant underperformance. However, unlike Europe, ESG integration also leads to higher risk, with significantly worse performance across most key risk measures. For instance, the semi-deviation and downside deviation increase by 0.001, whereas the historical expected shortfall deteriorates by 0.003. The return–risk ratio also decreases by 0.254, further reinforcing the relative inefficiency of the ESG version. This suggests that, in this instance, ESG portfolios fail to achieve the intended risk reduction.

For Portfolio 2, ESG integration results in slightly lower returns (0.211 vs. 0.227), with a delta of −0.016, though the difference is not statistically significant. ESG portfolios also exhibit slightly higher risk levels, and these differences are statistically significant. Although the return–risk ratio increases by 0.573, this improvement is not statistically significant, suggesting that the apparent efficiency gains may be driven by noise rather than a meaningful advantage. Moreover, the return–DD ratio declines by 22.095, indicating that ESG assets may not offer effective protection against extreme losses or tail risks. Overall, this mixed performance does not support a clear case for ESG outperformance in the US market. In relation to the US-focused literature, these findings align with Plagge and Grim (2020) and Huang (2024), who observed no significant performance differences over the long term, and partially with Dumitrescu et al. (2023), who reported underperformance of ESG ETFs over a comparable period (2010–2020). However, they contrast with Miralles-Quirós et al. (2019), who found evidence of outperformance. Similar to our results, ESG integration increases the return–risk ratio, but in our study, this improvement is not statistically significant.

5.3.2.2 | Pre-Crisis Subperiod. In the pre-crisis subperiod, similar to the European case, Portfolio 1 with ESG investments continues to show lower returns (0.001 vs. 0.004) and return–risk ratios. However, unlike in Europe, it again exhibits higher risk compared to the non-ESG portfolio, with the exception of the VaR measure. All differences are statistically significant, reinforcing the underperformance of ESG integration in this strategy. In sum, although the return delta of −0.003 is modest, it is accompanied by increases of 0.001 in semi-deviation and 0.002 in standard deviation, which jointly result in a 0.060 decline in the return–risk ratio—highlighting the negative impact of ESG integration on performance efficiency in this subperiod.

For Portfolio 2, ESG assets generate a slightly higher return with a delta of 0.010 (0.122 vs. 0.112), though the difference is not statistically significant. The ESG portfolio shows a marginally higher risk profile, with statistically significant increases in key risk measures. Despite this slight rise in risk, the return–risk ratio improves by 0.452; however, this improvement is not statistically significant. These findings align with Dumitrescu et al. (2023) and are consistent with Valadkhani and O'Mahony (2024), who report mixed ESG performance depending on timing and fund selection in their subperiod analysis.

5.3.2.3 | COVID-19 Transition Phase. Similar to the European case, during the COVID-19 transition phase, Portfolio 1 with ESG investments continues to underperform in terms of returns (−0.032 vs. −0.017) and return–risk ratios. However, unlike in Europe, it exhibits higher risk levels, with these differences being statistically significant. The return delta of −0.015, along with a decline in the return–risk ratio of 0.080 points, illustrates the underperformance and inefficiency of ESG integration during this period in the risk-minimization strategy. This reinforces the notion that ESG assets fail to provide effective risk mitigation in volatile market conditions, particularly when the primary objective is minimizing risk.

However, in the US case and for Portfolio 2, the ESG portfolio significantly outperforms its non-ESG counterpart (1.380 vs. 0.377), delivering higher returns and return–risk ratios despite a slightly elevated risk profile, with most differences being statistically significant. This return delta of 1.004 is the largest observed across all periods, highlighting the strong positive impact of ESG integration. However, although the return–risk ratio improves by 3.228, this difference is not statistically significant. Although this performance is among the strongest observed across all periods, it may not fully reflect a meaningful advantage, especially considering the lack of statistical significance in the return–risk improvement. These findings align with prior studies reporting mixed or phase-dependent ESG ETF performance (Valadkhani and O'Mahony 2024; Meehan and Corbet 2025) and partially with those showing ESG outperformance during crisis periods (Huang 2024; Kanamura 2021; Landi et al. 2024; Nofsinger and Varma 2014). However, they partially contrast with Omura et al. (2021), who find no such advantage during the COVID-19 crisis.

