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Mechanisms for implementing fossil fuel divestment in portfolio management with impact on risk, return and carbon reduction

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ABSTRACT

Mechanisms to incentivize divestment strategies, such as divestment schedules, are an important component of carbon reduction strategies. We use dynamic asset allocation methodologies to assess this impact over time on index portfolios (S&P 500 and FTSE 100), and global exchange-traded funds (ETFs). Although return profiles are not affected, the risk profile of S&P 500 divestment portfolios is impacted by rapid divestment strategies as divestment concentration increases. Instantaneous divestment may benefit management structure, while slower divestment provides greater stability in portfolios' tracking errors and benefits carbon reduction, especially from reinvested capital. Divesting from energy and utilities sectors reduces carbon footprint of up to 7%, while ETFs' divesting from highly carbon concentrated ETFs offers further carbon footprint reductions. Investing in funds with low carbon footprint results in lower dividend returns and management fees. Although ETFs' returns are insensitive to divestment strategies and schedules, their risk profiles are affected, proportionally to their carbon intensity, especially for rapid divestment and at the expense of higher tracking errors. Divestment strategies based on ESG rating screening of FTSE 100 portfolios improve diversification and impact risk/return performance. Our study underscores the importance of considering investors' demographics, such as dividends, management structure, and carbon reduction targets.

1. Introduction

Fossil fuel divestment strategies are important for climate risk mitigation in asset management. Public discourse shifts (Bergman, 2018) are incentivizing ethically motivated investors to consider divesting to reduce the carbon footprint of their portfolios (Frankel et al., 2015, Richardson, 2017 and Scipioni et al., 2012) or influence the fossil fuel industry to reduce carbon emissions (Arabella-Advisors, 2015 and Dawkins, 2018). The increasing global focus on the macroeconomic domain of environmental, social, and governance (ESG) has driven change in investment practices with priority on addressing elements of climate change in addition to the classical risk/return trade-offs.

Balancing the long-term economic feasibility of ESG objectives and meeting financial objectives in the investment process is an ongoing challenge in divestment practice. Furthermore, the speed with which ESG attributes are integrated in investments has been identified as an important consideration (Eccles et al., 2014). Often the class being considered for divestment practices relates to companies that are primary producers of fossil fuel, such as oil and gas companies. These companies are so entrenched in investor portfolios that they have become too large and too widely held for divestment to be performed easily and rapidly without significant cost and impact on drawdown, capital loss, and dividend cash flow reduction. Pension and investment funds have held sizable positions of carbon-intensive companies in their portfolios (Mooney, 2017), and selling all positions in short periods can negatively impact the market and be a costly operation. Fund managers are also often required by regulation and as a fiduciary duty to investors to follow practices that govern best execution and risk management when making large divestment decisions. It is typically impractical for large portfolios to implement an instantaneous divestment strategy that involves one-time withdrawal of capital from all unfavorable assets.

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Environmental and financial performance considerations posit the need for investors to review the different rates at which portfolios are divested over time. Financial attributes such as dividends, management fees, and diversification should also be factored in. Thus, three pertinent questions arise for investors: What factors influence the decision on the optimal rate of divestment? How does the rate of divestment affect portfolio risk/returns and carbon reduction strategies? How does the rate of divestment affect different investor demographic profiles that target aspects such as, ESG target, dividend yield, management fees, effective tracking error performance, or diversification? This paper addresses these types of questions.

We conduct three comprehensive case studies, over a 10-year period (2010–2020), on dynamic portfolio active management for various divestment strategies and schedules to address divestment rates. These studies investigate divestment practice based on a broad sector portfolio invested in S&P 500 companies, a managed funds perspective based on ETFs, and an ESG rating screening perspective based on FTSE 100 companies. More specifically, we employ a multi-period portfolio optimization approach with divestment schedules to assess the impact of divestment rates over long-term horizons and for a comprehensive list of portfolio construction methodologies. Beyond the risk/return profile and the carbon reduction of the divested portfolios, the assessment is based on practical attributes such as the consistency of behavior of the portfolios' risk profile, diversification structure, and their tracking error. We also extend the analysis to examine these effects from an investors' demographic stance, including effects on dividend yields, management structure, and diversification.

The first case study focuses on S&P500 divestment strategies and refines the three main questions by firstly investigating the impact of divestment schedules on the stability of portfolio weights and on the relative performance, and the stability[1] of risk/return profiles overtime. We find an overall consistency in stability of the relative risk/return over time between the different rates of divestment strategies is observed. Even though the difference in mean returns between the original and divested portfolios is not statistically significant, the effect on risk profiles becomes increasingly evident as divestment concentration increases. Furthermore, short positions in rapid divestment are far less volatile of the leverage position than those in the slow divestment (or no divestment) option, implying that an increasing rate of divestment may benefit management fees. Therefore, investors indifferent to returns performance may favor rapid divestment to avoid leverage fees. Slow divestment also provides better tracking performance, thus may be more attractive to fund managers/investors who prioritize tracking performance.[2]

To evaluate the efficiency of carbon reduction of S&P 500 divestment strategies, we introduce two new measures based on the reinvestment principle, namely, divesting/reinvesting sector weights and the carbon divesting-reinvesting (CDR) ratio. We demonstrate that industrials, information technology, financials, health care, and discretionary sectors benefit from divestment by getting a further injection of capital from divested assets. Another novelty of this analysis is identifying the differences between divesting by withdrawing capital and divesting by shorting stock (and then reinvesting). We find that divesting from the energy and utilities sectors, the two leading sectors with substantial incentives for carbon reduction, offers the highest carbon reduction. However, short positions in energy and utilities strongly and negatively impact carbon reduction targets. In addition, we investigated the impact of divestment on diversification and correlation structure and confirmed diversification benefits in divestment strategies. These results underscore the importance of reinvestment designs and diversification benefits in the performance of divestment strategies.

The second case study considers the effects of divestment schedules on less diversified portfolios (compared to the S&P 500), the developed and emerging market ETFs with higher concentration in fossil-fuel related assets. We explore the impact of divestment on the distribution of excess returns, and the stability of overall performance of ETF portfolios overtime, their performance tracking, tracking error, as well as effects on dividend yields and management fees. We find that divestment schedules do not affect the return profiles of the underlying ETFs but significantly impact their risk profiles, especially for ETFs with high concentration in carbon-intensive assets. We also build a causal regression relationship to evaluate impact of divestment practice in relation to ESG score, carbon reduction, management fees, and dividend yield. Based on a selection of five iShares ETFs of considerable size, with dividend payouts and varying levels of concentration on fossil-fuel stocks (reaching 48%), we find that divestment strategies have a negative impact on dividends and management fees.[3] Investing in funds with a low carbon footprint (or high ESG score) results in lower dividend yields and management fees at any rate of divestment. Thus, investors may incur a penalty for requiring fund managers to meet ESG targets and dividend yield reductions potentially driven by additional charges in the production processes of less-technologically advanced industries.

In the third case study, we explore the role of divestment screening from the FTSE 100 asset universe based solely on ESG ratings criteria and its influence on portfolios risk/return profiles, correlation structure, and diversification.[4] More specifically, to evaluate the effect of divestment on diversification, we propose a novel measure, namely Portfolio Diversification Ratio (PDR), which is decomposed to three parts, the sector variance contribution ratio (SVCR), the sector-excluded variance ratio (SEVR), and the sector-excluded correlation (SEC). We find that, while reinvestment leads to an increase in variation within the sectors, divestment based on ESG rating screening has the reverse effect. For all sectors, as the intensity of divestment increases, the overall diversification and diversification between sectors improve. Thus, divesting from corporations with low environmental ratings may improve portfolios' diversification, affect risk/return performance, while provides a robust covariance structure of the divested portfolios.

The study makes three key novel contributions to advance research on asset management divestment practices. Firstly, our study is one of the very few studies that addresses the critically unexplored gap in academia and practice with respect to the impact of the rate of divestment. The importance and impact of gradual transition on divestment decisions has been verified by Flora and Tankov (2023), but only in relation to energy transition projects. The impractical assumption of most studies conducted on fossil fuel divestment is instantaneous divestment. Divestment from fossil fuels and utilities achieves higher risk/adjusted returns by including clean energy through instantaneous divestment from fossil fuel industries and reinvestment in green industries (Henriques and Sadorsky, 2018 and Hunt and Weber, 2019), but Trinks et al. (2018) finds contradictory effects based on companies classified by Standard Industry Classification (SIC) codes or Carbon Underground 200 (CU200). Bolton and Kacperczyk (2021) find that high-emitting firms earn higher returns, yet their divestment strategies

[1] Stability refers to the consistency of standardized performance measures over time. For a detailed explanation of this concept, refer to Appendix E.

[2] Tracking performance refers to the ability to keep minimal difference in return/risk measures between the benchmark or original portfolio and the divested portfolio.

[3] We assume that ETF reinvests the funds within their investment universe. We take this approach as it is unlikely in practice that an ETF will give up all its capital.

[4] This is an interesting case study because in the major UK market index portfolios there is a significantly different mix of assets by market capitalizations (compared to S&P 500.) Furthermore, the selection of the divestment set is not based on the CU200 list which is largely US focussed but instead was performed based on Environmental, Social and Governance (ESG) ratings.

are based only on scope 1 intensity emission screening and fossil-fuel-intensive industries. In addition, the effectiveness of decarbonization in the energy stock market fluctuates significantly (Kuang, 2021 and Abid et al., 2023). Divestment announcements also decrease the share price of fossil fuel companies, thus divestment can impact the financial performance of affected companies (Dordi and Weber, 2019).[5] We contribute to this research direction by performing a comprehensive analysis of divestment practice with practical relevance, as we model and study the impact of divestment schedules. Furthermore, our analysis offers a dynamic assessment based on the evolution of the impact of divestment strategies over time. Most fossil fuel divestment research excludes all high-carbon stocks throughout the study period and assumes that the fossil-free portfolio remains unchanged over time. Thus, these studies provide only an aggregate assessment of divestment strategies, while our study offers a dynamic assessment based on the evolution of the impact of divestment strategies over time. In fact, we quantify a far more substantial impact on the risk profiles of divestment strategies over time.

Second, we assess the impact of divestment schedules on risk-return profiles and on carbon reduction, both for broad sector portfolios[6] and from a more targeted managed funds perspective based on ETFs. Studies in different equity markets have documented empirical evidence on the diverse impact of divestment strategies on portfolio performance, see for instance Henriques and Sadorsky (2018), Trinks et al. (2018) and Bolton and Kacperczyk (2021). Note that, decarbonization of equity mutual funds in the US and Europe, associated with divestment from carbon-intensive stocks, leads to an average decrease of stock prices of divested firms and, to an average reduction of their carbon emissions (Humphrey and Li, 2021, Huynh et al., 2021, and Rohleder et al., 2022[7]). Furthermore, decarbonization may induce herding behaviors in hedge funds (Benz et al., 2020). We show that, even though some of these results typically hold, the coverage of these effects may vary over time and is affected by divestment schedules. Also, in line with (Rahat and Nguyen, 2022), who show that divestment based on environmental scores or carbon intensity improves performance (in the BRICS stock markets), we also confirm the benefits of divestment practice based on environmental score screening in the FTSE 100 case.

Third, we assess divestment practice through the lens of trade-offs between factors of practical relevance such as ESG targets, management fees, tracking errors, dividends, and diversification. This aspect of the analysis is of critical importance as it informs the financial implications of divestment strategies. The trade-off between carbon footprint, tracking error, and expected returns of decarbonized indexes is assessed by Andersson et al. (2016) using constrained optimization techniques. Social pressure to contribute to carbon emission targets by holding socially responsible investments is material in the mutual funds industry regardless of attracting higher management fees and lower returns (Riedl and Smeets, 2017 and Humphrey and Li, 2021). We show that ETFs with a high carbon footprint attract higher management fees. Furthermore, the comovements between European stock prices and carbon prices identified by Millischer et al. (2023) can provide an incentive for firms to decarbonize, as it benefits stock returns. We investigate the impact on both the return and risk profiles of ETFs and find that risk profiles are also affected proportionally to their intensity of carbon, especially for rapid divestment and at the expense of higher tracking errors. Also, we find that carbon divestment in ETF portfolios may be related to lower dividend yields (Chen and Guo, 2005). Regarding diversification, we show that generally divesting from FTSE 100 companies with low environmental ratings improves diversification (Trinks et al., 2018 and Naqvi et al., 2022). In conclusion, by employing a multi-period portfolio optimization approach with divestment schedules, our study extends these idealistic approaches to enable a robust, dynamic, and realistic representation and assessment of divestment strategies. It details divestment effects in equities and ETFs and integrates assessment on risk/return profiles, carbon reduction and practical aspects such as ESG targets, dividends, and management fees.[8]

The remainder of this paper is structured as follows. Section 2 explains the methodology and the experimental design. The dynamic impact of divestment schedules on S&P 500 portfolios and ETF markets is presented in Section 3 and Section 4, respectively. FTSE 100 portfolio diversification effects of divestment strategies based on ESG considerations are analyzed in Section 5. Section 6 concludes and discusses financial implications.

2. Methodology and experimental design

The novelty of this paper pertains to the manner in which we design the study of divestment practice and its influence on the performance of a given portfolio in terms of four important criteria: return dynamics, risk profile, portfolio stability in position concentrations, and risk/return performance, and importantly, carbon footprint reduction. Unlike existing studies on divestment practice, we consider four dimensions of the divestment challenge jointly: (1) what effect the divestment rate has on the risk/return characteristics of a portfolio, (2) how divestment practice influences the stability of a portfolio's performance over time, (3) what is the optimal selection of the divestment asset sets that reduces the carbon footprint of a portfolio; and importantly, (4) how to quantify the carbon reduction achieved by portfolio divestment. Each of these dimensions is also explored in the context of investor's demographics, meaning whether the investor may be non-satiated, risk-averse, seeking growth or may be retiring and seeking consistency in cash flow and dividend yields or enhanced growth potential. Lastly, we examine two classes of investor types. Investors who would invest with a broad market diversification perspective and those who target specific objectives in investing as delineated in a specialized investment vehicle, such as actively managed ETFs. Accordingly, we consider a large US market, e.g. the S&P 500, as well as international markets through ETFs selected from a variety of developed and emerging markets. We propose divestment strategies accommodating a range of divestment schedules and a multi-period assessment of the performance of the divested portfolios.

[5] See Whelan et al. (2021) for an overview on ESG and financial performance, and Engle et al. (2020) and El Ouadghiri et al. (2022) for a textual-based analysis to model investor attention on climate change risks and fossil fuel divestment. Via a Media Climate Change Concerns index, Ardia et al. (2023) find that in an unexpected increase in climate change concerns, the green (brown) firms' stock prices benefit (decrease). Although divestment is recognized as one of the strategies to actively manage climate risks, evidence suggests that institutional investors believe alternative strategies such as engagement and risk management are more effective in combating this risk (Krueger et al., 2020).

[6] For example, studying both FTSE 100 and S&P 500 as special case studies offers a richer, more diverse analysis that can influence divestment outcomes. While the S&P 500 is more technology-centric, the FTSE 100 traditionally leans towards sectors like energy and commodities.

[7] This result is in line with the equilibrium theory of Heinkel et al. (2001), and derived from a measure of portfolio decarbonization based on a *weighted average carbon intensity* index compiled by the Task Force of Climate-related Financial Disclosure and a *decarbonization selling pressure* metric on stocks that isolates the "decarbonization trades" of fund-quarters.

[8] Based on the divestment strategies and evaluation methods proposed in this paper, we have also developed an open-source software, called *Divfolio*, which can be accessed on GitHub at . This publicly available portfolio analytics software tool enables the construction of a variety of portfolios (from personal to elaborate institutional portfolios) that consider decarbonization and ESG investing, and evaluates/compares performance of divestment practices. The tool grants users access to data and facilitates the application of divestment strategies to portfolios, especially those based on assets listed in global indices. Guidelines for its use along with examples on divestment strategies construction and evaluation are detailed in the paper by Marupanthorn et al. (2023). This software can also be used to reproduce the results of the paper.

2.1. Rate of divestment

The sale of fossil fuel firm shares as a result of divestment should exert downward pressure on the share price, making it more difficult for the company to attract capital. The key to a divestment strategy is to divest the stocks of companies with significant carbon emissions and invest simultaneously in the stocks of greener companies in the portfolio. However, divestment may affect the risk profile and performance of the portfolio. This becomes challenging for funds such as pension funds and ETFs, which have specific investment objectives and/or governing regulation compliance constraints. We propose a divestment schedule as a time-dependent decaying “box constraint” on the sum of the weights of stocks in a divestment list. This divestment schedule controls the amount of divested carbon assets across time and allows a gradual divestment to occur rather than an instantaneous divestment can have market impacts and slippage. Recall that instantaneous divestment refers to one-time withdrawal of capital from all unfavorable assets.

Let the divestment schedule $D(t)$ be a decreasing function along time t, $\mathbf{w}^{div}$ be a vector of weights of the stocks to divest from, and $\mathbf{w}^{inv}$ be a vector of weights of stocks not in the divestment list. One then invests, such that $\mathbf{1}^{\mathbf{T}}\mathbf{w}^{div}+\mathbf{1}^{\mathbf{T}}\mathbf{w}^{inv} = 1$, where $\mathbf{1}$ is a column vector with entry one. Here $D(t)$ is a bound of the sum of the weights of stocks to divest, where we separate the divestment listed assets into those with long positions, of which there are L such assets to divest, and where the divestment bound over time imposes the restriction that the net position in such assets is reduced over time by $\sum_{l\in L} \mathbf{w}_l^{div} \leq D(t)$. We also limit the short position of the stocks to divest, where there are S such assets to divest, and we aim to maintain minimal interaction with such assets by imposing a restriction $\sum_{s\in S} \mathbf{w}_s^{div} \geq -D(t)$.[9] The divestment schedule is calculated and applied when the portfolio is rebalanced (which is monthly in this paper). Since the divestment schedule is time-dependent, optimal portfolio weights need to be calculated under the time-dependent constraint. An example of a valid divestment schedule can include, for instance, the monotonically decreasing functional form $D(t) = 1/t^a$, where a is a positive constant that controls the rate of divestment or a simple linear functional form with a negative slope as seen in Fig. 1.

Specifically, we consider three levels of divestment schedules, namely, slow, fast, and instantaneous divestment. The *slow divestment* approach is modeled by using a linear decay rate specified by the equation

$$D_{slow}(t) = mt + c, \tag{1}$$

where t is a time in a month, c is an initial sum of weights of the assets to divest, and $m < 0$ is the rate of the linear divestment.[10] Fig. 1 depicts the linear decay rate for $m = -c/120$. The *fast divestment* schedules are generated by the decreasing function of the form

$$D_{fast}(t) = \begin{cases} 1/t^a, & t \leq 120, \\ 0, & t > 120, \end{cases} \tag{2}$$

where a is an exponent of the decay rate. In this study, a is set to 1.5 as a representative “medium-speed” decay rate so we can observe the decreasing behavior of the divestment schedule. The instantaneous divestment method has been used extensively in research. All divesting assets are excluded instantaneously at the start of the study period. The divestment schedule for instantaneous divestment is given by

$$D_{inst}(t) = 0, \tag{3}$$

for all t. Since the divestment schedule is time-dependent, optimal portfolio weights, such as the global minimum variance portfolio, need to be calculated under the time-dependent constraint. Thus, the problem becomes a multi-period portfolio optimization. We accordingly seek an approximate solution by solving a multiple sequence of progressively constrained single-period problems through time with consecutive portfolio rebalancing. Each single-period problem consists of two steps. First, the weights of the standard portfolio are calculated. Second, the weights are scaled according to the divestment schedule, as detailed in the following section.

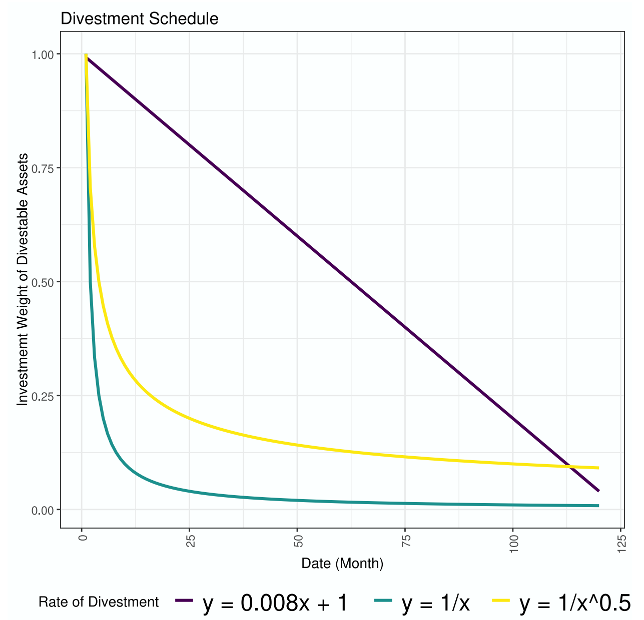


Fig. 1. Example of three rates of the divestment schedules: linear, exponential with $D(t) = 1/x^{0.5}$, and exponential with $D(t) = 1/x$.

2.2. Portfolio construction

The rate of divestment may yield different risk profiles for portfolios. To comprehensively assess the impact of the rate of divestment on the risk profile and performance of portfolios, we consider five portfolio construction methodologies. **Passive Equal-Weighted Portfolio** (PEW) is a buy-and-hold portfolio that serves a long-term investment strategy with minimal interaction with the market. The weights of all assets are set to be equal and to never change through time, that is, $w_i = 1/N$, for i in the assets universe, which contains N assets and prohibits short positions. **Active Equal-Weighted Portfolio** (AEW) is a portfolio that balances the weights to obtain relative equal weighting. In other words, it is a return-weighted portfolio that aims to obtain the same return from each asset. **Global Minimum Variance Portfolio** (GMV) portfolio seeks the diversification of the assets with the least portfolio risk as measured by variance (Markowitz, 1968, 1952). The optimal weights are allocated by an optimization problem subject to minimizing the variance of the return of the portfolio. The GMV’s optimization is given by

$$\min_{\mathbf{w}} \frac{1}{2}\mathbf{w}\mathbf{\Sigma}\mathbf{w}^{\mathbf{T}} \quad \text{s.t.} \quad \mathbf{w}\mathbf{1} = 1, \tag{4}$$

[9] Note that the short position is also bounded by the divestment schedule on account of the short-selling mechanism. Shorting a stock can temporarily drop the price by borrowing the stock from a broker. Here, we assume stocks are highly liquidity, therefore borrowing is available for short positions. However, we need to buy the stock and return it to the broker when the short position is closed. Therefore, the short-selling mechanism indirectly supports carbon companies at the times the short positions are adjusted.

[10] For instance, monthly rebalancing between January 1, 2010, to November 1, 2020, implies that $t = 1, 2, \ldots, 130$.

where Σ is the covariance matrix of the returns, $\mathbf{w}$ is the vector of the asset weights, and $\mathbf{1}$ is the column vector with one entry.[11] **Maximum Sharpe Ratio Portfolio** (MS) is a portfolio that serves as a benchmark to achieve the highest return per unit risk. The weights are allocated by the optimization problem subject to maximizing the Sharpe ratio of the portfolio (Maller et al., 2010). The MS's optimization is given by

$$\max_{\mathbf{w}} \ \mathbf{w}^T \mu - \frac{1}{2}\mathbf{w}\mathbf{\Sigma}\mathbf{w}^\mathbf{T} \quad \text{s.t.} \quad \mathbf{w1} = 1, \tag{5}$$

where μ is the expected portfolio return.[12][13] Lastly, **Principal Portfolios** (PC) is constructed by a convex combination of the sub-portfolio generated by each principal component of the covariance matrix. The convex weight coefficient is given by the eigenvalues,

$$R_{PC} = \sum_{k=1}^{d} \widetilde{\lambda}_k \sum_{i=1}^{N} v_{i,k} R_i, \tag{6}$$

where i is an index of the asset in universe with N assets, and k is an index of the principal component with d outstanding principal components such that $0 \le d \le N$, $\widetilde{\lambda}_k$ is a normalized eigenvalue of the principal component k such that $\sum_{k=1}^{d} \widetilde{\lambda}_k = 1$, and v_{ik} is the coordinate of the principal component k of asset i (Yang, 2015). The method to generate the PC's weights is detailed in Appendix B.

As short and long positions are allowed in portfolio construction, except for the PEW portfolio, an extreme weight may occur when performing asset allocations that result in an excessive concentration of positions in a few assets.[14] In the hedge fund industry, the short-selling portion of a portfolio is usually limited by the Federal Reserve Board Regulation T to be 50% of the portfolio weight, i.e., 150–50 fund investment strategy.[15] In practice, the short-selling ratio ranges from 120–20 to 150–50, with 130–30 being the most common. Consequently, we limit the sum of the short-selling weights to no more than 30% of all positions by a box constraint.[16] We approximate the box constraint in the multi-period portfolio optimization by renormalizing asset weights progressively rather than adding them to the optimization. We also approximate the optimization by rounding approximation as the process is significantly faster and more stable than solving the optimization directly, as demonstrated in Appendix C.

[11] The analytic solution for Eq. (4) is $\mathbf{w} = \mathbf{\Sigma}^{-1}\mathbf{1}/\mathbf{1}^T\Sigma^{-1}\mathbf{1}$.

[12] The analytic solution of Eq. (5) is $\mathbf{w} = \mathbf{\Sigma}^{-1}\mu/\mathbf{1}^T\Sigma^{1}\mu$.

[13] Note that GMV and MS are based on the covariance approach. The covariance matrix is calculated using the past six months of historical data. The covariance matrices are usually numerically unstable when the number of asset becomes large. To control for this, we employ the robust estimation of the covariance matrix to prevent numerical instability in calculating the portfolio weights. In practice, the covariances of asset returns of the covariance-based portfolio need to be estimated since it is usually close to being singular. To overcome this problem, the robust estimator of the covariance matrix is used. The details are given in Appendix A.

[14] The only constraint is that weights must sum to unity.

[15] See Federal Regulations: Part 220 - Credit by Brokers and Dealers (Regulation T), 220.12 Supplement: Margin requirements in https://www.ecfr.gov/current/title-12/chapter-II/subchapter-A/part-220.

[16] The computation process is to scale the sum of the short positions to 0.3, if the sum of the short ratio is greater than 0.3,

$$w^s_{box} = \begin{cases} 0.3 \times (w^s / \sum_{s\in S} w^s), & \sum_s w^s > 0.3, \\ w^s, & \sum_s w^s \le 0.3, \end{cases} \tag{7}$$

where w^s is a short-selling weight with index s in a short-selling asset universe. Next, a sum of long positions is normalized to be 1.3 when the long ratio exceeds the limit,

$$w^l_{box} = \begin{cases} 1.3 \times (w^l / \sum_{l\in L} w^l), & \sum_l w^l > 1.3, \\ w^l, & \sum_l w^l \le 1.3, \end{cases} \tag{8}$$

where w^l is a long position weight with index l in a long position asset universe.

2.2.1. Multi-period divestment and reinvestment weights

In this section, we outline a methodology that can be used to solve the multi-period divestment problem.[17] Note that, the divestment practice adds an additional constraint on the portfolio optimization problem. Thus, we propose an approximation[18] of the optimization problem for divestment and reinvestment as outlined in the following three stages:

Stage 1: Rebalancing

The portfolio is rebalanced at time t, where we calculate the weight of the portfolio by the standard formula used in the portfolio construction methodology with box constraints of the 130–30 portfolio.

Stage 2: Divestment

Consider sets L and S to be sets of indices of the long-position and short-position assets, respectively, and the superscript $\cdot^{div}$ stands for the asset to divest. If the sum of the weight of the divesting assets reaches the bound $D(t)$, $\sum_{l\in L} w^{l,div}_{box} \ge D(t)$ or/and $\sum_{s\in S} w^{s,div}_{box} \le -D(t)$, then it is limited at the bound by scaling,

$$\widetilde{w}^{l,div} = D(t) \times \frac{w^{l,div}_{box}}{\sum_{l\in L} w^{l,div}_{box}} \quad \text{or/and} \quad \widetilde{w}^{s,div} = -D(t) \times \frac{w^{s,div}_{box}}{\sum_{s\in S} w^{s,div}_{box}}. \tag{9}$$

Otherwise, we keep the weights without scaling, e.g., $\widetilde{w}^{s,div} = w^{s,div}_{box}$ or/and $\widetilde{w}^{l,div} = w^{l,div}_{box}$.

Stage 3: Reinvestment

The excess weights from the divestment are allocated to the assets to invest according to their proportion in the portfolio. Thus, they can be calculated by

$$w_{ex} = \begin{cases} \sum_{l\in L} \widetilde{w}^{l,div}_{box} - D(t), & \text{if } \sum_{l\in L} w^{l,d}_{box} \ge D(t) \\ \sum_{s\in S} w^{s,div}_{box} + D(t), & \text{if } \sum_{s\in S} w^{s,div}_{box} \le -D(t) \\ \sum_{l\in L} w^{l,div}_{box} + \sum_{s\in S} w^{s,div}_{box}, & \text{if } \sum_{l\in L} w^{l,div}_{box} \ge D(t) \text{ and } \\ & \quad \sum_{s\in S} w^{s,div}_{box} \le -D(t) \\ 0, & \text{otherwise.} \end{cases} \tag{10}$$

Thus, assets with heavier weights gain more than those with less weight,

$$\widetilde{w}^{inv} = w^{inv} + \frac{w^{inv}}{\sum_{l\in L} w^{inv}} \times w_{ex}. \tag{11}$$

It is not difficult to verify that $\widetilde{\mathbf{w}}^{l,div}\mathbf{1} + \widetilde{\mathbf{w}}^{s,div}\mathbf{1} + \widetilde{\mathbf{w}}^{inv}\mathbf{1} = 1$. Here the superscript $\cdot^{inv}$ stands for the asset to invest. Aside from scaling the proportion of all non-divesting assets, other weight allocation methods can also be applied in Step 3.

