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Enhancing portfolio performance through ESG theme subdivision: a two-step selection approach with Shapley value decomposition

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ABSTRACT

This study investigates the impact of incorporating subdivided ESG assets into investment portfolios, focusing on improvements in Sharpe Ratios (SRs), elasticity, and diversification. We compare subdivided ESG indexes—such as security, water, and diversity—with general ESG and pillar indexes over a 10-year period, including the stressed COVID-19 period. Results show that subdivided indexes offer higher SRs, lower correlations, and enhanced diversification. Notably, energy and GHG indexes outperform pillar counterparts in elasticity across both periods. Using Modern Portfolio Theory, we integrate these assets into a benchmark portfolio of stocks, real estate, and bonds, achieving a 38% SR and 6% Diversification Ratio improvement. A two-step portfolio construction approach further enhances performance, especially during stressed markets. The Shapley Value method confirms that subdivided ESG assets positively contribute to excess returns while mitigating downside risks. These findings offer actionable insights for investors aiming to align financial performance with sustainability through more targeted ESG integration.

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ESG investment; optimal asset allocation; diversification; COVID-19; Shapley value

1. Introduction

Environmental, Social, and Governance (ESG) investing integrates sustainability criteria into investment decisions, distinguishing itself from traditional investment approaches that focus solely on financial performance. ESG investing has demonstrated resilience during market downturns while offering moral satisfaction to investors, making it an increasingly popular alternative investment strategy (Sahut and Pasquini-Descomps 2015). The rapid adoption of ESG investing is driven by the integration of the three ESG pillars – Environmental (E), Social (S) and Governance (G) – into investment practices. This growth is evident in the Global Sustainable Investment Alliance report (GSIA 2018), which highlighted that ESG assets reached $30.7 trillion in 2018, reflecting a 34% increase in just two years. By 2021, professionally managed portfolios incorporating ESG

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assessments exceeded $17.5 trillion, while ESG-focused investment products surpassed $1 trillion. Additionally, the United Nations Conference on Trade and Development (UNCTAD 2020) projects that the ESG exchange-traded fund (ETF) market will exceed $500 billion by 2030, assuming a 5% annual growth rate. This surge is not only fuelled by ethical motivations but also by the potential for enhanced financial performance (Amel-Zadeh and Serafeim 2018).

From a firm manager's perspective, several studies (Inigo and Albareda 2019; Margolis, Elfenbein, and Walsh 2009; Orlitzky, Schmidt, and Rynes 2003; Przychodzen and Przychodzen 2015; Statman and Glushkov 2009) have demonstrated that integrating ESG factors enhances financial performance across multiple dimensions. For instance, El Ghoul et al. (2011) found that strong ESG performance can lower a company's cost of capital, while Fauser and Utz (2021) concluded that responsible business practices help mitigate litigation risks, protect corporate reputations, and further reduce capital costs. Additionally, Giese et al. (2019) showed that ESG information helps manage a company's systematic and idiosyncratic risk profiles through three key transmission channels: cash flow stability, reduced idiosyncratic risk and improved valuation. Conversely, Gompers, Ishii, and Metrick (2003) identified a negative relationship between poor governance performance and risk-adjusted returns, highlighting the financial consequences of weak corporate governance. Moreover, Makridou, Doumpos, and Lemonakis (2024) examined the relationship between ESG impacts and financial performance in the European energy sector, finding that ESG performance has a marginally negative effect on profitability, with a particularly significant negative impact stemming from environmental responsibility.

Despite the rapid growth of ESG investing, its financial performance remains a topic of debate. Several studies (Bauer, Koedijk, and Otten 2005; Brammer, Brooks, and Pavelin 2006; Friedman 2007; García García et al. 2022; Plinke and Knorzer 2006; Weston and Nnadi 2023) suggest that ESG assets often fail to deliver consistent excess returns, creating scepticism about their economic value. Additionally, the relatively short history of ESG ETFs and ESG funds – key vehicles for ESG investment – poses challenges for conducting long-term performance analyses (Cappucci 2018). Previous research has used metrics such as historical Sharpe Ratio (SR) and Diversification Ratio (DR) to evaluate ESG performance (Alvarez and Rodríguez 2015; Muley, Tiwari, and Gidwani 2019; Naffa and Fain 2020; Reboredo, Quintela, and Otero 2017). Furthermore, the post-pandemic investment regime has introduced both challenges and opportunities for ESG investing (Fabozzi, Focardi, and Sharma 2021).

Our study addresses these gaps by exploring subdivided ESG themes as distinct investment categories and applying advanced methodologies, such as the Shapley Value (SV) approach, to quantify their contributions to portfolio performance. We provide a practical framework for integrating multiple subdivided ESG themes into a benchmark portfolio with dynamically optimised asset weighting. Our work demonstrates that by subdividing ESG themes and employing a two-step investment approach, one can achieve excess returns. Treating ESG factors as a single entity fails to unlock their full potential, which lies at the core of the ongoing debate surrounding ESG investing performance.

This study overcomes the limitation of short historical records in ESG ETFs by using thematic indexes with approximately 10 years of market data. Performance is evaluated under general market conditions and stressed periods (e.g. the COVID-19 pandemic) (Fabozzi, Focardi, and Sharma 2021). Using Modern Portfolio Theory (MPT), optimal asset weights are determined, and the two-step investment approach is applied. The key findings reveal that subdivided ESG indexes, such as security, water, and diversity, exhibit lower correlations and higher SRs than general ESG and pillar indexes. Incorporating these subdivided ESG assets as distinct asset classes, rather than confining them to a single ESG pillar, enhances portfolio diversification (Anson 2022; Jacobs, Müller, and Weber 2014).

Additionally, incorporating three or more subdivided ESG indexes into a benchmark portfolio significantly improves SR and DR, outperforming traditional ESG portfolios. The SV method highlights that subdivided ESG assets contribute positively to returns while reducing losses, with varying impacts across themes (Renneboog, Ter Horst, and Zhang 2008), and these performance improvements are particularly pronounced during stressed periods, reinforcing the resilience of subdivided ESG portfolios in volatile markets.

To summarise, this study makes several innovative contributions to ESG investing. First, it introduces the subdivision of ESG themes, categorising ESG factors into nine detailed themes to provide a granular analysis of their individual performance and diversification benefits (Bender and Sun 2024). Second, it presents a structured two-step investment approach that optimises both SR and DR, offering a practical framework for ESG portfolio construction (Miralles-Quirós, Miralles-Quirós, and Nogueira 2019). Third, the application of Shapley Values (SVs) to quantify the contribution of each subdivided ESG asset introduces a novel analytical dimension to ESG portfolio evaluation (Renneboog, Ter Horst, and Zhang 2008). Lastly, by examining both long-term and stressed periods, this study delivers actionable insights for ESG investment management under different market conditions (Fabozzi, Focardi, and Sharma 2021). To the best of our knowledge, this is the first study to combine thematic ESG subdivision, long-term performance analysis, a two-step optimisation approach, and SV analysis within ESG investing. The findings offer practical insights for investors and fund managers aiming to enhance portfolio diversification and financial performance through sustainable investing.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on ESG investment performance and diversification. Section 3 outlines the datasets and indexes used. Section 4 details the methodologies applied, including Sequential Least Squares Programming, two-step optimisation and SV analysis. Section 5 presents the empirical findings. Section 6 discusses operational and practical implications. Finally, conclusions, limitations and future research directions are provided in Section 7.

2. Literature review and hypotheses

The main motivation for incorporating ESG assets into the conventional stock-bond-real estate portfolio is to constitute a new portfolio which is more diversified and achieves a better financial performance. The benefits of diversification have been confirmed by a plethora of research. Saiti and Noordin (2018), Meyer and Rose (2003) all presented the diversification benefits by adding innovative stock indexes or unit trusts into the stock portfolio in Chinese and New Zealand stock markets. We highlight the importance of the inclusion of real estate assets as the diversification and hedging effectiveness of the stock-bond-real estate portfolio have been confirmed by Yang, Zhou, and Leung (2012), Szumilo et al. (2018).

Although stock–bond portfolios have long been considered as an effective way to provide diversification benefits for investors, Gomes and Taamouti (2016) and Perego and Vermeulen (2016) showed that as the regime of the market changes, there is a dynamic correlation between macroeconomic risk factors and the covariance of stock and bond markets. This indicates that there are potential common risk factors affecting investments in both sectors. Therefore, incorporating only these two assets into a portfolio cannot sufficiently diversify away the risk. Hence, in our study, following Panayiotou and Medda (2016), we consider a conventional stock-bond-real estate portfolio as the benchmark. As highlighted by Jacobs, Müller, and Weber (2014), diversified investments are well-balanced asset allocation over different asset classes as the diversification benefits are driven mainly from different asset classes rather than just investing in one sector.

Beyond general ESG investing, the importance of ESG thematic investing is further emphasised for achieving superior financial performance. Several ESG investment strategies like the sustainability-themed investing strategy which we also use in our paper, are introduced by GSIA. This strategy encompasses a range of themes, enabling investors to focus on specific areas closely linked to sustainable development. This strategy delves into sub-category ESG themes, offering a more granular approach beyond the traditional ESG pillars. Our subdivided ESG consideration includes specific themes that focus on a company's business practices and behaviour, such as greenhouse gas emissions and employee benefits, as highlighted by GSIA, Ielasi, Rossolini, and Limberti (2018) and Pellegrini (2022).

Many studies have explored the role of ESG theme indexes in portfolio construction. For example, Miralles-Quirós, Miralles-Quirós, and Nogueira (2019) evaluated the performance of six ETFs aligned with sustainable development goal (SDG) themes, incorporating each into a stock–bond portfolio. Their findings demonstrate that focusing on ESG themes such as economic growth and clear environmental improvements can enhance portfolio performance. Similarly, Renneboog, Ter Horst, and Zhang (2008) argued that positive risk-adjusted returns arise from 'value-relevant information', suggesting that ESG-enhanced portfolios only outperform when ESG assets capture thematically valuable insights. This perspective aligns with Giese et al. (2019), who attributed the lack of consensus on ESG performance to differences in underlying ESG data and varying methodologies, particularly in controlling for common factor exposures. While the potential value of ESG themes has been studied, a practical framework for portfolio construction that integrates multiple ESG themes into a benchmark portfolio – along with a method for dynamically determining the optimal weight of each asset based on its historical performance – remains underexplored.

Portfolio theories provide valuable insights supporting the subdivision of ESG themes beyond the three pillars. Factor investing theory is a key contributor in this regard. As noted by Bender, Sun, and Wang (2017), factor investing enables investors to capture key sources of return by focusing on transparent, cost-efficient indexes. Subdivided ESG themes can be viewed as additional factors that, when integrated with traditional factors, strengthen an ESG profile and enhance financial performance. Similarly, Kumar (2023) reviewed several studies using Fama-French factor models and finds that subdivided ESG themes contribute positively to portfolio Alpha, particularly in developed markets. Subdivided ESG indexes act as distinct factors, each providing unique sources of return. Research, such as Fama and French's multi-factor models (Fama and French 1993, 1995, 2012, 2016), shows that combining these factors strategically can lead to superior portfolio performance. Aggregating ESG themes can obscure these individual contributions, reducing the potential to capture specific risk premia.

Additionally, behavioural finance theory supports the subdivision of ESG themes. According to Deka et al. (2023), there exists a statistically significant relationship between investors' awareness of subdivided ESG themes and their risk perception, with greater awareness weakening the impact of cognitive biases on risk assessment. Afeef et al. (2022) further demonstrated that investors are sensitive to specific ESG factors, with preferences often influenced by issues like climate change or social equity. From a granular perspective, subdivided ESG themes allow investors to align their portfolios with their specific values and preferences, leading to better investment decisions and enhanced market behaviour. In this study, we show that subdivided ESG thematic indexes retain valuable information that is often lost when integrated into a comprehensive ESG index. To explain and evaluate the effectiveness of subdivided ESG assets in investment portfolios, we apply the SV method to quantify the contribution of each subdivided ESG asset to portfolio returns and losses.