5.3.2.4 | Crisis Subperiod. In the crisis subperiod, Portfolio 1 with ESG investments shows no significant difference in mean returns between the ESG and non-ESG versions (−0.033 for both). However, risk metrics are slightly worse for the ESG portfolio, with differences being statistically significant. Despite slightly better return–risk ratios for the ESG portfolio, with a delta value of 0.040, and statistically significant differences, the ESG assets do not provide the expected risk mitigation in this turbulent period.

However, similar to the European case, for Portfolio 2, the ESG portfolio once again outperforms the non-ESG version, delivering higher returns (0.201 vs. 0.108), with the differences being statistically significant. This return delta of 0.094 signals a strong performance improvement. Although risk metrics increase slightly (e.g., standard deviation by 0.028), the return–risk ratio improves significantly by 0.496, confirming the enhanced efficiency of the ESG portfolio. This suggests that ESG assets provide a degree of outperformance, particularly in challenging market conditions, without substantially increasing the overall risk profile. Similar to the previous subperiod, these findings are consistent with earlier research (Huang 2024; Kanamura 2021; Landi et al. 2024; Nofsinger and Varma 2014), which reports ESG ETFs outperformance in the United States during periods of crisis.

5.3.3 | Comparative Analysis Between Europe and the United States

To conclude, the findings across various time periods indicate that, in the European market, ESG investments consistently exhibit lower risk levels in risk-averse strategies such as Portfolio 1, reaffirming their effectiveness as tools for downside protection. However, this conservative profile often comes at the cost of lower returns and weaker return–risk ratios. Regarding the US case and Portfolio 1—focused on risk minimization—ESG investments consistently underperform, not only yielding lower returns but also exhibiting higher risk levels across all subperiods, although it should be noted that for the crisis phase, the return–risk ratio is slightly higher than that of the non-ESG portfolio. This contrasts with the expected protective role of ESG assets, suggesting that, in this context, they fail to deliver effective downside risk mitigation.

Specifically, when comparing deltas between Europe and the United States for Portfolio 1 during the transition and crisis periods, Europe shows a more significant reduction in risk, as measured by standard deviation (risk delta of approximately −0.035 during transition and −0.028 during crisis) compared to the United States, where risk deltas are positive (+0.017 in transition and +0.004 in crisis). Return deltas are negative in both markets, with Europe experiencing moderate reductions in returns (−0.013 transition; −0.010 crisis), whereas the United States shows larger negative return deltas in transition (−0.015) but negligible difference during crisis (0.000). This suggests that, for risk-focused portfolios, ESG ETFs deliver more favorable outcomes in Europe—particularly in terms of risk mitigation—than in the United States.

Extending this analysis to the entire period and pre-crisis subperiod confirms this pattern: in Europe, risk reductions are consistent (e.g., standard deviation delta of −0.025 in the entire period and −0.003 pre-crisis), whereas return deltas remain slightly negative (−0.003 entire period; −0.006 pre-crisis). In contrast, the United States shows a reverse dynamic: positive risk deltas (+0.015 entire period; +0.002 pre-crisis) and more pronounced return losses in the entire period (−0.012). This reinforces that ESG ETFs in the United States do not fulfill a risk-mitigation role for conservative strategies.

In contrast, for utility-maximizing strategies such as Portfolio 2, designed to balance return and risk, ESG integration consistently enhances financial performance in Europe—delivering significantly higher returns and improved return–risk ratios across all subperiods, including the COVID-19 transition and crisis phases. Notably, these benefits are achieved without a proportionate increase in risk, reinforcing the strategic value of ESG investing in dynamic market conditions. In the United States, Portfolio 2 shows a more favorable outcome for ESG integration than Portfolio 1 in periods of heightened market stress such as the COVID-19 transition phase and the crisis subperiod. In these scenarios, ESG portfolios outperform their non-ESG counterparts in terms of returns and return–risk ratios, despite a slightly higher risk profile. These results reinforce the notion that ESG strategies can enhance performance under volatile conditions when integrated within a more balanced investment framework.

