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Importance of portfolio optimization in SRI and conventional pension funds

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Abstract

This study assesses the portfolio concentration of socially responsible investment (SRI) pension funds, which may be subject to a potentially limited asset universe and have a higher concentration and lower performance than conventional funds. Nonetheless, in contrast to previous studies on SRI funds, this study considers the information-advantage theory, positing that skilled managers should increase their concentration in assets in which they possess valuable information, departing from optimization models to achieve outperformance. This study first compares actual fund concentration with concentration obtained from several traditional and modern portfolio optimization techniques (minimum variance, global minimum variance, optimal portfolio, naïve diversification, risk parity, and reward-to-risk timing) to understand whether SRI pension funds concentrate portfolios and deviate from optimization model solutions. Unlike previous studies, the actual fund assets are considered in the optimization models to take into account the real investment profiles of SRI funds. The results indicate that SRI pension funds are less concentrated than conventional funds, and SRI and conventional pension funds largely diversify their portfolios, presenting lower concentration than portfolios formed with the optimization models. Furthermore, concentration strategies positively influence performance in SRI and conventional funds, revealing the use of information advantage. However, SRI and conventional fund managers present poor skills (picking, timing, and trading) to exploit information advantages due to overconfidence issues, which affect performance with concentration strategies. This situation may be modified if SRI funds follow modern optimization models and conventional funds follow traditional optimization models, improving managers' performance and skills.

Keywords: Concentration, Managerial skill, Pension fund, Portfolio optimization, SRI

Introduction

Traditional asset-pricing theories propose that portfolios with a limited asset universe, such as socially responsible investment (SRI) funds, are subsets of the optimal portfolio (Barnett and Salomon, 2006; Gangi and Varrone 2018). As a result, SRI funds develop more concentrated portfolios and achieve lower performance than traditional funds focused on financial factors; that is, the so-called conventional funds (Barnett and Salomon, 2006; Gangi and Varrone 2018). Nevertheless, this argument is empirically underexplored because the SRI niche is still growing, and the SRI boundaries have been

insufficiently studied. With currently available information, only Helliard et al. (2022) compared the concentration in the top-10 holdings of SRI and conventional mutual funds with basic mean tests, yet did not examine the overall SRI-fund concentration. Hence, whether SRI funds develop more concentrated portfolios than conventional funds and whether this concentration results in underperformance remain unanswered in the literature. This study attempts to fill this research gap by considering the overall fund concentration and the novel perspective of information-advantage theory to better understand SRI-fund concentration strategies.

Furthermore, the study of portfolio concentration in SRI pension funds deserves special attention because their motivation, time horizon, clientele, and investment restrictions may further limit their asset universe. Pension funds are subject to stricter regulations than other institutional investors because they should manage large retirement savings in the best interest of beneficiaries with long-term and prosocial investments (Sandberg 2013). Additionally, pension funds are one of the largest long-term institutional investors in SRIs (Cox et al. 2004). Consequently, SRI pension funds might face a narrower asset universe due to their dual nature as retirement-saving vehicles and socially responsible investments. This may result in concentration patterns that differ from mutual funds.

This study examines the concentration patterns of SRI and conventional equity pension funds in the United Kingdom's (UK) world-leading pension-fund industry. Specifically, the SRI and conventional pension fund datasets are matched using the nearest-neighbor matching with a propensity score estimated using a logistic similarity measure based on fund features. Moreover, the fund concentration of SRI and conventional pension funds is compared using nonparametric and parametric methodologies.

In addition, there are three aspects to consider when analysing the SRI-fund concentration. First, if SRI funds are subsets of the optimal portfolio (Barnett and Salomon, 2006; Gangi and Varrone 2018), their asset allocation will differ from that provided by optimization models. However, many portfolio optimization models exist, offering different solutions based on the rationale of each model. Thus, SRI portfolios may not follow traditional optimization techniques but present correct diversification. Second, traditional asset-pricing theories do not consider the informational advantage theory. The latter theory proposes that more concentrated portfolios may be optimal when fund managers concentrate on assets in which they possess valuable information, leading to outperformance (Choi et al. 2017). Third, the two previous considerations may be affected by managerial skills because portfolio optimization models may not capture managerial skills, and the success of concentration strategies with information advantage is subject to managers' skills in processing and exploiting valuable information. Hence, in contrast with previous research, this study considers these three aspects.