To deepen the understanding and practical implementation of ESG investing, our study tests four research hypotheses, each rooted in fundamental diversification principles. These principles – law of large numbers (LLN), correlation, mean-variance optimality and risk parity – are identified by Koumou (2020) as the foundational 'DNA' of portfolio selection and asset pricing theories. Our work rigorously applies these principles to assess ESG-focused investment strategies:

- **H1**: Subdivided ESG indexes exhibit higher historical SRs and elasticities (defined in Section 4.2) compared to general ESG and pillar indexes.

This follows the LLN principle, which has been widely applied for diversification purposes (Hsu et al. 2018; Jacobs, Müller, and Weber 2014; Pflug, Pichler, and Wozabal 2012). Greater diversification across distinct ESG themes should enhance portfolio efficiency and stability, supporting the premise that subdivided ESG themes contribute to superior risk-adjusted returns.

- **H2**: The correlations among subdivided ESG indexes are expected to be lower than those among the Environmental (E), Social (S) and Governance (G) pillars of general ESG indexes.

Correlation principle, a core component of mean-variance models (Cumova and Nawrocki 2014; Koumou 2020; Markowitz and Markowitz 1967; Rockafellar, Uryasev, and Zabarankin 2007), suggests that lower correlations indicate that subdivided ESG indexes provide greater diversification benefits, reducing overall portfolio risk more effectively than traditional ESG classifications. This would support the argument that subdivided ESG themes function as distinct asset categories, improving risk management in sustainable investing.

- **H3**: Incorporating a specific configuration of subdivided ESG indexes into a benchmark portfolio (comprising stocks, real estate and bonds), with optimal asset weights determined using mean-variance optimisation under MPT, results in higher SR and DR than the benchmark portfolio.

This hypothesis is based on the mean-variance optimality principle, which predicts optimal mean-variance and supports various weighting schemes (de Jong 2018; Kontosakos 2020; Yanushevsky and Yanushevsky's's 2015). This would suggest that strategically integrating subdivided ESG themes can enhance portfolio performance, aligning with fundamental asset pricing and diversification theories.

- **H4**: A two-step portfolio construction strategy, made of (1) maximising SR and (2) selecting an optimal portfolio with the highest DR among the top SR candidates, results in a subdivided ESG portfolio that outperforms the benchmark and portfolios containing the benchmark and general ESG indexes.

The base of this hypothesis is the risk parity principle which has been applied in both asset class and individual asset diversification (Anderson, Bianchi, and Goldberg 2012; Asness, Frazzini, and Pedersen 2012; Chaves et al. 2011; Clarke, De Silva, and Thorley 2013; Qian 2011). This would provide an empirical evidence that weighting assets based on risk contribution enhances portfolio performance, demonstrating that ESG subdivision improves investment efficiency and return attribution.

Building on this foundation, our research advances the study of subdivided ESG themes in portfolio construction. By assessing their diversification benefits and risk-adjusted performance, we examine whether subdivided ESG portfolios outperform both general ESG investments and traditional benchmarks, offering deeper insights into their role in sustainability-themed investing.

3. Data sources and subdivided ESG indexes

Each of the selected subdivided ESG indexes follows the positive screening principle, see, Dorfleitner, Halbritter, and Nguyen (2015). The effectiveness of positive screening and active ownership is confirmed in the global survey of Amel-Zadeh and Serafeim (2018) and reflected in the expected alpha increase shown by Henriksson et al. (2019). The long-term thematic subdivided ESG indexes that we managed to find, are summarised in Table 1. All the data is collected from Bloomberg securities database. We selected Bloomberg as our primary data source due to its alignment with the ESG theme focus and our subdivided ESG assets. Narula et al. (2024) highlighted the divergence in ESG focuses among various rating agencies, noting Bloomberg's emphasis on transparency and detailed corporate disclosure. This focus is further supported by Koutoupis et al. (2021), which underscores that during the COVID-19 period, disclosure and risk management emerged as critical themes in research. Each index is selected based on two criteria, first it must have a close matching description to a specific ESG relative theme and second

Table 1. Selected nine subdivided ESG indexes.

Pillar	Theme	Subdivided index
Environment	Greenhouse gas emission (GHG)	S&P GSCI Carbon Emission Allowances (EUA)
Environment	Clean energy business (Energy)	S&P Global Clean Energy Index
Environment	Environmental markets and technologies (Production)	FTSE Environmental Opportunities Waste and Pollution Control 30 Index
Environment	Water business (Water)	World Water Total Return Index
Environment	Waste business (Waste)	SGI Global Waste Management Index
Social	Consumer Products and Services (Supply)	EURO STOXX Consumer Products and Services Index
Social	Network security business (Security)	ISE Cyber Security Index
Governance	Diversity and equal opportunity (Diversity)	Solactive BBVA ixG Global Governance & Board Diversity EUR Index
Governance	Renewable and employee benefits (Employee)	Solactive Employee Well Being Select Index AR 5%

The indexes are from Bloomberg securities database. Variable names created in this study are in brackets.

to have around 10-year historical data spanning from 10/06/2011 to 21/05/2021. In what follows, the descriptions of themes of Table 1 are provided as sourced from Bloomberg:

- **GHG**: A benchmark that tracks the investment performance of the European Union Carbon Emission Allowances (EUA) market.
- **Energy**: It is the measurement of the performance of companies in global clean energy-related businesses.
- **Production**: It tracks the companies having at least 20% of their business derived from environmental markets and technologies.
- **Water**: It is a hypothetical basket of companies with the biggest share in water utilities, infrastructure and treatment.
- **Waste**: It tracks companies which have a significant part of their activities dedicated to the collection, transport, processing and recycling or disposal of waste.
- **Supply**: It tracks European companies whose revenues are mainly from providing better consumer products and services.
- **Security**: It tracks companies that either work to develop hardware or software that safeguards access to files, websites and networks.
- **Diversity**: It tracks companies with top performers in corporate governance, the best female-director ratios and diversity policies.
- **Employee**: Only companies providing good employee benefits, health and safety are eligible for inclusion in the index.

The importance of portfolio management in COVID-19 pandemic period has been discussed by Outlaw, Smith, and Wang (2021). And the historical data includes the COVID-19 pandemic period (from 03/01/2020 to 21/05/2021) which is considered as the stressed market period. This is based on the first WHO report from Wuhan, China, on 31 December 2019 (Ryan 2020). A 'serious outbreak period' is considered from 24/01/2020 to 19/06/2020 according to France's three cases of novel coronavirus, see, Ryan (2020).

The data of the conventional asset indexes and integrated ESG indexes are also retrieved from Bloomberg. We use SPX 500 as the stock index, REIT Index as the real estate index, and Bloomberg Barclays US Treasury Index (LUATTRUU Index) as the US treasury bond index. In our work, a comprehensive ESG index is either GSIN Index from MSCI Ltd. or SGESGSEP Index from STOXX Ltd. The three pillars of E, S and G indexes are either GEIB Index, MXWOSOCR Index and M2CXRSC Index (collected from MSCI Ltd.) or SGENVDSP Index, SESOCDSP Index and SGGOVDSP (collected from STOXX Ltd.). For the risk-free rate, we follow the selection of Sahut and Pasquini-Descomps (2015) and use the daily return on three-month US treasury bills (13 Week US Treasury Bill, '^IRX' from Yahoo Finance).

In the out-of-sample testing, where we construct the tradable subdivided ESG portfolios, all the data is collected from Bloomberg. The tradable funds or ETFs included in the portfolios are summarised in Table 2. Among the subdivided ESG indexes of Table 1, only Energy, Water and Security have the exact corresponding fund or ETF in the market. Because of this, for the remaining subdivided ESG indexes, we have instead selected alternative ETFs that based on their description should follow similar themes. For the out-of-sample testing, we aim for a longer investment horizon and therefore exclude the Waste variable, resulting in an available time-span of approximately two years (from 30/08/2019 to 24/06/2021) with eight available subdivided ESG tradable assets.

In what follows, the description of themes of Table 2 are provided as sourced from Bloomberg:

- **GHG**: It is exposed to shares listed in EU with good performance of carbon emission to compensate for the carbon footprint.
- **Energy**: It is an exchange-traded fund incorporated in the US. The ETF tracks the performance of the S&P Global Clean Energy Index.
- **Production**: It invests globally in companies providing leading clean and new energy technologies and other solutions that enable sustainability.

Table 2. Tradable ETFs or funds used.

Variable	Theme	Tradable asset
GHG	Greenhouse gas emission	THEAM QT-EUR CLM CARB-1
Energy	Clean energy business	ISHARES GLOBAL CLEAN ENERGY
Production	Environmental markets and technologies	ESSEX ENVIRON OPPORT-INST
Water	Water business	LYXOR WORLD WATER DR
Waste	Waste business	GLOBAL X WASTE MANAGEMENT ET
Supply	Consumer Products and Services	ISHARES EUROPE600 RETAIL DE
Security	Social network security business	L&G CYBER SECURITY UCITS ETF
Diversity	Diversity and equal opportunity	UBS ETF GL GENDER EQ USD
Employee	Renewable and employee benefits	THEAM QUANT-EQ WL EM SC II-C
Stock	Stock asset	SPDR S&P 500 ETF TRUST
Real Estate	Real estate asset	SPDR DOW JONES REIT ETF
Bond	Government bond asset	SPDR Bloomberg Barclays U.S. Treasury Bond UCITS ETF
ESG-pillar	Comprehensive ESG	FLEXSHARES STOXX GLOBAL ESG
E-pillar	Single E-pillar	PICTET-GLOBAL ENVIRONMENT-IE
S-pillar	Single S-pillar	THREADNEEDLE-EURP SOC BD-IE
G-pillar	Single G-pillar	MAPFRE AM-GOOD GOVERNANCE-IE

The index and description are from Bloomberg securities database.

- **Water**: The fund tracks the performance of the World Water Index CW.
- **Waste**: The fund tracks the performance of the Solactive Global Waste Management Index.
- **Supply**: The fund tracks the performance of the STOXX Europe 600 Retail index.
- **Security**: It tracks the performance of ISE Cyber Security Index that tracks the performance of companies engaged primarily in cyber security business activities.
- **Diversity**: It tracks the performance of the 'Solactive Equileap Global Gender Equality 100 Leaders Net Total Return Index'.
- **Employee**: The fund exposed to the BNP Paribas WRE Total Return Index. Working in the renewable energy industry has fewer health and safety issues compared with traditional energy industries. More policy benefits (e.g. tax benefits, lower costs) are given to this industry, see, Lund (2009), and we assume that these can be transferred to employee benefits, see, Solactive (2014).
- **Stock**: The ETF that tracks the S&P 500 Index.
- **Real Estate**: The fund that tracks the performance of the DJ US Select REIT Index.
- **Bond**: The fund that tracks the performance of the US treasury bonds known as LUATTRUU Index.
- **ESG-pillar**: The fund tracks the performance of STOXX Global ESG Select KPIs Index.
- **E-pillar**: The fund invests in companies with a low environmental footprint.
- **S-pillar**: The fund invests in securities that are considered to support socially beneficial activities.
- **G-pillar**: This fund invests in companies with good governance.

The whole dataset includes 543 weekly observations for each index. For the experiments, we divide the data into the long-term market period with 9870 observations and the stressed period with 1533 observations. Table 3 shows the descriptive statistics of the ESG data. We note that the log-return distribution of each index is negative

Table 3. Descriptive statistics: Subdivided ESG indexes.