2.2.2. Measuring portfolio performance and stability

We gauge the performance of each portfolio by constructing a sequence of risk profiles that were taken progressively using the historical daily performance of each portfolio strategy measured over the last τ days, where we set $\tau = 100$. The risk profiles comprise 10 risk and performance measures, each calculated on a daily basis and consisting of features that characterize the dynamic risk profile of each portfolio.

[17] This is a multi-period divestment problem because the divestment schedule, $D(t)$, depends on time.

[18] The approximation method has three distinct advantages when used in practical applications for large portfolios over many portfolio rebalancing periods. Its performance is computationally far superior in compute time compared to optimal solvers, especially when large portfolios of 100's of assets are considered. Secondly, it is very accurate in the approximation performance when compared to exact solvers. Thirdly, it is very simple to implement in practice, making it more reliable and stable than equivalent solvers that attempt exact solutions. A detailed analysis of the performance is provided in Appendix C.

These features are calculated at the portfolio level and correspond to the following set of daily values: expected return $ER_{t,\tau}$; cumulative expected return $CER_{t,\tau}$; standard deviation of returns $SD_{t,\tau}$; Sharpe ratio $SR_{t,\tau}$; Maximum Draw-Down $MDD_{t,\tau}$; Value-at-Risk $VaR_{t,\tau}$; Omega ratio $OR_{t,\tau}$; Sortino ratio $SorR_{t,\tau}$; Beta ratio $BR_{t,\tau}$; and Treynor ratio $TR_{t,\tau}$, all of which are detailed in Appendix D. In this notation, we use the first sub-index to indicate the date of calculation in days from the initial time of study and τ the lookback window from day t used to calculate this performance or risk measure, which is calculated during the interval $[t-\tau, t]$. To assess the divestment's effect on the stability of the behavior of the given portfolios, we apply the Clustering Large Applications (CLARA) algorithm to the time series of the risk profiles (Kaufman and Rousseeuw, 1986). The technical and computational details are explained in Appendix E.

2.3. Case studies: Methods & data descriptions

We analyze three different types of asset universes in order to carry a comprehensive study of divestment practice. These included: a broad sector US market based on the S&P 500 assets, a specialized collection of global portfolios representing various thematic ETFs, and, the FTSE 100 universe of assets representing the UK equity market. This allowed us to undertake studies that have international significance and for different investor types.

We construct portfolios using the financial time series of the constituent companies of the S&P 500 index and collections of assets screened according to the selection criteria of various themed ETFs and the FTSE 100. The sample period for our empirical studies extends from January 1, 2010, to November 1, 2020. This range was intentionally selected to avoid required adjustments to account for the extremities of the 2008 Financial Crisis, the Covid-19 outbreak, and the global energy crisis.[19] The S&P 500 Composite index and the FTSE 100 are chosen as the investible universes. In the case of the S&P 500, it is the broadest index to reflect the overall US equity universe with approximately 75% of all market capitalization, with FTSE 100 representing a similar weight in the UK. Furthermore, each asset universe represents a broad spectrum of companies within sectors and industries making up the economy in the US and the UK. Missing prices are linearly interpolated. The prices are transformed into a relative return, $R_t = P_t/P_{t-1} - 1$, where R_t is a relative return at time t and P_t is a close price at time t, to achieve stationarity. Portfolios are rebalanced monthly, and when the portfolios are rebalanced, the corresponding asset weights are also recalculated based on the three-stage procedure outlined in Section 2.2.1.[20]

2.3.1. S&P 500 broad market study: selection of divestment and reinvestment sets of assets

In the first case study, we consider the assets in the S&P 500 index and assess the impact of divesting high-carbon assets under the two divestment set scenarios. The first divestment asset set excludes the high-carbon companies listed commonly in the CU200 and S&P 500 (as listed on September 30, 2021), which include 23 stocks and represent 4.904% of the portfolio's assets. Most divestment assets belong to the energy sector (20 stocks out of 23), and most assets in the energy sector in the S&P 500 are also listed in CU200 (20 stocks out of 21). The CU200, provided by FFI Solutions (https://fossilfreefunds.org/), identifies the top 100 publicly traded coal reserves and top 100 publicly traded oil and gas reserves in the world, sorted by the potential carbon emissions content of their claimed reserves. Most of the common assets between CU200 and S&P 500 belong to the energy sector, which represents direct producers and is the sector with the second-highest carbon intensity (Table 1).

The utilities sector has the highest carbon intensity. Unlike companies in the energy sector, companies in the utilities sector may not be primary producers of fossil fuels. However, many industries in the utilities sector, such as transportation, also release carbon from their secondary consumption of fossil fuels as part of their business activity. Therefore, in the second divestment asset set scenario, the list of assets considered for divestment includes all assets in the energy and utilities sectors of the S&P 500, with the proportion of the divestable asset to the total number of assets (in the S&P 500) given by 9.879% (49 stocks out of 496).[21] The daily historical close price of the stocks was retrieved from the Bloomberg database, and the amount of direct carbon emission of the companies in the S&P 500 was retrieved from the Refinitiv Datastream database.

The S&P 500 index consisted of 504 stocks in 2020, and we fix the list of the assets over the 10-year study period. For practicality, some companies with less than one year of available historical data and the subsidiaries with high correlation, such as Google (GOOGL and GOOG from Alphabet), are excluded from the analysis, leaving 496 assets remaining.[22]

2.3.2. Global markets ishares ETFs: selection of divestment and reinvestment sets of assets

The meteoric rise of ETFs is a recurrent topic in financial studies of passive versus active wealth management; see discussion in Deville (2008). Most supporters of low-cost index funds have welcomed these investment vehicles that typically have simple portfolios constructed around a common theme, sometimes called thematic investing, which includes: classical index tracking (total market, mega-cap, large-cap, mid-cap, and small-cap collections fo assets), sector index tracking (health care, industrials, etc.) all the way through to more specialized themes such as algorithmic (momentum, low volatility, covered call hybrids of equities and derivatives, leveraged) and specific themes such as (energy, green energy, solar, wind, robotics, automation, blockchain, agricultural commodities, metals, real-estate REITS, etc.). Hence, we see that typically, ETFs are established to target specific investment objectives within a selected theme, these may include passive or active management styles that seek to track for instance index volatility or obtaining a high dividend. Moreover, ETF managers need to follow more stringent regulations than those for a standard index fund.

Thus, to gauge the effect that the divestment practice may have on this important component of the wealth management industry, we assess the impact of certain divestment strategies on the risk profiles and performance of various selected ETFs from a large ETF provider known as iShares. iShares is a group of ETFs provided by BlackRock, which purchased the name and company from Barclays in 2009. To date, iShares has managed more than 900 ETFs. We select the largest ETFs that have net assets exceeding \$100 billion. We also select ETFs according to the proportion of carbon assets in their portfolio holdings to assess the impact of divestment on the risk profiles and performance

[19] To mitigate the effects of the global energy crisis, which commenced in December 2020, and the Covid-19 outbreak, we stop the sample period in November 2020. Our divestment process, specifically the full divestiture from carbon assets across all portfolios was completed prior to the onset of the pandemic, namely, in January 2020. Even though we could have controlled for the associated effects, we decided to not further complicate the analysis by considering additional controls/adjustments.

[20] Aiming at a market timing evaluation, Rahat and Nguyen (2022) consider portfolio rebalancing based on changes in sustainability factors and find that this portfolio construction benefits the market timing of green portfolios.

[21] This divestment selection makes our study comparable to the studies of Trinks et al. (2018), Yook and Hooke (2020), and Plantinga and Scholtens (2021).

[22] We assume a static asset universe, where divested capital is reinvested in existing investable assets. In practice, portfolios usually consist of top-quality assets selected for liquidity and return stability. Rebalancing typically adjusts the investment weights of these assets, maintaining the portfolio's risk/return profile. Exceptions may arise if an asset underperforms due to unforeseen events.

Table 1
Average environmental scores and amount of carbon emission of some companies in S&P 500 separated by Global Industry Classification Standard (GICS) sector ranked by direct CO_2 emissions, where n_{co2} is the number of the assets available for calculating the amount of carbon emissions, and N_{co2} is the number of whole assets in the sector.

Rank	GICS.Sector	E score	CO_2 Emissions (Ton)	CO_2 Emissions (%)	n_{co2}	N_{co2}
1	Utilities	14.90	29,884,383.57	46.06	21	28
2	Energy	15.64	16,488,511.67	25.41	15	21
3	Materials	13.08	6,951,694.12	10.71	24	28
4	Industrials	7.38	3,572,568.61	5.51	45	74
5	Communication Services	1.19	2,566,298.00	3.96	13	24
6	Consumer Staples	7.42	2,539,331.17	3.91	24	30
7	Consumer Discretionary	4.00	1,384,162.29	2.13	41	63
8	Information Technology	3.45	618,047.76	0.95	48	73
9	Real Estate	3.55	390,973.88	0.60	24	29
10	Health Care	1.49	337,598.75	0.52	39	64
11	Financials	1.56	147,601.10	0.23	38	64

Note: We cannot obtain the amount of carbon emissions from all companies in S&P 500. The coverage ratio can be calculated by n_{co2}/N_{co2}.

of the portfolios as the proportion of the divested assets increases. A description of the five selected ETFs follows.

The **iShares MSCI United Kingdom ETF (EWU)** replicates the investment performance of the FTSE Index, with 11% of the holdings on fossil-fuel stocks from the total of 89 assets and the relative carbon footprint (RCF) of 97 emissions per unit of investment (tonnes CO_2/\$1M USD invested).

The **iShares Global Clean Energy ETF (ICLN)** mirrors the investment performance of an index made up of global clean energy equities, called the S&P Global Clean Energy Index, with 19% of the holdings in fossil-fuel stocks from the total of 84 assets and the RCF of 279 emissions per unit of investment (tonnes CO_2/\$1M USD invested).

The **iShares Select Dividend ETF (DVY)** replicates the investment performance of an index of relatively high-dividend-paying U.S. stocks, called the Dow Jones U.S. Select Dividend IndexSM, with 32% of the holdings on fossil-fuel stocks from the total of 102 assets and the RCF of 434 emissions per unit of investment (tonnes CO_2/\$1M USD invested).

The **iShares U.S. Infrastructure ETF (IFRA)** replicates the investment performance of an index comprising of stocks of U.S. corporations with infrastructure exposure, called the NYSE FactSet U.S. Infrastructure Index, and that may benefit from an expansion in domestic infrastructure activity. It holds 37% in fossil-fuel stocks from the total of 152 assets with the RCF of 832 emissions per unit of investment (tonnes CO_2/\$1M USD invested).

The **iShares Global Infrastructure ETF (IGF)** replicates the performance of an infrastructure index comprising developed market shares, called the S&P Global Infrastructure Index, with 48% of the holdings on fossil-fuel stocks from the total of 77 assets and the RCF of 534 emissions per unit of investment (tonnes CO_2/\$1M USD invested).

In this second case study, the divestment set is again based on the CU200, the oil/gas industry, the coal industry, and the carbon-second consumer in the scope 1 and 2 emissions. Additional data are collected for the ETF case study, including the RCF and the number of fossil fuel assets, which were each compiled from the Fossil Free Fund.[23] The absolute greenhouse gas footprint of a portfolio is measured in tons of carbon dioxide equivalents (tCO2e). Based on the "ownership principle", this metric calculates the total annualized greenhouse gas emissions for which an equity portfolio is accountable. This is accomplished by adding up the proportionate carbon emissions of the portfolio's companies based on the ownership stake of the investor. Furthermore, the cross-section data of the equity ETFs, such as holdings, Net Expense Ratios (NERs), Net Assets Values, Market Types, TD Returns, MSCI ESG Quality Scores, and 2-month Trailing Yield (dividends), are obtained from the iShares fact sheet (https://www.ishares.com). To simplify the analysis, all of the assets universe, divestment assets, and cross-sectional data are fixed according to the date that the data are retrieved is September 30, 2021.

2.3.3. FTSE 100 broad market study: selection of divestment and reinvestment sets of assets

In the third case study, we consider the assets in the UK FTSE 100 index and assess the impact of divesting practice based on ESG rankings.

The asset universe comprises all FTSE 100 assets from which their ESG scores can be obtained (77 of 100 assets). The ESG score ranges from 0 to 100, with high scores suggesting that companies are managing ESG risks well compared to peers. Four scenarios are considered where the selection of corporations for divestment are made based on removing those with the lowest environmental, social, governance, and overall ESG scores over the investment horizon. The portfolios with divestable assets may include 10%, 20%, 30%, 40%, 50%, 60%, and 70% of corporations with the lowest environmental, social, governance and overall ESG scores. The divestment processes on divesting on AEW and GMV are long-only and optimized-based portfolios with monthly rebalancing. The linear divestment schedules with $c = 0.91$ and $m = -0.0075$, and $c = 1.3$ and $m = -0.0108$ are applied for the AEW and GMV. The simulation focuses on the environmental score, as it is considered an indirect indicator of carbon emissions.

Overall, this study achieves two additional objectives not covered by the first two case studies on the S&P 500 and the ETF case studies. It explores the role of ESG in divestment practice and studies the role of divestment concentration and loss of diversity in portfolios due to divestment asset screening based on popular ratings, such as ESG. This can negatively impact the risk/return of the portfolio, due to reduced diversification, and reduce the overall rating of the subsequent portfolios' ESG score. This highlights the importance of careful consideration by investment managers when undertaking the screening process required to select the divestible assets, as there are often non-trivial trade-offs.

3. Carbon divestment from assets in the S&P 500

We use the assets in the S&P 500 to construct five types of portfolio strategies (see the five core portfolio allocation strategies presented in Section 2.2, namely, PEW, AEW, GMV, MS, and PC) and consider two divestment asset set scenarios with various divestment schedules. We run three levels of divestment schedules, slow, fast and instantaneous divestment (see Eqs. (1), (2) and (3), respectively) from January 1, 2010 to January 1, 2020 (120 months). In each case, we utilize the three-stage method of divestment optimal portfolio strategy outlined previously on the time series of the returns of the assets in S&P 500 detailed in Section 2.2. To comprehensively examine the effects of the rate of divestment on investors' behavior, we assess the impact of the rate of divestment based on four attributes: dynamics of portfolio weight during divestment, stability of the portfolios' risk profile over time, risk/return performance, and carbon reduction of the divested

[23] See https://fossilfreefunds.org/.

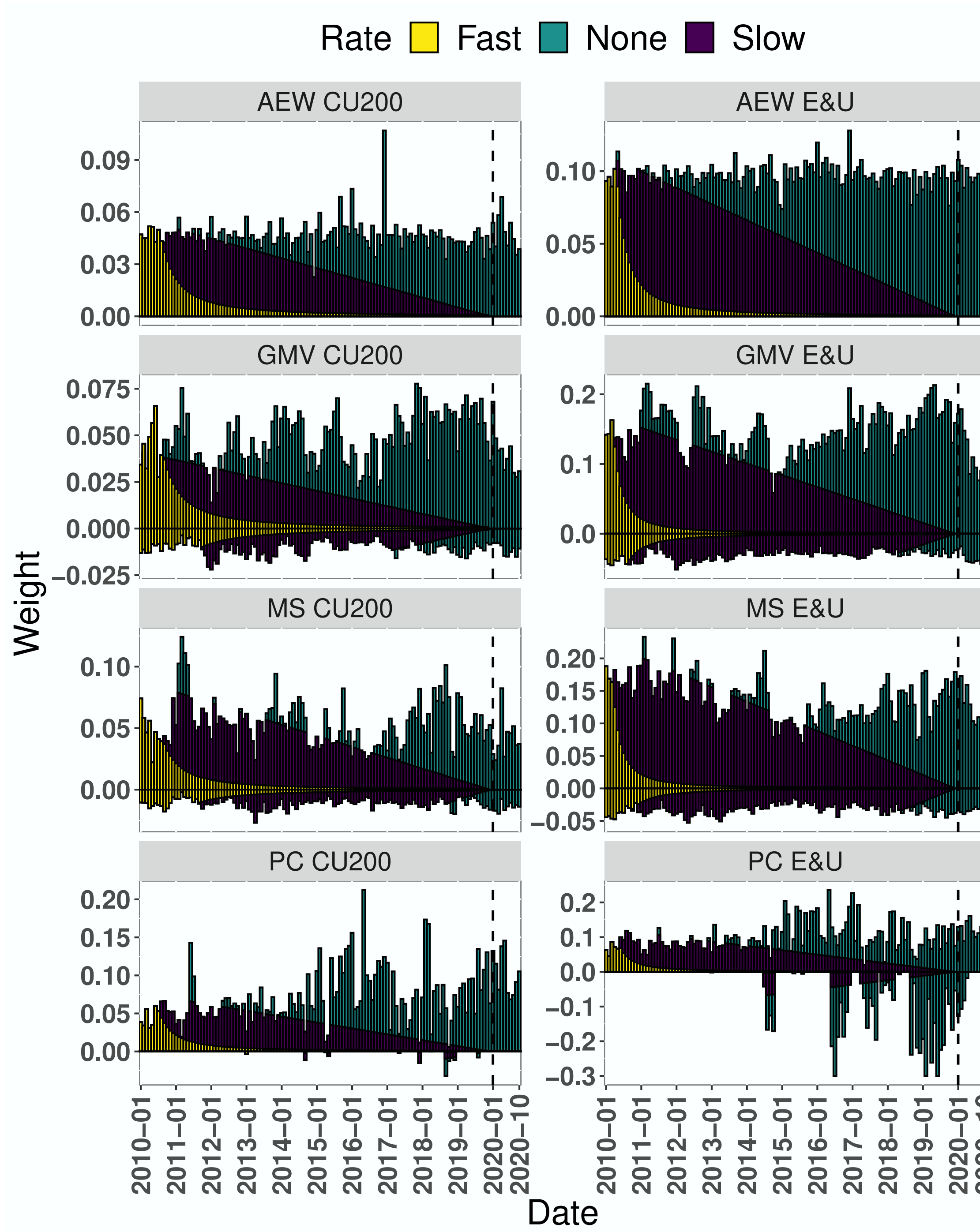


Fig. 2. Time series of the sum of the fossil fuel weights when divesting from CU200 (left panels) and the energy and utilities sectors (right panels) with benchmark (no divestment), fast and slow divestment rates for the five core portfolios: AEW, GMV, MS and PC portfolios. Note that PEW and the instantaneous divestment rate are not included in the plot since the weight does not change over time, and the weight is zero at the beginning.

portfolios. To this end, we investigate the following questions: How does the rate of divestment/divestment strategy affect the stability of portfolio weights? What is the impact of divestment on the relative performance and stability of risk/return profiles overtime? Which sectors benefit from the divestment of CU200 or the energy and utility sectors in terms of reinvestment value? How efficient does divestment strategy impact on reducing the portfolio carbon footprint? What is the impact of divestment on diversification and correlation structure?

3.1. Dynamics of portfolio weight during divestment

We begin with a discussion on the behavior of portfolio weights for long and short net positions for each portfolio strategy for various divestment set scenarios and rates of divestment. The bar plots in Fig. 2 illustrate the sum of the portfolio weights of the assets to divest in each divestment set scenario: CU200 (left) and energy and utilities sectors (right) over time with the three levels of divestment schedule rates for the five core portfolios. If the investment sum of the assets in the divestment list exceeds the bounds, $D(t)$, the excess weight will be reallocated to the other assets in the given portfolio under consideration. The dashed vertical line in each plot is the terminal time when the weight of the assets to divest hits zero.

Several observations can be made. First, the decreasing trend of the total weight of divesting assets bounded by the divestment schedules can be seen clearly in all portfolios. In the short term, a large withdrawal of capital from the divesting assets occurs in the fast divestment, while it gradually occurs in the slow divestment.[24] The fast and instantaneous divestment may result in a sudden change or shock in the risk profiles of the portfolios under consideration in a short period, whereas the slow divestment may cause less impact on the risk profiles as it is dissipated over a longer time span.

Second, the short positions under slow divestment exhibit greater volatility over time for a range of portfolio strategies, including the GMV, MS, and PC portfolios, and both the divestment set scenarios, namely, the CU200 and energy and utilities sectors.[25] The rapid divestment scenario displays far less volatility in the short positions compared to the slow divestment scenario for both GMV and MS portfolios, an outcome that is consistent in both divestment set scenarios. This is relevant to consider as such volatility in asset short positions may significantly impact the funding rate of the portfolio, which would subsequently have a carry-on effect on management structure fees. A portfolio with variability in the short positions would potentially attract higher management fees. From this analysis, if one is indifferent to all other attributes, a rapid divestment would be the preferred option.

Third, the PC portfolio strategy results demonstrate some interesting findings in divestment of energy and utilities sectors. If one compares the non-divestment PC portfolio (no divestment is considered), a significant variability over time is evident in the asset positions reaching levels of −0.289, with more often and greater magnitude change compared to other portfolio strategies that changing reach maximum levels of −0.050, see Fig. 2. If one then adds divestment into the PC portfolio strategy, with either divestment set scenario, it is observed that for all rates of divestment, the addition of divestment practice has a tendency to both reduce significantly and stabilize the volatility of short-position asset weights. Thus, for the PC portfolio strategies, divestment provides stability to the short-position dynamics of portfolio weights, and it typically proves to be easier to manage risk. We find that the PC portfolio strategy without divestment is not favorable from risk/return and portfolio stability perspectives. However, this reverses completely when divestment is incorporated; the PC portfolio with divestment is one of the best-performing portfolio strategies. This is because the PC portfolio does not produce significantly sized short positions, and so lower leverage and portfolio management would be required, which would subsequently attract lower management fees.

3.2. Stability of portfolio risk profiles over multi-period divestment horizons

We are now interested in understanding how the stability of the portfolio performance is affected over time by various divestment practices. To assess portfolio stability, we adopt widely accepted benchmark risk and performance measures of the wealth management industry. The risk measures are assessed dynamically overtime on a daily basis, and each day they produce an observed feature vector $\{ER_{t,\tau}, CER_{t,\tau}, SD_{t,\tau}, SR_{t,\tau}, MDD_{t,\tau}, VaR_{t,\tau}, OR_{t,\tau}, SorR_{t,\tau}, BR_{t,\tau}, TR_{t,\tau}\}$. When such feature vectors are calculated daily over the study period, a collection of observed portfolio risk features is produced that can be studied to assess the stability of the risk performance of each of the portfolio strategies and divestment practice combinations. This allows us to accurately determine the role that divestment practices have on portfolio stability over time. Furthermore, this analysis is performed over each portfolio strategy as it is not at all obvious whether stability in performance is more affected by the strategy type, divestment asset set, or rate of divestment.

Given the collection of portfolio feature vectors observed over time, we quantify stability using a class of statistical unsupervised learning methods known in the domain of clustering methodology as CLARA (Kaufman and Rousseeuw, 1986). We define portfolio stability as consistency in the temporal characteristics of a given portfolio strategy's risk/return profile. This is quantified in our framework by consistency in the clustering outcome in the observed risk/return feature space of the portfolio over time. Such consistency in cluster assignment quantifies a measure of homogeneity/stability in the observed risk/return performance feature set for each portfolio type over time.[26] Therefore, we analyze the changes in cluster groupings over time to provide a measure of the stability of the divested portfolios. We display the results of this stability analysis as a collection of heatmaps that demonstrate the sequential clustering results obtained over time from the time series of the labels for the divestment sets of the CU200 and energy and utilities sectors as shown in Figs. 3 and 4, respectively.

We find that for investors who hold portfolios that constitute a broad market exposure, comprised of assets from all sectors in the S&P 500, when CU200 divestment is introduced to their portfolio, most risk profiles for a given portfolio strategy, irrespective of divestment rate, remain stable and consistent throughout the divestment time horizon. The feature sets summarizing the portfolio risk/return dynamic, where multi-period divestment is performed, belong to the same cluster grouping through time. This is evident from the consistency of the label within the group of portfolio types, separated by the solid black line in the heatmap (benchmark, slow rate, fast rate, and instantaneous rate). The clustering label of the heatmap plots rarely changes across time as the returns change.[27] However, the risk profiles obtained from fast and instantaneous divestment schedules show more variation in cluster labels from the baseline than those obtained from slow divestment, especially for the PC portfolios.

This result is highly consequential as it demonstrates that divestment rate does not tend to create portfolio instability in terms of the risk/return profile of a given portfolio strategy over time when one has diversification offered by portfolios with exposure to a broad market set of investment assets, encompassing all sectors of the S&P 500. Furthermore, since the selection of a portfolio strategy type is typically affected by the attributes of a given investor demographic, this result indicates that divestment practice does not affect a particular sub-investor category or demographic. To further elaborate on this, consider the following investor sub-demographic partition given by age stratification. One may expect that younger investors will naturally select portfolio strategies based on capital growth potential with the view to building a secure net worth in the future, and they would therefore be willing to take on excess risk to achieve their financial objectives compared to those closer to retirement age or in retirement. This second investor demographic would be significantly more risk averse, and their portfolio strategy objectives and construction would reflect such risk aversion compared to those in younger demographics. We demonstrate that when this type of investor demographic decomposition is considered, there is no adverse selection or burden placed

[24] All portfolio weights are similar in the long term (after January 1, 2020, dashed line) for every divestment schedule owing to the exclusion of divesting assets from all portfolios.

[25] For example, the total weight of carbon assets in the GMV portfolio with CU200 reaches −0.023 and −0.012, for slow and fast rates before decreasing to zero at the end of the divestment period in January 2021. In contrast, portfolios employing instantaneous divestment strategies start with zero weight in carbon assets, eliminating the need for short positions.

[26] To assess such stability, we determine whether clustering between all the different combinations of portfolio strategies varies or remains consistent over time.

[27] For example, the max draw-down of the MS portfolios with fast and instantaneous divestment schedules was categorized into a different group from their benchmark and slow divestment in 2012.

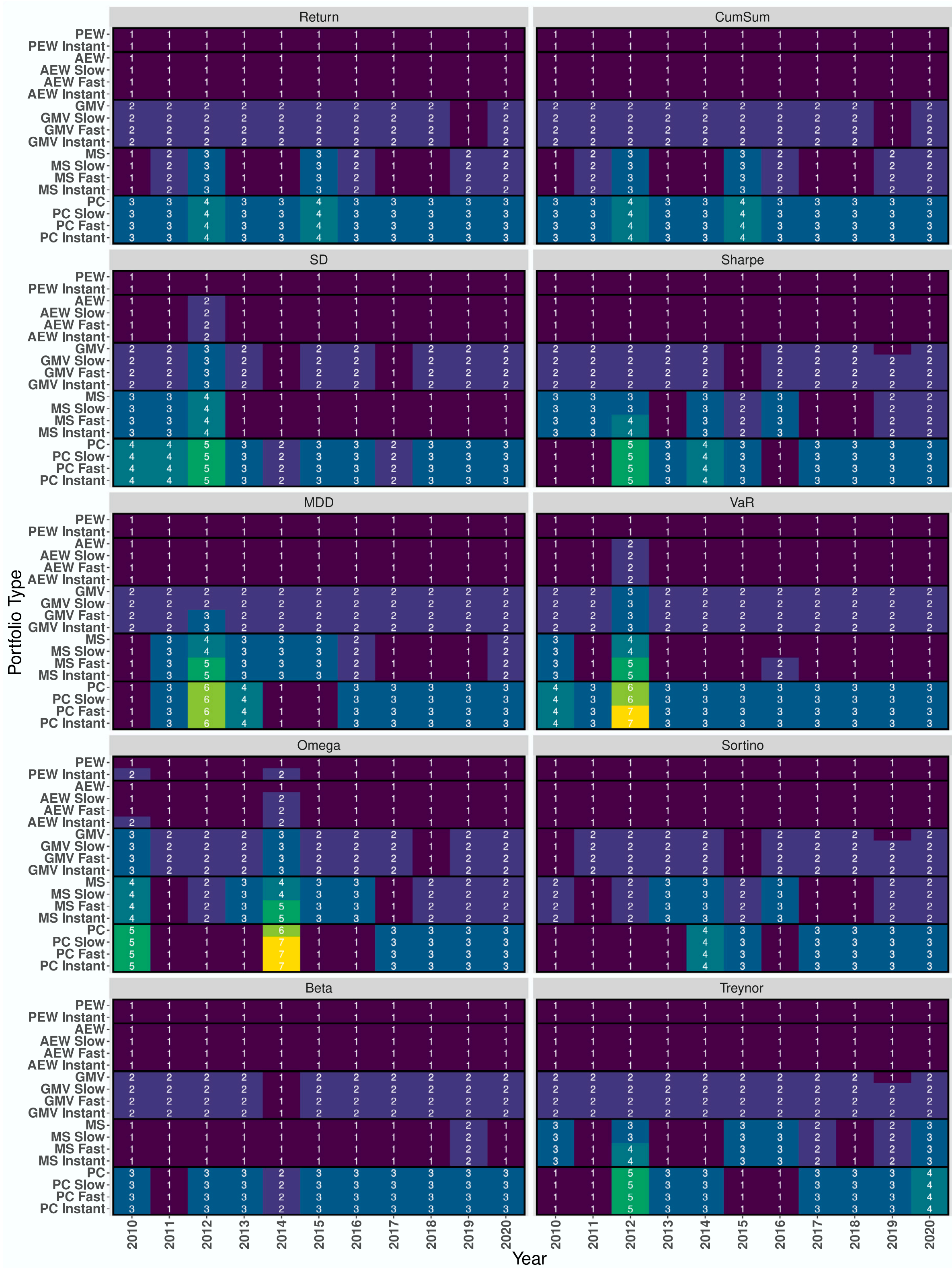


Fig. 3. Heatmap of the time series of the cluster labels for 18 portfolio types (including the five core portfolios with different divestment schedules — instantaneous, slow, and fast) separated by the risk profiles of the portfolios containing the assets in S&P 500 with CU200 divestment between 2010 and 2020. The risk measures are expected return, cumulative expected return, the standard deviation of returns, Sharpe ratio, Maximum Draw-Down (MDD), Value-at-Risk (VaR), Omega ratio, Sortino ratio (SR), Beta, and Treynor ratio.