Specifically, in the transition period, Europe shows a return delta of +0.075 with a slight increase in risk (+0.011), whereas the United States exhibits a much higher return delta of +1.003 accompanied by a larger risk increase (+0.030). This results in a return–risk ratio improvement of +0.231 in Europe and a larger +3.228 in the United States, although this latter improvement is not statistically significant. These results indicate that conclusions regarding ESG outperformance in the United States during the transition period should be interpreted with caution. In the crisis period, Europe presents a return delta of +0.062 with a minor risk increase (+0.004), whereas the United States also improves returns (+0.094) but with a higher risk increase (+0.028). Interestingly, the return–risk ratio delta during the crisis is again higher in the United States (+0.496) compared to Europe (+0.414), and in this case, the difference is statistically significant, indicating superior risk-adjusted efficiency for US ESG portfolios under stress, despite the greater risk associated with their higher returns.

Looking at the entire period and pre-crisis phases, Europe exhibits clear performance advantages for Portfolio 2. The return delta reaches +0.067 over the full period and +0.116 in the pre-crisis phase, both with negligible risk changes (−0.003 entire; +0.007 pre-crisis), resulting in robust improvements in return–risk ratios (+0.518 entire; +0.897 pre-crisis). In contrast, the United States shows a negative return delta for the entire period (−0.016) and only a modest gain in the pre-crisis phase (+0.010), whereas risk increases in both (+0.010 and +0.005, respectively), which compresses return–risk efficiency. Although the return–risk ratios for the United States increase by +0.573 and +0.452 during the entire and pre-crisis periods, respectively, these improvements are not statistically significant.

Overall, the findings highlight that ESG ETFs not only demonstrate resilience but also outperform traditional ETFs in terms of risk-adjusted returns during crisis periods in Europe and especially in the United States when utility-maximizing strategies are applied. Furthermore, an important insight emerges when comparing long-term performance: Whereas ESG ETFs consistently outperform traditional ETFs across all subperiods in Europe within utility-maximizing portfolios, their performance in the United States is more conditional, showing strong results only during crisis periods—likely reflecting differences in regulatory maturity and investor attitudes toward ESG. Table 13

TABLE 13 | Comparative analysis of ESG and non-ESG portfolios by indicators, investor types, markets, and time horizons.

	Risk-averse investors (P1)			Risk–return investors (P2)		
	Europe	**USA**	**Better market**	**Europe**	**USA**	**Better market**
Period	**Return/risk/ return–risk**	**Return/risk/ return–risk**		**Return/risk/ return–risk**	**Return/risk/ return–risk**	
Entire period	Under/out/ under	Under/under/ under	Europe	Out/out/out	Marginal under/under/ marginal out	Europe
Pre-crisis	Under/out/ under	Under/under/ under	Europe	Out/under/out	Marginal out/under/ marginal out	Europe
Transition	Under/out/ under	Under/under/ under	Europe	Out/under/out	Out/under/ marginal out	Europe
Crisis	Under/out/ under	≈/under/out	Europe	Out/under/out	Out/under/out	United States

Note: P1 denotes Portfolio 1 (risk-averse investors), and P2 denotes Portfolio 2 (risk–return optimizing investors). "Out" indicates outperformance of ESG portfolios relative to non-ESG portfolios, whereas "Under" indicates underperformance. "Marginal out" and "Marginal under" refer to outperformance or underperformance that is not statistically significant. The "Better market" is selected based on risk for risk-averse investors (P1) and based on return–risk for risk–return investors (P2).

summarizes the performance comparison between ESG and non-ESG portfolios across different periods and markets, based on return, risk (standard deviation), and return–risk. It highlights which market shows better relative performance for each portfolio type and period.

Based on the results, for the European market, Hypotheses 1 and 2 would be accepted for both portfolios. Outperformance is interpreted as lower risk for risk-averse investors (Portfolio 1) and higher risk-adjusted returns for risk–return investors (Portfolio 2). Hypothesis 1, as previously discussed, is based on *modern portfolio theory* and *stakeholder theory*, which emphasize diversification and stakeholder engagement as key drivers of financial performance. Hypothesis 2 is supported by *risk management theory* and the *resource-based view*, which highlight how ESG capabilities enhance resilience in volatile contexts, such as during financial or health crises. However, Hypothesis 3, grounded in *agency theory*, is rejected based on the observed data, as the expected negative impact of agency problems on ESG investment performance was not evident in our analysis. This may reflect lower managerial opportunism or window dressing in European ESG funds, possibly due to stronger regulatory and market pressures. However, the underlying factors contributing to these results will be explored later in this section.