Index	Mean	SD	Min	Max	Skewness	Kurtosis	Observations
GHG Price	46.2337***	33.3742	11.8700	196.5800	1.3531	1.6685	543
Energy Price	838.4052***	361.1909	444.5600	2720.7900	2.7000	8.1462	543
Production Price	465.8209***	104.7529	269.2400	715.7000	0.0336	−0.8684	543
Water Price	4411.8838***	1621.1179	1878.1900	8392.2300	0.1950	−0.7900	543
Waste Price	162.1037***	50.3185	82.1300	293.2100	0.2498	−0.8557	543
Supply Price	217.4484***	89.1778	96.8500	479.3800	0.7767	−0.1580	543
Security Price	282.1478***	138.3005	83.3400	680.5200	0.8501	0.1740	543
Diversity Price	2395.6348***	780.0838	1008.9800	3920.4200	−0.1848	−1.1684	543
Employee Price	145.2511***	26.2776	86.0500	191.6300	−0.7250	−0.7655	543
GHG log-return	0.0021	0.0697	−0.4121	0.2317	−0.8351	4.3824	542
Energy log-return	0.0010	0.0379	−0.2466	0.1660	−0.5664	5.1705	542
Production log-return	0.0014	0.0206	−0.1349	0.0986	−0.9193	6.6376	542
Water log-return	0.0025**	0.0225	−0.1424	0.1109	−1.0910	6.9821	542
Waste log-return	0.0019**	0.0223	−0.1441	0.1101	−0.9461	6.3337	542
Supply log-return	0.0027**	0.0261	−0.1750	0.0780	−0.8212	4.5009	542
Security log-return	0.0034**	0.0315	−0.1551	0.1509	−0.0651	3.1572	542
Diversity log-return	0.0021**	0.0224	−0.1376	0.0989	−1.2559	7.0396	542
Employee log-return	0.0011	0.0204	−0.2100	0.0634	−2.6569	23.7809	542

t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

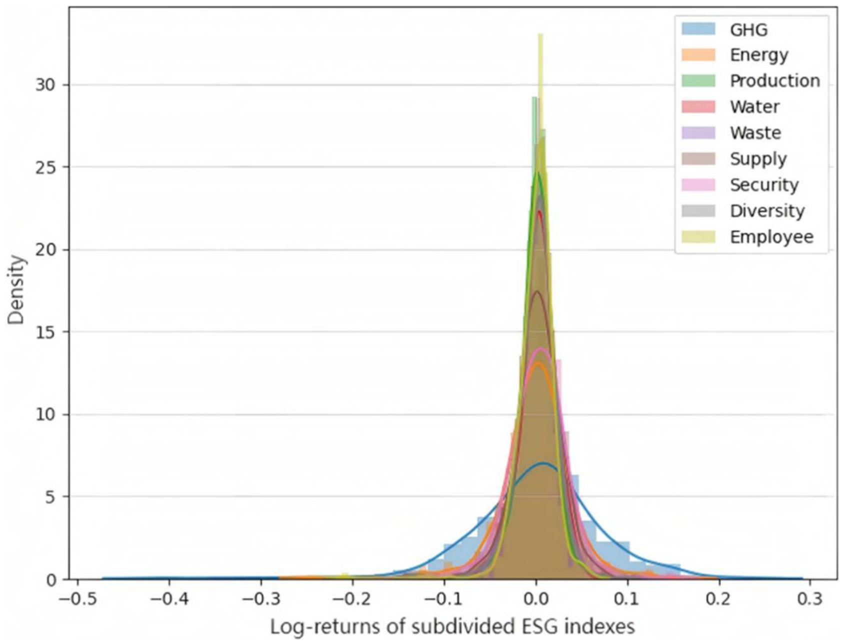

Figure 1. Log-return distributions of the nine subdivided ESG indexes.

skewed leptokurtic, which is consistent with Miralles-Quirós, Miralles-Quirós, and Nogueira (2019). Furthermore, Figure 1 shows the log-return distributions of the nine subdivided ESG indexes. To account for sectoral differences, we analyse the performance of 10 sector indexes based on the Global Industry Classification Standard (GICS) and follow the MSCI World Sector Index interpretations. The selected indexes are: (1) Energy: MXWO0EN Index, (2) Materials: MXWO0MT Index (3) Industrials: MXWO0IN Index (4) Utilities: MXWO0UT Index (5) Healthcare: MXWO0HC Index (6) Financials: MXWO0FN Index (7) Consumer Discretionary: MXWO0CD Index (8) Consumer Staples: MXWO0CS Index (9) Information Technology: MXWO0IT Index (10) Communication Services: MXWO0TC Index, from Bloomberg.

4. Methodology

4.1. Sharpe ratio

To test H1, we calculate the mean SR of each index's return in both the long-term span (around 10 years) and the stressed short-term span (over 1 year). Also, we calculate elasticity of each index's return in the post-COVID-19-outbreak period. This period is defined as one year after the accumulation of the log-returns has reached its lowest point. We can then rank the indexes based on their SR and elasticity, following the method used by Panayiotou and Medda (2016) to evaluate the individual asset performance. SR is the quantification of the trade-off between risk and return and is widely accepted as a criterion to test asset performance, see, Maller, Roberts, and Tourky (2016), Maller, Durand, and Jafarpour (2010), and Kircher and Rösch (2021). Based on the definition of Bernstein and Fabozzi (1998) and the interpretation of Skrepnek and Sahai (2013), we use the ex-post SR to reflect the daily risk-free rate:

$$\text{Sharpe Ratio } = \frac{E(R_i - R_f)}{Var(R_i - R_f)} \tag{1}$$

In Equation (1), R_i is the simple weekly returns of an asset or portfolio, E is the expected value, R_f is the weekly risk-free rate and $V\,ar(\cdot)$ is the variance.

4.2. Elasticity

The concept of elasticity in economics can be traced back to Surányi-Unger (1949); Reilly (1940), where it is used to represent the responsiveness of one economic factor to changes in another. Building on this foundation, the elasticity theory of demand and supply has been widely applied to explain how price fluctuations influence the supply and demand of a product or service (Dela Cruz et al. 2023; Hadji Acmad, Vigonte, and Abante 2024; Pyles 2019; Soderbery 2015). Beyond this traditional application, elasticity theory in economics extends to the elasticity of substitution, which serves as a measure of resilience (Karagiannis, Palivos, and Papageorgiou 2005). Additionally, Dormady et al. (2022) explored the relationship between firms' resilience to catastrophic events with the elasticity of substitution. In line with this perspective, this study identifies elasticity, as conceptualised by Haugen and Wichern (1974) and Kraft (2003), as a key determinant of relative price volatility. This factor is employed to assess an asset's resilience in terms of accumulative log-returns, adjusted over time, particularly during stressed market conditions. The elasticity formula is defined by:

$$Elasticity(y, t0, T) = \frac{y^* - min_{t0 \leq s \leq T}(y_s)}{number\ of\ weeks\ in\ a\ calendar\ year} \tag{2}$$

In Equation (2), $Elasticity_{(y,t0,T)}$ represents elasticity of y with respect to time, t_0 is the start of the COVID time, T is the end of the testing period in our model, y_s is the accumulative log-return of assets from t_0 to s, y^* denotes the accumulative log-return value one year after y_s has reached its lowest point in the stressed period and $\min_{t0 \leq s \leq T}(y_s)$ is the lowest value of y_s in the stress period. This metric indicates the rebound power of the assets from its lowest point, i.e. the higher the metric, the faster the recovery. The Pearson correlation coefficient is used to calculate the pairwise correlations of all assets, with statistical significance tested using STATA (v.14.0). STATA was chosen due to its widespread use among researchers in economics and management, offering robust statistical functionality and repeatability, see, MacKie-Mason (1992) and Renfro (2004).

4.3. Sequential least squares programming

To test H3, we follow the principles of MPT introduced by Fabozzi, Markowitz, and Gupta (2008), Miller (1960) and follow Sequential Least Squares Programming (SLSQP). The latter method is applied by minimising an objective function with multiple constraints. This method has been widely used to construct the optimal portfolio in MPT, see, Prasad et al. (2021), Wu, Wang, and Wu (2022), Tchoudi and Sergeenko (2022), Gotardelo and Goliatt (2024) and Guimarães (2021). As introduced by Gong et al. (2023), SLSQP is chosen for its ability to fully utilise gradient and Hessian matrix information compared to the other two methods – COBYLA and trust-constr – provided by Python's scipy.optimize library (v.3.11.5) for solving constrained optimisation problems. Furthermore, SLSQP is recommended for cases involving iteration with equally spaced arrays, which aligns with the requirements of this study, see, Gong et al. (2023).

In our work, long-only portfolios are considered due to the liquidity limitation of subdivided ESG relative assets. Additionally, by adopting sustainability-themed investing, we prioritise long-term value and ethical considerations, aligning with the fundamental goals of ESG investing (Schoenmaker and Schramade 2019). As a result, short selling is not incorporated into our strategy. This approach is also prevalent in major markets such as the US, Europe and Japan, as noted by Iwata, Orpiszewski, and Thompson (2024), who found that few unconstrained investors take active short positions to profit from negative ESG incidents. The optimisation problem is done by minimising the following objective function which is equivalent to maximising the SR:

$$\min_{\omega i}\left(-\frac{E(R_p - R_f)}{\sqrt{Var(R_p - R_f)}}\right) \tag{3}$$

$$\text{s.t. } \omega i \ \geq \ 0 \quad \text{and} \quad \sum_{i=1}^{n} \omega_i = 1$$

In Equation (3), $R_p = \sum_{i=1}^{n} \omega_i \cdot R_i$ is the simple return of the portfolio p, R_i is the mean historical simple return of asset i, ω_i is the capital weight assigned to asset i, and $V\,ar(R_p - R_f)$ is the variance of $R_p - R_f$. Note that

$$-\frac{E(R_p - R_f)}{\sqrt{Var(R_p - R_f)}} = -\frac{\sum_{i=1}^{n} \omega_i \cdot E[R_i] - R_f}{\sqrt{\sum_{i=1}^{n} \omega_i^2 \cdot \sigma_i^2 + \sum_{i=j,i\neq j}^{n} \omega_i \cdot \omega_j \sigma_{ij}}} \tag{4}$$

In Equation (4), ${\sigma_i}^2$ is the variance of the simple return of asset i, and σ_{ij} is the covariance between simple returns of asset i and j. Python scipy.optimize library is used to solve Equation (3) and find the approximated optimal weights. If the convergence does not occur, we consider equal weights, see, Ozelim et al. (2023). Our objective function in Equation (4) is subject to two key constraints, as outlined in Equation (3). The first constraint, Non-Negativity of Weights ($\omega_i \geq 0$), ensures that the portfolio consists solely of long positions, prohibiting short-selling. The second constraint, Weight Sum Equals One ($\sum_{i=1}^{n} \omega_i = 1$), ensures that the entire available capital is fully allocated to the assets, with no uninvested cash. This forces the investor to make trade-offs between assets and fully utilise the budget, optimising the portfolio's expected return.

Together, these constraints ensure that the portfolio reflects a 'long-only' strategy, aligning with typical investment mandates that prohibit short-selling due to its risks. The weight sum constraint guarantees that capital is fully invested in selected assets, supporting a diversified, fully allocated portfolio. This also emphasises the importance of strategic asset selection, where the investor maximises returns within the limits of the available capital.

4.4. Diversification ratio

The DR of portfolios is calculated by the following formula:

$$\text{Portfolio DR} = \frac{\sum_{i=1}^{n} \omega_i \cdot \sigma_i}{\sigma_p} \tag{5}$$

In Equation (5), σ_p is the standard deviation of the portfolio p. Portfolio DR is widely accepted in portfolio construction to create the most-diversified portfolio (MDP) by maximising this ratio, see, Choueifaty, Froidure, and Reynier (2013), Holst (2013), Koné (2020) and Maguire et al. (2014). This criterion is selected to manage portfolio risk during periods of market stress, such as the COVID-19 pandemic. The superior performance of MDP has been demonstrated by Choueifaty, Froidure, and Reynier (2013) and Clarke, De Silva, and Thorley (2006), who found that MDP is able to capture a larger risk premium compared to portfolios from other strategies, such as minimum-variance, equal-weighted and maximum SR portfolios. Moreover, its performance is particularly notable during stressed market conditions, where the correlation of risk in asset returns increases.

4.5. The two-step investment approach

To test H4, we introduce a two-step investment approach to build our optimal portfolios. Initially, investors decide on the number (denoted as n_s) of subdivided ESG assets to be incorporated into the benchmark portfolio. Based on this number, we identify a collection of all potential portfolios, each comprising the assets of the benchmark portfolio plus a sample of n_s assets selected from the set of subdivided ESG assets. Then, as the first step in this approach, the SR optimal weights of each portfolio are calculated by using the SLSQP method of Python's scipy.optimize library to solve the optimisation problem in Equation (3). Then, in the second step, we use these optimal weights to calculate each portfolio's DR, following Equation (5), and select the portfolio with the highest DR.