This study first compares the actual fund concentration with the concentration that the funds would have obtained using several traditional and modern portfolio optimization models (the minimum variance, the global minimum variance, the optimal portfolio, the naïve diversification, the risk-parity, and the reward-to-risk timing models). Contrary to past research, optimization models start from the actual fund assets to consider the funds' investment profiles and managers' information signals in the optimization process. This study also addresses the scarcity of analyses on SRI optimization,

which simulated SRI portfolios without considering actual SRI-fund investment patterns (Oikonomou et al. 2018). Thus, previous studies did not explore the argument that SRI funds develop more concentrated portfolios and underperform due to a limited asset universe. The results of this study will also determine whether the asset allocations developed by the SRI and conventional pension funds deviate from the optimization-model solutions, assessing the impact of the asset allocation technique on fund performance. Furthermore, this study analyses the concentration–performance relationship from an information-advantage perspective and whether optimization models can guide managers' asset allocations to exploit informational advantages and improve skills, concentration strategies, and performance.

The findings of this study demonstrate that SRI funds can overcome the limited asset universe boundary and build less concentrated portfolios than conventional funds. Contrary to expectations, pension funds largely diversify their portfolios, approaching naïve diversification. The results also indicate that SRI and conventional managers have poor picking, timing, and trading skills to manage information advantages. Optimization models can help managers improve fund performance and skills through better asset allocation decisions. Overall, these results contribute to filling the gap in the concentration–diversification dilemma of UK SRI and conventional equity pension funds.

The remainder of this study is organized as follows. Sect. "Literature review and research hypotheses" presents the literature review and the research hypotheses. Sect. "Market overview, data, and variables" presents a market overview, data, and variables. The methods and empirical findings are presented in Sect. "Empirical findings". Sect. "Conclusions" presents the conclusions.

Literature review and research hypotheses

Diversification is the basis of portfolio asset allocation (Platanakis et al. 2019); however, portfolios with a limited asset universe, such as SRI funds, may be forced to build concentrated portfolios, departing from optimization models' asset allocation (Barnett and Salomon, 2006; Gangi and Varrone 2018). Previous studies have found that conventional mutual fund managers sometimes diversify portfolios to a lesser extent than the level recommended by portfolio choice models, obtaining positive outcomes (Choi et al. 2017; Fulkerson and Riley 2019; Kacperczyk et al. 2005). This evidence is consistent with the information advantage theory (versus the traditional asset-pricing theory), positing that deviations from the perfectly diversified market portfolio may be optimal for some investors due to the information advantages in some assets (Merton 1987; Van Nieuwerghugh and Veldkamp 2010). According to the information-advantage theory, managers who know more about a financial/nonfinancial risk factor than average managers tilt their portfolios significantly toward assets loading on that factor, deviating from the perfectly diversified market portfolio (Choi et al. 2017; Fulkerson and Riley 2019). Hence, from the information advantage perspective, SRI managers may have more specialized knowledge about environmental, social, and governance (ESG) risks and use this knowledge to concentrate their portfolios on some ESG assets. If SRI funds use valuable ESG information to select superior firms, the limited ESG asset universe may provide investment opportunities, undermining the argument that SRI funds concentrate portfolios and underperform due to the limited asset universe. With currently available

information, only Helliard et al. (2022) compared cash percentages and the concentration in the top-10 holdings of SRI and conventional mutual funds. Applying a t-test mean, Helliard et al. (2022) found that SRI funds have smaller cash holdings and lower investments in the top-10 portfolio holdings. Although these authors did not research the overall fund concentration (unlike this study), their results indicate that SRI funds can develop less concentrated portfolios than conventional funds. Thus, portfolio concentration is expected to depend on managers' information rather than on the conventional/SRI nature of the fund. Considering these arguments, the first hypothesis is as follows:

H1. SRI pension funds do not present more concentrated portfolios than conventional pension funds.