On the other hand, for the US market, the results are more phase dependent. In this case, Hypothesis 1 would be rejected and Hypothesis 3 would be accepted for the entire period and the pre-crisis period for both portfolios, as in these phases, portfolios including ESG ETFs underperform traditional portfolios. This could be explained by the perception that ESG actions are symbolic or insincere. This hypothesis is based on *agency theory* and its extensions, which suggest that ESG initiatives can reduce firm value when driven by managerial self-interest or window dressing practices. As for Hypothesis 2, it would not be accepted for Portfolio 1 (risk-averse investors) but would be accepted for Portfolio 2 (risk–return investors) during the crisis subperiod and partially during the transition subperiod. In the transition phase, ESG portfolios show outperformance in terms of risk-adjusted return, but the differences are not statistically significant.

These results may be attributed to a combination of structural and behavioral factors. Structural elements include the regulatory framework, ESG disclosure rules, the size and maturity of the ETF market, and fiscal incentives, among others. Behavioral factors relate to the degree of investor interest in ESG, public opinion pressure, and cultural preferences, among others. Table 14 provides a concise overview of the key institutional and behavioral differences between the European

TABLE 14 | Factors influencing ESG ETF performance in Europe and the United States.

Factors	Europe	United States
Institutional factors		
Regulation and disclosure	• Harmonized ESG reporting framework (NFRD, CSRD, EFRS)	• Less extensive regulatory framework, recent climate rules with narrower scope, regulatory rollbacks in 2025
	• Robust rules and clear mandates for nonfinancial disclosure	• Climate-related SEC rules less comprehensive and consistent
Market size and maturity	• Large sustainable fund market (USD 2.67 trillion)	• Smaller market (USD 329 billion)
	• Strong presence of insurers, pension funds, and developed financial markets	• Less mature structurally and lower institutional presence
Fiscal incentives	• Combination of national tax measures and supranational regulations (SFDR, EU Taxonomy)	• Project-level tax credits and accelerated depreciation (Inflation Reduction Act 2022)
Behavioral factors		
Investor behavior	• Greater cultural alignment with sustainability objectives	• Stronger return orientation, heterogeneous ESG integration among portfolio managers
	• High financial literacy and stronger social pressure	• Nearly 50% of retail investors not motivated to invest in ESG without clear financial rationale
Risk of symbolic practices (greenwashing)	• Lower incidence due to continuous transparency and stricter regulations	• Higher prevalence of window dressing and opportunistic practices like green window dressing
	• Regulation limits symbolic ESG commitments	• Studies document greater use of vague or selective disclosures

and US markets regarding ESG ETFs performance. The following discussion elaborates on these contrasts. Regarding the first structural factor, Europe benefits from a harmonized regulatory framework and disclosure architecture that offers a robust foundation for ESG integration. Notably, the analysis period begins in 2014, coinciding with the implementation of the NFRD, which marked the start of more formalized ESG reporting across the EU. As outlined in the Introduction, this trajectory has been reinforced by subsequent regulations, such as the CSRD and the adoption of the EFRS, which expand the scope and depth of nonfinancial disclosures. Although the US regulatory framework is also relevant, it remains comparatively less extensive, with recent climate-related disclosure rules from the SEC covering a narrower scope than their European counterparts. Moreover, political shifts—such as the regulatory rollbacks initiated in 2025—have introduced further discontinuities.