This approach facilitates the integration of both the SR and the DR into the asset selection process, resembling the asset selection through multi-objective evolutionary algorithms (MOEAs) discussed by Bueno (2019), where the two objectives are allocated across two distinct steps. It is inspired by the risk parity concept introduced by Qian (2011), which demonstrated the relationship between maximising the SR and achieving equal risk contributions from all assets in a portfolio. This concept emphasises the importance of each asset's risk contribution in achieving true diversification. In the first step, we calculate the optimal SR to achieve risk parity. In the second step, we use the DR – the ratio between the weighted average volatility and the portfolio's overall volatility (similar to the calculation of risk contributions) – to construct a diversified portfolio.

This two-step process is further supported by Mattesi et al. (2023), who utilised quantum annealers to solve a novel Quadratic Unconstrained Binary Optimization (QUBO) formulation. This formulation integrates maximising the SR in the first step and maximising portfolio diversification in the second step for portfolio optimisation.

Unlike our study, their approach defines portfolio diversification as a penalty for investing in assets within the same sector, rather than using the DR. Additionally, the complexity of this non-trivial task poses challenges for classical solvers, which may limit its practical application. The performance of our portfolios is then tested by the out-of-sample testing data.

To carry out a robust performance testing of the two-step approach, we use one passive (called Strategy 1) and two active investment strategies (called Strategy 2 and Strategy 3) to train and implement it with multiple criteria. ESG investors support both passive and active management strategies. For instance, Amon, Rammerstorfer, and Weinmayer (2021) and Jin (2022) highlighted that passive management is favoured by ESG investors as a cost-effective approach to managing systematic ESG risk. Conversely, Jin (2022) suggested that active management becomes advantageous during market downturns. Furthermore, Abou Tanos et al. (2024) found that higher-return companies, on average, had higher prior ESG ratings, enabling active managers to enhance performance by excluding lower-performing ESG stocks. In Strategy 1 (passive), the training dataset is formed using the non-tradable indexes from 10/06/2011 to 23/08/2019. The entire training dataset is used to implement the two-step approach, i.e. to calculate SR optimal weights and portfolio DR. After the portfolio is selected, asset weights remain constant in the testing dataset which is from 30/08/2019 to 24/06/2021.

In Strategy 2 (active), we update the portfolio on a weekly basis, where in each week, we use a rolling window to train and obtain the optimal weights. In order to obtain the optimal rolling window, we use a portion of the training dataset, called a validation set (which is from 01/03/2019 to 23/08/2019) to tune the optimal window length for which we achieve the highest accumulative portfolio log-return (see the range of this rolling window in Table A1 in the Appendix). In Strategy 3 (active), we follow the same process as in Strategy 2, but the dataset is made up of tradable ETFs (from 29/03/2019 to 24/06/2021) rather than non-tradable indexes. Note that the validation set in Strategy 3 is shorter than the one in Strategy 2 (from 24/05/2019 to 23/08/2019), due to the limited availability of tradable ETFs data. All three strategies share the same testing set from 30/08/2019 to 24/06/2021. The testing set includes data from the COVID-stressed period, ensuring that this period's data is not used for training or cross-validation purposes.

To estimate portfolio performances, multiple criteria are used including annualised return and volatility, the ratio return/volatility, SR, Treynor Ratio, Jensen's Alpha, Sortino Ratio, Information Ratio (IR) and Maximum Drawdown (MDD). After the portfolio performance has been obtained, we use SV method to measure the contribution of each portfolio's component in achieving the excess return (if any). The SVs indicate that the incorporated subdivided ESG assets contribute positively in achieving the excess return. Portfolio returns are divided into positive and negative groups and the contribution from each asset to each group is considered separately.

4.6. The Shapley value method

The SV method is developed by Shapley (1953) and is used for solving fair allocation problems, see, Moulin (2004). Then many researchers have extended its usage to decompose an aggregate economic variable. Chantreuil and Trannoy (2013), Rongve (1995) and

Shorrocks (2013) applied the SV method to the distributional analysis focusing on the decomposition of inequality into economic components. In portfolio construction, Mussard and Terraza (2008) applied SV to determine the contribution of each portfolio's component in its risk. Similarly, Shalit (2021) used SV to decompose the risk of optimal portfolios and rank each asset's comprehensive contribution on portfolio risk. Also, Hagan et al. (2023) used SV to allocate portfolio risk to each asset and interpret the components of enterprise risk measures. Morelli (2023) extended the procedure of Shalit (2021) and studied the SRI focusing on the clusters of firms' environmental performance (E-score). SV is used to select assets based on their contributions towards both the CVaR and the E-score of a portfolio. Goulet Coulombe et al. (2023) used SV to interpret each asset's contribution to the portfolio returns predicted by multiple Machine Learning (ML) models.

The SV offers a natural framework for constructing well-diversified portfolios that meet specific investor goals without the need for additional formal constraints (Simonian 2019). Investors and portfolio managers can apply the SV method in two key areas: optimal portfolio construction and asset contribution interpretation. For optimal portfolio construction, the SV method helps investors predict the precise impact of adding or removing specific securities from their portfolios. By minimising portfolio risk based on SVs, investors can make more informed decisions about their holdings, as demonstrated by Shalit (2020b, 2021), Morelli (2023) and Simonian (2019). Regarding asset contribution interpretation, the SV method allows both portfolio risk and returns to be analysed, as shown in studies of Hagan et al. (2023), Colini-Baldeschi, Scarsini, and Vaccari (2018), and Chen and Gao (2024) for risk, and Moehle, Boyd, and Ang (2021) and Shalit (2020a) for returns.

However, one of the main challenges of using the SV method is its computational complexity, particularly as the number of assets (players) increases. This issue is detailed in Colini-Baldeschi, Scarsini, and Vaccari (2018). To address this, some researchers have proposed more efficient approximation methods, such as Monte Carlo techniques, as seen in the works of Touati, Radjef, and Lakhdar (2021), Sun et al. (2024) and Goldshmidt and Horovicz (2024). Other innovative approaches are also explored like the network centrality algorithm by Michalak et al. (2013), the randomization-based linear approximation method by Fatima, Wooldridge, and Jennings (2008), and the sampling algorithms by Castro, G´omez, and Tejada (2009) and Okhrati and Lipani (2021) which aimed to make the SV method more practical and scalable in financial applications.

Although the Laspeyres and Divisia index methods are two of the most commonly used decomposition techniques (Ang and Zhang 2000), due to their inherent limitations, we adopt the SV method in this study. A significant drawback of the Laspeyres index method is its imperfect decomposition, which results in the presence of a residual term after decomposition, see, Ang and Zhang (2000) and Ang (1995). While this issue is addressed by a refined approximation of the Divisia index method – the Logarithmic Mean Divisia Index (LMDI) – which employs a logarithmic mean weight function, introduced by Ang and Choi (1997), the LMDI method introduces another limitation known as the 'zero-value problem', making it unsuitable for studying asset prices (Ang 1995). More closely to our research, Moehle, Boyd, and Ang (2021) applied the SV method in an attribution analysis of portfolio returns. They show that

Shapley attribution is the preferred method as it is the only one that meets: fairness, correct baseline, full attribution, and monotonicity that are four desired properties of attribution methods. Following this research, we incorporate Shapley attribution in our study of the portfolio return analysis. In our setup, the target variable is the portfolio return, and we would like to find the attribution of each subdivided ESG asset in the achieved return.

Suppose that function $f_t(\cdot)$ represents a portfolio return and $\mathbf{r}_t(\cdot)$ denotes a vector of individual returns of the portfolio's assets at time point t. Let vector $\omega_t(\cdot)$ denotes the allocated weights of each asset at the time point t in the portfolio with the same size of the return vector. We use a scalar b_t to represent the return at time t of a benchmark portfolio made of three categories of assets which are stocks, real estates, and US treasury bonds. The set of these three classes of assets is denoted by C. Then the three-dimensional vector of benchmark asset returns at t is written as $\mathbf{r}_t(C)$. In this case, $\omega_t(C)$ has the same dimension as $\mathbf{r}_t(C)$, and we have:

$$b_t = f_t(C) = \omega_t(C) \cdot \mathbf{r}_t(C) \tag{6}$$

In Equation (6), $\omega_t(C) \cdot \mathbf{r}_t(C)$ is the dot product of the $\omega_t(C)$ and $\mathbf{r}_t(C)$.

Assume that there are n potential selectable subdivided ESG assets and j of them ($0 \leq j \leq n$) are included in a portfolio by an investor. Let X denote the set $\{x_1, x_2, \ldots, x_j\}$ where $x_i, i = 1, 2, \ldots, j$ is the *i-th* subdivided ESG asset. Based on our portfolio construction procedure, after X is determined, we union C and X to get the set S representing all included assets in the portfolio, i.e. $S = C \cup X$. Then the subdivided ESG portfolio return value at t is denoted by R_t and equal to:

$$R_t = f_t(S) = \omega_t(S) \cdot \mathbf{r}_t(S). \tag{7}$$

Note that if $X = \emptyset$ then $R_t = b_t$. Next, to estimate the marginal contribution of a newly added subdivided ESG asset i, we naturally define it as the change in portfolio returns after and before this asset is added, this is represented by $\delta_{it}(S)$ and equal to:

$$\delta_{it}(S) = f_t(S \cup \{x_i\}) - f_t(S) = \omega_t(S \cup \{x_i\}) \cdot \mathbf{r}_t(S \cup \{x_i\}) - \omega_t(S) \cdot \mathbf{r}_t(S) \tag{8}$$

Marginal contributions are associated with the existing portfolio configuration S. If j subdivided ESG assets are included, then there are $j!$ possible permutation sequences to add *i-th* subdivided ESG asset x_i and the probability of each sequence is $\frac{i}{j!}$ (equal probability). For each sequence at time point t, we calculate its δ_{it}. Then, we multiply $\frac{i}{j!}$ by the sum of marginal contributions for all sequences to obtain the Shapley Value at time point t of this asset i which is shown by a_{it} and equal to.

$$a_{it} = \frac{1}{j!} \cdot \sum_{\pi} \delta_{it} = \frac{1}{j!} \cdot \sum_{\pi} [f_t(S_\pi \cup \{x_i\}) - f_t(S_\pi)] \tag{9}$$

In Equation (9), π is a permutation, $S_\pi = C \cup X_\pi$, and X_π denotes the set of subdivided ESG assets made of predecessors of subdivided ESG asset i appearing in the specific permutation π. For example, if $\pi = (1,2,3)$, $i = 2$, then $X_\pi = \{x_1\}$, and if $\pi = (3,1,2)$, and $i = 2$, then $X_\pi = \{x_3, x_1\}$.

In this study, the SV method is used to explain the marginal contribution of subdivided ESG assets in portfolio returns, in the out-of-sample testing. For a specific subdivided ESG asset i, a_{it} is calculated at each time point in the testing dataset and divided by the achieved portfolio return R_t to obtain the Shapley Value percentage at time point t. Then based on these percentage values, a distribution is obtained to show the total contribution performance.

5. Experimental setups, results and discussions

5.1. Hypothesis 1

In the first experiment, we test H1 and summarise the ranking of historical SR and elasticity of all indexes in both the 10-year long-term and COVID-stressed periods. The results are shown in Table 4. In the long-term period, although the MSCI-G pillar index outperforms the general and other pillar indexes, the subdivided security and water indexes achieve a higher SR than the MSCI-G index. Additionally, other subdivided indexes, such as waste, supply and diversity, deliver better SRs compared to both general and other pillar ESG indexes.

In terms of elasticity performance, although the MSCI-E pillar index outperforms other general and pillar indexes, the GHG and energy subdivided indexes exhibit better elasticity than the MSCI-E index. Additionally, the security subdivided index demonstrates superior elasticity compared to other pillar indexes. However, other subdivided indexes do not perform as well as the pillar indexes.