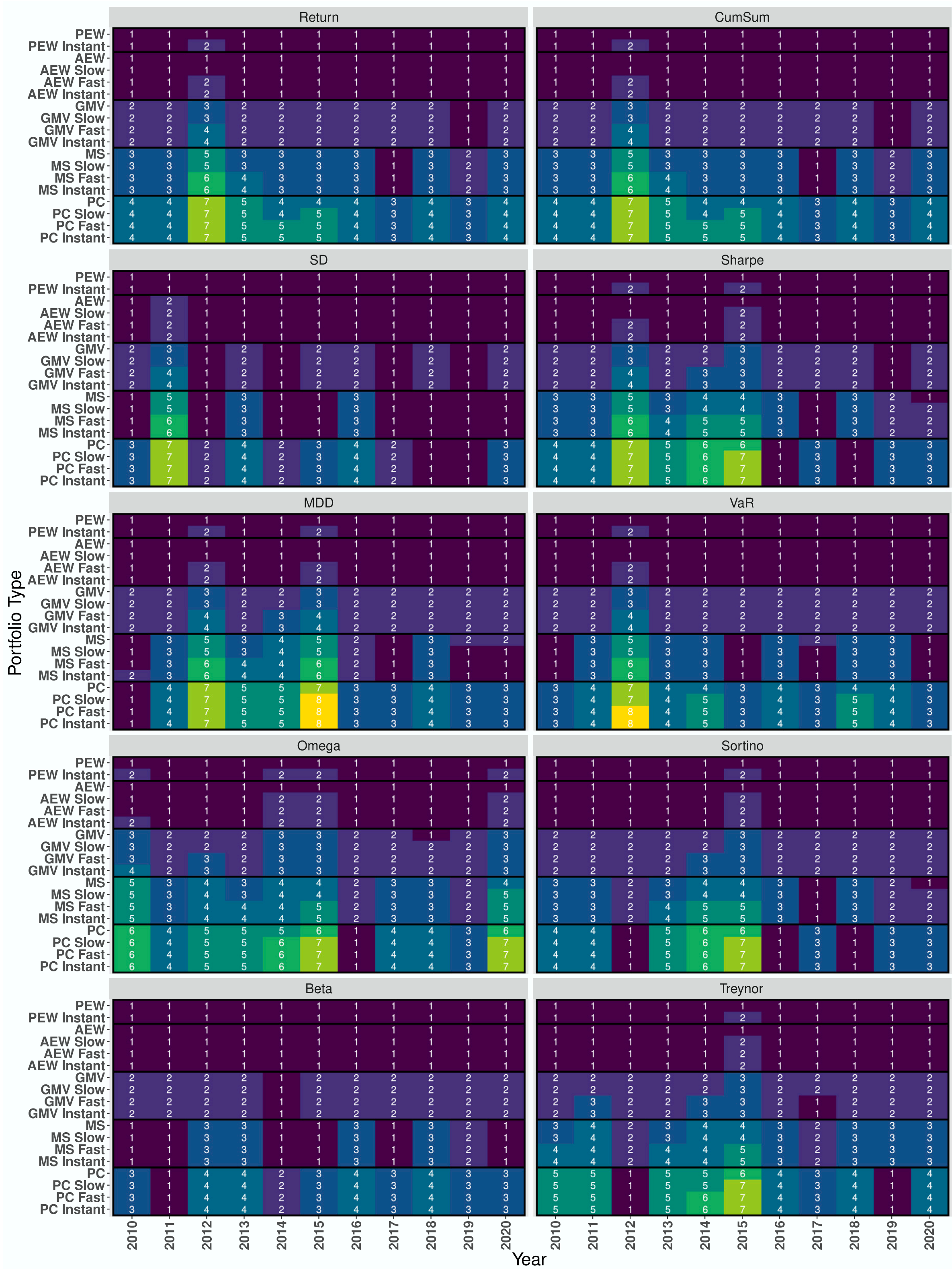


Fig. 4. Heatmap of the time series of the cluster labels for 18 portfolio types (including the five core portfolios with different divestment schedules — instantaneous, slow, and fast) separated by the risk profiles of the portfolios containing the assets in S&P 500 with the energy and utilities sectors divestment between 2010 and 2020. The risk measures are expected return, cumulative expected return, the standard deviation of returns, Sharpe ratio, Maximum Draw-Down (MDD), Value-at-Risk (VaR), Omega ratio, Sortino ratio (SR), Beta, and Treynor ratio. PEW is not included as it does not divest, and the instantaneous rate does not appear as the weight is zero at initiation.

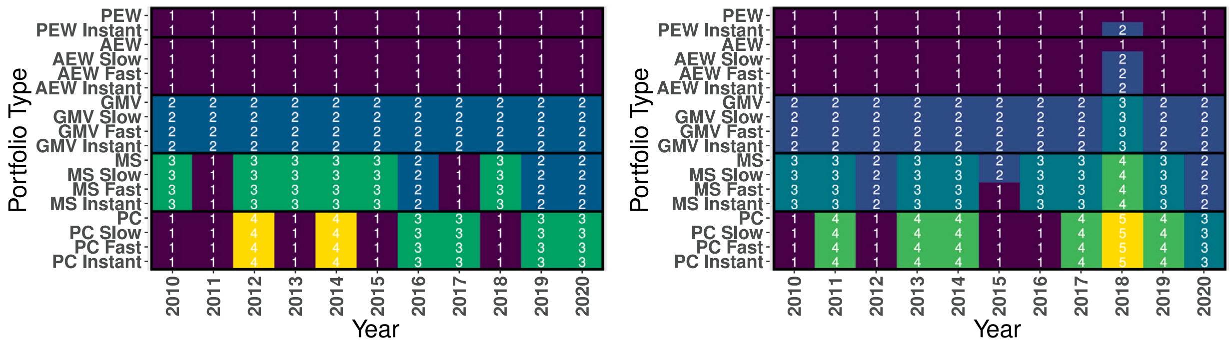


Fig. 5. Heatmap of time series of the cluster labels for 18 different portfolio types (including the five core portfolios with different divestment schedules — instantaneous, slow and fast) with overall risk profiles of the portfolios containing the assets in S&P 500 with CU200 divestment (left) and with the energy and utilities sectors divestment (right) between 2010 and 2020.

on any particular group. More precisely, there is no excess risk borne by one investor demographic compared to another when it comes to divestment practices. In each type of investment strategy that characterizes a variety of risk profiles held by different investor demographics, the effect on the stability of the investment portfolio strategy is not materially impacted over time by the divestment practice, whether it be fast or slow divestment. This should be understood purely from financial risk and return perspective since the clustered feature set focused on portfolio characteristics is based on these classical measures of performance.

As one may expect, as the size of the set of divestable assets is increased, such as when we consider divesting assets from both the energy and utilities sectors in the S&P 500 (outlined in Section 2.3.1), then a market effect of divestment on stability prevails. While most portfolio strategy risk profiles remain consistent in the cluster grouping they belong to — demonstrating the same cluster consistently over time, a measurable separation between the clusters of the benchmark and the slow, fast, and instantaneous divestment rates is apparent and more frequent compared to the CU200 divestment. Passive investors who are typically investing in non-active funds over long periods and may be seeking low fund management fees or low churn and trading costs — often in wealth management packages offered to retail investors via banks and pension funds — may begin to experience less portfolio risk/return stability compared to more actively managed investment portfolios. This difference may reasonably imply that the degree of portfolio diversification present in a given portfolio strategy prior to any form of divestment strategy application will be a core determinant of the resulting stability of the portfolio during a divestment exercise. This is consistent with what is expected from standard Markowitz modern portfolio theory.

To complete the assessment based on the stability and performance of the divested portfolios, we also consider the aggregate performance clustering generated by a combination of all risk profiles to control for biases of risk profiles over time. Accordingly, we cluster the core portfolios over time by considering all risk profiles as a collection of features that are structured into a feature matrix over time to represent each core portfolio in a particular year.[28] Fig. 5 depicts the results of this aggregate assessment that largely echo the findings just presented.

3.3. Risk/return performance of portfolio strategies over multi-period divestment horizons

This section presents a risk/return performance assessment of divested portfolios. The analysis is consistent with the portfolio stability analysis undertaken in Section 3.2. This would allow us to understand if the stability analysis is consisted across all dimensions of performance and risk analysis or is largely influenced by a few particular features. This is important for investors to further refine their perspectives on divestment approaches and the potential influence such investment practices may have on core metrics regarding the performance of their portfolios. Accordingly, we examine each component of the portfolio performance risk/return feature vector used in the stability analysis, given by $\{ER_{t,\tau}, CER_{t,\tau}, SD_{t,\tau}, SR_{t,\tau}, MDD_{t,\tau}, VaR_{t,\tau}, OR_{t,\tau}, SorR_{t,\tau}, BR_{t,\tau}, TR_{t,\tau}\}$.

To assess the impact of the divestment on the portfolio's risk profile, we also calculated the average monthly risk profile for each portfolio strategy combination of divestment set and divestment rate over the study period from 2010 to 2020. For each portfolio strategy, we consider as a reference benchmark comparison the given portfolio strategy with no divestment. Then for each of these reference portfolio sets of averaged performance results, we also present the results of the same strategy, including the divestment for each divestment asset set and divestment rate. These divestment results are presented as a relative change compared to the given portfolio reference. All results are averaged over the study time period, and the standard deviation of these results is also reported. We measure relative performance to the benchmark for each portfolio strategy based on a relative change calculated as follows:

$$RC^p = \frac{RP^p_{div} - RP^p_{non-div}}{RP^p_{non-div}}, \tag{12}$$

where RC^p is the relative change, RP^p_{div} is the risk profile of the divested portfolio, and $RP^p_{non-div}$ is the risk profile of the non-divested portfolio p. The results of this S&P 500 divestment analysis using two divestment sets, namely, CU200 and energy and utilities sectors, are shown in Table 2 and Table 3, respectively.

This decomposed analysis provides further insight into the influence of divestment on particular measures of risk/return performance. A measurable difference can be seen in certain risk measures when assessing a strategy with and without divestment. Even though this difference is not significant in the overall stability assessment of the portfolios, it is meaningful in practice to gauge where such deviations in the risk profiles of a strategy may occur due specifically to divestment. Regarding the effects on the relative changes in returns, we find that, across all portfolio strategies, the proposed divestment strategies generally produce portfolios with performance that outperform the average returns of an equivalent non-divestment strategy but these results are

[28] For example, the clustering generated by the PC core portfolio in 2012 is obtained by first calculating all the daily risk profiles over a 100-day sliding window for 2012 and then using all these as a feature matrix to cluster the portfolios. Next, all risk profiles over this period are fed into the clustering algorithm to determine the cluster grouping for a particular year.

Table 2
Average monthly risk profiles from January 1, 2010, to November 1, 2020, of the portfolios containing the assets in S&P 500 with the CU200 divestment.

Portfolio	Divestment Rate	Return (%)	Cumulative Return (%)	Standard Deviation (%)	Sharpe Ratio	Max Draw-down	VaR (%)	Omega	Sortino	Beta	Treynor (%)
PEW	None	0.060	1.248	0.919	0.124	−2.051	−1.322	1.683	0.188	0.961	0.072
		(±0.196)	(±4.094)	(±0.683)	(±0.218)	(±0.501)	(±1.157)	(±1.117)	(±0.329)	(±0.109)	(±0.214)
	Δ Instant	0.037	0.038	−0.009*	0.033	0.000	−0.012*	0.020	0.031	0.003	0.028
		(±0.192)	(±3.994)	(±0.673)	(±0.222)	(±0.512)	(±1.138)	(±1.197)	(±0.335)	(±0.109)	(±0.207)
AEW	None	0.059	1.223	0.916	0.123	−2.058	−1.319	1.670	0.186	0.962	0.069
		(±0.197)	(±4.115)	(±0.680)	(±0.218)	(±0.508)	(±1.153)	(±1.100)	(±0.328)	(±0.108)	(±0.213)
	Δ Slow	0.029	0.029	−0.006*	0.024	−0.002	−0.009*	0.014	0.023	0.003	0.019
		(±0.192)	(±3.999)	(±0.669)	(±0.220)	(±0.513)	(±1.138)	(±1.143)	(±0.332)	(±0.105)	(±0.205)
	Δ Fast	0.035	0.036	−0.009*	0.032	−0.001	−0.013*	0.018	0.028	0.003	0.027
		(±0.191)	(±3.987)	(±0.668)	(±0.222)	(±0.516)	(±1.134)	(±1.166)	(±0.333)	(±0.106)	(±0.204)
	Δ Instant	0.036	0.037	−0.010*	0.033	−0.000	−0.013*	0.018	0.029	0.003	0.029
		(±0.191)	(±3.984)	(±0.668)	(±0.222)	(±0.517)	(±1.133)	(±1.168)	(±0.333)	(±0.107)	(±0.204)
GMV	None	0.055	1.158	0.739	0.133	−2.112	−1.064	1.735	0.198	1.156	0.052
		(±0.159)	(±3.285)	(±0.573)	(±0.227)	(±0.607)	(±0.983)	(±1.319)	(±0.335)	(±0.143)	(±0.141)
	Δ Slow	0.032	0.033	−0.006*	0.022	−0.000	−0.009*	0.014	0.022	−0.004	0.047
		(±0.156)	(±3.228)	(±0.564)	(±0.229)	(±0.623)	(±0.968)	(±1.389)	(±0.339)	(±0.154)	(±0.140)
	Δ Fast	0.030	0.031	−0.006*	0.020	−0.001	−0.010*	0.013	0.019	−0.005	0.057
		(±0.156)	(±3.224)	(±0.563)	(±0.229)	(±0.622)	(±0.966)	(±1.399)	(±0.339)	(±0.158)	(±0.141)
	Δ Instant	0.033	0.033	−0.007*	0.020	−0.001	−0.012*	0.013	0.019	−0.004	0.060
		(±0.155)	(±3.215)	(±0.563)	(±0.229)	(±0.622)	(±0.965)	(±1.397)	(±0.338)	(±0.159)	(±0.140)
MS	None	0.064	1.332	0.901	0.123	−2.069	−1.290	1.651	0.184	0.949	0.074
		(±0.183)	(±3.809)	(±0.665)	(±0.212)	(±0.555)	(±1.111)	(±1.072)	(±0.316)	(±0.111)	(±0.200)
	Δ Slow	0.006	0.006	−0.001	0.009	−0.001	−0.002	0.007	0.008	−0.003	0.003
		(±0.180)	(±3.744)	(±0.660)	(±0.213)	(±0.555)	(±1.104)	(±1.107)	(±0.318)	(±0.115)	(±0.195)
	Δ Fast	0.007	0.008	−0.003	0.013	0.000	−0.005	0.013	0.016	−0.004	0.006
		(±0.180)	(±3.737)	(±0.659)	(±0.214)	(±0.558)	(±1.102)	(±1.144)	(±0.322)	(±0.117)	(±0.194)
	Δ Instant	0.004	0.005	−0.004*	0.010	0.001	−0.005	0.012	0.014	−0.003	0.004
		(±0.179)	(±3.733)	(±0.659)	(±0.214)	(±0.560)	(±1.101)	(±1.139)	(±0.322)	(±0.117)	(±0.194)
PC	None	0.072	1.498	1.178	0.114	−2.050	−1.677	1.613	0.172	0.733	0.148
		(±0.254)	(±5.315)	(±0.824)	(±0.214)	(±0.496)	(±1.360)	(±1.038)	(±0.319)	(±0.159)	(±0.471)
	Δ Slow	0.047	0.048	−0.007*	0.034	−0.004	−0.011	0.014	0.037*	0.008*	0.051
		(±0.245)	(±5.110)	(±0.813)	(±0.215)	(±0.501)	(±1.337)	(±1.058)	(±0.322)	(±0.161)	(±0.477)
	Δ Fast	0.057	0.058	−0.009*	0.045	−0.003	−0.014*	0.020	0.048*	0.006	0.064
		(±0.245)	(±5.103)	(±0.812)	(±0.217)	(±0.503)	(±1.335)	(±1.074)	(±0.325)	(±0.162)	(±0.477)
	Δ Instant	0.059	0.060	−0.009*	0.047	−0.002	−0.014*	0.021	0.049	0.006	0.067
		(±0.245)	(±5.104)	(±0.812)	(±0.218)	(±0.505)	(±1.334)	(±1.075)	(±0.325)	(±0.162)	(±0.477)

The table displays the relative change between the performance of the divested portfolio and its benchmark (no divestment) for slow, fast, and instantaneous divestment. * refers to the p-value of the t-test being significant at a confidence level of 95%. This implies that the monthly average risk profile is statistically different from the non-divestment benchmark. The highlighted cells indicate the highest (red) and the lowest (green) difference in the performance for each risk profile.

typically[29] not statistically significant in mean. This level of relative change is ordered by the rate of divestment.

Furthermore, across all portfolio strategies for the CU200 divestment set, the only portfolio risk features that are noticeably influenced by divestment are the standard deviation and VaR.[30] This difference is most pronounced when comparing the non-divestment portfolio and instantaneous divestment portfolio in each portfolio strategy type. With regard to the energy and utilities sectors divestment set, when comparing non-divestment and instantaneous divestment strategies, we find that portfolios' standard deviation, VaR, Beta, and Treynor display a statistically significant difference for each strategy type. These findings confirm the importance of the premise of the current study, that no matter the investor demographic or profile there is a relevance to considering the divestment rate as well as the divestment asset sets.

In addition, an assessment of each portfolio's tracking performance.[31] for the S&P 500 broad market portfolios relative to the index is performed. We find that the best tracking performances are obtained from the slow divestment across all portfolio strategy types, while the worst tracking performance is obtained from the fast divestment practice, comparing based on the minimum and maximum change across all risk measures, as indicated by green blocks and red blocks, respectively, in Tables 2 and 3. This result has implications for fund managers who recognize a tension between performance fees is often linked to tracking error performance and the desire of investors to divest as soon as possible to meet ESG reporting expectations. This could be particularly important in the ETF fund management context and thus is explored further next in the second case study in greater detail.

3.4. Carbon reduction efficiency

Would divestment from CU200 and the energy and utilities sectors benefit other sectors in terms of reinvestment value and reduction of the carbon footprint of portfolios? We address these questions next.

3.4.1. Assessment of sectors which benefit from divestment

S&P 500 can be cataloged into 11 sectors according to the GICS characterization.[32] We assume that the assets in the same sectors have similar emission profiles because of their activity in production or common product types. To assess the *benefit* that the attained sectors received from divestment and reinvestment, we introduce an average weight for reinvestment/divestment for each sector as an indicator.

[29] The only exceptions with statistically significant difference in the mean of returns, at 95% confidence, include: the PEW portfolio with instantaneous divestment shows a 5.9% difference in the energy sector, and the GMV portfolio with instantaneous divestment shows a 7.2% difference in the utilities sector.

[30] There is some statistical significance indicating a change in performance between the non-divestment and divestment portfolios.

[31] The tracking performance can be evaluated by Eq. (12).

[32] See Table 1 for the full list of the GICS sectors.

Table 3
Average monthly risk profiles from January 1, 2010, to November 1, 2020, of the portfolios containing the assets in S&P 500 with the energy and utilities sectors divestment.

Portfolio	Divestment Rate	Return (%)	Cumulative Return (%)	Standard Deviation (%)	Sharpe Ratio	Max Draw-down	VaR (%)	Omega	Sortino	Beta	Treynor (%)
PEW	None	0.060 (±0.196)	1.248 (±4.094)	0.919 (±0.683)	0.124 (±0.218)	−2.051 (±0.501)	−1.322 (±1.157)	1.683 (±1.117)	0.188 (±0.329)	0.961 (±0.109)	0.072 (±0.214)
	Δ Instant	0.059* (±0.199)	0.058* (±4.138)	0.017* (±0.676)	0.030 (±0.224)	0.000 (±0.513)	0.016* (±1.152)	0.029 (±1.271)	0.033 (±0.340)	−0.028* (±0.110)	0.091* (±0.220)
AEW	None	0.059 (±0.197)	1.223 (±4.115)	0.916 (±0.680)	0.123 (±0.218)	−2.058 (±0.508)	−1.319 (±1.153)	1.670 (±1.100)	0.186 (±0.328)	0.962 (±0.108)	0.069 (±0.213)
	Δ Slow	0.037 (±0.195)	0.037 (±4.066)	0.008* (±0.670)	0.019 (±0.220)	−0.000 (±0.511)	0.006 (±1.145)	0.015 (±1.162)	0.020 (±0.333)	−0.013* (±0.108)	0.049 (±0.211)
	Δ Fast	0.055 (±0.197)	0.055 (±4.105)	0.016* (±0.671)	0.029 (±0.223)	0.000 (±0.515)	0.014* (±1.145)	0.026 (±1.230)	0.028 (±0.337)	−0.025* (±0.110)	0.085* (±0.215)
	Δ Instant	0.061 (±0.198)	0.060 (±4.116)	0.017* (±0.671)	0.031 (±0.223)	−0.000 (±0.516)	0.016* (±1.146)	0.028 (±1.235)	0.030 (±0.338)	−0.027 (±0.109)	0.093* (±0.216)
GMV	None	0.055 (±0.159)	1.158 (±3.285)	0.739 (±0.573)	0.133 (±0.227)	−2.112 (±0.607)	−1.064 (±0.983)	1.735 (±1.319)	0.198 (±0.335)	1.156 (±0.143)	0.052 (±0.141)
	Δ Slow	0.038 (±0.160)	0.037 (±3.322)	0.015* (±0.562)	0.017 (±0.229)	0.001 (±0.583)	0.022* (±0.985)	0.010 (±1.345)	0.018 (±0.339)	−0.018* (±0.144)	0.062* (±0.144)
	Δ Fast	0.064 (±0.163)	0.061 (±3.372)	0.025* (±0.563)	0.035 (±0.234)	0.001 (±0.588)	0.031* (±0.989)	0.035 (±1.508)	0.040 (±0.349)	−0.032* (±0.151)	0.129* (±0.150)
	Δ Instant	0.072* (±0.163)	0.069 (±3.371)	0.026* (±0.563)	0.037 (±0.233)	0.000 (±0.586)	0.031* (±0.989)	0.034 (±1.500)	0.042 (±0.348)	−0.033* (±0.152)	0.140* (±0.150)
MS	None	0.064 (±0.183)	1.332 (±3.809)	0.901 (±0.665)	0.123 (±0.212)	−2.069 (±0.555)	−1.290 (±1.111)	1.651 (±1.072)	0.184 (±0.316)	0.949 (±0.111)	0.074 (±0.200)
	Δ Slow	0.011 (±0.183)	0.011 (±3.802)	0.012* (±0.659)	−0.004 (±0.212)	−0.003 (±0.525)	0.016* (±1.104)	−0.002 (±1.067)	−0.003 (±0.317)	−0.016* (±0.111)	0.028 (±0.200)
	Δ Fast	0.034 (±0.186)	0.034 (±3.878)	0.027* (±0.662)	0.010 (±0.216)	0.001 (±0.531)	0.028* (±1.107)	0.014 (±1.135)	0.014 (±0.325)	−0.034* (±0.112)	0.072* (±0.207)
	Δ Instant	0.035 (±0.187)	0.035 (±3.885)	0.028 (±0.663)	0.009 (±0.216)	0.002 (±0.533)	0.029* (±1.108)	0.014 (±1.138)	0.014 (±0.325)	−0.034 (±0.112)	0.075* (±0.207)
PC	None	0.071 (±0.253)	1.479 (±5.293)	1.171 (±0.827)	0.114 (±0.214)	−2.050 (±0.496)	−1.668 (±1.363)	1.614 (±1.040)	0.172 (±0.319)	0.747 (±0.202)	0.146 (±0.471)
	Δ Slow	0.050 (±0.234)	0.052 (±4.875)	−0.032* (±0.807)	0.053* (±0.217)	−0.005 (±0.499)	−0.036* (±1.319)	0.029 (±1.110)	0.060* (±0.328)	0.034* (±0.188)	−0.002 (±0.459)
	Δ Fast	0.067 (±0.235)	0.069 (±4.899)	−0.032* (±0.807)	0.062 (±0.219)	−0.003 (±0.506)	−0.037* (±1.320)	0.036 (±1.136)	0.069 (±0.331)	0.029* (±0.186)	0.019 (±0.460)
	Δ Instant	0.072 (±0.236)	0.074 (±4.913)	−0.030* (±0.808)	0.064 (±0.219)	−0.003 (±0.507)	−0.035* (±1.322)	0.039 (±1.146)	0.071 (±0.331)	0.027* (±0.185)	0.024 (±0.461)

The table displays the relative change between the performance of the divested portfolio and its benchmark (no divestment) for slow, fast, and instantaneous divestment. * refers to the p-value of the t-test being significant at a confidence level of 95%. This implies that the average risk profile is statistically different from the non-divestment benchmark. The highlighted cells indicate the highest (red) and the lowest (green) difference in the performance for each risk profile.

Here *benefit* refers to the reinvest weights from the divestment capital reallocation into other sectors. Let k be a sector index from the set K of the 11 GICS sectors; h be a position index for $h \in \{\text{Long, Short}\}$; p be a non-benchmark portfolio index from the set P of 13 portfolios;[33] t be a time in a day for $t \in \{1, 2, \ldots, t_{end}\}$; $|T|$ be the number of days during the study period; i is an asset's index for I_k, where I_k is a set of assets i in the sector k; and j is an index of all assets in the universe of S&P 500 where $j \in \{1, \ldots, 469\}$. The average reinvestment/divestment weights are calculated by the difference between the benchmark and divested portfolio, defined by

$$\bar{\Delta}_j = \frac{1}{|T|} \sum_{t \in T} \left(w^p_{j,t} - \tilde{w}^p_{j,t} \right) \quad \text{for } j \in \{1, \ldots, 469\}, \tag{13}$$

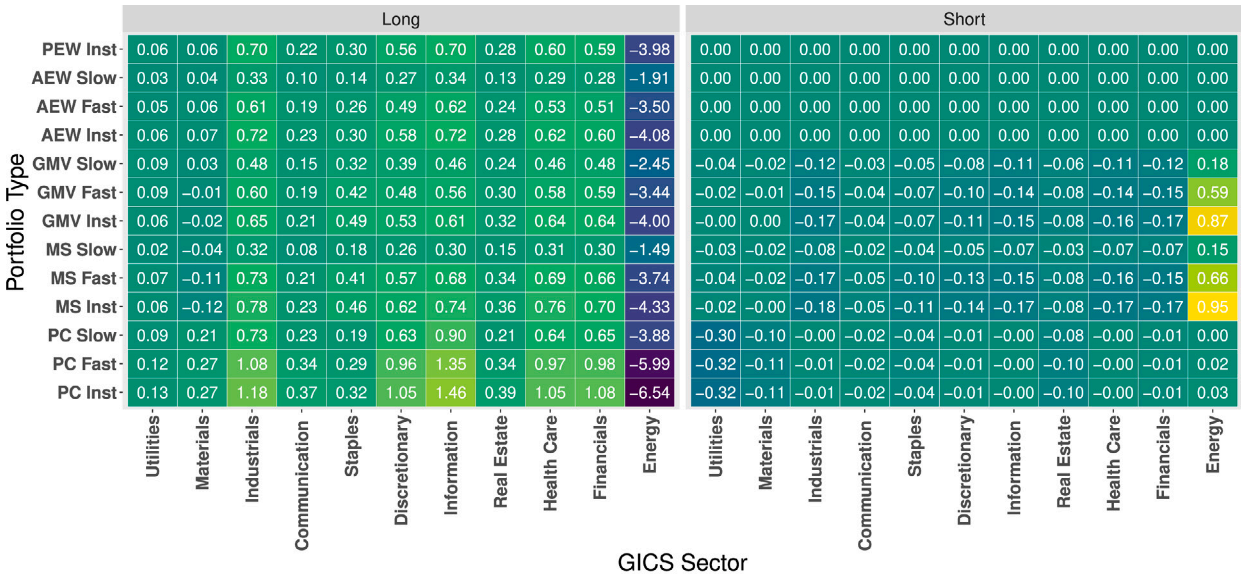
where $\tilde{w}^p_{j,t}$ is a portfolio weight of the j-asset in the divested portfolio of type p, and $w^p_{j,t}$ is the portfolio weight of the benchmark portfolio p, with no divestment at time t. $\bar{\Delta}_j$ indicates a change of portfolio weight after the divestment of the asset j. Next, we separate the $\bar{\Delta}_j$ according to the sector, holding position, and portfolio types, $\bar{\Delta}^{h,p}_i$. The average reinvestment/divestment weight of each sector is defined by

$$\bar{w}^{h,p}_k = \sum_{i \in I_k} \bar{\Delta}^{h,p}_i \quad \text{for } h \in H,\ p \in P \text{ and } k \in K. \tag{14}$$

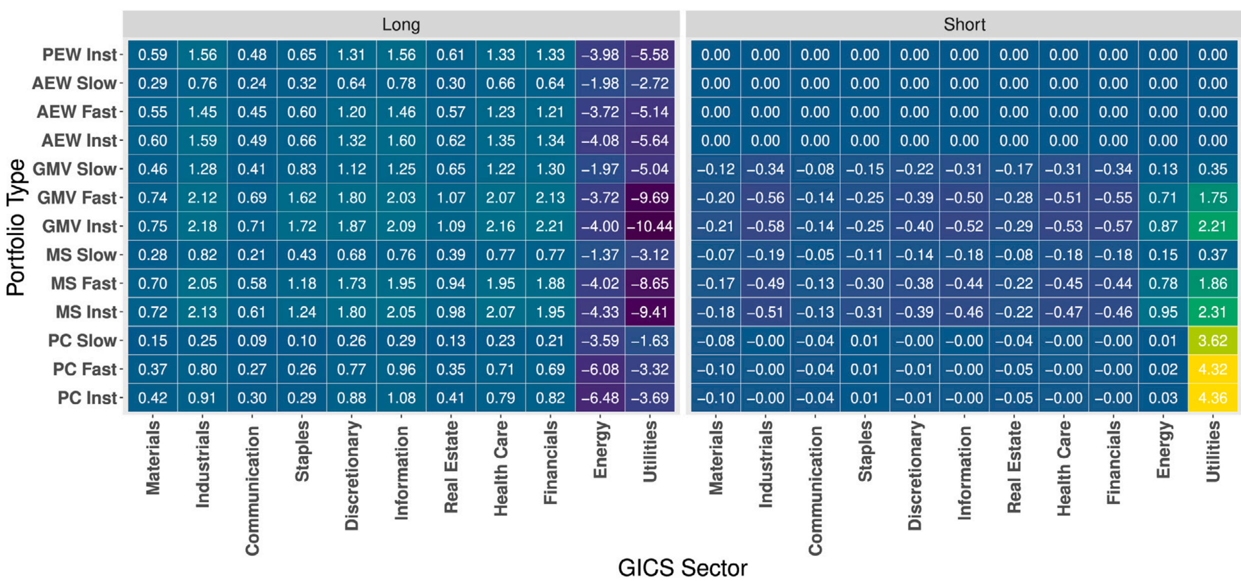
For the divested sector, $\bar{w}^{h,p}_k$ is an average divestment weight with a sign that is opposite to the holding position. Otherwise, it represents an average reinvestment weight with a similar sign to the holding position. We separate the average reinvestment/divestment weight by the holding position to prevent the cancellation of the signs because we divest the carbon assets separately for short and long positions. Accordingly, the reinvestment/divestment weight of each sector, $\bar{w}^{h,p}_k$, is used to observe the average weight allocations to each sector from divestment and reinvestment.