Another structural driver that may be underpinning results concerns market size and maturity. According to Morningstar Sustainalytics (2025a, 2025b), Europe accounts for approximately USD 2.67 trillion in sustainable fund assets compared to USD 329 billion in the United States, representing 84% and 10% of the global total, respectively—a pattern consistent with previous quarters. This structural predominance is supported by factors such as the expansion of insurance companies and pension funds, well-developed financial markets, widespread ICT adoption, financial accessibility and literacy, and a highly educated population (Marszk and Lechman 2024). Fiscal incentives further differentiate the two markets: Whereas the United States relies primarily on project-level tax credits and accelerated depreciation—most notably expanded under the Inflation Reduction Act of 2022—the EU framework combines national tax measures with supranational regulatory initiatives (e.g., Sustainable Finance Disclosure Regulation [SFDR], EU Taxonomy) that indirectly stimulate demand for sustainable investment products (European Commission, Directorate-General for Taxation and Customs Union 2025; Organisation for Economic Co-operation and Development (OECD) 2024).

Behavioral factors complement this picture. Investors in Europe appear, on average, more culturally aligned with sustainability objectives (Amel-Zadeh and Serafeim 2018; Maignan 2001), whereas United States investors display a stronger return orientation shaped by a more fragmented regulatory landscape. Portfolio managers in the United States also show greater heterogeneity in ESG integration (Van Duuren et al. 2016), and nearly half of US retail investors report no motivation to invest in ESG products unless there is a clear financial rationale (Giglio et al. 2025). Recent evidence in the US context also shows that institutional investors, while adding high-ESG firms to their portfolios, often assign them relatively low weights—suggesting a more symbolic than substantive stance and raising concerns of greenwashing (López-de-Silanes et al. 2024). Further, Parise and Rubin (2023) document a practice of strategic green window dressing in which US mutual funds temporarily increase ESG exposure before disclosure dates to enhance ratings and attract inflows, only to reduce it afterwards. These patterns are less prevalent in European markets, where continuous transparency requirements under frameworks such as the SFDR and EU Taxonomy constrain such short-term positioning. This aligns with prior research highlighting the moderating role of institutional and regulatory environments in the incidence of greenwashing: Baum (2012) identifies a higher frequency of vague or unverified environmental claims in US advertising compared to the United Kingdom; Marquis et al. (2016) show that weaker regulatory and societal pressures are linked to greater use of selective disclosure; and Mateo-Márquez et al. (2022) find that voluntary and less stringent disclosure regimes allow greater latitude for such practices. Although none of these studies explicitly conclude that greenwashing is more prevalent in the United States than in Europe, their combined insights reinforce the interpretation that stronger and more harmonized regulatory frameworks, as found in parts of Europe, limit the scope for symbolic ESG commitments and contribute to the more consistent performance of ESG ETFs in those markets. In sum, the more opportunistic behaviors observed in the United States resonate with the theoretical underpinnings of Hypothesis 3, grounded in *agency theory* and its extensions, which posit that managers may undertake ESG initiatives not solely to maximize long-term shareholder value but also to pursue personal reputational gains, respond to social pressure, or divert attention from operational underperformance. In such cases, ESG engagement risks becoming window dressing, where symbolic commitments outweigh substantive action, potentially leading to resource misallocation and weaker financial outcomes.

Connecting with existing literature, the results of this research generally align with previous European studies (Landi et al. 2024; Chakrabarty et al. 2017) but add new insights by recognizing ESG ETFs' protective role during downturns. In the United States, they confirm underperformance in the long term (Dumitrescu et al. 2023) but support ESG resilience during crises (Nofsinger and Varma 2014; Kanamura 2021). This study also diverges from others—such as Miralles-Quirós et al. (2019), Plagge and Grim (2020), and Omura et al. (2021)—that report contrasting conclusions on ESG ETFs' performance. Additionally, it contributes to the phase-dependent findings of Valadkhani and O'Mahony (2024) and Meehan and Corbet (2025). The identified discrepancies may stem from several factors, including differences in the time frames analyzed, the methodological approaches employed—such as variations in portfolio construction, risk-adjusted performance metrics, or benchmark selection—and the specific sectoral composition of the ESG ETFs considered. These variations are summarized in Table 1, which highlights key differences across the studies reviewed. Additionally, variations in ESG scoring methodologies and inclusion criteria may also contribute to divergent results, as they affect which firms are classified as ESG-compliant. Moreover, some studies may focus on narrow crisis periods, whereas others adopt broader windows that smooth out short-term dynamics. Taken together, these design choices can significantly shape the observed performance of ESG investments and partially explain the inconsistencies found across the literature. For this reason, further research is needed. Despite the growing academic interest in ESG ETFs, as evidenced by the increasing number of recent publications, the field remains relatively limited in scope, particularly in terms of standardized methodologies and cross-market comparisons.