Although the concentration of SRI funds may pursue to exploit information advantages, the problem of SRI-fund concentration is also related to the failure of the diversification bases of modern portfolio theory in SRI funds because ethical portfolios are subsets of the market portfolio due to complying with ESG standards (Barnett and Salomon, 2006; Bauer et al. 2006; Gangi and Varrone 2018). Oikonomou et al. (2018) explained that SRI funds may outweigh optimization model solutions. Nevertheless, no previous studies have analyzed the portfolio optimization model followed by SRI funds or whether SRI funds deviate from optimization model solutions. The scarce literature on SRI optimization is limited to exploring how to construct SRI portfolios based on Markowitz's mean–variance optimization frameworks (Ballesterio et al. 2012; Utz et al. 2014). However, Markowitz optimizations suffer from significant estimation risk, resulting in input-sensitive solutions and unstable and poorly diversified portfolios (DeMiguel et al. 2009; Oikonomou et al. 2018). Moreover, Utz et al. (2014) found no significant differences in SRI and conventional mutual fund asset allocations with the Markowitz optimization after a screening stage.

Only Oikonomou et al. (2018) has analyzed the optimization model's impact in simulated SRI portfolios, finding that more formal optimization models result in SRI portfolios with lower risk, higher risk–return trade-offs, more unstable intertemporal asset allocations, and lower diversification than more simplistic optimization models. Oikonomou et al. (2018) also argued that the optimization method for SRI portfolios should be based on models considering risk and return to capture the higher estimation risk of SRI assets. However, despite the many models, previous studies have not identified a winning optimization model due to contradictory performance outcomes (Jacobs et al. 2014). Many studies have found that the naïve portfolio selection is superior to more sophisticated methods due to its stability (Fischer and Gallmeyer 2016; Kirby and Ost-diek 2012, among others). This study attempts to fill the gap in the SRI funds' optimization strategy by comparing the real fund concentration with the concentration obtained from six optimization models. The six optimization models are divided into three traditional models (minimum variance, global minimum variance, and optimal portfolio) and three more modern approaches (naïve diversification, risk-parity, and reward-to-risk timing models) because SRI funds may deviate from traditional mean–variance models and the more modern models are based on investing intuition (Oikonomou et al. 2018).

Nonetheless, market conditions vary and managers must rebalance their portfolios; that is, optimization models must be recalculated with new information. This process can be costly, especially with the computing effort of some models, such as traditional

mean–variance frameworks (Oikonomou et al. 2018). Hence, SRI and conventional fund managers are expected to rebalance their portfolios without recurrently implementing the optimization models, and deviate from the optimization models. Considering these arguments, the second hypothesis is as follows:

H2. SRI and conventional funds deviate from the asset allocations of optimization models.

The dilemma of developing more concentrated SRI portfolios and deviating from the perfectly diversified market portfolio is also due to performance penalties. Nonetheless, considering the information advantage theory, if managers choose stocks based on valuable ESG information, ESG standards might not impose a boundary. Greater portfolio concentration on valuable assets allows managers to raise the weight of the best investments, increasing the expected alpha (Choi et al. 2017). Previous SRI literature has found that intense ESG screening criteria may improve performance (Friede et al. 2015; Oikonomou et al. 2018). Soler-Domínguez et al. (2021) also found that funds with higher sustainability intensity perform better.