During the stressed period, the energy, MSCI-E pillar, and GHG indexes achieve the top three highest SRs. The MSCI-E index outperforms both the general and other pillar indexes, while the energy subdivided index surpasses it, achieving the best performance across all indexes. The GHG and security subdivided indexes also perform better than the general and other pillar indexes, although other subdivided indexes do not. Our results

Table 4. Historical performance of individual indexes: the benchmark assets, ESG, the three pillars, and subdivided ESG.

	10-year long-term				Stressed period	
Index	SR	Elasticity	SR rank	Elasticity rank	SR	SR rank
Stock	0.6589	0.5181	6	5	0.7335	7
Real estate	0.4557	0.4352	10	11	0.3574	14
Bond	0.1030	0.0590	16	16	0.3625	13
MSCI-ESG	0.4496	0.4950	11	7	0.6639	9
MSCI-E	0.4661	0.8529	9	3	1.1661	2
MSCI-S	0.4811	0.4974	8	6	0.7288	8
MSCI-G	0.7825	0.4911	3	8	0.8614	5
GHG	0.3958	0.9001	13	2	1.1539	3
Energy	0.2419	0.9153	15	1	1.1782	1
Production	0.4199	0.3414	12	14	0.4529	12
Water	0.7912	0.4440	2	10	0.5939	10
Waste	0.6089	0.3797	7	13	0.5554	11
Supply	0.7460	0.4634	4	9	0.8260	6
Diversity	0.6737	0.4133	5	12	0.2932	15
Employee	0.2889	0.2449	14	15	−0.0225	16
Security	0.8099	0.5954	1	4	0.9195	4

Both SR and elasticity are calculated by annualised simple return mean values. Long-term period is 10/06/2011–21/05/2021. The stressed period is 03/01/2020–21/05/2021. Top 5 rank indexes are illustrated in bold.

demonstrate the stable financial returns and resilience of subdivided ESG indexes during the COVID-19 stressed market environment, aligning with related studies such as Cardillo, Bendinelli, and Torluccio (2023), Meehan and Corbet (2025) and Díaz, Esparcia, and López (2022). These findings provide investors with actionable insights into the advantages of subdivided ESG assets, showcasing their ability to deliver stable returns and mitigate risks during economic downturns. Fund managers can utilise these results to align portfolios with ESG principles, enhancing resilience against future crises and advocating for sustainable investment frameworks that promote long-term financial stability.

To explore sectoral differences in greater detail, we categorise industries into 10 sectors based on the GICS: Energy, Materials, Industrials, Utilities, Healthcare, Financials, Consumer Discretionary, Consumer Staples, Information Technology and Communication Services. Sector indexes are then collected, and their historical performances are evaluated over a 10-year long-term period as well as during the COVID-19 stressed period. Detailed results are provided in Table A2 and Table A3 in the Appendix.

We also use the E, S, G-pillar, and general ESG indexes from STOXX, and the results are consistent with our previous findings. Based on these outcomes, we confirm H1 by concluding that specific subdivided ESG indexes demonstrate higher historical SRs and elasticities than both the general and pillar ESG indexes in both general and stressed market environments. Notably, most subdivided ESG indexes outperform the general and pillar ESG indexes in the long-term market environment, whereas this performance is less pronounced in stressed market conditions.

5.2. Hypothesis 2

In the second experiment, we test H2. Table 5 presents the pairwise correlations of subdivided ESG indexes over the long-term historical period, while Table A4 shows the pairwise correlations of pillar indexes. A comparison between these tables reveals that the correlations among subdivided ESG indexes are significantly lower than those of the general ESG pillar indexes. This finding suggests that, to enhance diversification, investors should consider including subdivided ESG indexes rather than relying solely on general ESG pillar indexes. Additionally, diversification benefits can be achieved by incorporating multiple subdivided ESG indexes within a single pillar.

These findings align with the conclusion of Jacobs, Müller, and Weber (2014), which identified subdivided ESG indexes as distinct asset classes and highlighted their potential diversification benefits when integrated into a portfolio. They also reflected the results of prior studies on ESG thematic funds, such as Alvarez and Rodríguez (2015), Reboredo, Quintela, and Otero (2017), Ielasi, Rossolini, and Limberti (2018) and Ielasi and Rossolini (2019). Consistent with these studies, the results demonstrate that investors can achieve diversification benefits by incorporating multiple subdivided ESG assets, even if they originate from a single pillar, into a conventional portfolio. Similar experiments were conducted with STOXX pillar indexes, yielding consistent results. Based on these findings, we confirm H2 with the conclusion that the historical correlations between subdivided ESG indexes are lower than those between the E, S and G pillar indexes.

Table 5. 10-year period Pearson correlation coefficient (subdivided ESG indexes).

Variables	GHG	Energy	Production	Water	Waste	Supply	Diversity	Employee	Security
GHG	1.000								
Energy	0.249***	1.000							
Production	0.239***	0.688***	1.000						
Water	0.170***	0.572***	0.767***	1.000					
Waste	0.170***	0.554***	0.774***	0.873***	1.000				
Supply	0.163***	0.554***	0.740***	0.708***	0.653***	1.000			
Diversity	0.199***	0.606***	0.801***	0.904***	0.880***	0.735***	1.000		
Employee	0.176***	0.607***	0.773***	0.828***	0.774***	0.792***	0.838***	1.000	
Security	0.157***	0.570***	0.655***	0.554***	0.523***	0.531***	0.628***	0.551***	1.000

t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3. Hypothesis 3

We use the third and fourth experiments to test H3. Building on the findings from H1 and H2, it is possible to leverage the high SR and diversification benefits of subdivided ESG indexes in portfolio construction. While these indexes are not tradable assets, their long-term historical data can inform the design of portfolios composed of tradable assets. In the third experiment, we calculate the optimal SRs for multiple subdivided ESG portfolios. Figure 2 presents box plot distributions of the optimal SRs obtained by incorporating varying numbers of subdivided ESG indexes into the benchmark assets. Specifically, for each selected number of subdivided ESG indexes, all possible combinations of these indexes and benchmark assets are evaluated, and the optimal portfolio configuration is determined by solving Equation (3) using the SLSQP method from Python's scipy.optimize library, based on a historical dataset spanning approximately 10 years.

Similarly, we calculate the optimal SR for portfolios consisting of the benchmark and the ESG pillars, with each horizontal line in Figure 2 representing the SR of such portfolios. Our findings indicate that the MSCI-G pillar portfolio is the most competitive when compared to the subdivided ESG portfolios. However, by incorporating just one subdivided ESG index, we can construct an optimal portfolio that achieves a higher SR than the MSCI-G pillar portfolio. Furthermore, adding three subdivided ESG indexes raises the median SR above that of the MSCI-G pillar portfolio, while the lowest SR of portfolios with four subdivided ESG indexes remains higher than the benchmark SR. Notably, the highest SR of portfolios with four subdivided ESG indexes represents a 38% improvement over the benchmark SR. Overall, we observe an upward trend in SR as the number of subdivided ESG indexes increases.

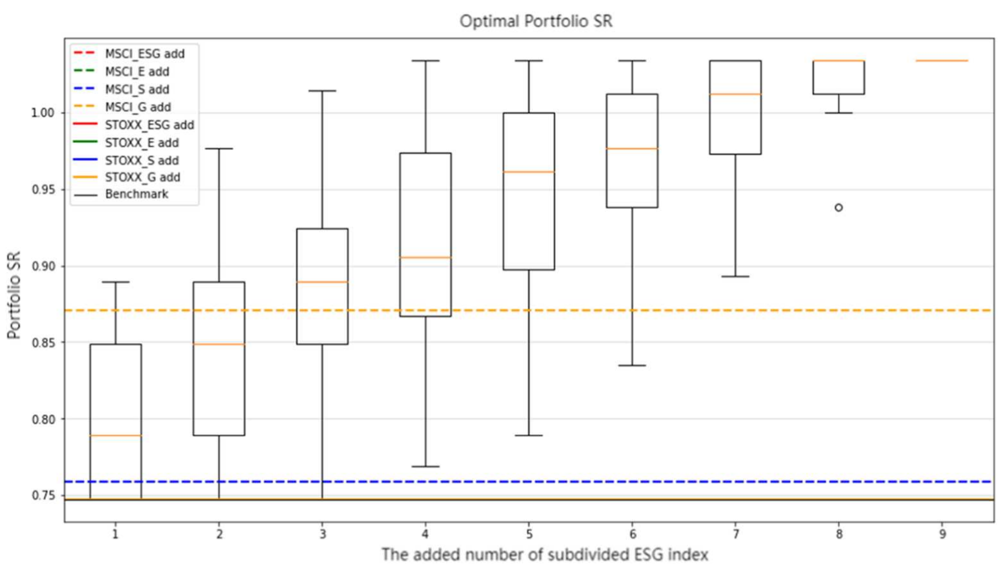

Figure 2. The optimal SR of all possible combinations of subdivided ESG indexes and the benchmark portfolio, comparing with the optimal SR of the benchmark and pillar portfolios. The horizontal line in each box represents the median value of a SR distribution. The time span is 10/06/2011–21/05/2021.

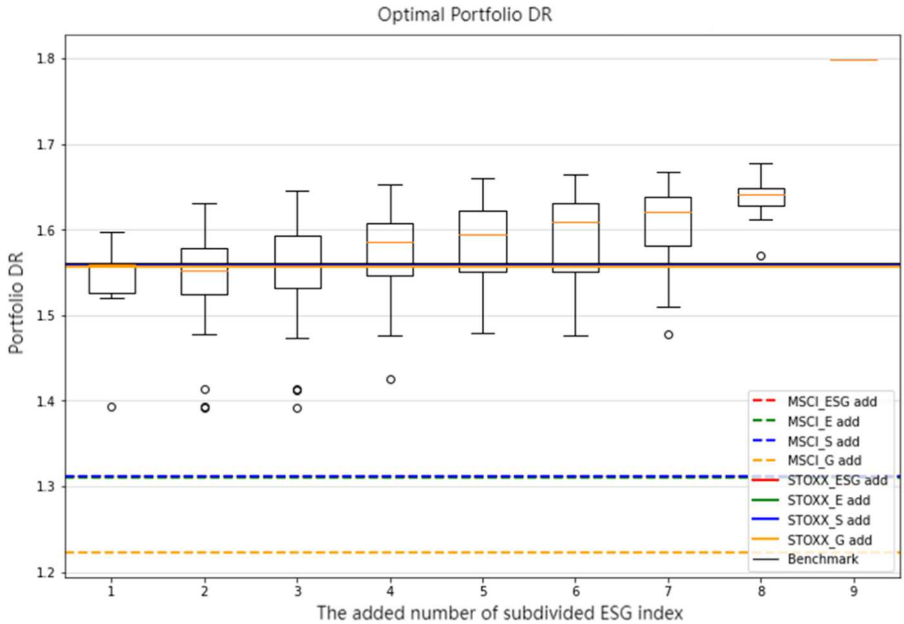

Figure 3. Each box plot represents the DR of optimal portfolios of Figure 2 made of the benchmark plus a fixed number of the subdivided ESG indexes. The horizontal line in each box represents the median value. The time span is 10/06/2011–21/05/2021.

Furthermore, in the fourth experiment, we calculate the DR of each portfolio using the optimal weights of each index (determined by the SLSQP method). The results are summarised in Figure 3. We observe that the median value of the DR distribution exceeds the benchmark only when more than three subdivided ESG indexes are added. Adding three subdivided ESG indexes is sufficient to match the benchmark's DR, while incorporating four subdivided ESG indexes results in a 6% improvement in the highest DR. Our findings are consistent with studies supporting the positive effects of ESG factors, such as Przychodzen and Przychodzen (2015), Statman and Glushkov (2009) and Miralles-Quirós, Miralles-Quirós, and Nogueira (2019). Additionally, our results align with Díaz, Esparcia, and López (2022) and Alvarez-Perez, Diaz-Crespo, and Gutierrez-Fernandez (2024), which highlighted the crucial role ESG assets play in enhancing diversification and improving the financial performance of traditional portfolios.