TABLE 15 | Recommended investment strategy depending on investor profile.

Investor profile	Recommended region	Portfolio type	Practical implication
Conservative (risk-minimizer)	Europe	Portfolio 1	ESG ETFs may reduce risk but often deliver lower returns; favor funds with strong regulatory backing
Moderate risk tolerance	Europe	Portfolio 2	ESG integration improves risk–return balance across all periods in Europe, including crises; in the United States, benefits are more pronounced during periods of market stress
Short-term/tactical	United States	Portfolio 2	ESG ETFs in the United States can offer tactical hedging benefits mainly during market turmoil, with less consistent performance outside crisis periods

5.4 | Practical Implications for Investors and Policymakers

The results presented in this study carry relevant implications for both investment decision-making and sustainability-related financial regulation.

5.4.1 | Implications for Investors

First, the findings indicate that ESG ETFs, particularly those listed in Europe, contribute positively to utility-maximizing portfolio strategies (Portfolio 2). In this context, ESG integration does not imply a trade-off between risk and return; rather, it provides diversification and conditional hedging benefits, which remain relevant during periods of heightened market stress, such as the COVID-19 crisis. Investors with moderate to long-term horizons and a balanced risk appetite may therefore benefit from including European ESG ETFs in their portfolios.

Second, the evidence suggests that ESG ETFs are less effective in pure risk-minimization frameworks (Portfolio 1), particularly in the US market, where they were associated with lower returns and higher volatility. For more risk-averse investors, ESG integration should be approached with greater selectivity, potentially favoring European-domiciled funds with stronger regulatory backing and more transparent sustainability disclosures.

Third, ESG ETFs exhibit time-varying performance, often demonstrating resilience and enhanced returns during periods of financial turmoil, both in Europe and the United States—particularly when incorporated within utility-maximizing portfolio strategies. This behavior supports their classification as conditional safe-haven assets rather than constant hedging instruments. Tactical or dynamic allocation strategies may therefore benefit from ESG exposure during volatile market regimes.

Table 15 offers a summary of recommended ESG investment strategies tailored to different investor profiles, portfolio objectives, and regional considerations, based on the empirical findings of this study.

5.4.2 | Implications for Policymakers

The results also reveal an important interaction between ESG financial performance and the regulatory environment. Overall, the superior behavior of European ESG ETFs—in terms of both returns and volatility—may reflect the credibility and consistency provided by regulatory initiatives such as the NFRD, the CSRD, and the SFDR. These measures improve transparency and comparability, facilitating investor decision-making and contributing to more efficient ESG markets.

In contrast, regulatory fragmentation and policy rollbacks in the United States may have negatively impacted investor confidence and the financial performance of US-listed ESG ETFs, particularly in the entire period and pre-crisis phase. Weak or inconsistent ESG standards can hinder the development of credible ESG products, dilute the quality of disclosures, and ultimately reduce the perceived legitimacy of sustainable investing.

This evidence underscores the strategic importance of maintaining strong regulatory frameworks in Europe. Although recent decisions by the European Parliament have delayed new corporate sustainability and due diligence rules—citing administrative and competitiveness concerns amid global regulatory disparities—our findings highlight the risks such delays pose to the consistency, credibility, and long-term viability of ESG investments. Reversing progress made through policy frameworks like the SFDR and the EU Taxonomy could undermine both sustainability objectives and the financial benefits ESG assets provide to investors.

Maintaining a stable, transparent, and harmonized regulatory environment is therefore essential—not only to advance sustainability goals but also to ensure that ESG assets continue to deliver risk-adjusted financial benefits to investors.

6 | Conclusions

This study investigates the evolving role of SRI, particularly through ESG ETFs, which have gained prominence due to the increasing corporate disclosure of ESG information. Specifically, the research focuses on the role of ESG ETFs within diversified portfolios and their potential for risk reduction in both Europe and the United States during periods of stability and crisis, with particular attention to market-specific differences. It aims to address the scarce and inconclusive results in the previous literature regarding ESG ETFs' performance while also analyzing SRI in a context where sustainability regulations are increasingly being challenged by shifting political trends.