The information advantage theory further proposes that when information is valuable enough and the portfolio is sufficiently diversified, the marginal benefit of increasing concentration offsets the marginal costs of higher volatility with greater concentration (Fulkerson and Riley 2019; Kacperczyk et al. 2005). In other words, concentrated funds may present correct diversification by investing in several assets that minimize the idiosyncratic fund risk.¹ Thus, managers should balance the expected returns and volatility by considering whether greater concentration produces benefits (Fulkerson and Riley 2019). When managers follow the principles of the information advantage theory, concentration is expected to positively influence performance, despite the conventional/SRI fund nature. In line with these premises, the third hypothesis is as follows:

H3. A higher portfolio concentration improves SRI and conventional pension fund performance.

Another important factor in concentration strategies is that concentration is conditioned by managerial skills (Chen and Lai 2015). Managers should be able to use and process valuable information; otherwise, the information advantage is useless. Kacperczyk et al. (2014) defined skill as the cognitive ability to process information (public or private) in a limited time to generate a high-performance portfolio. Specifically, selectivity (or stock-picking) and market-timing skills are representative of this cognitive ability, indicating the capacity to choose assets and invest/disinvest at the correct moment, respectively (Bauer et al. 2006; Stein 2022). Managers with superior skills are able to learn and specialize in assets in which they have information advantage, exploiting the information advantage with more concentrated portfolios (Choi et al. 2017). That is to say, skilled managers will present portfolios with a higher concentration.

Kacperczyk et al. (2008) pointed out that managers may also have hidden managerial skills because of unobserved trading activities. Hence, these authors proposed the return gap measure to evaluate unobserved trading fund actions. The return gap captures hidden benefits and hidden costs to assess the value added/subtracted by the manager

¹ The author thanks an anonymous referee for pointing out this argument.

(Kacperczyk et al. 2008). Although no previous studies have examined the relationship between the return gap and concentration, skilled managers who undertake unobserved trading actions may exploit this skill with concentration strategies. Hence, the following hypotheses are proposed:

H4. The managers of more concentrated funds present superior stock-picking skills.

H5. The managers of more concentrated funds present superior market-timing skills.

H6. The managers of more concentrated funds present superior unobserved trading skills (i.e., a larger return gap).

Superior skills will likely lead to better performance because the stock-picking skill is based on holding more stocks with higher realized returns; that is, picking stocks that outperform others at the same level of non-diversifiable risk (Kacperczyk et al. 2014). Similarly, correct market timing refers to increasing holdings when market returns are high, expanding exposure to the market portfolio (Kacperczyk et al. 2014). In addition, a positive return gap shows the trading ability to add value due to hidden trading benefits regarding the value subtracted due to hidden trading costs (Kacperczyk et al. 2008). If concentration strategies' success depends on managerial skills, managers with superior skills will likely develop more concentrated portfolios and obtain higher performance. Thus, the final hypothesis is proposed as follows:

H7. The combined effect of superior skills (stock-picking, timing, or unobserved trading -return gap) and higher concentration results in greater performance.

Market overview, data, and variables

Market overview and data

This study examines UK SRI and conventional pension funds because of the UK pension fund industry's unique characteristics. The UK pension fund industry is the second-largest global pension fund market, with more than €2.7 trillion in 2023 (INVERCO 2024). Additionally, the UK is a pioneer in developing a specific regulation on pension funds' ESG disclosure (UKSIF 2018; UK Statutory Instruments No. 988 Pensions, 2018). The development of the UK SRI pension fund niche makes it possible to study the portfolio concentration of SRI pension funds and investigate whether SRI and conventional pension funds have distinct concentration patterns.

The data are drawn from several sources. The pension fund data are obtained from the Morningstar Direct database and include all equity pension fund share classes domiciled in the UK from January 1999 to August 2021. Morningstar Direct does not contain data at the fund level but provides data for all the fund's share classes. The data are divided into conventional- and SRI-fund share classes with the dichotomous "Socially Conscious" label (yes/no) provided by Morningstar. Hence, the data include 580 share classes labeled as "Socially Conscious" (i.e., SRI-fund share classes) and 14,216 share classes not labeled as "Socially Conscious" (i.e., conventional-fund share classes).