The numbers in the heatmaps in Figs. 6(a) and 6(b) represent the average reinvestment/divestment weights of each sector (%) of core portfolio types calculated by Eq. (14) for CU200 divestment and the energy and utilities sectors divestment, respectively. Most assets listed in CU200 belong to the energy sector, thus we use the energy sector as a reference. The opposite sign to the holding position refers to the weight from the divested sector. The numbers in the divested sector show the excess weight from the divestment schedule, and in the non-divested sector, the numbers show the allowed reinvesting weight. For example, in the first row (PEW Inst) of the long position heatmap, we divest the energy sector with the weight of 3.98%, then reinvested this with the following weights: 0.06% in utilities, 0.06% in materials, 0.71% in industrials, 0.22% in communication, 0.30% in staples, 0.59% in discretionary, 0.71% in information, 0.28% in real estates, 0.60% in

[33] The 13 portfolios include PEW Inst, AEW Slow, AEW Fast, AEW Inst, GMV Slow, GVM Fast, GMV Inst, MS Slow, MS Fast, MS Inst, PC Slow, PC Fast, and PC Inst.



6.a: CU200 divestment



6.b: Energy and utilities sectors divestment

Fig. 6. The average reinvestment/divestment weights of each sector (%) of core portfolios types of the CU200 divestment (top panel) and the energy and utilities sectors divestment (bottom panel).

health care, and 0.60% in financials.[34] The sectors that benefit from the divestment energy sector can be identified by the brightness of the gradient color on the heatmap.

We find that (for most core portfolio types), Industrials, Information Technology, Consumer Discretionary, Financials, and Health Care are consistently the main sectors that benefit by divesting from the energy and utilities sectors. This result is robust for both divestment strategies considered in this study, with more pronounced effects when divesting from the energy and utilities sectors, compared to divesting from CU200. The rank is strongly correlated to the number of assets in the sector, as shown in Table 1. We separate short and long positions to prevent the sign cancellation in portfolio calculation, given that short selling can be considered an indirect support to carbon-intensive companies. Another finding from the divested weights of the energy sector is that a faster rate of divestment can eliminate more carbon asset weights in the portfolios over time (see the last column of both heatmaps in Fig. 6(a) and the second last column in Fig. 6(b)).

3.4.2. Assessment of carbon footprint efficiency

Beyond the top carbon-emitting sectors of energy and utilities, other sectors from the S&P 500 index also directly emit carbon in the process of producing their products or running their businesses. Table 1 presents the direct carbon emissions of each sector. In the proposed divestment strategy, capital is diverted from divestment set assets to other assets in the portfolio, based on the weight allocations of the given portfolio strategies for each non-divestment asset. Accordingly, we aim to assess how efficient or effective this strategy may be in reducing the portfolio carbon footprint for each possible portfolio strategy studied. For instance, is there any relationship between risk

[34] Note that the sum of all divestment and reinvestment weights is not equal to zero because of the average over time in Eq. (13), but it should approximate to zero.

Table 4
The carbon divesting-reinvesting ratio in Eq. (15) for the energy sector (E), and the energy and utilities sectors (E&U) divestment of each portfolio. The dash in the short positions refers to the absence of the short position.

	PEW	AEW			GMV			MS			PC		
	Inst	Slow	Fast	Inst	Slow	Fast	Inst	Slow	Fast	Inst	Slow	Fast	Inst
(Long) E	0.117	0.119	0.119	0.119	0.229	0.262	0.274	0.195	0.234	0.259	0.152	0.146	0.142
(Short) E	–	–	–	–	0.917	0.339	0.260	0.800	0.407	0.309	–	33.333	25.000
(Long) E&U	0.070	0.070	0.070	0.070	0.089	0.098	0.100	0.093	0.101	0.103	0.144	0.119	0.115
(Short) E&U	–	–	–	–	0.300	0.125	0.109	0.185	0.113	0.102	0.014	0.013	0.013

aversion, as demonstrated through the selection of a particular portfolio strategy, and the resulting portfolio carbon footprint after divestment is performed?

Let K_{div} denote the set of sectors selected to be divested from and K_{inv} to be the complement of this set, corresponding to the set of sectors selected for investment. To evaluate the effectiveness of the divestment strategy, we propose the CDR,[35] which is defined as the ratio between an estimated amount of the carbon generated from reinvested capital in sectors contained in set K_{inv} obtained from the capital diverted from divested assets in sectors K_{div} calculated by

$$CDR^{h,p} = \left| \frac{\sum_{k \in K_{inv}} C_k \bar{w}_k^{h,p}}{\sum_{k \in K_{div}} C_k \bar{w}_k^{h,p}} \right|, \text{ for } h \in H \text{ and } p \in P, \tag{15}$$

where C_k is the amount of carbon emitted by sector k from Table 1.[36] The numerator of the CDR represents the portfolio-weighted average amount of carbon reinvested in the non-divested sectors over time, while the denominator is the average amount of carbon in the divestment sectors if their capital is not re-allocated to other sectors over time. Therefore, CDR represents the proportion of carbon generated by the divestment strategy and the carbon generated by the sectors in a portfolio without carbon management. A successful divestment strategy would yield a CDR of less than one with an ideal of zero CDR for the most efficient optimal divestment strategy.

Table 4 displays the CDRs obtained by Eq. (15) for the two different divestment sets given by the energy sector (CU200) and the energy and utilities sectors separated by the holding position for all divested portfolios. Most CDRs are smaller than one, which indicates that the amount of carbon generated by divested portfolios is smaller than that of the portfolio strategy reference without divestment. The results of this analysis also clearly demonstrate that for the portfolio strategies GMV, MS, and PC, the slow divestment rate produces the lowest value of CDR over time. This interestingly indicates that slow divestment seems to be optimal, not only based on the risk/return profile of a portfolio but also with regard to the benefit of the carbon reduction effect arising from reinvested capital being re-deployed to other industries or sectors not contained in the divestment list of assets. This finding is consistent across both sets of divestment assets.

The best carbon reduction for long positions is reported for the instantaneous divestment in the PEW portfolio (generated only 11.7% and 7.0% for the energy sector and energy and utilities sectors divestment, respectively), compared to its reference non-divestment equivalent portfolio. Conversely, the worst reinvestment results are associated with the short positions of the PC portfolios, with a substantial increase in carbon intensity. The high values of CDRs for the short-selling positions of PC portfolios with fast and instantaneous divesting suggest that the short-selling positions of those portfolios tend to reinvest more into carbon-intensive assets compared to their reference non-divestment portfolio. Indeed, the PC portfolios with fast and instantaneous divesting reduce carbon intensity in long positions but require more investment in short positions. However, covering short-selling positions can be considered as an indirect support to high-carbon companies as it involves the purchase of the borrowed stock in order to return it to the lender.[37]

Regarding carbon footprint reduction benefits, divesting from the energy and utilities sectors is more efficient than divesting only from the energy sector. The best-performing portfolios for both divestment strategies are the basic portfolios: PEW and AEW, while the more dynamically constructed PC portfolios (with energy sector divestment) involving short positions tend to increase carbon intensity. Thus, to fully appreciate carbon emission reduction benefits from divestment, it is important to be mindful of the variability of the outcomes based on the divestment assets set and reinvestment strategies.[38]

3.5. Impact of divestment practices on portfolio diversification and correlation

The role of correlation between assets in a portfolio is critical to understanding the degree of diversification present in a given portfolio. Therefore, it is meaningful to assess the change in portfolio correlations and diversification over time as divestment is applied for each of the portfolio strategies considered. To understand conceptually why this is relevant to divestment practice assessment, consider the following perspective. In the energy sector, the carbon-intensive products supplied by primary carbon producers, such as fossil fuel, oil, and gas companies, subsequently become a direct input to the production of products from companies in another sector, which may be considered as secondary producers of carbon and not necessarily have direct inclusion in a resulting divestment set. Let us consider for example energy companies producing oil or gas and their customers such as aviation or transportation companies. In this example, divesting from primary carbon producers, such as oil and gas companies, but not from transportation consumer companies, that directly utilize the products of such divested companies, may adversely influence the risk measure performance of a portfolio. For instance, draw-down may increase in a portfolio that re-allocates capital significantly to any non-divestment assets that have a significant positive correlation with the assets in the divestment set. Thus, in a framework involving divestment and reinvestment as proposed in this study, we identify the sectors that one should consider to reinvest diverted capital in order to ensure that the portfolio is not overly correlated to or exposed to adverse price movements in divested assets. These instances may arise as a consequence of increased divestment practices over time.

The results of this analysis are presented in correlation matrix heatmaps shown in Fig. 7. These plots depict the linear correlation between the returns of the assets in S&P 500 ordered by sector in January 2010 (left) and November 2020 (right). A strong positive correlation between and within sectors is evident in many sectors, including the energy sector, with the effects marginally stronger in

[35] Recall that CDR stands for carbon divesting-reinvesting ratio.

[36] In this study, we use parameter C_k that remains constant over time and acknowledge that it is an approximation.

[37] Note that the capital invested in carbon-intensive assets in the short position did not reach the divestment schedule of the slow rate, preventing the calculation of the CDR in this context.

[38] More dynamic assessment tools, in line with the ones employed in our study, can reveal very different outcomes.

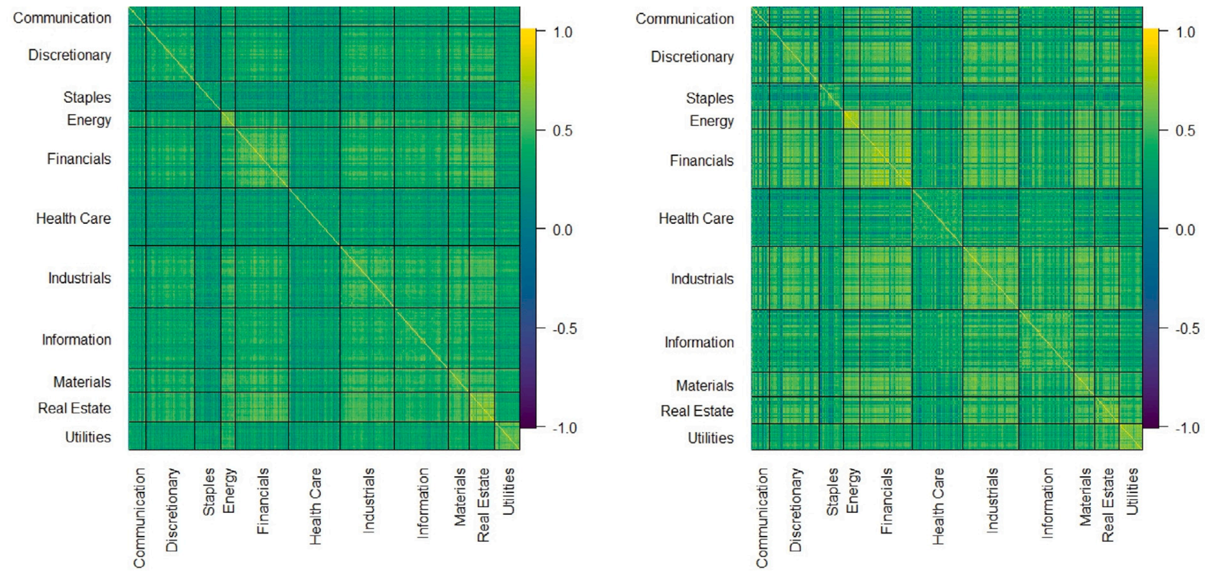


Fig. 7. The correlations matrix of the returns ordering assets by GICS sector during January 2010 (left) and November 2020 (right). The solid lines separate the block of the GICS sectors.

2020 than in 2010. The brightness of the block-diagonal structure represents a high correlation within the sector. The health care and consumer staple sectors are reasonably independent of others, and as demonstrated in Table 1, typically have less carbon emission compared to other sectors. Thus, an effective divestment/reinvestment strategy in terms of diversification is to divest from the high-carbon sectors, such as energy and utilities, and reinvest in low-carbon emission sectors such as health care and consumer staple, which are least correlated with the divestment assets in the energy and utilities sectors.

4. Carbon divestment on leading global ETF portfolios

ETFs offer flexibility as they are aligned with different attributes; some with dividend cash flow, some with growth, and some with particular sectors such as energy and technology. However, ETFs tend to be less diversified in terms of global market exposure compared to the broad market portfolios such as the S&P 500. Therefore, we evaluate the extent of the influence of divestment practice on the stability and performance of such ETF funds and in what aspects this influence occurs. Specifically, we investigate the following questions: What is the impact of divestment on dividend yields and management fees? Which portfolio strategy of the clone portfolios closely mimics the portfolio strategy of the ETFs? What is the impact of divestment on the performance tracking, tracking error, the distribution of excess returns, and the stability of overall performance of ETF portfolios overtime?

We gauge the effects of divestment strategies on these specialized portfolios and their impact on the investor by studying the role of divestment and its effect on portfolio weights, risk profile, and relative performance of divested portfolios. In addition, we explore in the ETF context the influence divestment has on investor cash flows from such investment through the dividend returns as well as the influence that may arise from changes in the management fees. These can be influenced by changes in available investible assets and changes in tracking performance that may arise from divestment at different rates. These are important considerations as ETFs typically attract significant management fees to investors, which depending on the ETF structure, may be aligned with performance, growth, high-yield dividend returns, reference benchmark tracking, or out-performance.

To offer a comprehensive assessment, we select a collection of five global iShares ETFs. These are chosen as they have a sufficiently large capital allocation to funds under management and are representative of a global market study, including developed and developing economies. These ETFs are also selected to include dividend payouts, and they have varying levels of concentration in fossil-fuel stocks included in their investment portfolios, reaching up to 48%. The selected ETFs include the MSCI United Kingdom ETF (EWU), Global Clean Energy ETF (ICLN), Select Dividend ETF (DVY), U.S. Infrastructure ETF (IFRA), and Global Infrastructure ETF (IGF).[39] Most of the selected ETFs aim to track the index return, except the iShares Select Dividend ETF (DVY), which is made to track the dividend rather than the return.

4.1. Impact of fossil-fuel divestment on the dividend yields and management fees of an ETF

While fund managers are mindful of integrating ESG criteria when constructing investment strategies for ETFs, investors becoming increasingly concerned about the impact of management fees on their funds. Two natural questions then arise. First, would investors incur a penalty for requiring fund managers to meet their ESG expectations? Second, would an additional premium be required by fund managers to incentivize them to divest aiming to meet ESG expectations? In this section, we seek empirical support to determine whether: (a) ESG/Carbon Footprint performance can influence management fees, as measured by the Net Expense Ratio (NER),[40] and (b) ESG/Carbon Footprint can influence the yield an investor would receive if they had held their investment in the fund over the last 12 months, which is captured by the 12-month trailing yield (TY).

To investigate the impact of the divestment on the NER and the dividend return (via TY) of ETFs, we control for the following key variables: Relative Carbon Footprint (RCF), Net Assets (NA), Binary Market type indicator for developed versus developing markets (MAR), Yield-to-date Return (YTDR) and MSCI ESG Quality Score (ESG).[41]

We begin this analysis by exploring the relationships between the covariates and regression responses. Fig. 8 shows the linear correlation between each pair of variables. It is evident that RCF holds a

[39] See Section 2.3.2 for a detailed description of these funds.

[40] NER (%) is the fee charged to investors, including Management Fee, Acquired Fund Fees and Expenses, and Foreign Taxes and Other Expenses. NER is one of the factors that investors consider when selecting an ETF. It represents the administrative and overhead costs that are generally covered by investors. Such costs represent a small percentage of investment and depend upon the type of ETF and underlying investment strategy. The growth in the

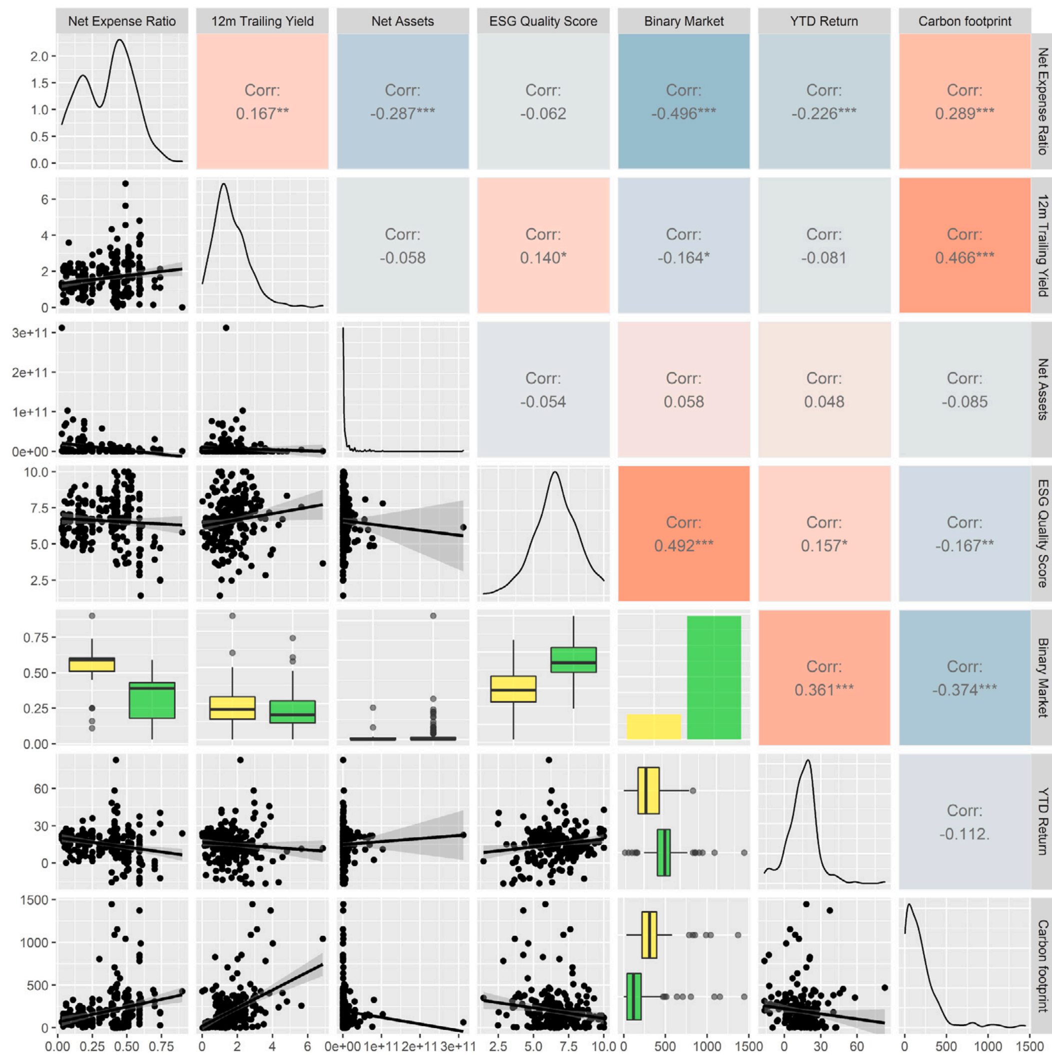


Fig. 8. Linear correlation between pairs of the factors on the upper triangular block, their plots with the regression and boxplot (for the type of market) on the lower triangular block, and the distribution plot of each factor on the diagonal block. The types of the binary market are Developed (yellow) and Emerging (green). Note *,**,*** means statistical significant from the t-test for the slope at $\alpha = 0.05, 0.01$ and 0.005, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

statistically significant correlation with all variables, except the NA and YTDR. The sign of the correlation between the RCF and all other factors is negative, with the exception of the TY. The TY holds the strongest positive correlation with the RCF, indicating that carbon divestment aligns with a reduction of the ETF dividend. It is historically the case that the high-carbon intensive companies often have paid high dividends, including companies in the energy sector such as fossil-fuel production companies like Exxon Mobil Corp. Note that these companies not only drill and refine such fossil fuel products, but they also often operate vast networks of pipelines that allow them to act as suppliers. They are able to transport energy, which in turn generates a consistent cash flow from their customers who consume on a regular basis the fossil fuels produced and piped on demand. Given that energy demand is relatively predictable and recession-resistant, they can often afford to keep paying high dividends and even raise them over time to incentivize investments. Hence, if ETFs hold large concentrated sub-portfolios in such fossil-fuel-based companies, then divestment should lead to a reduction in the RCF, which in turn is likely to lead to a reduction in the dividends paid to investors. This outcome could be consequential for some demographics of investors who may seek these ETF investments in order to obtain a consistent cash flow. Thus, divestment may materially influence their investment outcomes and cause them to shift their capital from such funds in search of greater dividend yield.

Fig. 8 also displays pairs of boxplots. These boxplots represent comparisons of each pair of variables based on the binary market indicator, thereby allowing for a distinction between developed and emerging markets. The results show that the ETFs in emerging markets tend to hold more carbon stocks than those in developed markets. ETFs in the developed market tend to have taken more decisive actions to date owing to the increasing focus and expectations of investors on carbon reduction and ESG policies. The NER in the emerging market is also more expensive than that in the developed market. This may arise since a fund manager who incorporates emerging market assets

ETF industry has generally driven the expense ratios down, making them more affordable.

[41] RCF describes the greenhouse gas footprint of a monetary investment. It is calculated using metric tonnes of CO_2 or CO_2 equivalents per \$1 million USD invested. The carbon footprint of a fund takes into consideration both direct and indirect emissions (fossilfreefunds.org). NA is the net assets of the fund in USD. MAR is categorical variables representing the characteristics of the market: (1) Developed and (0) Emerging markets. YTDR (%) is the annual profit or loss realized by an investment. MSCI ESG Quality Score (ESG) (0–10) is the weighted average of the ESG scores of fund holdings.

Table 5
Parameter estimates.

Panel A: Net expense ratio			
	Estimate	Std Error	p Value
(Intercept)	0.000	0.053	1
12 m Trailing Yield	−0.019	0.062	0.759
Net Assets	−0.234	0.053	1.787e−05***
ESG Quality Score	0.216	0.063	0.001***
Binary Market	−0.534	0.069	2.421e−13***
YTD Return	−0.045	0.057	0.425
Carbon Footprint	0.110	0.064	0.089·
Panel B: 12-month trailing yield			
	Estimate	Std Error	p Value
(Intercept)	0.000	0.056	1
Net Expense Ratio	−0.021	0.070	0.759
Net Assets	0.000	0.059	0.997
ESG Quality Score	0.286	0.066	2.414e−05***
Binary Market	−0.129	0.081	0.114
YTD Return	−0.032	0.060	0.598
Carbon Footprint	0.469	0.0610	4.351e−13***

Panel A reports the parameter estimates of regression (16) for the Net Expense Ratio. Residual standard error: 0.149 on 229 degrees of freedom; Multiple R-squared: 0.3609, Adjusted R-squared: 0.3414; F-statistic: 18.48 on 7 and 229 DF, p-value: 2.2e−16. Panel B reports the parameter estimates of regression (17) for the 12-month Trailing Yield. Residual standard error: 0.84 on 229 degrees of freedom; Multiple R-squared: 0.3144, Adjusted R-squared: 0.2935; F-statistic: 15 on 7 and 229 DF, p-value: 4.302e−16. The *,**,*** denote the 10%, 5% and 1% level of significance, respectively.

may take on additional risks, such as those related to geo-political differences, compared to the risk profiles of investments in developed economics. Furthermore, reporting, regulation, and taxation regimes are significantly more complex to manage when working between a developed market and an emerging market. Subsequent additional due diligence analysis of investments would be more onerous as a result of less standardization in the adoption of reporting and transparency requirements found in developed nation economies. Hence, it would be expected that they would charge a greater management fee to compensate for the additional difficulties in management, differences in regulation standards, and less liquidity in markets that could produce market frictions.

With regard to the strong connection between the RCF and the NER, we conjecture that this is most likely an indirect effect arising from the fact that many high-carbon producing companies are in the emerging market, which charges an expensive management fee. The NER has a strong negative correlation with the NA and YTD due to expense ratio calculation, that is, expense ratio as the ratio of total cost to total asset.

To further refine the arguments above, we identify the factors that causally affect the NER and the TY of ETFs, by undertaking the following two regressions[42]:

$$\mathrm{NER} = \beta_0^{NER} + \beta_1^{NER}\mathrm{RCF} + \beta_2^{NER}\mathrm{NA} + \beta_3^{NER}\mathrm{ESG} + \beta_4^{NER}\mathrm{YTDR} + \beta_5^{NER}\mathrm{TY} + \beta_6^{NER}\mathbb{I}_{\mathrm{MAR}} + \varepsilon^{NER}, \quad (16)$$

$$\mathrm{TY} = \beta_0^{TY} + \beta_1^{TY}\mathrm{RCF} + \beta_2^{TY}\mathrm{NA} + \beta_3^{TY}\mathrm{ESG} + \beta_4^{TY}\mathrm{YTDR} + \beta_5^{TY}\mathrm{NER} + \beta_6^{TY}\mathbb{I}_{\mathrm{MAR}} + \varepsilon^{TY}, \quad (17)$$

where ε^{NER} and ε^{TY} denote the i.i.d. Gaussian errors from regressions (16) and (17), respectively. The estimated coefficients are shown in Table 5.[43]

The (standardized) coefficients in Panel A of Table 5 reveal that market type, NA, ESG quality score, and carbon footprint are influential factors that causally affect the management fees (measured by the NER). As expected, the management fees are significantly impacted by the type of market (developed versus emerging markets), while the carbon emission variables, namely, ESG score and carbon footprint, also positively impact the management fees. Therefore, we conclude that investors may incur a penalty for requiring fund managers to meet their ESG expectations, despite the fact that this may have a negative impact on the capital of fund managers (NA). Since NA under management is significantly and negatively related to NER, fund managers must be willing to reduce their NER to attract significant amounts of capital. This is consistent with findings in a mutual funds study demonstrating that social pressure to deliver carbon emission targets is reflected in higher management fees (Riedl and Smeets, 2017). Panel B of Table 5 displays the influential factors affecting the dividend returns (measured by TY). We find that carbon intensity indicators, namely, carbon footprint and ESG score, are positively and significantly associated with TY. Consequently, we postulate that fund managers may require an additional premium to be paid by investors when the climate risk exposure within ETF portfolios increases. Thus, carbon divestment in ETF portfolios may be related to lower dividend yields.

For a more comprehensive and targeted assessment, we also examine the impact of carbon divestment on management fees and dividend yields, with a sub-analysis based on an ETF that is tracking dividend yield, namely, the Select Dividend ETF (DVY). The methodology used for this sub-analysis and the associated results are presented in Appendix F. These results further confirm that investors investing in funds with low carbon footprints can expect lower dividend yields and management fees. Furthermore, if a fund divests and reduces its portfolio carbon footprint, this has a tendency to reduce the dividend yield to investors. Nonetheless, it may be possible to offset this effect with a subsequent future reduction in management fees, thereby allowing funds to still retain and attract new capital.