The findings show that the effectiveness of ESG ETFs is neither universal nor consistent across regions. In the European context, ESG integration proves particularly beneficial for utility-maximizing strategies (Portfolio 2), consistently delivering statistically significant improvements in returns and return–risk ratios across all subperiods, without a proportionate increase in risk. This suggests that ESG characteristics may act as strategic assets (McWilliams and Siegel 2011), reinforcing firm resilience and supporting the *resource-based view theory* of competitive advantage. Conversely, for risk-minimizing strategies (Portfolio 1), ESG investments systematically reduce risk but often at the expense of lower returns, which limits their overall financial performance enhancement. In this case, the role of ESG may be best understood through the *risk management theory* (Bouslah et al. 2013), as a mechanism for mitigating volatility rather than enhancing returns.

In contrast, the US results present a more mixed picture. For Portfolio 1, ESG ETFs consistently underperform by delivering lower returns and exhibiting higher risk across all subperiods—challenging the notion of ESG's protective function in conservative investment strategies. However, for utility-maximizing strategies (Portfolio 2), ESG integration leads to superior performance, particularly during periods of elevated market uncertainty such as the COVID-19 transition and crisis phases. In these scenarios, ESG portfolios significantly outperform their non-ESG counterparts in terms of returns and return–risk ratios, despite slightly higher risk levels. These findings may be explained by the evolving role of ESG in shaping investor and stakeholder behavior, particularly under conditions of market stress. They are consistent with Lins et al. (2017), who show that US firms with stronger CSR profiles outperformed during the 2008–2009 financial crisis, and Moalla and Dammak (2023), who find that ESG performance functioned as a form of financial "insurance" during the COVID-19 pandemic in the US stock market. *Stakeholder theory* (Freeman 1984) and the concept of "moral capital" (Godfrey et al. 2009) may help explain why firms with strong ESG practices are perceived as more trustworthy, thereby attracting investor confidence in times of crisis.

In sum, the regional disparities identified reinforce this study's contribution by expanding the geographic scope of ESG analysis to both Europe and the United States, addressing the persistent US bias highlighted in prior studies (Rathner 2013; Stellner et al. 2015). Furthermore, the variation in outcomes across investment strategies and time periods highlights a key feature of this study's broader and more recent temporal scope, which enables a comprehensive assessment of ESG performance before, during, and after major global crises.

Differences across regions likely reflect the maturity of ESG regulations and prevailing investor attitudes. In Europe, harmonized disclosure frameworks like the CSRD and EU Taxonomy offer a stable basis for ESG integration, alongside greater cultural alignment with sustainability objectives (Amel-Zadeh and Serafeim 2018; Maignan 2001). Conversely, the United States has only recently begun formalizing ESG disclosures, and investor behavior remains more return-driven within a fragmented regulatory landscape. Greater heterogeneity among US portfolio managers in applying ESG data (Van Duuren et al. 2016), combined with less stringent transparency requirements, may increase the risk of symbolic ESG practices such as greenwashing (López-de-Silanes et al. 2024; Parise and Rubin 2023). Additionally, differences in fiscal incentives further shape market dynamics and ESG adoption in both regions. Although it is well established that these institutional and behavioral factors influence ESG ETF performance, determining the relative contribution of each factor lies beyond the scope of this research and represents a promising avenue for future investigation.

From a policy standpoint, the results suggest that regulatory coherence is crucial for effective ESG integration. In the United States, frequent shifts in ESG disclosure requirements—such as those introduced by the SEC and then rolled back under the Trump administration (Green Central Banking 2025)—create uncertainty and undermine long-term investor trust. Even in Europe, recent delays in implementing sustainability regulations (European Parliament 2025) reveal the fragility of political commitment. To ensure effective ESG adoption, governments should prioritize consistent, enforceable, and internationally harmonized standards, along with greater oversight of ESG ratings and transparency infrastructure. Targeted incentives—such as tax relief or capital benefits—could also encourage broader implementation, particularly in markets where voluntary ESG adoption remains limited. Ultimately, without sustained regulatory commitment and clear incentives, the integration of ESG principles may remain inconsistent, undermining both investor confidence and broader sustainability goals.