The data collected for each share class include the monthly and daily return, monthly total net assets (TNA, in pounds), monthly portfolio sustainability score, inception fund date, obsolete fund date (i.e., the end date of the fund if applicable), annual expense ratios, investment area (the UK, Europe, the USA -United States of America-, Japan, global markets, and emerging markets), firm name, quarterly portfolio holdings (weights invested in each stock), a load/no-load dummy, and an institutional investor dummy.

Following previous studies, because the data are not at the fund level, all share classes belonging to a fund are aggregated to operate at the fund level (Kacperczyk et al. 2014; Renneboog et al. 2011). Thus, the following variables are calculated at the fund level: monthly weighted average return, expense ratios, and sustainability scores of a given fund's share classes. The monthly TNAs of all the share classes of a fund are also aggregated. Nonetheless, quarterly portfolio holdings of all the share classes belonging to a fund are common; thus, this information is already at the fund level. In addition, the pension fund data are monthly, but the portfolio holdings are quarterly; hence, quarterly holding data for the three months of each quarter are used to obtain monthly portfolio holdings, following Brown et al. (2021). Finally, the qualitative fund characteristics (inception and obsolete dates) are those of the oldest share class.² The final data comprise 80 SRI pension funds and 1548 conventional pension funds. Live and dead funds are included to avoid survivorship bias.

Size differences between the SRI and conventional fund datasets may produce biased results and prevent adequate comparisons (Ammann et al. 2019; Bilbao-Terol et al. 2017). Hence, the r:1 nearest-neighbor matching method is applied for selecting matched conventional funds (Ammann et al. 2019; Bilbao-Terol et al. 2017; Rubin 1973). This method is widely used in comparative studies of SRI and conventional funds because it provides a balance between samples, improves parametric statistics with reduced standardized bias across covariates, and reduces endogeneity issues and omitted variable concerns (Ammann et al. 2019; Bilbao-Terol et al. 2017; Joliet and Titova 2018). This technique matches the control group (conventional funds) and the treated group (SRI funds) by the smallest distance regarding fund characteristics. The propensity score is used as a similarity measure between funds and is estimated using a logistic regression on the following fund characteristics: fund size, fund age, expense ratio, investment area, and firm name. This method allows control funds to be matched several times. Therefore, the 4:1 nearest-neighbor matching is applied, providing two balanced datasets comprising 80 SRI funds and 84 matched conventional funds.

Additionally, stock market information is obtained on the 11,688 different stocks in which the 80 SRI and the 84 matched conventional funds invested over the study period to calculate skill measures (see the skill variable description in Sect. "Variables"). The stock market information is obtained from the Datastream database and includes monthly stock prices, monthly stocks' market capitalization, each stock's market benchmark name, monthly market index prices of the benchmarks, and monthly market capitalization of the benchmarks. The market benchmarks are the equity market indices associated with each stock developed by Datastream.³ The price data are used to

² The oldest share class in a fund is usually the first established share class by a fund firm.

³ Each market index represents all the stocks traded in each of the 66 stock markets analyzed. Specifically, the equity market indices are from: Argentina, Australia, Austria, Bangladesh, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Croatia, Cyprus, the Czech Republic, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Korea, Lithuania, Luxemburg, Malaysia, Malta, Mauritius, Mexico, Morocco, the Netherlands, New Zealand, Nigeria, Norway, Oman, Pakistan, Peru, the Philippines, Poland, Portugal, Qatar, the Republic of Namibia, Romania, Russia, Saudi Arabia, Singapore, Slovenia, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Thailand, Turkey, the United Arab Emirates, the UK, the USA, and Vietnam. Clarify that some stocks have no stock market indices from Datastream and/or no information about the market index; however, these stocks are part of the Financial Times Stock Exchange (FTSE) All-World index, in which case the FTSE All-World index is used as the benchmark.

calculate the stock returns and market index returns. Next, the stock fund weights from the Morningstar database are matched with the stock returns of each stock held by a fund.