4.2. Analysis of performance tracking of portfolio strategies synthesizing actual ETFs

Since we seek to study a variety of ETFs and their performance under divestment at the individual portfolio level, we are required to synthesize or clone these portfolio strategies. This is necessary because while we can identify the holdings of each of the ETFs at the present time, we are unable to have access to each of these ETFs' specific portfolio strategy. Hence, we must first determine if the proposed synthetic clone portfolios adequately replicates or approximates the portfolio dynamics of the ETFs under study without any divestment practice incorporated. If we find that our portfolio strategies adequately mirror the risk/return profiles of the ETFs, then we may develop a suite of scenarios based on our cloned portfolio strategies to study these individual ETFs under various divestment settings.[44]

Hence, we assess the results obtained from a specialized portfolio study that utilizes the same portfolio strategies used in the S&P 500 case study ($\{PEW, AEW, GMV, MS, PC\}$). However, we set up a collection of investment scenarios that produces more concentrated portfolios than the broad market S&P 500 portfolio, where this collection of 5 investment scenarios mirrors the holdings of each of the ETFs used in this study. Our replication scenario studies use the assets in the given ETFs to construct each portfolio strategy and assume that no new assets are added during the study period.[45]

[42] The direct effect of the factors on these two response variables is investigated via the regression coefficients (the magnitude and sign) of such regression relationships.

[43] We consider the regression models on the standardized variables so the estimated coefficients are on comparable scales.

[44] Note that this analysis is based on historical price data from January 1, 2010, to November 1, 2020.

[45] One can think of these scenario studies as a method to simulate effective clones or replicate portfolios with the same assets as the original ETFs. Then we are able to use these clone portfolios to explicitly test the effect of divestment on these less diversified ETF-type portfolios under a variety of risk aversion levels as captured by the different portfolio strategies.

Table 6
Average percentage of the excess return between the ETF's real returns and core portfolio types.

	PEW	AEW	GMV	MS	PC
DVY	−0.0061%	−0.0039%	−0.0048%	−0.0039%	−0.0215%
	(±0.2621)	(±0.2781)	(±0.3438)	(±0.3476)	(±0.6252)
EWU	−0.0393%	−0.0504%	−0.0373%	−0.0491%	−0.0249%
	(±0.7075)	(±0.7297)	(±0.8533)	(±0.8379)	(±0.9858)
ICLN	−0.0464%	−0.0528%	−0.0225%	−0.0458%	−0.0724%
	(±1.0195)	(±1.1173)	(±1.3379)	(±1.2233)	(±2.0227)
IFRA	−0.0170%	−0.0115%	−0.0286%	−0.0233%	−0.0580%
	(±0.4703)	(±0.5723)	(±0.5636)	(±0.5726)	(±0.8604)
IGF	−0.0198%	−0.0216%	−0.0190%	−0.0303%	−0.0615%
	(±0.6018)	(±0.6409)	(±0.8235)	(±0.7003)	(±1.0612)

The number in the parenthesis is the tracking error (standard deviation of the excess return), and the highlighted cells are the nearest portfolios to the selected ETFs according to both excess return and tracking error.

To assess the effectiveness of such a methodology, we seek to evaluate the closeness of the five portfolio strategy types to the performance of the given ETFs. Finding the closest clone portfolio strategy is then achieved by considering the excess return and the tracking error. The excess return is calculated by subtracting the return of the clone from the ETF. The tracking error is approximated by the standard deviation of the excess returns. The negative average excess return indicates the clone's returns are superior to the original ETFs. The nearest clone portfolio gives the average excess return closest to zero and the lowest tracking error. Therefore, we combine these two criteria when undertaking the selection of the closest clone portfolio strategy by finding the minimum weighted combination of the average excess return (AER) and the tracking error (TE), $0.5|\text{AER}|+0.5\text{TE}$. We exclude the PEW from this analysis since it can be divested only at the instantaneous rate.

Table 6 presents the average excess returns (in percentage terms) of all clone portfolio strategies that seek to mirror the ETFs, with the tracking errors in the brackets. The closest clone portfolios to the selected ETFs are shown in the highlighted cells. It is not surprising that all closest clones are AEW portfolio type as the ETFs hold long positions only.[46]

4.3. ETFs divestment: Performance and stability analysis

The results in Section 4.2 confirm that the clone portfolios replicate adequately the performance of the ETFs based on the proposed portfolio strategies. Therefore, we can proceed with the performance and stability analysis of the selected ETFs' divestment. We reconstruct clone portfolios from the portfolio strategy types using the assets in the ETFs from iShares: EWU, ICLN, DVY, IFRA, and IGF. We apply the divestment methodology with three rates of divestment, namely, instantaneous, fast and slow divestment, similar to the S&P 500 study (see Eqs. (1), (2), and (3), respectively).[47] Tables 7 to 11 present the impact of divestment strategies on the risk/return profile of the EWU, ICLN, DVY, IFRA, and IGF ETFs, respectively. We also add an extra column of the dividend yield in Table 9 to verify the results regarding the impact of divestment on the dividend yield discussed in Section 4.1.

The following results emerge. First, for all ETFs (except ICLN with MS portfolios), we find no statistically significant impact of divestment strategies on the returns, irrespective of the portfolio type and divestment schedules. Indeed, the returns might increase or decrease depending on the type of portfolio and the number of carbon assets to divest. However, the behavior of the return rarely changes in a statistically significant manner when compared to the non-divestment performance. This finding indicates that even in these less diversified portfolios, the implementation of various divestment strategies do not materially impact the return performance. Second, although the risk profile of the ETF with the lowest concentration in carbon-intensive assets (EWU 11%) is not sensitive to divestment strategies, the risk profile of the other ETFs is impacted to some extent depending on the types of portfolios under consideration, and the rate of divestment. For example, the standard deviation, VaR, and Beta for GMV and MS portfolios for the ICLN ETF (with 19% on divested assets) exhibit significant differences. Similarly, the standard deviation and VaR for GMV and MS portfolios demonstrate significant increases in Beta in all portfolios of the DVY ETF (with 32% on divested assets). For the IFRA ETF (with 37% on divested assets), all divestment schedules yielded statistically different values of the standard deviation, VaR, and Beta for all portfolios except for PC portfolios, where this is present in only fast and instantaneous divestment schedules (and the Treynor coefficient for GMV and MS portfolios only). The ETF with the highest concentration in our study, IGF, (48% on divested assets) displays a significant difference in the risk profile (standard deviation and VaR) of GMV and MS portfolios, whereas divestment has a significant impact on the Beta for all portfolios.

Fig. 9 depicts the boxplots of the excess returns and reveals that the divestment rate has a clear impact on the distribution of the excess return.[48] For any divestment schedule, there is no significant difference in the excess return for each portfolio strategy when considering a broad market diversified portfolio, as in the S&P 500 index portfolio. However, as the rate of divestment increases the impact on tracking error on the ETFs is substantial, with DVY, ICLN, IFRA, and IGF experiencing the strongest effect. There is also a clear trend between the tracking error and the proportion of the assets to divest. The more carbon assets are divested, the stronger the impact on the portfolios' tracking error. Consequently, fund managers who seek to control tracking errors are advised to divest slowly over time to balance the trade-off of meeting investor and regulatory ESG reporting requirements. While maintaining the feasibility of tracking performance, this often directly influences the remuneration and management fees of the fund managers, thus incentivizing the maintenance and feasibility of such ETF active fund management.

To enhance the assessment of the divestment effects on the stability of the ETFs' risk measure, we again apply the same clustering methodology as outlined previously on the risk/return measures of each ETF clone portfolio over time. Fig. 10 depicts the overall clustering performance of the portfolio strategies replicating each of the ETFs and suggests that the risk profiles of ETFs change from the baseline model more when the proportion of the assets to divest increases. The EWU and ICLN ETFs show a more stable pattern than the other ETFs considered in this study. Thus, divestment may change the structure or stability of the risk profile if the proportion of the assets to divest is large enough.

Overall, there is no significant difference in the return profile for most of the ETFs, but the risk profiles of the ETFs are impacted, with the most significant effect shown in the ETFs with the largest proportion of divestable assets: IGF (48%), IFRA (37%) DVY (32%), and ICLN (19%). The risk profiles of the ETFs, depending on the portfolio type, are impacted to some extent by divestment strategies, with the effects mainly on the standard deviations, VaR, and Beta for GMV and MS portfolio types, with differences also within the divestment schedules. With the uncertainty of future information, the divestment schedule is a useful tool to help fund managers to manage the risk they can accept due to divestment, especially for a fund holding significant portions of carbon assets to divest.

[46] A high excess return and tracking error may occur when the target ETFs diversify the assets using different techniques from the five core portfolio types. The fund adding new assets regularly may be difficult to track due to the fact that we use fixed assets in the simulation. This could require increasing the universe of assets over time, a consideration excluded in this study.

[47] The divested assets account for direct and indirect (scope 1 and 2) emissions that covers CU200, and oil/gas.

[48] The length of the body of a boxplot measures the interquartile range that can be used to robustly estimate the tracking error.

Table 7
Monthly average performances over ten years of the fossil-fuel divestment from the iShares MSCI United Kingdom (EWU) ETF with 11% divested assets and the relative carbon footprint of 97 emissions per unit of investment.

Portfolio	Divestment Rate	Return (%)	Cumulative Return (%)	Standard Deviation (%)	Sharpe Ratio	Max Draw-down	VaR (%)	Omega	Sortino	Beta	Treynor (%)
PEW	None	0.041	0.864	0.846	0.097	−2.081	−1.226	1.618	0.153	0.783	0.081
		(±0.203)	(±4.361)	(±0.556)	(±0.238)	(±0.557)	(±0.998)	(±1.212)	(±0.358)	(±0.252)	(±0.291)
	Δ Instant	0.061	0.063	−0.005	0.032	−0.004	−0.012	0.013	0.028	−0.016*	0.059
		(±0.204)	(±4.374)	(±0.542)	(±0.239)	(±0.559)	(±0.968)	(±1.227)	(±0.359)	(±0.253)	(±0.304)
AEW	None	0.052	1.099	0.850	0.111	−2.075	−1.235	1.703	0.172	0.766	0.107
		(±0.213)	(±4.581)	(±0.551)	(±0.247)	(±0.634)	(±1.045)	(±1.275)	(±0.369)	(±0.261)	(±0.344)
	Δ Slow	0.034	0.035	−0.005	0.025	−0.005	−0.009	0.008	0.025	−0.000	0.025
		(±0.216)	(±4.631)	(±0.543)	(±0.248)	(±0.627)	(±1.023)	(±1.287)	(±0.371)	(±0.258)	(±0.360)
	Δ Fast	0.044	0.045	−0.006	0.039	−0.007	−0.016*	0.019	0.041	−0.007	0.007
		(±0.216)	(±4.631)	(±0.540)	(±0.249)	(±0.625)	(±1.023)	(±1.334)	(±0.374)	(±0.257)	(±0.364)
	Δ Instant	0.044	0.045	−0.005	0.036	−0.007	−0.019*	0.019	0.041	−0.014	0.015
		(±0.215)	(±4.624)	(±0.540)	(±0.248)	(±0.629)	(±1.022)	(±1.333)	(±0.375)	(±0.257)	(±0.365)
GMV	None	0.038	0.799	0.721	0.098	−2.055	−1.032	1.625	0.149	0.773	0.096
		(±0.160)	(±3.438)	(±0.448)	(±0.244)	(±0.673)	(±0.827)	(±1.323)	(±0.359)	(±0.309)	(±0.291)
	Δ Slow	0.074	0.079	0.012*	0.020	−0.000	0.008	0.018	0.016	−0.032*	0.357
		(±0.162)	(±3.464)	(±0.444)	(±0.245)	(±0.623)	(±0.811)	(±1.566)	(±0.363)	(±0.315)	(±0.418)
	Δ Fast	0.101	0.107	0.019*	0.031	0.003	0.017	0.016	0.021	−0.040*	0.401
		(±0.162)	(±3.467)	(±0.445)	(±0.246)	(±0.631)	(±0.814)	(±1.551)	(±0.361)	(±0.313)	(±0.428)
	Δ Instant	0.134	0.141	0.022*	0.047	0.004	0.017	0.018	0.034	−0.045*	0.410
		(±0.162)	(±3.474)	(±0.445)	(±0.246)	(±0.633)	(±0.814)	(±1.554)	(±0.360)	(±0.312)	(±0.430)
MS	None	0.050	1.065	0.925	0.087	−2.033	−1.345	1.516	0.138	0.633	0.129
		(±0.193)	(±4.142)	(±0.541)	(±0.219)	(±0.606)	(±1.017)	(±1.000)	(±0.327)	(±0.242)	(±0.387)
	Δ Slow	0.045	0.049	−0.009	0.007	0.000	−0.011	0.000	0.002	−0.008	0.113*
		(±0.192)	(±4.128)	(±0.483)	(±0.221)	(±0.596)	(±0.862)	(±0.996)	(±0.328)	(±0.251)	(±0.403)
	Δ Fast	0.056	0.061	−0.007	0.014	−0.001	−0.007	0.005	0.008	−0.017	0.119
		(±0.194)	(±4.159)	(±0.484)	(±0.223)	(±0.590)	(±0.863)	(±1.017)	(±0.330)	(±0.249)	(±0.409)
	Δ Instant	0.048	0.053	−0.008	0.008	0.002	−0.008	0.005	0.003	−0.021*	0.109
		(±0.193)	(±4.147)	(±0.484)	(±0.223)	(±0.597)	(±0.862)	(±1.019)	(±0.331)	(±0.245)	(±0.409)
PC	None	0.028	0.563	1.240	0.041	−2.112	−1.811	1.359	0.069	0.487	0.218
		(±0.277)	(±5.992)	(±0.673)	(±0.239)	(±0.589)	(±1.139)	(±0.948)	(±0.344)	(±0.252)	(±1.127)
	Δ Slow	0.129	0.138	−0.024*	0.087	−0.010	−0.024*	0.011	0.064	0.031*	−0.033
		(±0.275)	(±5.945)	(±0.656)	(±0.240)	(±0.577)	(±1.141)	(±0.956)	(±0.346)	(±0.242)	(±0.987)
	Δ Fast	0.227	0.243	−0.022*	0.134	−0.018	−0.027*	0.010	0.096	0.030	−0.013
		(±0.274)	(±5.907)	(±0.656)	(±0.237)	(±0.583)	(±1.147)	(±0.927)	(±0.343)	(±0.236)	(±0.982)
	Δ Instant	0.190	0.205	−0.022*	0.103	−0.017	−0.029*	0.005	0.071	0.027	−0.019
		(±0.272)	(±5.876)	(±0.656)	(±0.236)	(±0.585)	(±1.147)	(±0.921)	(±0.342)	(±0.235)	(±0.982)

The table displays the relative change between the performance of the divested portfolio and its benchmark (no divestment) for slow, fast, and instantaneous divestment. * refers to the p-value of the t-test being significant at a confidence level of 95%. This implies that the average risk profile is statistically different from the non-divestment benchmark. The highlighted cells indicate the highest (red) and the lowest (green) difference in the performance for each risk profile. The box around the portfolio type indicates the closest to the original ETF according to the excess return and tracking error.

5. Divestment by ESG rating screening: The FTSE 100 case

Portfolio diversification is an important consideration for retail investors, wealth managers, and pension funds. To assess the role of divestment and its potential to induce a loss of portfolio diversity in broad market portfolios, it is necessary to consider a different screening criterion than simply selecting divestable assets from the most carbon-intensive primary industries, as assumed in Section 3. We now focus on the effect of divestment from an ESG rating screening perspective and explore the practical impact that arises when divestable assets are screened based on ESG, E, S, or G score with varying thresholds on the performance of each company's ESG scores.[49] With such screening criterion, divestment can be setup using underperforming assets across all sectors, not just energy and utilities. Thus, the proportion of divestable assets would vary across the asset universe. The asset universe comprises all FTSE 100 assets (from which their ESG scores can be obtained) and we utilize a linear divestment schedule and varied the proportion of relevative ESG, E, S or G score ratings to determine divestible assets in each sector of the FTSE 100. Most specifically, the divestable assets are selected from the 10%, 20%, 30%, 40%, 50%, 60%, and 70% of corporations with the lowest E, S, G, and overall ESG scores, see Section 2.3.3 for the full details of the experimental design. Accordingly, we address the question of how the proportion of divestable assets impacts the tracking performance and portfolio diversification. Thus, the following questions are investigated: What is the impact of divestment by E, S, G, ESG rating screening on the portfolio risk/return performance and correlation structure? and What is the impact of divestment by ESG rating screening on the diversification of FTSE 100 portfolios?

5.1. Impact on portfolio risk/return performance and correlation structure

Fig. 11 displays all divestment results based on environmental score scanning. Figs. 11.a and 11.b illustrates the boxplots of the excess returns between portfolios with and without divestment of AEW and GMV. The tracking error can be determined by observing the breadth of the boxplots' bodies and the scattering data. One can see a direct correlation between the fraction of divestable assets and tracking errors in this study.[50] Similar to the previous section, the tracking

[49] This is a controversial rating being increasingly adopted to assess Environmental, Social, and Governance relative scores of companies across a broad range of criteria; see Christensen et al. (2022), Berg et al. (2022) for discussion on the challenges associated with the scoring and ratings from various ESG rating providers. We do not enter into this debate in this work.

[50] The tracking errors for the AEW portfolio range from 0.0005 to 0.0020, while those for the GMV portfolio range from 0.0005 to 0.0030. These values correspond to the concentration of the scanning criteria from 0% to 70% divestment.

Table 8
Monthly average performances over ten years of the fossil-fuel divestment from the iShares Global Clean Energy (ICLN) ETF with 19% divested assets and the relative carbon footprint of 279 emissions per unit of investment.

Portfolio	Divestment Rate	Return (%)	Cumulative Return (%)	Standard Deviation (%)	Sharpe Ratio	Max Draw-down	VaR (%)	Omega	Sortino	Beta	Treynor (%)
PEW	None	0.001	0.016	0.008	0.108	−2.065	−0.012	1.776	0.160	0.759	0.001
		(±0.002)	(±0.065)	(±0.005)	(±0.281)	(±0.494)	(±0.010)	(±1.839)	(±0.417)	(±0.345)	(±0.005)
	Δ Instant	0.164	0.165	0.085*	−0.003	−0.005	0.086*	−0.008	−0.030	−0.106*	0.359
		(±0.003)	(±0.072)	(±0.005)	(±0.290)	(±0.486)	(±0.010)	(±1.591)	(±0.424)	(±0.350)	(±0.007)
AEW	None	0.001	0.020	0.009	0.119	−1.987	−0.012	1.815	0.179	0.698	0.002
		(±0.003)	(±0.067)	(±0.006)	(±0.277)	(±0.460)	(±0.010)	(±1.692)	(±0.409)	(±0.365)	(±0.010)
	Δ Slow	0.143	0.129	0.037	0.026	0.002	0.051*	0.010	0.014	−0.038*	0.364
		(±0.003)	(±0.071)	(±0.006)	(±0.282)	(±0.454)	(±0.011)	(±1.700)	(±0.414)	(±0.368)	(±0.014)
	Δ Fast	0.182	0.168	0.073*	0.017	−0.003	0.089*	0.016	0.007	−0.097*	0.514
		(±0.003)	(±0.074)	(±0.006)	(±0.290)	(±0.447)	(±0.011)	(±1.702)	(±0.426)	(±0.353)	(±0.014)
	Δ Instant	0.169	0.154	0.074*	0.010	−0.001	0.092*	0.013	−0.005	−0.102*	0.477
		(±0.003)	(±0.074)	(±0.006)	(±0.290)	(±0.441)	(±0.011)	(±1.705)	(±0.426)	(±0.346)	(±0.014)
GMV	None	0.000	0.008	0.007	0.094	−2.117	−0.010	1.644	0.143	0.770	0.001
		(±0.002)	(±0.045)	(±0.005)	(±0.258)	(±0.669)	(±0.010)	(±1.450)	(±0.372)	(±0.425)	(±0.007)
	Δ Slow	0.094	0.086	0.075*	0.021	−0.019	0.080*	0.017	0.029	−0.072*	0.066
		(±0.002)	(±0.048)	(±0.005)	(±0.262)	(±0.593)	(±0.010)	(±1.436)	(±0.383)	(±0.404)	(±0.008)
	Δ Fast	−0.063	−0.061	0.285*	−0.151	−0.008	0.284*	−0.030	−0.157	−0.362*	6.377
		(±0.002)	(±0.057)	(±0.005)	(±0.272)	(±0.610)	(±0.010)	(±1.277)	(±0.393)	(±0.372)	(±0.046)
	Δ Instant	−0.125	−0.098	0.298	−0.160	−0.009	0.299*	−0.032	−0.165	−0.373	6.262
		(±0.002)	(±0.058)	(±0.005)	(±0.272)	(±0.606)	(±0.010)	(±1.276)	(±0.394)	(±0.367)	(±0.043)
MS	None	0.001	0.016	0.009	0.095	−2.066	−0.014	1.650	0.147	0.632	0.010
		(±0.002)	(±0.063)	(±0.007)	(±0.250)	(±0.583)	(±0.010)	(±1.452)	(±0.367)	(±0.305)	(±0.091)
	Δ Slow	0.355*	0.340*	0.121*	0.071	−0.007	0.125*	0.035	0.065	−0.105*	0.108
		(±0.003)	(±0.072)	(±0.007)	(±0.252)	(±0.577)	(±0.013)	(±1.598)	(±0.374)	(±0.279)	(±0.092)
	Δ Fast	0.226	0.212	0.236*	−0.019	−0.005	0.282*	−0.010	−0.046	−0.251*	−0.611
		(±0.003)	(±0.078)	(±0.007)	(±0.252)	(±0.540)	(±0.014)	(±1.387)	(±0.372)	(±0.235)	(±0.015)
	Δ Instant	0.194	0.184	0.234*	−0.016	−0.002	0.282*	−0.013	−0.054	−0.253	−0.636
		(±0.003)	(±0.078)	(±0.007)	(±0.252)	(±0.536)	(±0.014)	(±1.380)	(±0.370)	(±0.230)	(±0.015)
PC	None	0.001	0.027	0.020	0.042	−2.038	−0.028	1.468	0.071	0.258	−0.257
		(±0.006)	(±0.163)	(±0.011)	(±0.274)	(±0.546)	(±0.017)	(±1.130)	(±0.410)	(±0.197)	(±2.626)
	Δ Slow	0.097	0.097	0.010	0.021	−0.007	0.006	0.008	0.014	−0.012	−0.619
		(±0.006)	(±0.161)	(±0.011)	(±0.273)	(±0.529)	(±0.016)	(±1.251)	(±0.408)	(±0.189)	(±1.132)
	Δ Fast	0.146	0.146	0.049*	0.024	−0.012	0.040*	0.012	0.005	−0.068*	−0.538
		(±0.006)	(±0.169)	(±0.012)	(±0.275)	(±0.532)	(±0.017)	(±1.272)	(±0.412)	(±0.177)	(±1.147)
	Δ Instant	0.107	0.114	0.048*	0.005	−0.012	0.042*	0.005	−0.034	−0.074*	−0.825
		(±0.006)	(±0.169)	(±0.012)	(±0.274)	(±0.518)	(±0.017)	(±1.266)	(±0.409)	(±0.174)	(±0.805)

The table displays the relative change between the performance of the divested portfolio and its benchmark (no divestment) for slow, fast, and instantaneous divestment. * refers to the p-value of the t-test being significant at a confidence level of 95%. This implies that the average risk profile is statistically different from the non-divestment benchmark. The highlighted cells indicate the highest (red) and the lowest (green) difference in the performance for each risk profile. The box around the portfolio type indicates the closest to the original ETF according to the excess return and tracking error.

error tends to increase as the proportion of divestable assets in the portfolio increases.[51] For the AEW, the relative behavior of the return observed from the stable cluster in the heatmap 11.c does not alter appreciably. As the returns move in the same direction but have different values, the stable cluster may produce a large tracking error. In contrast, the relative behavior of the GMV starts changing at the proportion 30%, see Fig. 11.d. The cumulative returns of the AEWs and GMVs are given in Fig. 11.e and 11.f. Both portfolios yield positive cumulative returns at the end of the study period, with the wealth levels approximately reaching 1.25.[52] The scanning criteria of 30% and 40% seem to yield better cumulative return performance, despite experiencing a significant downturn due to the Covid-19 pandemic. The AEW portfolios demonstrate a higher degree of resilience to divestment activities (compared to the GMV portfolios). This resilience is particularly evident in the disparity in ten year cumulative return outcomes as the percentage of divestable assets increases. More specifically, the maximum difference of the return in the ten year cumulative return levels of the AEW portfolios was less than 0.1, whereas for the GMV and GMV60 portfolios, the difference reached 0.3.

The stacked bar charts with the number of the remaining assets in the FTSE 100 in various ESG thresholds separated by their industry sector after complete divestment, are shown in Fig. 12. We find that, assets in the Energy, Industrials, and Utilities sectors are evaluated at high environmental risk scores compared to others, whereas the Financial Services sector is evaluated at high governance risk scores.

In addition, sector analysis of the tracking error is examined. The boxplots showing the excess return between the original and divested AEWs and GMVs are depicted in Figs. 13 and 14, respectively. It allows us to study the tracking error sources for each sector. Except of the Real Estate and Technology sectors, tracking errors in AEWs do not appear to differ considerably by industry. These two sectors are less impacted by divestment because the Real Estate industry has a stable ESG risk evolution across all score levels, while the Technology sector has only one asset. See Fig. 12 for a rudimentary illustration of the tracking error caused by divestment in the Energy, Industrials, and Utilities sectors, from which most holdings are sold. While the large tracking error caused by reinvestment can be found in the Financials sector, overall, these sectors produce significant tracking errors in both AEW and GMV portfolios.

Fig. 15 compares the cumulative return of the original and divested AEWs and GMVs based on their S, G, and overall ESG scores. According to the S and G scores, the divested AEWs are likely more profitable than

[51] The average wealth (cumulative return) of the divested portfolio exhibits statistically significant differences in mean from that of the original portfolio at a 95% confidence level, as determined by the t-test, across all portfolios.

[52] Over ten years, the cumulative return drops to 0.975 for the non-divested portfolio and reaches 1.042 with 30% divestment for the AEW. For the GMV, it drops to 0.866 with 60% divestment and reaches 1.074 with 30% divestment, as seen in Fig. 11.

Table 9
Monthly average performances over ten years of the fossil-fuel divestment from the iShares Select Dividend (DVY) ETF with 32% divested assets and the relative carbon footprint of 434 emissions per unit of investment.

Portfolio	Divestment Rate	Return (%)	Cumulative Return (%)	Standard Deviation (%)	Sharpe Ratio	Max Draw-down	VaR (%)	Omega	Sortino	Beta	Treynor (%)	Yield
PEW	None	0.035	0.737	0.911	0.083	−2.076	−1.312	1.500	0.130	0.918	0.056	3.206
		(±0.187)	(±3.893)	(±0.722)	(±0.209)	(±0.465)	(±1.182)	(±1.043)	(±0.316)	(±0.200)	(±0.214)	(±0.337)
	Δ Instant	0.016	0.003	0.119*	−0.033	0.002	0.115*	0.021	−0.014	−0.107*	0.482	−0.045
		(±0.217)	(±4.519)	(±0.738)	(±0.216)	(±0.486)	(±1.232)	(±1.166)	(±0.332)	(±0.194)	(±0.323)	(±0.523)
AEW	None	0.033	0.692	0.907	0.081	−2.073	−1.303	1.488	0.125	0.911	0.053	3.176
		(±0.189)	(±3.948)	(±0.707)	(±0.210)	(±0.456)	(±1.190)	(±1.029)	(±0.315)	(±0.200)	(±0.217)	(±0.413)
	Δ Slow	−0.020	−0.028	0.066*	−0.025	0.003	0.074*	0.008	−0.002	−0.047*	0.301	−0.010
		(±0.202)	(±4.211)	(±0.707)	(±0.213)	(±0.477)	(±1.205)	(±1.080)	(±0.325)	(±0.204)	(±0.284)	(±0.474)
	Δ Fast	−0.025	−0.039	0.112*	−0.046	0.005	0.120*	0.024	−0.014	−0.097*	0.414	−0.044
		(±0.214)	(±4.458)	(±0.712)	(±0.217)	(±0.487)	(±1.217)	(±1.202)	(±0.335)	(±0.194)	(±0.304)	(±0.545)
	Δ Instant	−0.004	−0.019	0.116	−0.039	0.005	0.124*	0.027	−0.009	−0.101	0.434	−0.057
		(±0.215)	(±4.478)	(±0.712)	(±0.218)	(±0.488)	(±1.217)	(±1.210)	(±0.335)	(±0.191)	(±0.305)	(±0.575)
GMV	None	0.034	0.710	0.746	0.082	−2.064	−1.071	1.526	0.128	1.005	0.048	4.376
		(±0.158)	(±3.261)	(±0.581)	(±0.213)	(±0.494)	(±0.943)	(±1.390)	(±0.324)	(±0.291)	(±0.180)	(±0.487)
	Δ Slow	0.015	0.002	0.058*	−0.012	0.001	0.054	0.009	0.002	−0.031*	0.105	0.025
		(±0.165)	(±3.425)	(±0.546)	(±0.213)	(±0.523)	(±0.953)	(±1.427)	(±0.327)	(±0.281)	(±0.188)	(±0.544)
	Δ Fast	0.075	0.058	0.072*	0.010	−0.003	0.064*	0.000	0.021	−0.056*	0.204	−0.034
		(±0.165)	(±3.431)	(±0.542)	(±0.211)	(±0.518)	(±0.950)	(±1.283)	(±0.324)	(±0.275)	(±0.192)	(±0.532)
	Δ Instant	0.085	0.067	0.072*	0.014	−0.002	0.064*	−0.001	0.023	−0.056*	0.211	−0.046
		(±0.166)	(±3.432)	(±0.542)	(±0.210)	(±0.520)	(±0.949)	(±1.261)	(±0.323)	(±0.275)	(±0.192)	(±0.507)
MS	None	0.033	0.691	0.876	0.076	−2.108	−1.250	1.441	0.114	0.888	0.055	4.382
		(±0.179)	(±3.728)	(±0.721)	(±0.211)	(±0.593)	(±1.129)	(±0.996)	(±0.305)	(±0.236)	(±0.234)	(±0.623)
	Δ Slow	−0.119	−0.126	0.083*	−0.062	0.001	0.082*	−0.018	-0.034	−0.050*	0.076	0.035
		(±0.198)	(±4.116)	(±0.770)	(±0.204)	(±0.570)	(±1.246)	(±0.900)	(±0.300)	(±0.231)	(±0.264)	(±0.839)
	Δ Fast	−0.076	−0.092	0.145*	−0.029	−0.006	0.142*	0.011	0.017	−0.114*	0.247	−0.031
		(±0.211)	(±4.390)	(±0.773)	(±0.211)	(±0.583)	(±1.256)	(±0.997)	(±0.317)	(±0.214)	(±0.289)	(±0.844)
	Δ Instant	−0.090	−0.106	0.146	−0.035	−0.006	0.143*	0.010	0.012	−0.114*	0.239	−0.052
		(±0.211)	(±4.398)	(±0.773)	(±0.211)	(±0.583)	(±1.257)	(±1.002)	(±0.317)	(±0.214)	(±0.290)	(±0.856)
PC	None	0.051	1.061	1.161	0.087	−2.012	−1.649	1.524	0.134	0.706	0.141	3.345
		(±0.242)	(±5.075)	(±0.889)	(±0.215)	(±0.430)	(±1.461)	(±1.074)	(±0.327)	(±0.222)	(±0.431)	(±0.777)
	Δ Slow	−0.037	−0.044	0.060*	−0.052	0.010	0.072*	−0.013	−0.040	−0.020	0.202	−0.016
		(±0.243)	(±5.079)	(±0.965)	(±0.212)	(±0.452)	(±1.540)	(±1.049)	(±0.323)	(±0.224)	(±0.669)	(±0.761)
	Δ Fast	−0.050	−0.061	0.086*	−0.073	0.014	0.097*	−0.019	−0.067	−0.055*	0.208	−0.037
		(±0.253)	(±5.275)	(±0.973)	(±0.213)	(±0.467)	(±1.560)	(±1.026)	(±0.322)	(±0.214)	(±0.682)	(±0.824)
	Δ Instant	−0.038	−0.049	0.090*	−0.072	0.014	0.101*	−0.017	-0.066	−0.060*	0.224	−0.045
		(±0.254)	(±5.309)	(±0.975)	(±0.213)	(±0.467)	(±1.562)	(±1.031)	(±0.322)	(±0.213)	(±0.684)	(±0.853)

The table displays the relative change between the performance of the divested portfolio and its benchmark (no divestment) for slow, fast, and instantaneous divestment. * refers to the *p*-value of the *t*-test being significant at a confidence level of 95%. This implies that the average risk profile is statistically different from the non-divestment benchmark. The highlighted cells indicate the highest (red) and the lowest (green) difference in the performance for each risk profile. The box around the portfolio type indicates the closest to the original ETF according to the excess return and tracking error.

the original portfolio, and the divested GMVs are less profitable than the original portfolio. Thus, the risk/return profile of a portfolio can be materially affected by the divestment screening criteria used to select the divestment set of assets, as well as the portfolio strategy type.