For investors, our results underscore the value of subdivided ESG assets in improving SR and building resilient, diversified portfolios, especially during volatile markets. Our findings can encourage the promotion of ESG subdivisions, and develop regulatory frameworks for ESG integration. Based on Figures 2 and 3, we confirm H3 and conclude that to surpass the historical performance of the benchmark – based on both the SR and DR criteria – at least three subdivided ESG indexes are required.

5.4. Hypothesis 4

Finally, we conduct the fifth and sixth experiments to test H4. In the fifth experiment, we construct tradable portfolios using three investment strategies based on subdivided ESG indexes and calculate their contributions to portfolio returns using the SV method. To compare the performance of the three strategies, we use a consistent testing period from 30/08/2019 to 24/06/2021 (approximately two years, encompassing the COVID period). The key results are summarised in Table 6, while the full results are provided in Tables A5–A7 in the Appendix. Across all three strategies, we observe that incorporating subdivided ESG assets enhances performance based on multiple criteria. In Strategy 1, all portfolios composed of subdivided ESG assets achieve higher Treynor ratios compared to the benchmark; however, only one portfolio (comprising six subdivided ESG assets) outperforms the G-pillar portfolio.

Similar results are observed for Jensen's Alpha, although none of the subdivided ESG portfolios outperforms the G-pillar portfolio. Portfolios with more than five added subdivided ESG assets achieve a higher SR than the benchmark but remain below the G-pillar portfolio. Additionally, adding an appropriate number of subdivided ESG assets (fewer than seven) significantly reduces the MDD. In Strategy 2, both the Treynor ratio and Jensen's Alpha improve significantly when fewer than six subdivided ESG assets are added. The 3-subdivided ESG portfolio is the only one to achieve a positive IR alongside the highest SR, while the 4-subdivided ESG portfolio achieves the lowest MDD. Moreover, the benefits of low-volatility portfolios are highlighted by Blitz (2023), who attribute these advantages to reduced exposure to systematic risk. In Strategy 3, adding subdivided ESG assets leads to significant improvements across all criteria, but the volatility and MDD are the highest among the strategies. According to Table 6, the 4-subdivided ESG portfolio demonstrates relatively superior performance across all criteria and strategies.

Figure 4 presents a comprehensive analysis of cumulative log-return performance and weight allocations across three investment strategies. The first column of the figure illustrates the performance of the strategies over time, segmented into four distinct market scenarios: before the COVID-19 stressed period (prior to the light grey area), during the 'serious outbreak period' (deep grey area), during the COVID-19 stressed period (light grey area) and after the COVID-19 stressed period (following the light grey area).

Before the COVID-19 stressed period, Strategy 3 performed comparably to the benchmark, while Strategies 1 and 2 underperformed relative to it. During the 'serious outbreak period', all three strategies outperform the benchmark, with Strategy 2 achieving the highest performance. However, as the market transitions into the COVID-19 stressed period, the benchmark begins to close the performance gap. This trend continues into the post-COVID-19 period, where the benchmark ultimately overtakes Strategy 1, showcasing stronger performance in a recovering market environment. While out-of-sample testing indicates that subdivided ESG portfolios provide significant stability during periods of market stress, their performance advantage diminishes in less volatile market conditions. Notably, the 4-subdivided ESG portfolio in Strategy 2 demonstrates remarkable stability throughout stressed periods due to its integration of SR and DR features, making it particularly appealing to extreme risk-averse investors and pension funds.

The second column of Figure 4 focuses on weight allocations for subdivided ESG assets across all three strategies during the 92-week experimental period. The vertical axis represents the concentration of weights assigned to the subdivided ESG assets, while violin plots depict the distribution of weights for individual assets over the

Table 6. Out-of-sample portfolio performance in three strategies.

	Strategy 1 (passive)					Strategy 2 (active)					Strategy 3 (active)				
Portfolios	Treynor ratio	Jensen Alpha	Information ratio	Sharpe ratio	MDD	Treynor ratio	Jensen Alpha	Information ratio	Sharpe ratio	MDD	Treynor ratio	Jensen Alpha	Information ratio	Sharpe ratio	MDD
Benchmark	0.2153	0.0047	Not applicable	0.8378	−1.2526	0.1040	−0.0956	Not applicable	0.4448	−6.1114	0.4723	0.0764	Not applicable	1.2855	−6.7165
ESG add	0.2153	0.0047	−0.8066	0.8376	−1.2513	0.1034	−0.0961	−0.4885	0.4420	−6.1224	0.4488	0.0672	−0.6400	1.2104	−7.4860
E-add	0.2153	0.0047	0.8067	0.8378	−1.2529	0.3468	0.0362	−0.1008	0.7814	−2.0066	0.4552	0.0729	−0.0478	1.1862	−6.5355
S-add	0.2153	0.0047	−0.8066	0.8373	−1.2489	0.1397	−0.0553	0.4088	0.5879	−6.2226	0.1748	−0.0047	−1.4400	0.4521	−15.1886
G-add	0.2712	0.0216	0.7403	1.0220	−1.5856	−0.0477	−0.0819	−0.6607	−0.1662	−3.9685	0.3780	0.0507	−0.5736	1.0530	−8.0465
1 sub-ESG	0.2600	0.0119	−0.2918	0.8132	−0.9339	0.2184	0.0051	−0.2648	0.6488	−7.2715	0.5341	0.0938	0.5259	1.3510	−5.4134
2 sub-ESG	0.2456	0.0097	−0.3265	0.8078	−1.0457	0.3069	0.0290	−0.1243	1.0309	−2.2849	0.8238	0.1509	0.5892	1.4912	−4.5204
3 sub-ESG	0.2456	0.0097	−0.3281	0.8075	−1.0450	0.5535	0.0705	0.0069	1.5092	−1.6275	0.8429	0.1579	0.6495	1.5030	−3.9214
4 sub-ESG	0.2455	0.0097	−0.3260	0.8080	−1.0468	0.5184	0.0609	−0.0451	1.4732	−1.3425	0.8541	0.1552	0.6129	1.5108	−3.8966
5 sub-ESG	0.2457	0.0097	−0.3249	0.8079	−1.0464	0.4703	0.0603	−0.0171	1.3032	−1.7968	0.8603	0.1563	0.6229	1.5213	−3.8670
6 sub-ESG	0.2753	0.0154	−0.0940	0.9010	−1.0539	0.0015	−0.0856	−0.6740	0.0053	−7.3844	0.8363	0.1536	0.5819	1.4534	−3.5617
7 sub-ESG	0.2436	0.0105	−0.0673	0.8612	−1.4143	0.0103	−0.0782	−0.6334	0.0363	−5.5644	0.9331	0.1649	0.6088	1.5036	−3.1360
8 sub-ESG	0.2378	0.0100	0.0803	0.8521	−1.2677	0.0797	−0.0482	−0.3997	0.2359	−4.6478	0.7427	0.1205	0.2809	1.3122	−3.7870

4 decimal digits are kept.

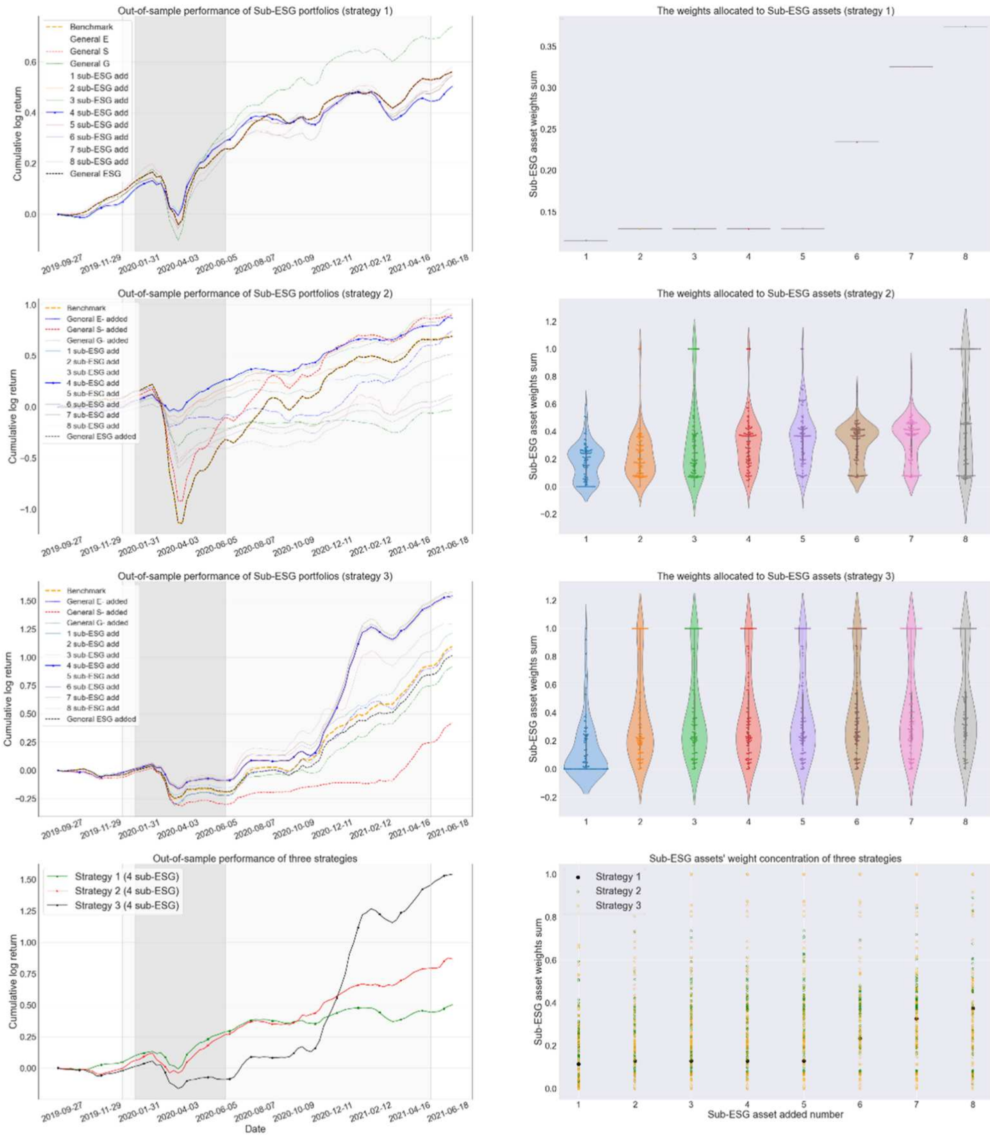

Figure 4. The left column: The light grey background area represents the COVID-19 stressed period from 03/01/2020 to 21/05/2021. The deep grey background area represents the 'serious outbreak period' mentioned in Section 3 from 24/01/2020 to 19/06/2020. The testing period is 30/08/2019–24/06/2021 updated weekly. The right column: The first three graphs show the optimal weight distribution of subdivided ESG assets. The last graph shows the subdivided ESG assets' weight concentration of the three strategies.

investment period. For example, in Strategy 3, we observe that for most weeks during the experiment, the addition of one subdivided ESG asset often had no impact on the optimal portfolio, as its corresponding optimal weight was zero.