These policy challenges are particularly relevant for investors managing long-term capital. The results indicate that ESG ETFs are not universally superior assets; their effectiveness depends on timing and strategy. Specifically, they prove more valuable within utility-maximizing approaches and during periods of elevated uncertainty, when their resilience is more apparent. Although our findings show ESG ETFs do not consistently outperform across all periods—in particular, underperforming in full-period analyses in the United States—their crisis resilience and alignment with evolving sustainability expectations support their role in strategically diversified, long-term portfolios.

Building on these insights, we recommend that regulators advance harmonized ESG disclosure frameworks while acknowledging the heterogeneity in ESG effectiveness across strategies and regions. Recognizing that ESG ETFs offer both financial and nonfinancial value primarily when aligned with long-term, utility-maximizing goals and under uncertain market conditions is essential, especially for institutional investors seeking resilient, values-aligned assets that maintain confidence during downturns.

Although this study offers important insights into ESG ETF performance across different markets and conditions, it is not without limitations. It focuses on a limited number of large, representative ETFs, which—despite their substantial assets under management and relevance to institutional investors—may not capture the full diversity of ESG investment strategies globally. In particular, emerging markets remain underexplored in this context. These regions are becoming increasingly active in sustainable finance and may offer distinct ESG integration patterns, challenges, and investor behaviors that differ from those observed in more mature markets. Therefore, a promising avenue for future research would be to analyze ESG ETFs in emerging economies, as doing so could shed light on how regulatory frameworks, market maturity, and socioeconomic contexts influence ESG performance. Moreover, although this study identifies notable performance differences between regions, the underlying determinants of these disparities require further, focused investigation—a topic that remains largely unexplored in the context of ESG ETFs and represents an important direction for future research. Additionally, given the evolving regulatory landscape—especially in the United States, where ESG-related policy remains a subject of political debate—future studies could also examine how shifts in political leadership and policy orientation shape the dynamics and outcomes of ESG investing.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Appendix

TABLE A1 | Dataset codebook: ETF identifiers and data sources.

ETF name	Ticker	Lipper RIC	Provider	Market region	Asset class	Category	Data source	Frequency	Currency conversion	Period
iShares € Aggregate Bond ESG UCITS ETF EUR (Dist)	IEAG.AS	LP68012649	iShares	Europe	Bond	ESG	Refinitiv Datastream via Eikon	Weekly	USD	01-Jan-2014 to 03-Dec-2024
SPDR Bloomberg SASB US HY Corp ESG UCITS ETF Dis	SJNK.L	LP68230383	State Street	USA	Bond	ESG	Refinitiv Datastream via Eikon	Weekly	USD	01-Jan-2014 to 03-Dec-2024
iShares MSCI Europe SRI UCITS ETF EUR (Acc)	IUSK.AS	LP68103809	iShares	Europe	Equity	ESG	Refinitiv Datastream via Eikon	Weekly	USD	01-Jan-2014 to 03-Dec-2024
iShares MSCI KLD 400 Social ETF	DSI	LP40112523	iShares	USA	Equity	ESG	Refinitiv Datastream via Eikon	Weekly	USD	01-Jan-2014 to 03-Dec-2024
iShares € High Yield Corp Bond UCITS ETF EUR D	IHYG.L	LP68060932	iShares	Europe	Bond	Broad Market	Refinitiv Datastream via Eikon	Weekly	USD	01-Jan-2014 to 03-Dec-2024
Vanguard Total Bond Market Index Fund ETF	BND.O	LP40113815	Vanguard	USA	Bond	Broad Market	Refinitiv Datastream via Eikon	Weekly	USD	01-Jan-2014 to 03-Dec-2024
Vanguard European Stock Index Fund ETF	VGK	LP40091346	Vanguard	Europe	Equity	Broad Market	Refinitiv Datastream via Eikon	Weekly	USD	01-Jan-2014 to 03-Dec-2024
SPDR S&P 500 ETF Trust	SPY	LP40061133	State Street	USA	Equity	Broad Market	Refinitiv Datastream via Eikon	Weekly	USD	01-Jan-2014 to 03-Dec-2024