Finally, we simulate the glasso for the AEWs and the GMVs portfolios using divestment based on E scores. As an illustration, Fig. 16 depicts the estimated spare matrix acquired from the glasso using the Industrials sector in the AEW, AEW30, and AEW70 (horizontal) at various times (vertical). The thickness of the links represents the estimated covariance, while the color green indicates a positive correlation. The divestment commenced on 2010-01-01 (first row) and concluded on 2020-01-01 (the last row). The divestable assets are completely eliminated on May 1, 2020 (the third row). We conclude that, robust correlation structure did not change when the divesting proportion increased until the weight of some assets was set to zero.[53] In other words, the portfolios' robust correlation structure may not be broken until certain assets are totally divested. Prior to 2020-05-01, the robust correlation structures of the AEW, AEW30, and AEW70 were comparable.[54]

5.2. Impact on portfolio diversification

To assess the impact of divestment by ESG rating screening on portfolio diversification, we propose the Portfolio Diversification Ratio (PDR) that is defined by the ratio of the portfolio variance and the sum of the portfolio assets variances, i.e., the sum of diagonal of the covariance matrix. The denominator of the ratio can be considered as the perfect diversification which zero correlation between assets. Accordingly, the portfolio diversification ratio is defined as,

$$PDR = \frac{\mathrm{Var}\left(\sum_{j=1}^{N} w_j R_j\right)}{\sum_{j=1}^{N} \mathrm{Var}\left(w_j R_j\right)} = \frac{\mathrm{Var}\left(\sum_{k=1}^{N_K} w_k R_k + \sum_{k'=1}^{N_{K'}} w_{k'} R_{k'}\right)}{\sum_{j=1}^{N} \mathrm{Var}\left(w_j R_j\right)}$$
$$= \underbrace{\frac{\mathrm{Var}\left(\sum_{k=1}^{K} w_k R_k\right)}{\sum_{j=1}^{N} \mathrm{Var}\left(w_j R_j\right)}}_{\text{SVCR}} + \underbrace{\frac{\mathrm{Var}\left(\sum_{k'=1}^{K'} w_{k'} R_{k'}\right)}{\sum_{j=1}^{N} \mathrm{Var}\left(w_j R_j\right)}}_{\text{SEVR}}$$
$$+ \underbrace{\frac{\sum_{k=1}^{K}\sum_{k'=1}^{K'} \mathrm{Cov}\left(w_k R_k, w_{k'} R_{k'}\right)}{\sum_{j=1}^{N} \mathrm{Var}\left(w_j R_j\right)}}_{\text{SEC}}, \tag{18}$$

where the index k stands for the constituents in the sector K with N_K assets, k' stands for the constituents in the remaining asset in portfolio without the sector K' with $N_{K'}$ assets, j stands for the index of all assets in portfolio with $N = N_K + N_{K'}$ assets. If the PDR is close to one means the portfolio is more well-diversified.

To observe impact of the divestment on portfolio diversification separated by the GICS sectors, the portfolio diversification, PDR, is decomposed into three parts. The sector variance contribution ratio (SVCR) indicates the proposition of the normalized variance of the sector K compared to the perfect diversified portfolio. The SVRC is non-negative and can be zero when all assets in the given sector are divested completely. Due to the cancellation of the covariance with other sectors, a high SVCR does not imply an increase in the portfolio's variance. The sector-excluded variance ratio (SEVR) indicates the variance of the sub-portfolio without constituents in sector K compared to the prefect

53 According to the proposed divestment strategy, the divestment and reinvestment investment weights are uniformly exchanged between the divestable and investable assets.

54 Rebalancing allows for the alteration of a portfolio's robust structure over time.

Table 10
Monthly average performances over ten years of the fossil-fuel divestment from the iShares U.S. Infrastructure (IFRA) ETF with 37% divested assets and the relative carbon footprint of 832 emissions per unit of investment.

Portfolio	Divestment Rate	Return (%)	Cumulative Return (%)	Standard Deviation (%)	Sharpe Ratio	Max Draw-down	VaR (%)	Omega	Sortino	Beta	Treynor (%)
PEW	None	0.000	0.010	0.010	0.074	−2.044	−0.015	1.454	0.112	0.747	0.001
		(±0.002)	(±0.045)	(±0.007)	(±0.222)	(±0.447)	(±0.012)	(±0.980)	(±0.325)	(±0.219)	(±0.003)
	Δ Instant	0.196	0.171	0.242*	−0.069	0.016	0.230*	0.016	−0.041	−0.207*	0.861*
		(±0.003)	(±0.060)	(±0.008)	(±0.232)	(±0.510)	(±0.013)	(±1.116)	(±0.345)	(±0.191)	(±0.006)
$\boxed{\text{AEW}}$	None	0.000	0.009	0.010	0.073	−2.053	−0.015	1.453	0.111	0.737	0.001
		(±0.002)	(±0.046)	(±0.007)	(±0.223)	(±0.455)	(±0.012)	(±0.996)	(±0.325)	(±0.224)	(±0.004)
	Δ Slow	0.156	0.162	0.120	−0.031	0.011	0.112*	0.008	−0.014	−0.090	0.614*
		(±0.003)	(±0.053)	(±0.008)	(±0.226)	(±0.486)	(±0.013)	(±1.086)	(±0.333)	(±0.233)	(±0.005)
	Δ Fast	0.244	0.230	0.233*	−0.046	0.008	0.227*	0.019	−0.022	−0.197*	0.911*
		(±0.003)	(±0.060)	(±0.008)	(±0.233)	(±0.510)	(±0.013)	(±1.138)	(±0.344)	(±0.203)	(±0.007)
	Δ Instant	0.244	0.240	0.239	−0.041	0.007	0.234	0.021	−0.019	−0.204	0.921*
		(±0.003)	(±0.060)	(±0.008)	(±0.233)	(±0.510)	(±0.013)	(±1.141)	(±0.345)	(±0.198)	(±0.007)
GMV	None	0.000	0.009	0.009	0.078	−2.071	−0.012	1.457	0.120	0.817	0.001
		(±0.002)	(±0.035)	(±0.007)	(±0.205)	(±0.505)	(±0.011)	(±1.022)	(±0.308)	(±0.303)	(±0.004)
	Δ Slow	0.250	0.237	0.175*	0.011	−0.004	0.178*	−0.004	−0.010	−0.083*	0.252
		(±0.002)	(±0.044)	(±0.007)	(±0.212)	(±0.490)	(±0.012)	(±0.912)	(±0.312)	(±0.284)	(±0.004)
	Δ Fast	0.318	0.277	0.379*	0.010	−0.017	0.394*	0.028	0.002	−0.245*	0.504
		(±0.003)	(±0.054)	(±0.008)	(±0.225)	(±0.481)	(±0.013)	(±1.046)	(±0.337)	(±0.214)	(±0.005)
	Δ Instant	0.295	0.251	0.387	0.011	−0.013	0.403	0.028	0.005	−0.251	0.462
		(±0.003)	(±0.055)	(±0.008)	(±0.225)	(±0.501)	(±0.013)	(±1.048)	(±0.336)	(±0.211)	(±0.005)
MS	None	0.000	0.010	0.010	0.071	−2.085	−0.014	1.376	0.104	0.702	0.001
		(±0.002)	(±0.041)	(±0.007)	(±0.199)	(±0.474)	(±0.012)	(±0.781)	(±0.286)	(±0.262)	(±0.003)
	Δ Slow	0.122	0.114	0.157*	−0.059	0.015	0.166*	0.003	−0.039	−0.094*	0.901
		(±0.002)	(±0.050)	(±0.008)	(±0.206)	(±0.518)	(±0.012)	(±0.858)	(±0.297)	(±0.235)	(±0.009)
	Δ Fast	0.265	0.225	0.352*	−0.075	0.014	0.360*	0.008	−0.056	−0.246*	1.279
		(±0.003)	(±0.061)	(±0.008)	(±0.210)	(±0.541)	(±0.013)	(±0.857)	(±0.303)	(±0.194)	(±0.010)
	Δ Instant	0.245	0.224	0.357	−0.073	0.013	0.364	0.008	−0.053	−0.250	1.270
		(±0.003)	(±0.061)	(±0.008)	(±0.209)	(±0.539)	(±0.013)	(±0.857)	(±0.302)	(±0.192)	(±0.010)
PC	None	0.001	0.017	0.014	0.080	−2.019	−0.019	1.508	0.121	0.514	0.003
		(±0.003)	(±0.065)	(±0.008)	(±0.225)	(±0.415)	(±0.014)	(±1.117)	(±0.336)	(±0.250)	(±0.021)
	Δ Slow	−0.185	−0.191	0.112*	−0.137	0.006	0.118*	−0.023	−0.130	−0.052	−0.394
		(±0.003)	(±0.072)	(±0.010)	(±0.227)	(±0.449)	(±0.015)	(±1.126)	(±0.342)	(±0.211)	(±0.020)
	Δ Fast	−0.198	−0.217	0.195*	−0.165	0.006	0.206*	−0.029	−0.156	−0.146*	−0.483
		(±0.004)	(±0.078)	(±0.010)	(±0.233)	(±0.463)	(±0.016)	(±1.096)	(±0.349)	(±0.183)	(±0.020)
	Δ Instant	−0.198	−0.213	0.202*	−0.164	0.005	0.211*	−0.028	−0.156	−0.152*	−0.476
		(±0.004)	(±0.078)	(±0.010)	(±0.234)	(±0.463)	(±0.016)	(±1.098)	(±0.349)	(±0.181)	(±0.020)

The table displays the relative change between the performance of the divested portfolio and its benchmark (no divestment) for slow, fast, and instantaneous divestment. * refers to the *p*-value of the *t*-test being significant at a confidence level of 95%. This implies that the average risk profile is statistically different from the non-divestment benchmark. The highlighted cells indicate the highest (red) and the lowest (green) difference in the performance for each risk profile. The box around the portfolio type indicates the closest to the original ETF according to the excess return and tracking error.

diversified portfolio. It measures the impact of the withdrawing all assets in sector K to portfolio diversification. High SEVR implies the sector K reduces the variance of portfolio. The last term is sector-excluded correlation (SEC) which measures the correlation between the sub-portfolio excluded sector K and the sub-portfolio of sector K. The sign of the SEC tells us the direction of the correlation of those two sub-portfolios. If the SEC is zero, sector K is uncorrelated with other portfolio assets, resulting in perfect diversification between the sector and portfolio. The SEC is less than zero, indicating that the sector K covariance cancels out that of other sectors, resulting in a decrease in the entire portfolio. Then, a high SVCR is advantageous to overall diversification. Otherwise, the SEC is greater than zero, indicating that the sector K reduces the overall portfolio variance, hence diminishing diversification.

We simulate portfolio divestment on the AEW and GVM portfolios with divestable assets being within 30% and 70% of the corporations with low E, S, G, and overall ESG score, and calculate the diversification measures based on Eq. (18). Figs. 17 to 19 depict the SVCR, SEVR, and SEC of ten sectors in the AEW, AEW30, and AEW70 portfolios.[55] The SVCRs for the Communication Services and Financial Services sectors increase as the proportion indicating that the divestment reduces diversification in the sectors holding the bulk of investable assets. The sectors in which the majority of constituents were divested yield the SVCR of approximately or equal to zero. Thus, while reinvestment leads to the increase in variation within the sector, divestment based on ESG rating screening has the reverse effect.

Further, in all sectors, the SEVRs of the divested portfolios are lower than their original values. Thus, the divestment improves the overall portfolio's diversification, rather than to increasing the sector's variation. As seen by their SVCRs, the majority of sectors experience a decrease in SVCR due to divestment, except for two sectors; nonetheless, the decline in the majority of the sectors contributes more than the increase in those two. The difference between the SEVR and SVCR can be used to determine the sector's variance contribution. Compared to other sectors, the differences between the SEVR and the SVCR in the Communication Services and the Financial Services sectors are rather substantial implying a large proportion of the variance contribution in the portfolios. For all sectors, the SECs drop as the intensity of divestment grows implying that divestment improves the diversification between the sectors.

[55] Notably, the Technology sector is omitted due to the undefined covariance of the single asset. Also, the differences in SVCR, SEVR, and SEC between the original and all divested portfolios are statistically significant, as determined by a *t*-test at the 95% confidence level.

Table 11
Monthly average performances over ten years of the fossil-fuel divestment from the iShares Global Infrastructure (IGF) ETF with 48% divested assets and the relative carbon footprint of 534 emissions per unit of investment.

Portfolio	Divestment Rate	Return (%)	Cumulative Return (%)	Standard Deviation (%)	Sharpe Ratio	Max Draw-down	VaR (%)	Omega	Sortino	Beta	Treynor (%)
PEW	None	0.000	0.007	0.007	0.097	−2.093	−0.009	1.669	0.142	0.962	0.001
		(±0.002)	(±0.041)	(±0.005)	(±0.260)	(±0.574)	(±0.009)	(±1.599)	(±0.380)	(±0.378)	(±0.002)
	Δ Instant	−0.029	−0.015	0.034	0.039	0.002	0.036	0.018	0.035	−0.263*	0.686
		(±0.002)	(±0.045)	(±0.004)	(±0.277)	(±0.519)	(±0.009)	(±1.591)	(±0.394)	(±0.355)	(±0.004)
$\boxed{\text{AEW}}$	None	0.000	0.008	0.007	0.096	−2.123	−0.010	1.655	0.142	0.893	0.001
		(±0.002)	(±0.043)	(±0.005)	(±0.261)	(±0.686)	(±0.010)	(±1.400)	(±0.379)	(±0.393)	(±0.006)
	Δ Slow	−0.056	−0.047	−0.010	0.035	−0.020	−0.008	0.032	0.041	−0.103*	−0.398
		(±0.002)	(±0.043)	(±0.004)	(±0.274)	(±0.533)	(±0.008)	(±1.633)	(±0.397)	(±0.400)	(±0.004)
	Δ Fast	−0.111	−0.093	0.019	−0.005	−0.012	0.033	0.029	−0.009	−0.246*	2.524
		(±0.002)	(±0.045)	(±0.004)	(±0.281)	(±0.557)	(±0.008)	(±1.673)	(±0.401)	(±0.374)	(±0.033)
	Δ Instant	−0.111	−0.094	0.024	−0.007	−0.013	0.044	0.029	−0.011	−0.261	8.621
		(±0.002)	(±0.045)	(±0.004)	(±0.280)	(±0.553)	(±0.009)	(±1.675)	(±0.400)	(±0.363)	(±0.105)
GMV	None	0.000	0.007	0.005	0.096	−2.058	−0.007	1.685	0.148	0.914	−0.002
		(±0.001)	(±0.029)	(±0.005)	(±0.261)	(±0.694)	(±0.008)	(±1.897)	(±0.395)	(±0.567)	(±0.015)
	Δ Slow	0.000	−0.001	−0.004	−0.030	0.011	−0.016	−0.039	−0.042	−0.097*	−0.697
		(±0.001)	(±0.029)	(±0.004)	(±0.257)	(±0.766)	(±0.007)	(±1.386)	(±0.376)	(±0.563)	(±0.009)
	Δ Fast	0.094	0.096	0.073*	0.015	0.028	0.045	−0.047	−0.022	−0.325*	−1.324
		(±0.001)	(±0.031)	(±0.005)	(±0.254)	(±0.750)	(±0.007)	(±1.208)	(±0.365)	(±0.504)	(±0.008)
	Δ Instant	0.125	0.120	0.073*	0.032	0.025	0.047	−0.047	−0.007	−0.327*	−1.411
		(±0.001)	(±0.031)	(±0.005)	(±0.252)	(±0.750)	(±0.007)	(±1.201)	(±0.361)	(±0.501)	(±0.008)
MS	None	0.000	0.009	0.007	0.088	−2.060	−0.010	1.550	0.125	0.795	0.005
		(±0.002)	(±0.044)	(±0.005)	(±0.253)	(±0.528)	(±0.008)	(±1.077)	(±0.364)	(±0.410)	(±0.062)
	Δ Slow	−0.116	−0.127	0.044*	−0.085	−0.032	0.058*	−0.012	−0.078	−0.099*	−1.247
		(±0.002)	(±0.047)	(±0.004)	(±0.252)	(±0.413)	(±0.009)	(±1.092)	(±0.370)	(±0.407)	(±0.028)
	Δ Fast	0.186	0.184	0.156*	−0.002	−0.020	0.154*	0.005	0.030	−0.363*	−35.543
		(±0.002)	(±0.049)	(±0.004)	(±0.251)	(±0.464)	(±0.009)	(±1.123)	(±0.364)	(±0.365)	(±1.746)
	Δ Instant	0.186	0.184	0.160*	0.001	−0.021	0.161*	0.005	0.032	−0.372	−8.061
		(±0.002)	(±0.049)	(±0.004)	(±0.250)	(±0.463)	(±0.009)	(±1.123)	(±0.363)	(±0.363)	(±0.286)
PC	None	0.001	0.017	0.012	0.093	−2.006	−0.017	1.924	0.146	0.447	0.013
		(±0.003)	(±0.070)	(±0.007)	(±0.275)	(±0.472)	(±0.014)	(±3.535)	(±0.426)	(±0.302)	(±0.086)
	Δ Slow	0.090	0.102	0.060*	−0.030	−0.006	0.051	−0.114	−0.027	−0.106*	1.159
		(±0.004)	(±0.079)	(±0.007)	(±0.274)	(±0.494)	(±0.013)	(±1.549)	(±0.413)	(±0.288)	(±0.171)
	Δ Fast	−0.077	−0.042	0.106*	−0.166	−0.004	0.112*	−0.147	−0.165	−0.266*	−0.827
		(±0.004)	(±0.084)	(±0.008)	(±0.273)	(±0.479)	(±0.013)	(±1.439)	(±0.409)	(±0.276)	(±0.085)
	Δ Instant	−0.090	−0.057	0.109*	−0.184	−0.004	0.120*	−0.150	−0.179	−0.285*	−0.717
		(±0.004)	(±0.084)	(±0.008)	(±0.274)	(±0.477)	(±0.013)	(±1.437)	(±0.410)	(±0.269)	(±0.079)

The table displays the relative change between the performance of the divested portfolio and its benchmark (no divestment) for slow, fast, and instantaneous divestment. * refers to the p-value of the t-test being significant at a confidence level of 95%. This implies that the average risk profile is statistically different from the non-divestment benchmark. The highlighted cells indicate the highest (red) and the lowest (green) difference in the performance for each risk profile. The box around the portfolio type indicates the closest to the original ETF according to the excess return and tracking error.

The results are consistent for the GMV portfolios, see Figs. 20 to 22.[56] Large sectors with several constituents, such as Financial Services and Communication Services tend to contribute greater variance to the overall portfolio and lead to higher variations due to divestment. For all sectors, SEVRs fall while SECs improve. Fig. 23 also demonstrates that PDRs of the divested AEWs and GMVs portfolios are superior to the original, particularly for the 70% divestment.[57] The GMVs permit a short position to reduce portfolio volatility, therefore their PDRs are much superior to those of the AEWs. Thus, portfolios with better environmental score are more diversified than the original portfolios.

Thus, FTSE 100 divestment strategies based on ESG screening can significantly impact portfolio diversification. Divesting from businesses with low environmental ratings on the FTSE 100 may improve portfolios diversification, while maintains the robustness of the covariance structure. This implies that portfolio diversification is possible while adhering to principles of responsible investing. However, if ratings of ESG scores are not accurately standardized and correctly reflect their intended assessments, this can have a material impact on performance. This contributes to an ongoing debate regarding the credibility of ESG scores (Berg et al., 2022).

6. Conclusion and financial implications

The impact of a company's carbon footprint on asset prices and the risk of stranded fossil fuel assets in reserve-owning companies can have a significant impact on investors' portfolios (Conolly et al., 2017). Divestment provides a means to protect investors from the "carbon bubble". More recently, the integration of environmental risks into the investment process has made divestment consistent with the fiduciary duties of investors, removing the prior held view of the fiduciary conflict between maximizing shareholder value and considering climate risk. However, the mechanisms by which divestment occurs can also significantly impact the risk and return of investors.

We analyze mechanisms to develop dynamic divestment strategies and schedules, offer a comprehensive assessment of their impact on investment performance, and further relate this analysis to investor demographic attributes such as management fees, dividends yields and carbon footprint reductions. We provide a comprehensive assessment of divestment practice based on three case studies. The first case study investigates divestment strategies from the broad S&P 500 asset set, while the second case study takes a more targeted approach to explore divestment in ETFs with high carbon concentration. While, carbon concentration is the typical screening criterion of divestment strategies,

[56] The differences in SVCR, SEVR, and SEC between the original and all divested portfolios are statistically significant, as determined by a t-test at the 95% confidence level.

[57] The PRDs of the original and all divested portfolio are statistically significant different at a 95% confidence level under the t-test assumption for both AEWs and GMVs.

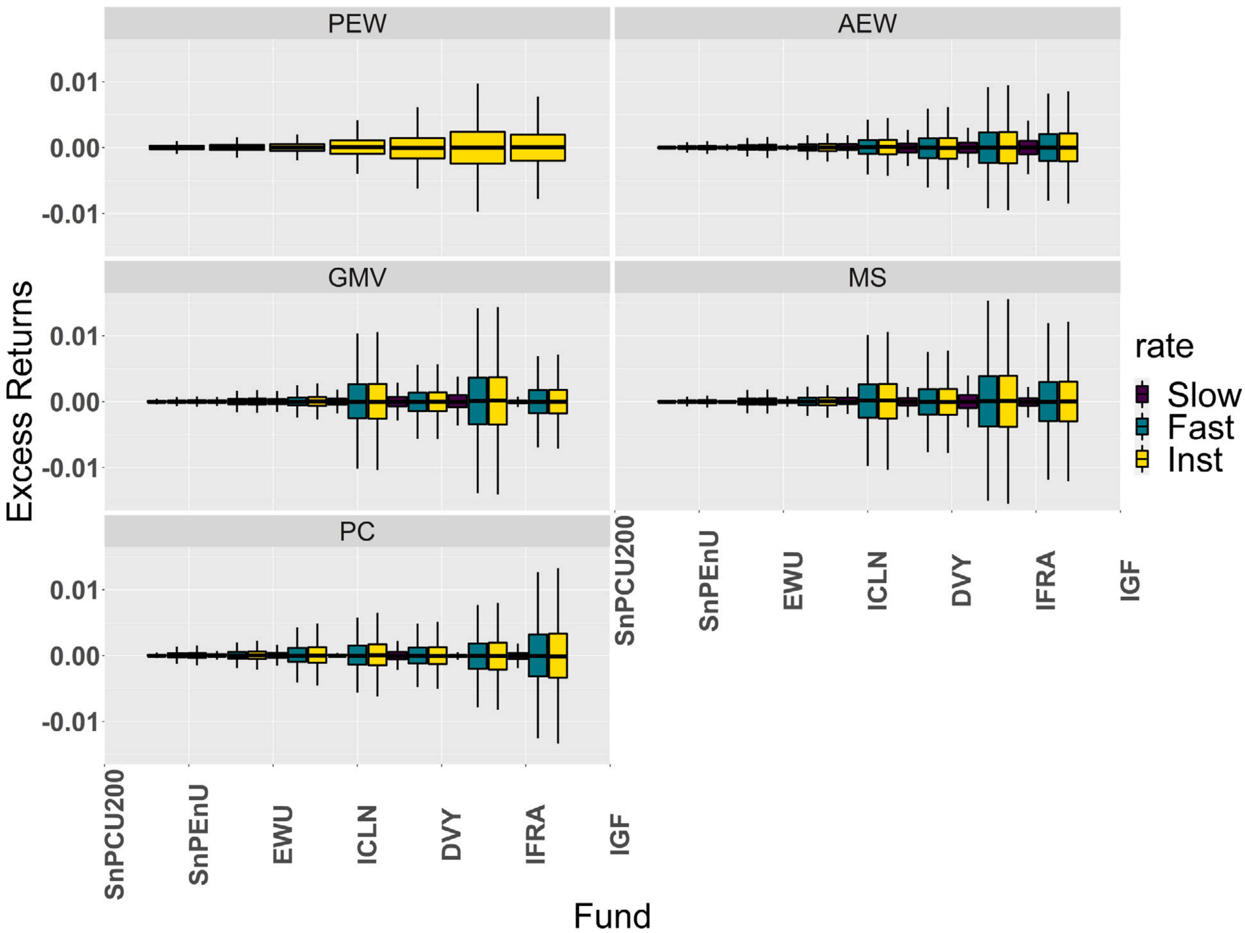


Fig. 9. Boxplots of the excess returns separated by the types of the portfolios.

which we also employ in the first two case studies, the third case study analyses ESG based screening for divestment decisions.[58]

Regarding the impact of divestment strategies on portfolio risk/returns and carbon reduction strategies, the key findings of our study follow. The analysis of the S&P 500 case study reveals that the stability of the risk/return and the mean returns (between original and divested portfolios) are not impacted by the rate of divestment. On the contrary, the risk profile of divestment portfolios (compared to non-divestment portfolios) is positively affected by the rate of divestment and the divestment set, with rapid (instantaneous and fast) divestment strategies having the most pronounced effects in the expense of higher tracking errors. Furthermore, by combining the findings from the second case study on ETFs, we conclude that across all portfolio strategies, as the size of divestment assets increases (from CU200 divestment to energy and utilities divestment to high concentration ETFs), the rate of divestment makes a measurable impact on the stability of the risk/return portfolios profiles, with fast rates introducing the most variation.

In terms of carbon reduction efficiency (from the S&P 500 case study), we find that slow divestment is optimal, not only based on the risk/return profile of a portfolio but also about the benefit of the carbon reduction effect arising from reinvested capital being re-deployed to other industries or sectors not contained in the divestment list of assets. Also, divesting by withdrawing capital versus shorting stock and reinvesting shows distinct offers carbon reduction benefits. Furthermore, divesting from high-carbon sectors (energy and utilities) and reinvesting in low-carbon sectors (healthcare and consumer staples) is effective for carbon reduction and portfolio diversification. Thus, effective divestment strategies need careful reinvestment to maintain portfolio performance and diversification.

Relative to dividend yields and management fees, which has direct applicability to the ETFs case study, we find that carbon divestment in ETF portfolios tends to relate to lower dividend yields and management fees. Investors in funds with low carbon footprints or high ESG scores can expect lower dividend yields at any rate of divestment. There is typically a penalty for requiring fund managers to meet ESG targets, reflecting higher management fees. These findings highlight the complexities and trade-offs involved in divestment strategies.