In the sixth experiment, we calculate the SV of each subdivided ESG asset and use it to partition the total optimal portfolio returns into two categories: positive returns and

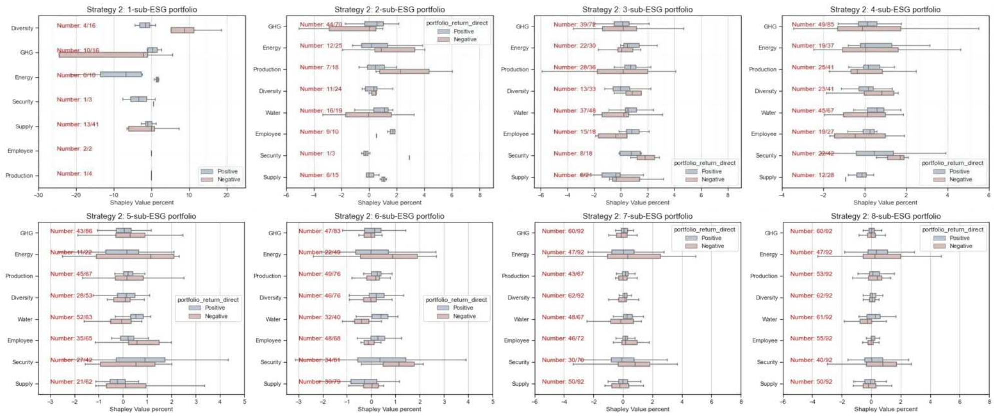

Figure 5. Shapley Value (divided by the portfolio return) of each subdivided ESG asset's contribution in the portfolio return for Strategy 2. The denominator of each red fractional value indicates the number of weeks that the subdivided ESG asset is selected by Strategy 2, and the corresponding numerator shows the number of weeks for which the optimal portfolio achieves positive excess return with respect to the benchmark. Outliers have been removed.

negative returns. Figure 5 illustrates the proportion of each subdivided ESG asset's SV relative to the total optimal portfolio returns in Strategy 2. Portfolio returns are categorised based on whether they are positive or negative, with negative values indicating losses. We observe that most subdivided ESG assets contribute positively to portfolios with positive returns and negatively to those with negative returns, demonstrating their dual role in enhancing returns and mitigating losses. Notable examples include GHG, water and employee ESG assets, which exhibit such contributions. Similar analyses for Strategies 1 and 3 are presented in Figures A1 and A2 in the Appendix.

Our results confirm the resilience of ESG investing when implemented with an appropriate strategy, consistent with the findings of ElBannan (2024), Mishra, Raj, and Chakrabarty (2023) and Ingebretsen (2023). The results demonstrate that subdivided ESG portfolios, particularly those with fewer than six ESG assets, offer superior performance across metrics like SR, Treynor Ratio and MDD, with the 4-subdivided ESG portfolio showing the best balance of return and risk. Strategy 2, which updates portfolios dynamically, provides notable resilience during stressful periods like the COVID-19 pandemic, making it ideal for risk-averse investors such as pension funds. Specific ESG themes, such as GHG emissions, water, and employee-related factors, play a dual role in enhancing returns and mitigating losses, emphasising the importance of thematic ESG selection. These findings highlight the advantage of detailed ESG subdivisions, standardise ESG metrics, and incentivise sustainable investing to enhance financial stability, especially during market crises. This can encourage institutional adoption and align investment flows with national sustainability goals.

Based on these outcomes, we confirm H4 by concluding that our two-step investment approach effectively enhances portfolio performance, as confirmed by multiple criteria. Furthermore, the application of the SV method allows us to attribute the realised excess returns to the positive contributions of subdivided ESG assets. Our findings also align with Renneboog, Ter Horst, and Zhang (2008), as our two-step approach leverages the ‘thematic valuable information’ of ESG assets to improve portfolio outcomes.

6. Operational, practical considerations and implications

While this study highlights the potential of subdivided ESG portfolios to enhance SRs, improve diversification, and achieve better financial performance, several key operational and practical considerations need to be addressed to ensure the robustness of these findings in real-world portfolio construction. Specifically, transaction costs, liquidity risks, and scalability challenges must be carefully considered, as they can significantly impact the implementation of subdivided ESG strategies in institutional investment practices. Moreover, the implications for both practitioners and policymakers are provided.

6.1. Transaction costs

One of the primary concerns for institutional investors is the impact of transaction costs when incorporating subdivided ESG assets into portfolios. Subdivided ESG themes, such as those focused on greenhouse gas emissions, water and employee benefits, may involve relatively less liquid securities or more specialised ETFs that trade with wider bid-ask spreads or higher fees. When ESG assets are divided into smaller subcategories, the frequency of rebalancing and trading may increase, particularly if the investor adopts an active management approach or attempts to adjust for market fluctuations. These transaction costs could offset some of the potential returns indicated by the SR and other performance metrics, particularly for larger institutional portfolios that involve higher trading volumes.

The solution to mitigate transaction costs is to carefully select the number of subdivided ESG assets to include in the portfolio, balancing the diversification benefits with the additional trading costs incurred. As our findings suggest, portfolios with fewer than seven subdivided ESG assets generally provide optimal performance. This number may allow for efficient portfolio construction while minimising the impact of transaction costs. For institutional investors, it is crucial to weigh the benefits of diversification against the costs of frequent rebalancing, especially when considering the implementation of a dynamic investment strategy.

6.2. Liquidity risks

Another significant challenge is liquidity risk, particularly when subdivided ESG assets are less widely traded or represent niche segments of the market. While ESG investing has grown in popularity, subdividing ESG themes may lead to investments in less liquid markets, especially when focusing on specific industries or regions that are less mature. For example, environmental assets such as water-related investments may have lower trading volumes than more broadly focused ESG portfolios. This could create challenges in executing trades at desired prices without adversely affecting the market, particularly during periods of market stress or when large portfolio adjustments are needed.

Institutional investors must consider the liquidity profiles of the subdivided ESG indexes they incorporate into their portfolios. Ensuring that sufficient liquidity exists for each asset is essential for smooth execution and to avoid the risks of price slippage, which could erode the expected returns. One way to address this challenge is through the use of liquidity-adjusted performance measures and a diversified allocation across more liquid and less liquid ESG themes. It is also important to establish clear guidelines for the maximum proportion of assets that can be allocated to less liquid segments of the ESG universe.

6.3. Scalability

Scalability is another critical concern for institutional investors looking to implement subdivided ESG portfolios at scale. As portfolios grow in size, the complexity of managing subdivided ESG assets increases. A large portfolio may require greater operational resources for monitoring and rebalancing individual assets, as well as more advanced technological infrastructure to handle the increased data flows and transaction volumes. Moreover, the growing complexity of managing multiple ESG themes – especially when incorporating strategies that depend on frequent adjustments – may lead to higher costs in terms of both time and resources.

To address scalability concerns, investors can use automated portfolio management tools, such as those powered by artificial intelligence (AI) or ML, to optimise allocations and rebalance portfolios more efficiently. Additionally, for larger portfolios, adopting a modular approach to subdivided ESG investing could be beneficial. This approach allows institutional investors to scale their investment in ESG themes gradually, starting with a smaller number of key subdivided ESG themes and progressively incorporating others as the portfolio grows.

6.4. Implications for practitioners

This study offers valuable insights for practitioners in ESG investing, particularly asset managers and institutional investors. Our findings suggest that incorporating subdivided ESG assets into portfolios can significantly enhance diversification, boost SRs, and improve resilience during periods of market volatility, such as the COVID-19 pandemic. These benefits are especially relevant for risk-averse investors and institutional funds that prioritise stability and long-term returns. By focusing on more specific ESG themes – such as greenhouse gas emissions, water management, and employee benefits – practitioners can construct more efficient portfolios that align with both financial and sustainability objectives.

The use of SV analysis further supports informed asset allocation decisions by quantifying the individual contributions of each ESG theme, allowing portfolio managers to better assess the potential impact of each asset on overall performance. However, while the findings suggest strong theoretical benefits, practitioners must consider real-world operational constraints, including transaction costs, liquidity risks, and the scalability of subdivided ESG strategies. These practical considerations may influence the effectiveness of such strategies in large-scale institutional portfolios. Thus, it is crucial for practitioners to balance the enhanced diversification benefits of subdivided ESG assets with the associated costs and potential liquidity limitations.

6.5. Implications for policymakers

For policymakers, this study highlights the benefits of granular ESG data in enhancing investment diversification. Encouraging detailed ESG disclosures can improve transparency and provide investors with better tools for informed decision-making. The findings demonstrate how subdivided ESG themes strengthen portfolio resilience, supporting policies that incentivise sustainable investments. Standardising ESG metrics would further address data consistency and comparability, fostering a more efficient and transparent ESG investment landscape.

7. Conclusion, limitations and future research

This study evaluates the performance of nine subdivided ESG indexes compared to comprehensive ESG and pillar indexes, introducing a novel investment approach that integrates subdivided ESG assets into portfolio construction. Our findings highlight the clear advantages of subdivided ESG indexes, including superior financial performance, lower correlations, and enhanced diversification, making them more effective than comprehensive or pillar ESG indexes. The two-step investment approach, which optimises SR and DR, demonstrates that incorporating subdivided ESG assets improves portfolio performance across multiple criteria. Key ESG themes – such as GHG emissions, water, and employee-related assets – play a critical role in driving returns and mitigating losses, particularly during stressed market periods.

These results underscore the growing importance of ESG thematic investing in aligning financial performance with sustainability goals. GHG and water-related assets resonate with global climate priorities, while employee-focused themes address social concerns, appealing to shifting investor preferences. The results support the integration of ESG themes into mainstream investment strategies, fostering more resilient and high-performing portfolios while advancing global sustainability objectives.

Despite the valuable insights provided, this study has several limitations that must be addressed in future research. One primary limitation is the relatively small sample size, both in terms of return data and the feature dimensions used to construct subdivided ESG indexes. The current market's limited availability of subdivided ESG indexes restricts our analysis to only nine such indexes, which limits the generalizability of the findings. As more subdivided ESG indexes become available in the future, further research could expand the sample size, enabling a more comprehensive analysis of the long-term benefits of subdivided ESG investing.

While the findings demonstrate the superior performance of subdivided ESG portfolios during the COVID-19 stressed market environment, caution must be exercised when generalising these results to normal market conditions. The observed outperformance may be context-specific, influenced by heightened market volatility and increased investor attention to sustainability during the pandemic. Future studies should analyse the performance of subdivided ESG portfolios across varying market environments to provide a more balanced perspective on their efficacy under normal, bullish, or bearish conditions.

Additionally, the computational complexity of SV analysis in large portfolios poses challenges for practical implementation. This complexity becomes particularly evident as the number of portfolio components increases, making the approach less scalable for real-world applications. Future research could explore more efficient approximation methods or alternative frameworks to enhance scalability and practicality without compromising the robustness of the analysis.

Furthermore, there are potential drawbacks to integrating multiple ESG subdivided themes into portfolios, particularly the risks of over-diversification and higher transaction costs. Over-diversification may dilute the impact of high-performing assets, leading to suboptimal portfolio returns. Managing multiple ESG sub-themes also introduces higher transaction costs, as frequent rebalancing and adjustments may be required to maintain portfolio alignment with evolving ESG factors. These operational frictions could erode the financial benefits of ESG investing if not carefully managed. Future research should explore cost-effective portfolio rebalancing strategies and assess the trade-off between enhanced diversification and its associated costs.

Finally, real-world factors such as transaction costs, liquidity constraints, and regulatory hurdles were not fully addressed in this study. These operational considerations can significantly affect the implementation and performance of subdivided ESG strategies. Incorporating these factors in future research would provide a more holistic understanding of the practical implications of subdivided ESG investing, enabling more informed decision-making.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. Cross validation window range.

Strategy 1 (passive)	Strategy 2 (active)	Strategy 3 (active)
Not applicable	[398, 252, 151, 50, 25, 13, 4, 3]	[8, 7, 6, 5, 4, 3]

Window range figures are in weekly basis.

Table A2. 10-year historical performance of individual indexes: 10 sectors.

Index	Annualised Return	Annualised Volatility	SR	Elasticity	SR Rank Top 3	Elasticity Rank Top3
Energy	−3.6616%	24.9419%	−0.1334	0.5723	Top1: Security Index(0.8099) Top2: Water Index (0.7912) Top3: MSCI-G Index (0.7825)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)
Materials	2.5652%	20.2509%	0.1403	0.6148	Top1: Security Index(0.8099) Top2: Water Index (0.7912) Top3: MSCI-G Index (0.7825)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)
Industrials	7.7044%	18.1858%	0.3917	0.5730	Top1: Security Index(0.8099) Top2: Water Index (0.7912) Top3: MSCI-G Index (0.7825)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)
Utilities	3.4065%	15.5471%	0.1791	0.2838	Top1: Security Index(0.8099) Top2: Water Index (0.7912) Top3: MSCI-G Index (0.7825)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)
Healthcare	11.3943%	14.9922%	0.6214	0.3486	Top1: Security Index(0.8099) Top2: Water Index (0.7912) Top3: MSCI-G Index (0.7825)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)
Financials	5.4876%	20.2831%	0.2805	0.5458	Top1: Security Index(0.8099) Top2: Water Index (0.7912) Top3: MSCI-G Index (0.7825)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)
Consumer Discretionary	12.1262%	17.3000%	0.6489	0.6530	Top1: Security Index(0.8099) Top2: Water Index (0.7912) Top3: MSCI-G Index (0.7825)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)
Consumer Staples	6.8033%	12.2069%	0.4047	0.2555	Top1: Security Index(0.8099) Top2: Water Index (0.7912) Top3: MSCI-G Index (0.7825)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)
Information Technology	16.4338%	18.2261%	0.8596	0.6035	Top1: Information index (0.8596) Top2: Security Index (0.8099) Top3: Water Index (0.7912)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)
Communication Services	5.5853%	14.9341%	0.2924	0.5085	Top1: Security Index(0.8099) Top2: Water Index (0.7912) Top3: MSCI-G Index (0.7825)	Top1: Energy Index (0.9153) Top2: GHG Index (0.9001) Top3: MSCI-E Index (0.8529)

Only top 3 assets are shown. All values are calculated by annualised simple return mean values. The time span is 10/06/2011–21/05/2021.