Lastly, the impact of divestment practices based on Environmental, Social, and Governance (ESG) ratings, as investigated in the FTSE 100 case study, shows that divesting based on ESG scores can negatively impact the risk/return profile of the portfolio due to reduced diversification. While divesting low ESG-scoring assets can reduce a portfolio's environmental footprint, it can also lead to decreased diversification and lower overall ESG scores. The study highlighted the critical role of ESG in divestment decisions and underscores the trade-offs between ESG improvements and potential reductions in diversification and portfolio performance.

Several practical financial implications stem from our findings, in relation to the speed of divestment, the re-investment and leverage decisions, and management fees considerations. Firstly, rapid rates of

[58] An examination of divestment within a dynamic asset universe that accommodates the addition of new equities and other asset classes (e.g., fixed income), and an inquiry into optimal reinvestment strategies tailored to other particular objectives, such as reinvesting to achieve minimum portfolio variance within the set of investable assets, necessitate more complex mathematical models which can be explored in future research. Furthermore, an exploration of the underlying factors contributing to risk spillovers can be another interesting research direction.

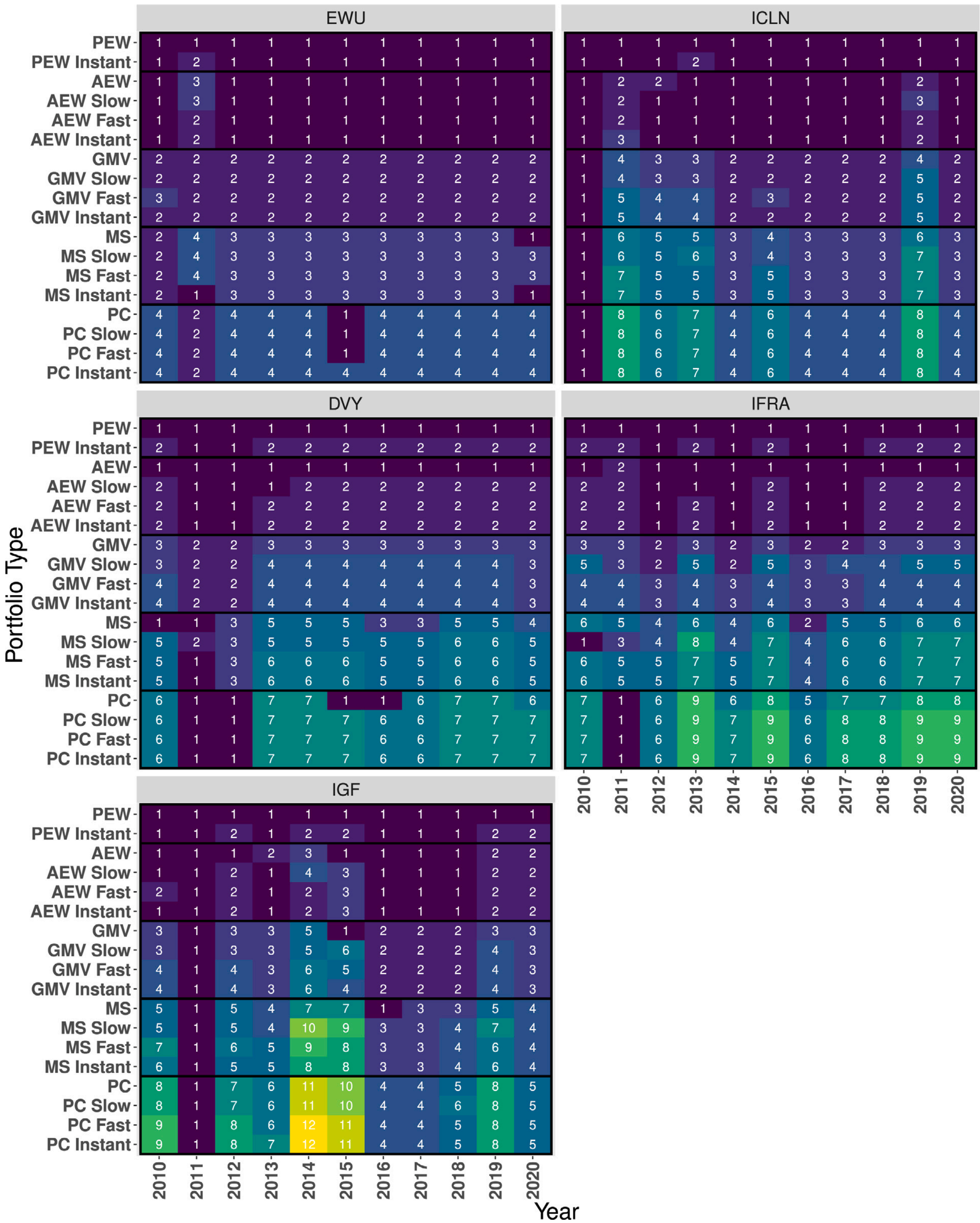
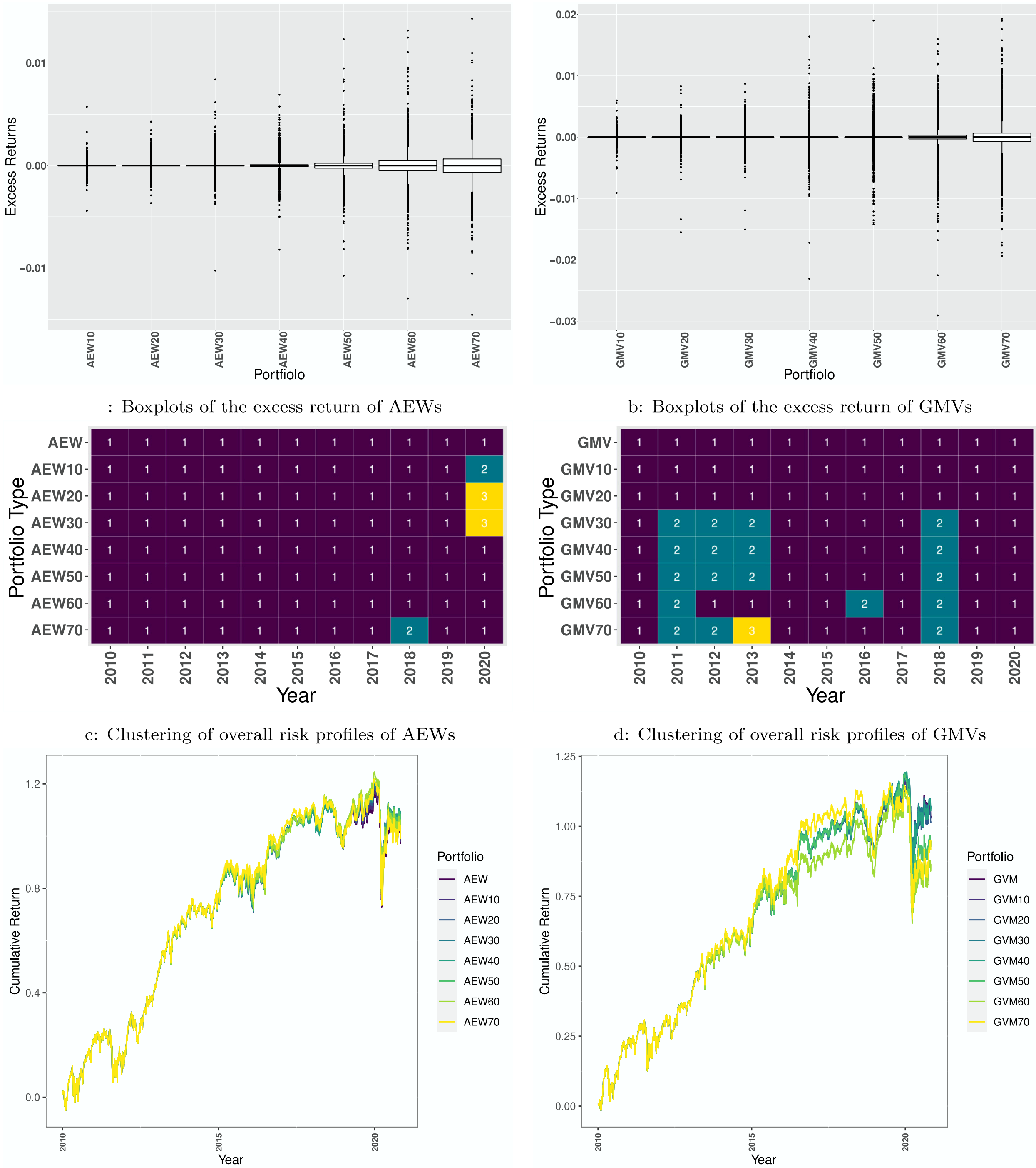


Fig. 10. Clustering overall performance of core-type portfolio ETFs.



: Boxplots of the excess return of AEWs

b: Boxplots of the excess return of GMVs

c: Clustering of overall risk profiles of AEWs

d: Clustering of overall risk profiles of GMVs

e: Cumulative return of AEWs

f: Cumulative return of GMVs

Fig. 11. Results from AEW and GMV constructed by the assets in FTSE 100 and their divested portfolios with several proportions of divestable assets of 10%, 20%, 30%, 40%, 50%, 60%, and 70% according to the environmental score.

divestment introduce instability and more risk in the portfolios performance, and consequently more tracking error. Thus, fund managers who aim to reduce carbon in an existing portfolio but need to control performance tracking may use a slow divestment schedule to avoid the instantaneous change in performance in the short term. If tracking performance is not a concern, then fast divestment strategies can be preferred as they accelerate the establishment of low-carbon risk portfolios and better control leverage in heavy shorting asset allocations. Secondly, there are important consideration regarding divesting from fossil-fuel intensive sectors and the reinvestment of this capital in other assets[59] compared to allowing divestment by using leveraged positions. Reinvested assets or sectors also emit carbon, as it cannot be assumed that reinvestment automatically leads to investment in, for example, renewables. Despite the increase in clean energy options, the limited scale

[59] The reinvestment allocation decision is based on risk profiles. A direction for further research could be determining the reinvestment allocation based on other types of constraints, such as based on carbon efficiency, see Andersson et al. (2016) for a simple dynamic strategy based on carbon footprint.

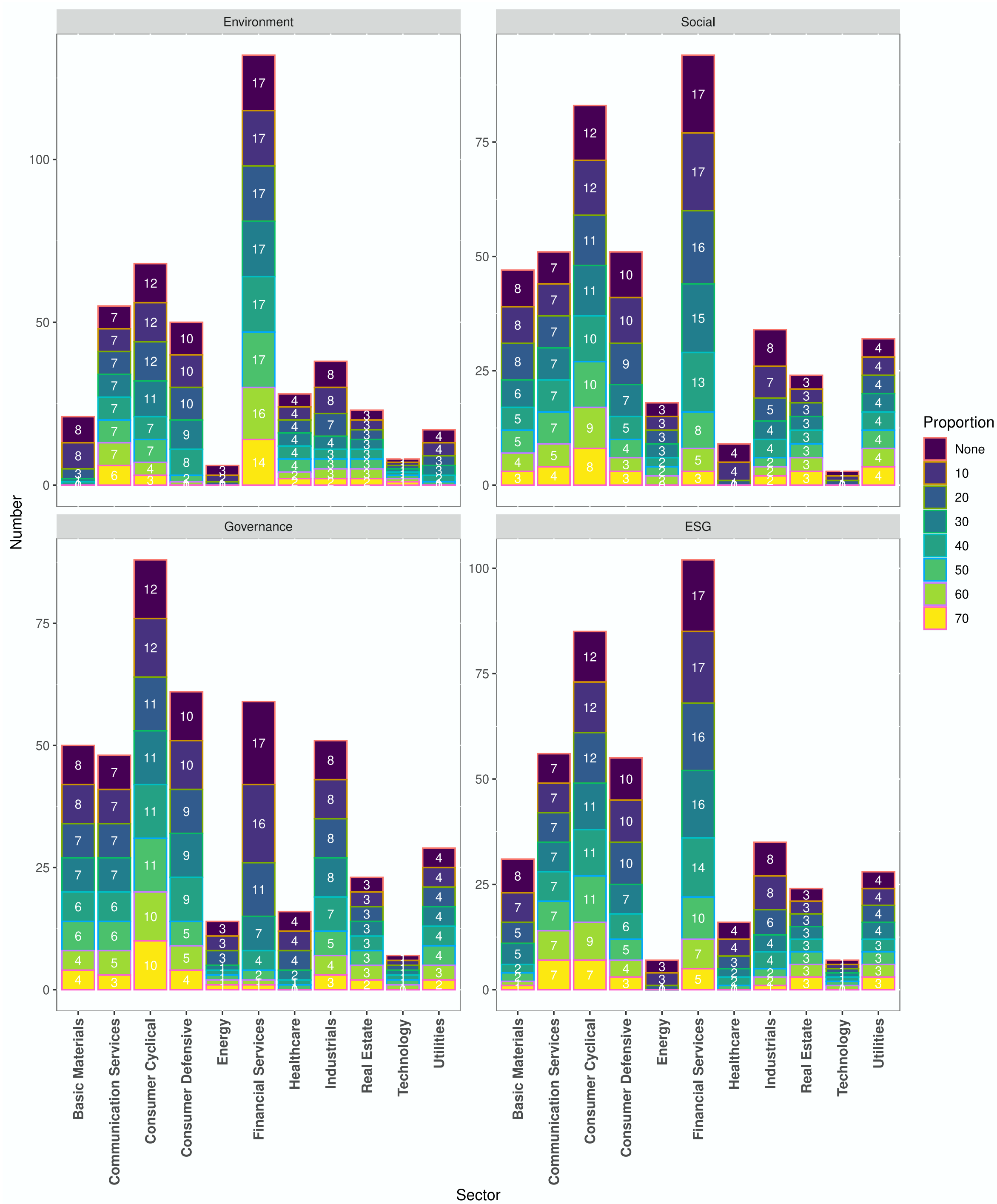


Fig. 12. Number of the remaining assets in portfolios with assets in FTSE 100 after divestment with proportions 10% to 70% ranking by the environmental, social, governance, and overall ESG scores separated by sectors.

is a major obstacle. From an environmental point of view, the divestment of energy and utilities in S&P 500 portfolios reduces the carbon footprint marginally, with leveraged positions in energy and utilities strongly and negatively impacting the carbon reduction targets.[60] Note also that the lower levels of gross leverage make it significantly easier to attract funding, decrease borrowing costs, and reduce the potential for erosion of equity value, but may attract higher tracking errors. Lastly, investors tend to pay a penalty (in the form of management fees) for requiring fund managers to meet carbon reduction targets fast. However, the financial case for the divestment of fossil fuels is strong with current market conditions and the outlook facing the coal, oil, and gas sectors. A potential increase in management fees can be settled by negotiation, with endowments and small funds that already pay fees for services making adjustments to include portfolio rebalancing. This study informs industry and academia on effective gradual divestment practices and underscores the importance of accounting for investors' demographic attributes of practical relevance.

[60] A direction for further research could be addressing the other social and environmental concerns that may arise from reinvestment, even if divestment does reduce carbon emissions.

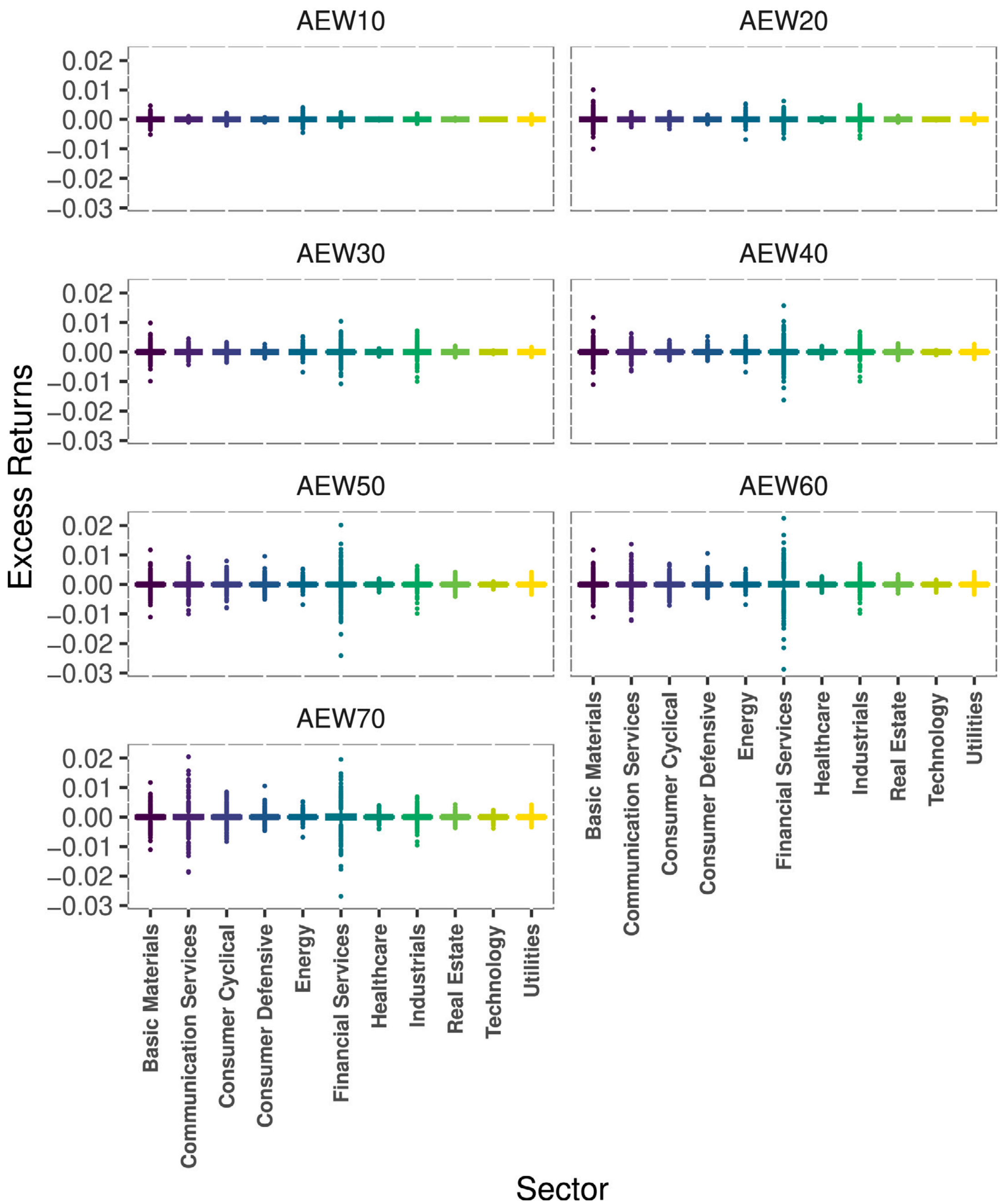


Fig. 13. Boxplots of the excess returns of the divested AEWs with several proportions of divestable assets of 10%, 20%, 30%, 40%, 50%, 60%, and 70% according to the environmental score, constructed by the assets in the index FTSE 100 by sectors.

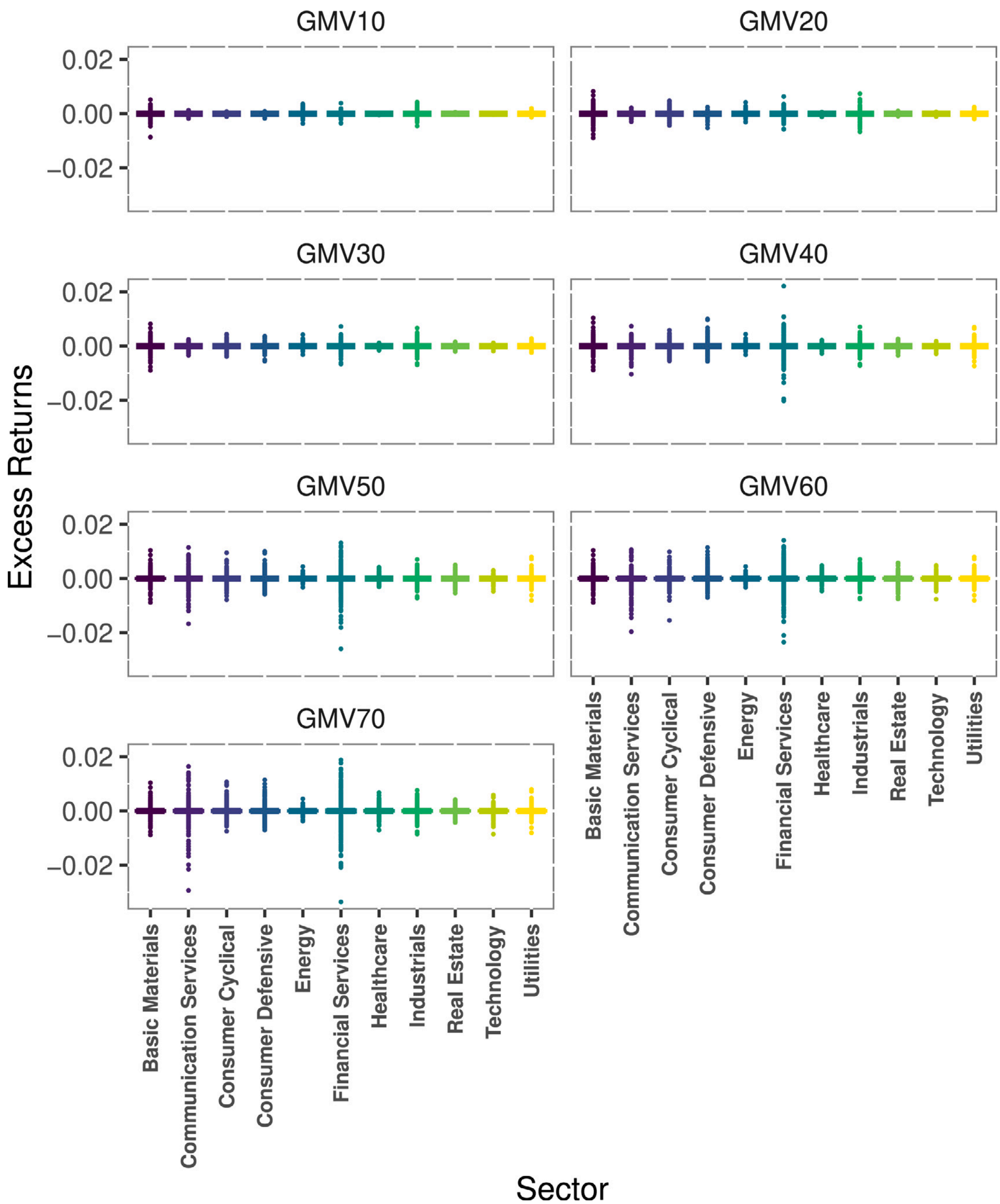
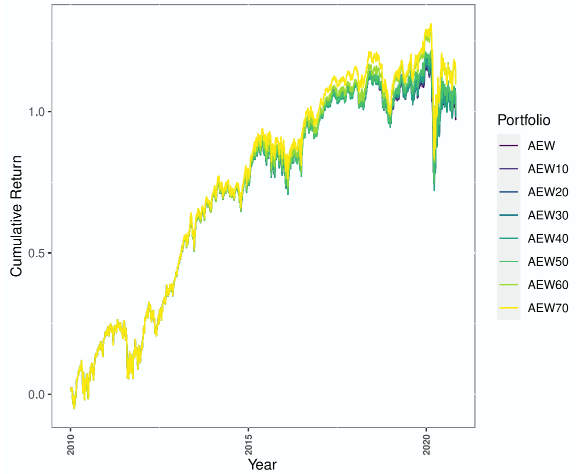
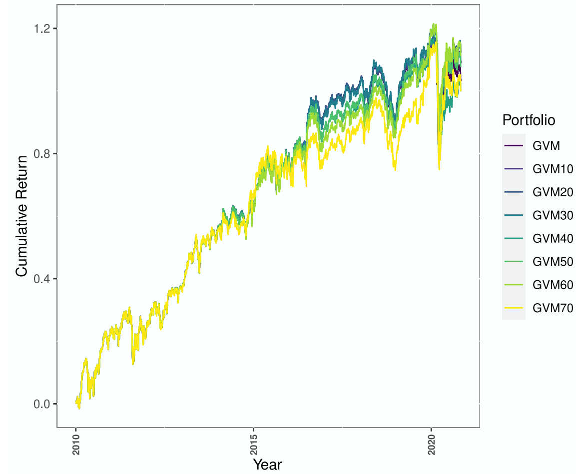


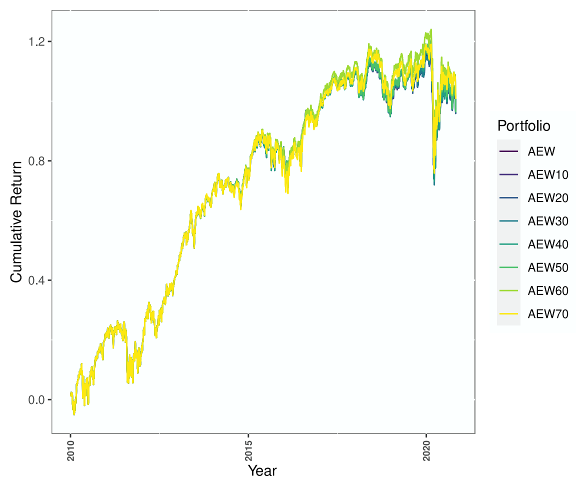
Fig. 14. Boxplots of the excess returns of the divested GMVs with several proportions of divestable assets of 10%, 20%, 30%, 40%, 50%, 60%, and 70% according to the environmental score, constructed by the assets in the index FTSE 100 by sectors.



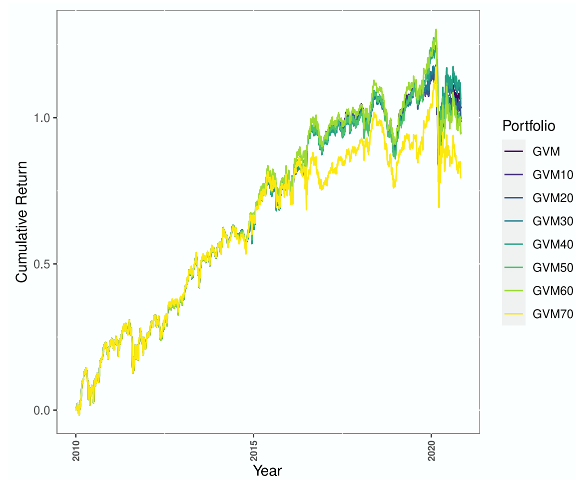
a: Cumulative return of AEWs divested based on social score rankings



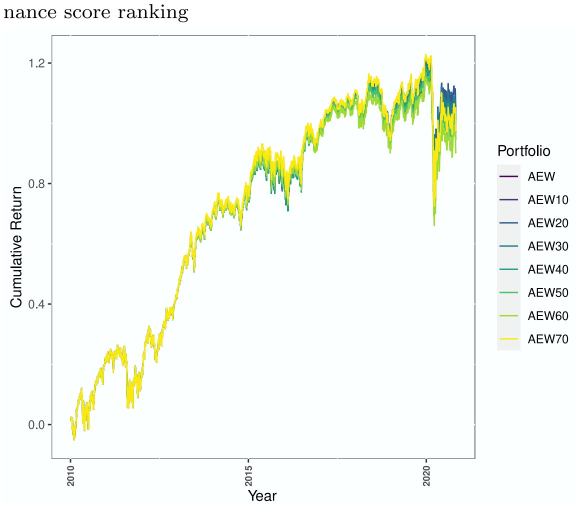
b: Cumulative return of GMVs divested based on social score ranking



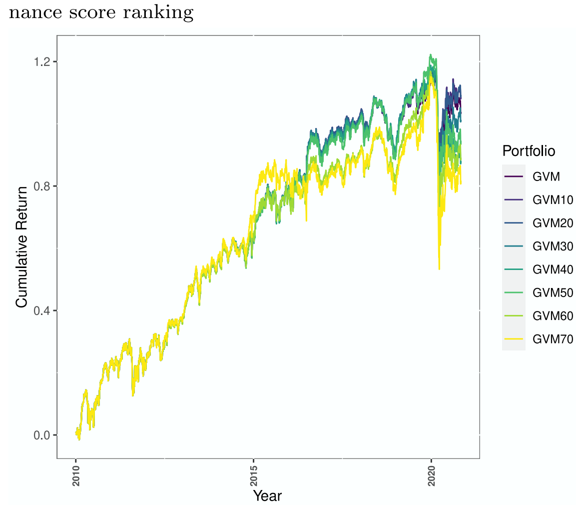
c: Cumulative return of AEWs divested based on governance score ranking



d: Cumulative return of GMVs divested based on governance score ranking



e: Cumulative return of AEWs divested based on overall ESG score ranking



f: Cumulative return of GMVs divested based on overall ESG score ranking

Fig. 15. Cumulative returns of the AEW and the GMV constructed by the assets in FTSE 100 and their divested portfolios with several proportions of divestable assets of 10%, 20%, 30%, 40%, 50%, 60%, and 70% according to the S, G and overall ESG scores.