Table A3. Stressed period historical performance of individual indexes: 10 sectors.

Index	Annualised Return	Annualised Volatility	SR	SR Rank Top 3
Energy	−11.8229%	46.7276%	−0.0471	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)
Materials	21.9918%	30.5263%	0.7735	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)
Industrials	14.6230%	31.9469%	0.5572	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)
Utilities	3.7170%	30.0759%	0.2405	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)
Healthcare	12.4868%	23.4210%	0.5778	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)
Financials	10.9157%	35.4280%	0.4418	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)
Consumer Discretionary	27.0663%	30.3018%	0.9099	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)
Consumer Staples	6.8414%	19.7155%	0.3858	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)
Information Technology	30.8352%	29.0091%	1.0394	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)
Communication Services	22.4977%	24.1672%	0.9205	Top1: Energy Index (1.1782) Top2: MSCI-E Index (1.1661) Top3: GHG Index (1.1539)

Only top 3 assets are shown. All values are calculated by annualised simple return mean values. The time span is 03/01/2020–21/05/2021.

Table A4. 10-year Pearson correlation coefficient (MSCI).

Variables	MSCI ESG	MSCI E	MSCI S	MSCI G
MSCI ESG	1.000			
MSCI E	0.892***	1.000		
MSCI S	0.996***	0.900***	1.000	
MSCI G	0.972***	0.852***	0.970***	1.000

t-statistics in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5. Out-of-sample results in strategy 1.

				Strategy 1 (passive)					
Portfolios	Annual Return	Annual Std	Return/Std	Sharpe Ratio	Treynor Ratio	Jensen Alpha	Sortino Ratio	Information Ratio	MDD
Benchmark	7.8459%	6.7389%	1.1643	0.8378	0.2153	0.0047	0.8810	Not applicable	−1.2526
ESG add	7.8399%	6.7331%	1.1644	0.8376	0.2153	0.0047	0.8812	−0.8066	−1.2513
E-add	7.8473%	6.7402%	1.1643	0.8378	0.2153	0.0047	0.8809	0.8067	−1.2529
S-add	7.8282%	6.7220%	1.1646	0.8373	0.2153	0.0047	0.8817	−0.8066	−1.2489
G-add	10.4661%	7.9552%	1.3156	1.0220	0.2712	0.0216	1.0580	0.7403	−1.5856
1 sub-ESG	6.9644%	5.9008%	1.1803	0.8132	0.2600	0.0119	1.1447	−0.2918	−0.9339
2 sub-ESG	6.9684%	5.9376%	1.1736	0.8078	0.2456	0.0097	1.0546	−0.3265	−1.0457
3 sub-ESG	6.9639%	5.9341%	1.1735	0.8075	0.2456	0.0097	1.0543	−0.3281	−1.0450
4 sub-ESG	6.9715%	5.9397%	1.1737	0.8080	0.2455	0.0097	1.0542	−0.3260	−1.0468
5 sub-ESG	6.9717%	5.9408%	1.1735	0.8079	0.2457	0.0097	1.0548	−0.3249	−1.0464
6 sub-ESG	7.5472%	5.9207%	1.2747	0.9010	0.2753	0.0154	1.0494	−0.0940	−1.0539
7 sub-ESG	7.6408%	6.2865%	1.2154	0.8612	0.2436	0.0105	0.9131	−0.0673	−1.4143
8 sub-ESG	8.1205%	6.9352%	1.1709	0.8521	0.2378	0.0100	0.7859	0.0803	−1.2677

4 decimal digits are kept.

Table A6. Out-of-sample results in strategy 2.

				Strategy 2 (active)					
Portfolios	Annual Return	Annual Std	Return/Std	Sharpe Ratio	Treynor Ratio	Jensen Alpha	Sortino Ratio	Information Ratio	MDD
Benchmark	13.2883%	24.8278%	0.5352	0.4448	0.1040	−0.0956	0.3603	Not applicable	−6.1114
ESG add	13.2162%	24.8250%	0.5324	0.4420	0.1034	−0.0961	0.3623	−0.4885	−6.1224
E-add	10.8258%	10.9337%	0.9901	0.7814	0.3468	0.0362	0.7582	−0.1008	−2.0066
S-add	15.3036%	22.0852%	0.6929	0.5879	0.1397	−0.0553	0.5476	0.4088	−6.2226
G-add	0.2151%	9.9748%	0.0216	−0.1662	−0.0477	−0.0819	−0.1439	−0.6607	−3.9685
1 sub-ESG	7.2760%	7.8074%	0.9319	0.6488	0.2184	0.0051	0.6724	−0.2648	−7.2715
2 sub-ESG	10.5995%	7.9546%	1.3325	1.0309	0.3069	0.0290	0.9701	−0.1243	−2.2849
3 sub-ESG	13.4501%	7.1801%	1.8732	1.5092	0.5535	0.0705	2.3595	0.0069	−1.6275
4 sub-ESG	12.2293%	6.5594%	1.8644	1.4732	0.5184	0.0609	2.0214	−0.0451	−1.3425
5 sub-ESG	12.8924%	7.9645%	1.6187	1.3032	0.4703	0.0603	1.2190	−0.0171	−1.7968
6 sub-ESG	2.0063%	12.7851%	0.1569	0.0053	0.0015	−0.0856	0.0039	−0.6740	−7.3844
7 sub-ESG	2.4021%	12.4032%	0.1937	0.0363	0.0103	−0.0782	0.0272	−0.6334	−5.5644
8 sub-ESG	5.4464%	14.4263%	0.3775	0.2359	0.0797	−0.0482	0.2000	−0.3997	−4.6478

4 decimal digits are kept.

Table A7. Out-of-sample results in strategy 3.

				Strategy 3 (active)					
Portfolios	Annual Return	Annual Std	Return/Std	Sharpe Ratio	Treynor Ratio	Jensen Alpha	Sortino Ratio	Information Ratio	MDD
Benchmark	15.9899%	10.3891%	1.5391	1.2855	0.4723	0.0764	1.5255	Not applicable	−6.7165
ESG add	14.7388%	10.0458%	1.4672	1.2104	0.4488	0.0672	1.3790	−0.6400	−7.4860
E-add	15.7351%	11.0827%	1.4198	1.1862	0.4552	0.0729	1.3328	−0.0478	−6.5355
S-add	5.9878%	8.4815%	0.7060	0.4521	0.1748	−0.0047	0.4639	−1.4400	−15.1886
G-add	13.3093%	10.2578%	1.2975	1.0530	0.3780	0.0507	1.0499	−0.5736	−8.0465
1 sub-ESG	17.8768%	11.2620%	1.5874	1.3510	0.5341	0.0938	1.8892	0.5259	−5.4134
2 sub-ESG	23.0145%	13.5949%	1.6929	1.4912	0.8238	0.1509	3.0408	0.5892	−4.5204
3 sub-ESG	23.8551%	14.0426%	1.6988	1.5030	0.8429	0.1579	3.3710	0.6495	−3.9214
4 sub-ESG	23.3463%	13.6341%	1.7124	1.5108	0.8541	0.1552	3.2963	0.6129	−3.8966
5 sub-ESG	23.4590%	13.6097%	1.7237	1.5213	0.8603	0.1563	3.3318	0.6229	−3.8670
6 sub-ESG	23.2821%	14.1551%	1.6448	1.4534	0.8363	0.1536	3.1407	0.5819	−3.5617
7 sub-ESG	24.0651%	14.1839%	1.6966	1.5036	0.9331	0.1649	3.2388	0.6088	−3.1360
8 sub-ESG	19.2911%	12.7272%	1.5157	1.3122	0.7427	0.1205	2.7248	0.2809	−3.7870

4 decimal digits are kept.

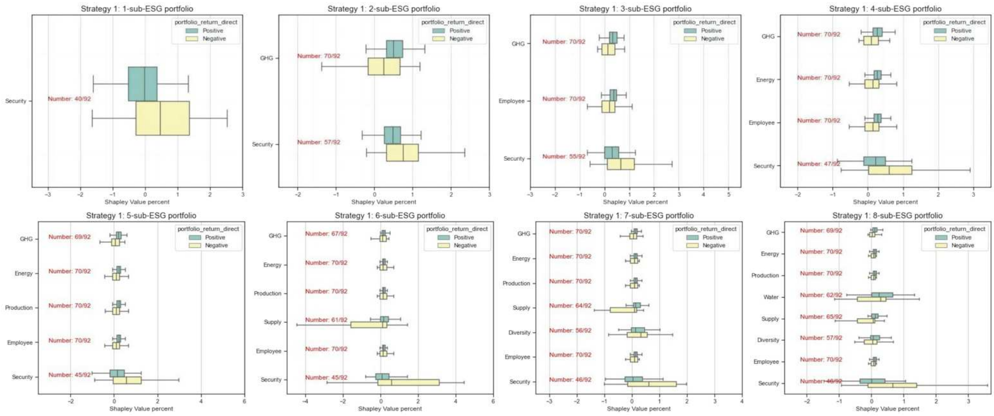

Figure A1. Shapley Value (divided by the portfolio return) of each subdivided ESG asset's contribution in the portfolio return for Strategy 1. The denominator of each red fractional value indicates the number of weeks that the subdivided ESG asset is selected by Strategy 1, and the corresponding numerator shows the number of weeks for which the optimal portfolio achieves positive excess return with respect to the benchmark. Outliers have been removed.

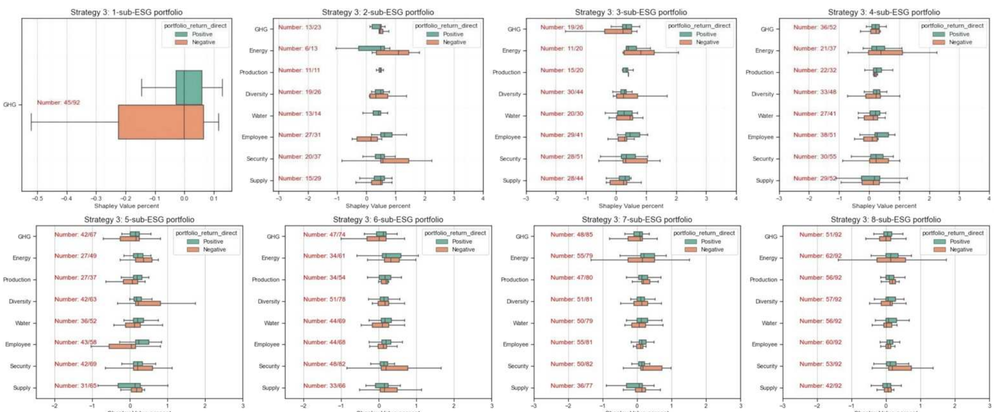

Figure A2. Shapley Value (divided by the portfolio return) of each subdivided ESG asset's contribution in the portfolio return for Strategy 3. The denominator of each red fractional value indicates the number of weeks that the subdivided ESG asset is selected by Strategy 3, and the corresponding numerator shows the number of weeks for which the optimal portfolio achieves positive excess return with respect to the benchmark. Outliers have been removed.