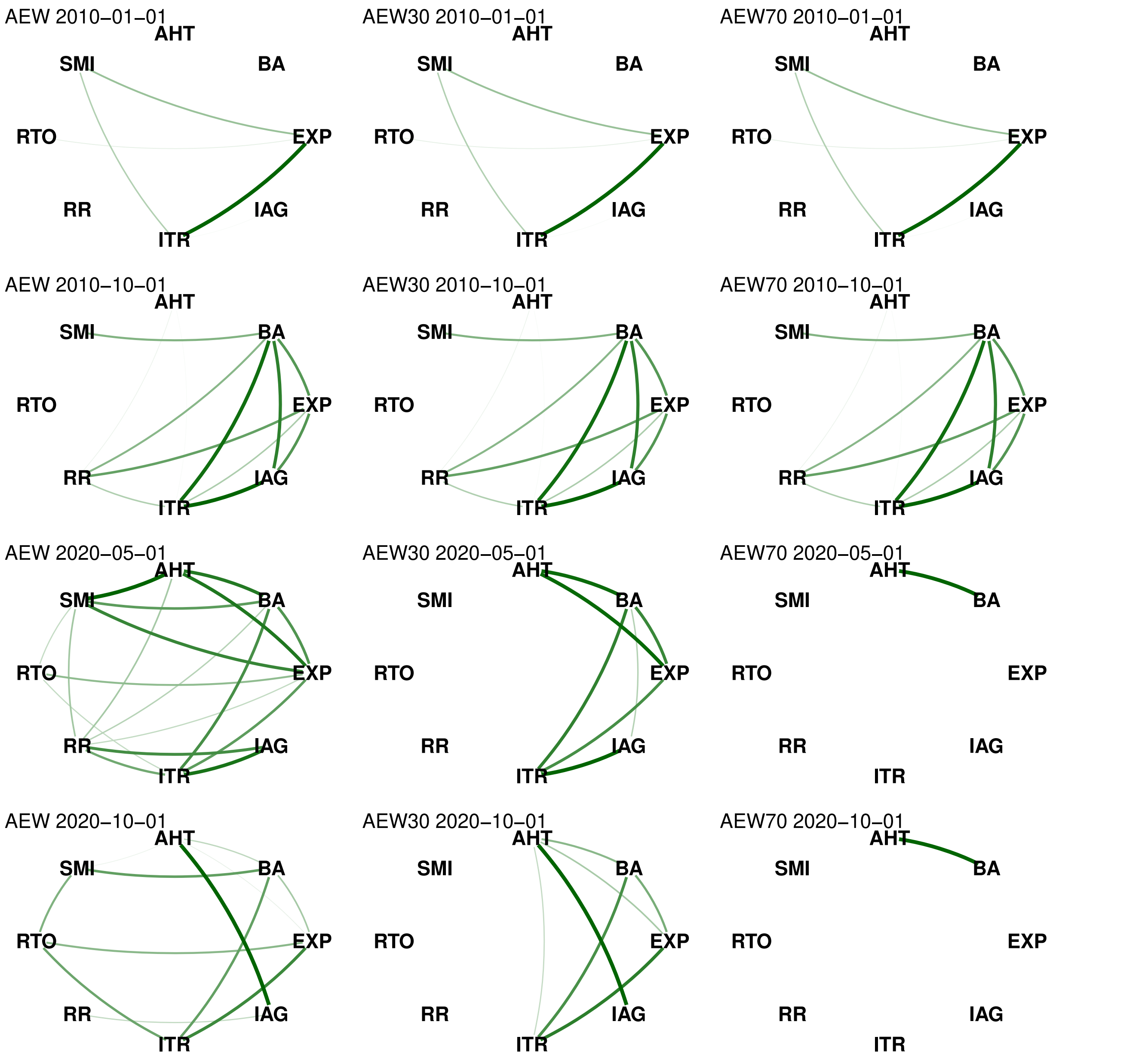


Fig. 16. Network of the regularized covariance from the glasso of the AEWs in industrials sector; Here we dropped .L after ticker for visualization purposes.

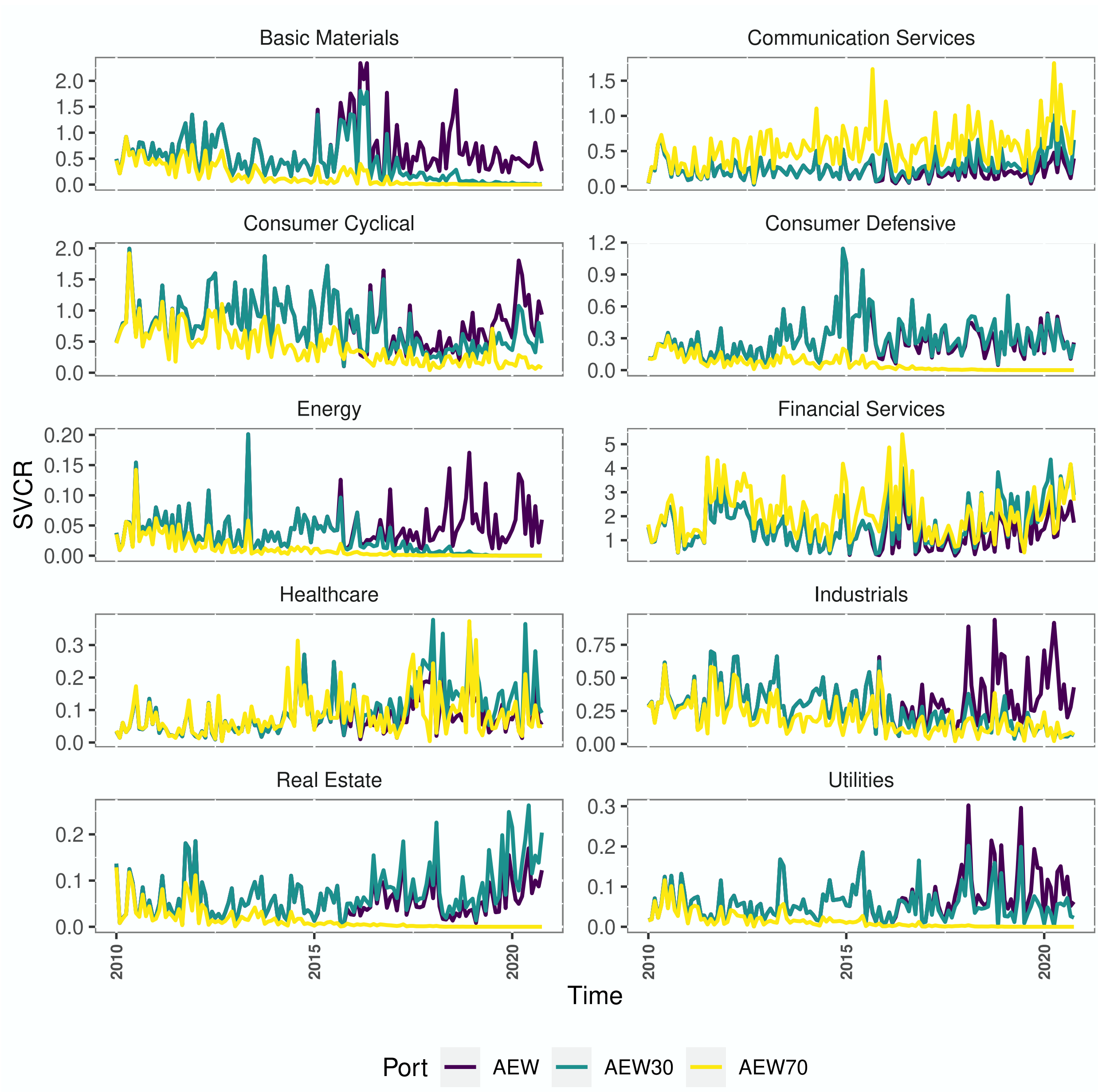


Fig. 17. The dynamic SVCR of the AEW and the AEWs divested by the environmental score of 30th and 70th percentiles.

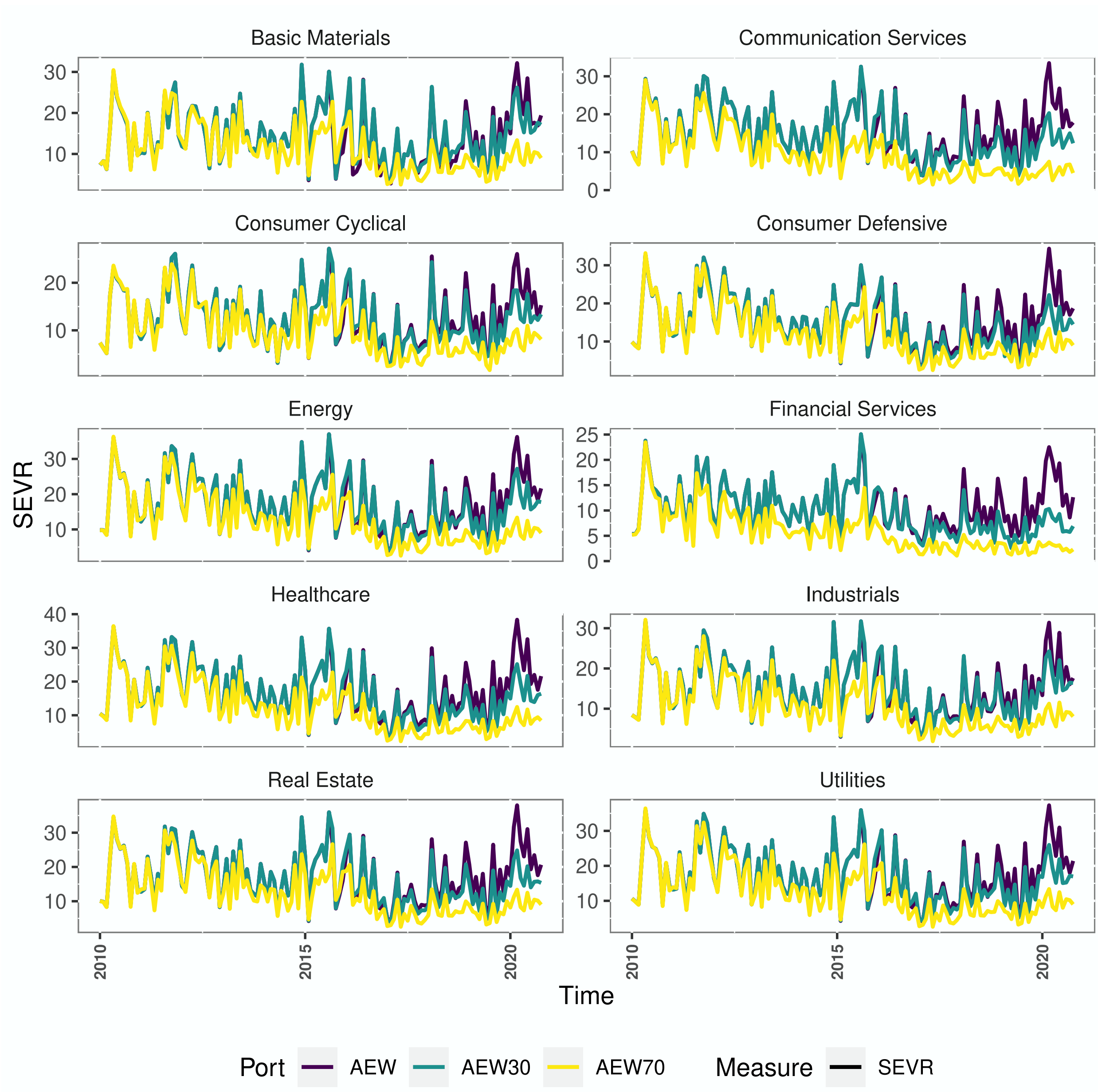


Fig. 18. The dynamic SEVR of the AEW and the AEWs divested by the environmental score of 30th and 70th percentiles.

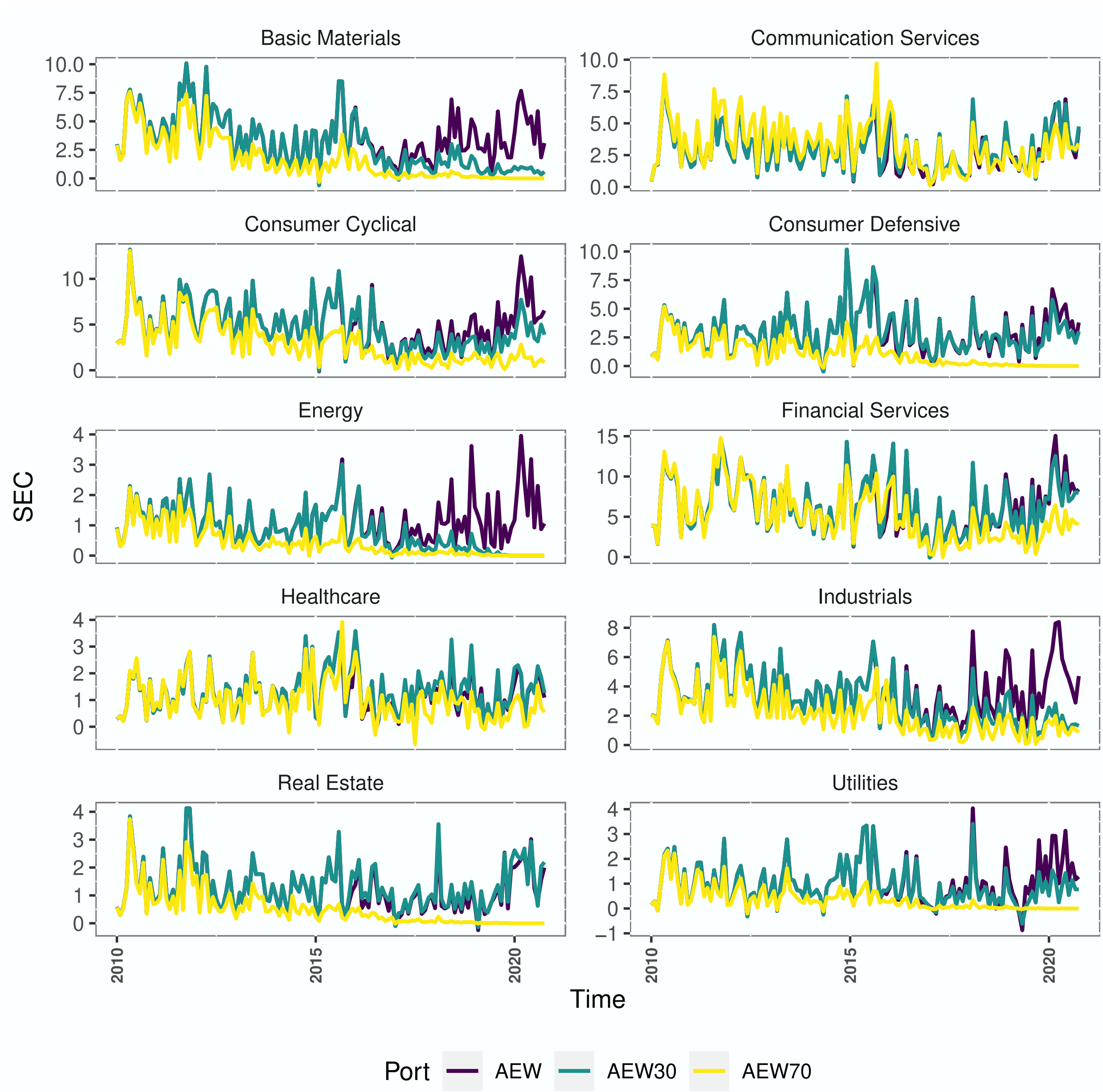


Fig. 19. The dynamic SEC of the AEW and the AEWs divested by the environmental score of 30th and 70th percentiles.

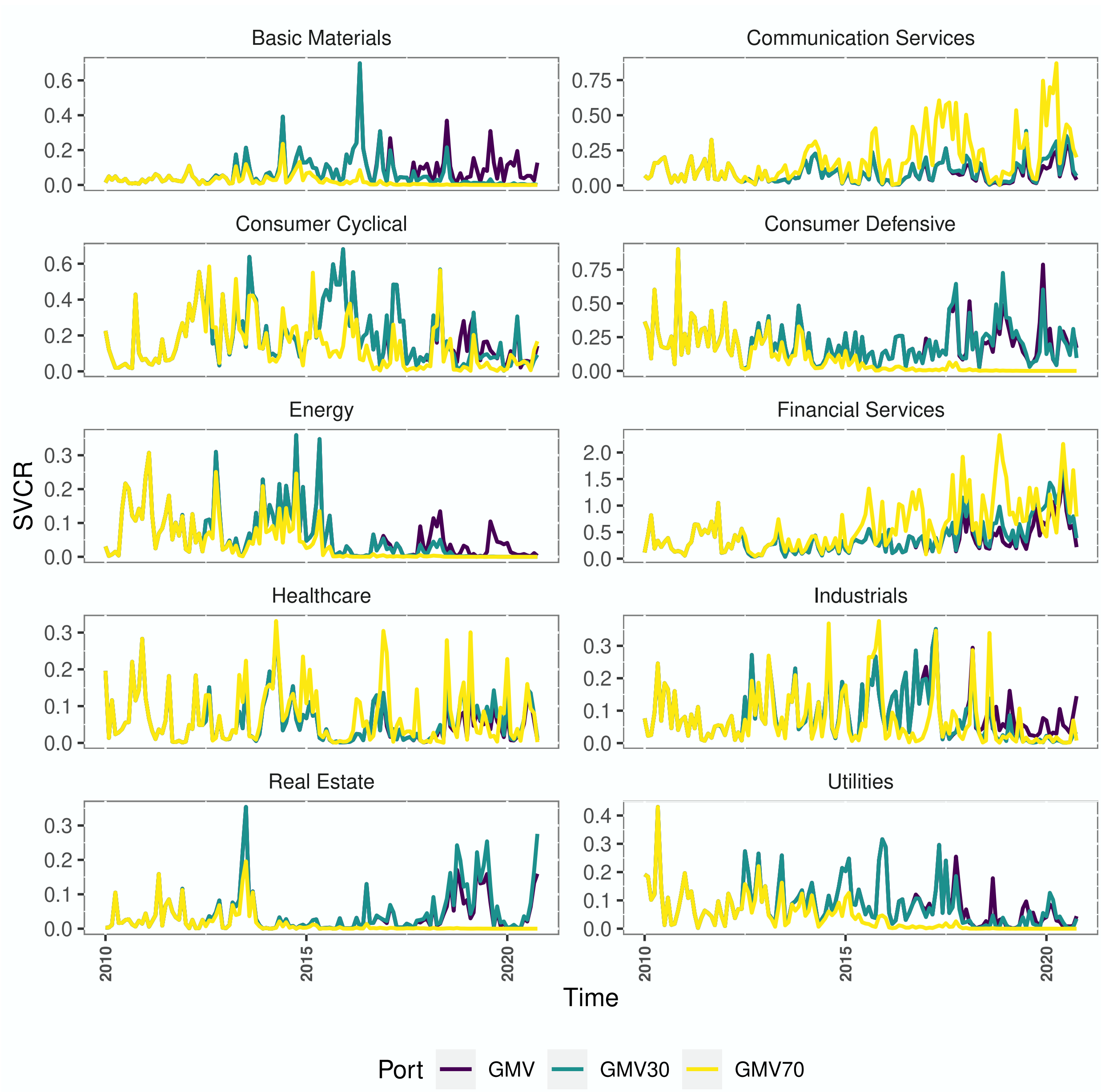


Fig. 20. The dynamic SVCR of the GMV and the GMVs divested by the environmental score of 30th and 70th percentiles.

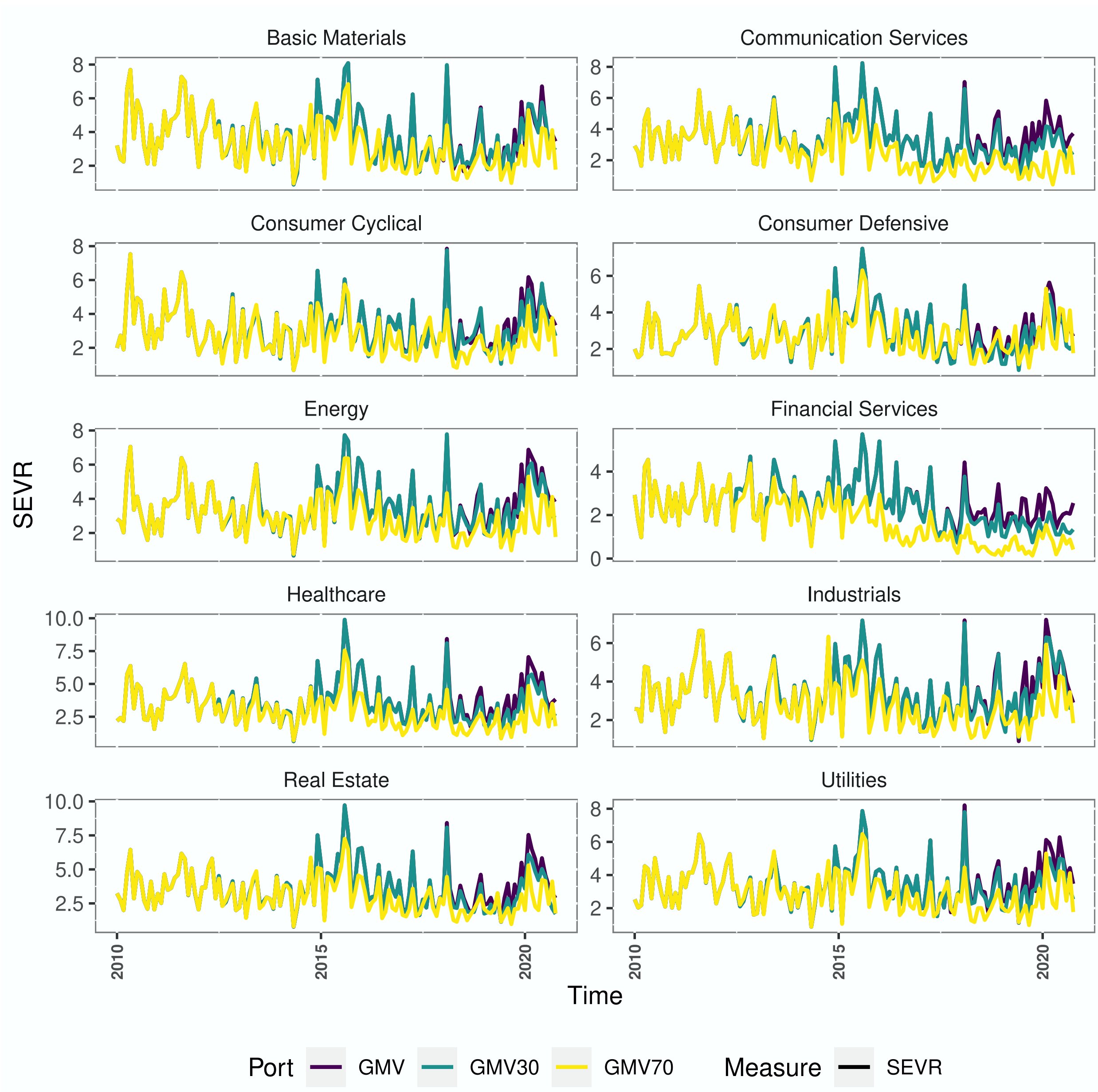


Fig. 21. The dynamic SEVR of the GMV and the GMVs divested by the environmental score of 30th and 70th percentiles.

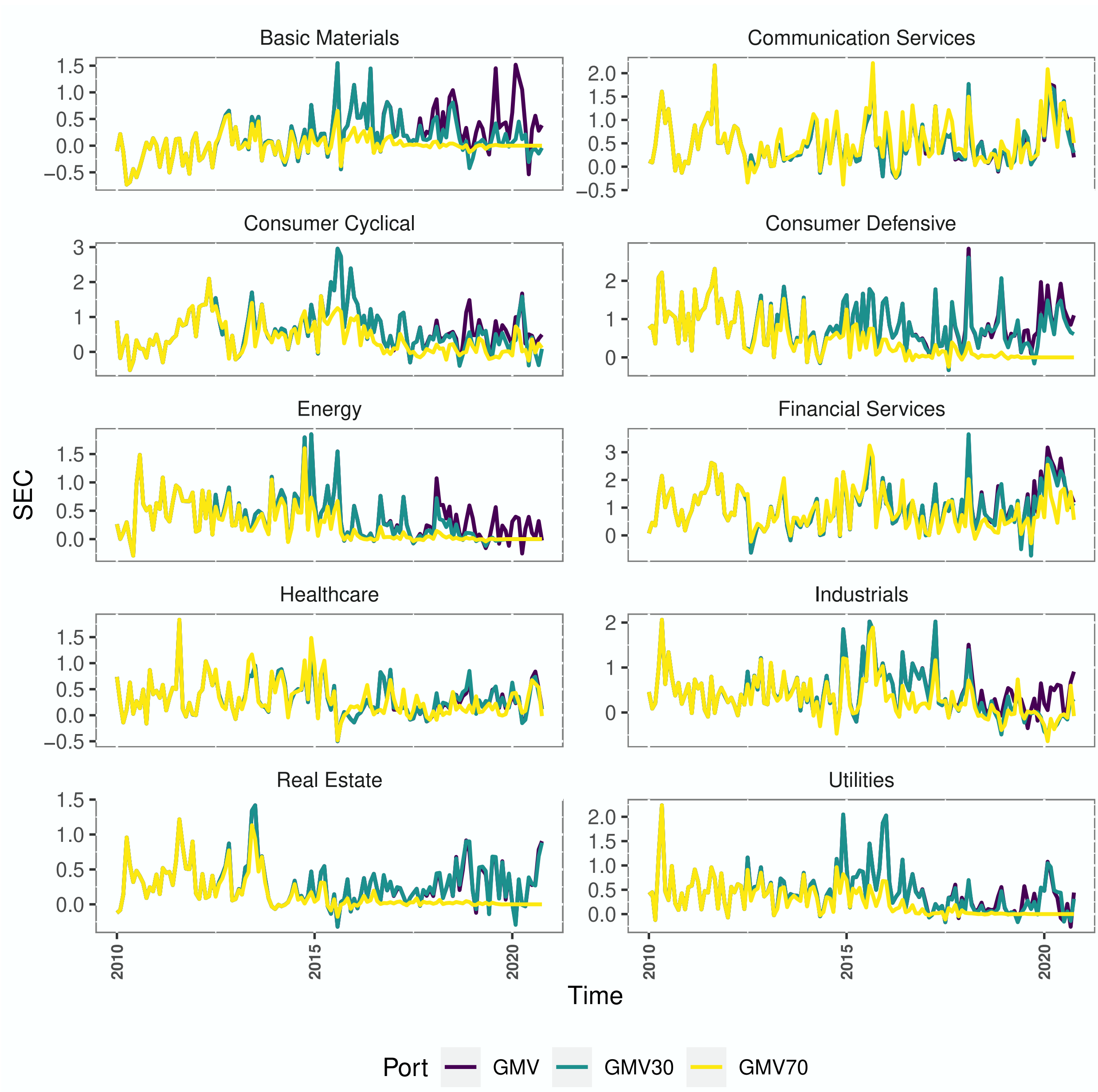


Fig. 22. The dynamic SEC of the GMV and the GMVs divested by the environmental score of 30th and 70th percentiles.

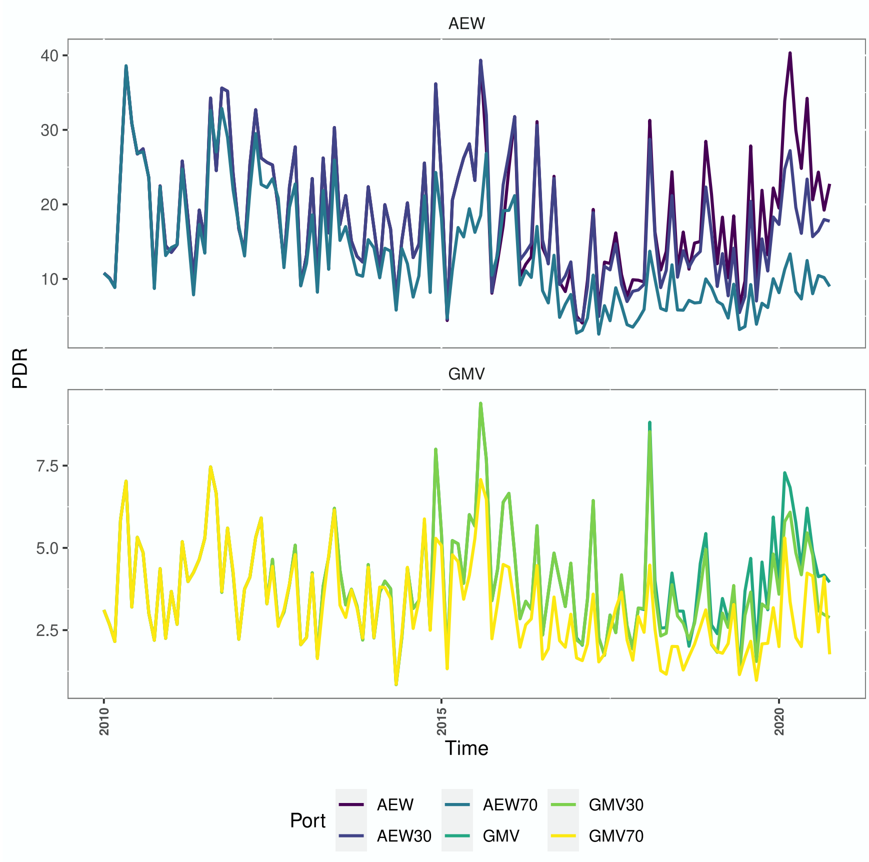


Fig. 23. Portfolio diversification ratio of the AEWs and GMVs with divested 30% and 70% of the worsen environmental score.

CRediT authorship contribution statement

Pasin Marupanthorn: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Christina S. Nikitopoulos:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Formal analysis, Conceptualization. **Eric D. Ofosu-Hene:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Gareth W. Peters:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Kylie-Anne Richards:** Writing – review & editing, Resources, Funding acquisition, Formal analysis, Conceptualization.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107724.

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