Finally, the monthly Organization for Economic Cooperation and Development (OECD) based recession indicators for the UK, Europe, the USA, Japan, OECD members, and non-OECD members are obtained from the Federal Reserve Economic Data⁴ to detect recession and expansion periods in funds investing in the UK, Europe, the USA, Japan, global markets, and emerging markets, respectively. These indicators are equal to 1 in recessions and 0 otherwise.

Variables

Following previous studies, two portfolio concentration measures are calculated. First, the Herfindahl–Hirschman Index measures the security concentration by considering the weights of all the stocks in a fund and period (Hirschman 1964). The Herfindahl–Hirschman Index (*HHI* henceforth) is obtained as follows:

$$HHI_t^i = \sum_{j=1}^N (\omega_{j,t}^i)^2 \quad (1)$$

where HHI_t^i is the Herfindahl–Hirschman concentration index of fund i in month t and $\omega_{j,t}^i$ is the weight of stock j in fund i in month t (where $j=1, \dots, N$; and N are the total stocks held by fund i in month t). *HHI* varies between 0 and 1, showing the lowest and the highest portfolio concentration, respectively.⁵

Second, following Bu and Harrisburg (2017), the concentration level of a fund's stocks is measured using the portfolio weighting of the top 10 weighted stocks by a fund. Although some funds hold many stocks, the weights of the most representative portfolio stocks concentrate most of the portfolio investments, distorting fund diversification. Measure (2) controls this issue. A higher/lower measure (2) shows a higher/lower concentration of the top 10 holdings in fund i in month t .⁶

$$Top10_t^i = \sum_{j=1}^{10} (\omega_{j,t}^i)^2 \quad (2)$$

In addition, multiple fund characteristics relevant to the concentration analysis are considered. First, fund volatility is calculated because higher fund concentration may increase fund risk (Fulkerson and Riley 2019; Kacperczyk et al. 2005; Sapp and Yan 2008). The fund risk of fund i in month t ($Risk_{i,t}$) is obtained as the standard deviation of the daily fund returns each month. Second, fund flows are calculated because previous studies found higher fund flows in more concentrated funds (Pandey and Sharma 2024). Monthly percentage fund flows are obtained following Sirri and Tufano (1998):

$$Flows_{i,t} = [(TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}))]/TNA_{i,t-1} \quad (3)$$

⁴ The data are obtained from the Federal Reserve Economic Data (<https://research.stlouisfed.org/fred2/>).

⁵ See Appendix A for a further explanation of *HHI*.

⁶ See Appendix A for a more detailed explanation of *Top10*.

where $TNA_{i,t}$ are the total net assets of fund i in month t , and $R_{i,t}$ is the return of fund i in month t .⁷

Third, the valuation certainty of fund i in month t ($Valuation_certainty_{i,t}$) is obtained because managers have fewer opportunities to diversify valuation errors when concentration increases; that is, the precision of managerial estimations may be affected if funds concentrate on stocks with lower certain intrinsic values (Fulkerson and Riley 2019). Following Fulkerson and Riley (2019), the fund valuation certainty is estimated as the addition of the fund exposures to profitability (RMW: robust minus weak) and investment (CMA: conservative minus aggressive) factors of Fama and French's (2015) model. These factors indicate whether funds invest in firms that are less profitable and firms that make larger investments because the intrinsic value of these stocks is often more difficult to assess. When a fund has a joint negative exposure to RMW and CMA, it invests in stocks that are difficult to value. The RMW and CMA factors for each investment area are obtained from French's data library.⁸

Moreover, the explicit and implicit costs of concentration are considered. On the one hand, transaction costs explicitly increase as the trading size of more concentrated funds grows, increasing expense ratios (Keim and Madhavan 1997). Hence, the $Expense_ratio_{i,t}$ of fund i in month t is used. In contrast, implicit costs may emerge due to liquidity motivations. When more concentrated funds face forced sales, the costs increase because funds hold fewer stocks to develop liquidity-motivated trades (Fulkerson and Riley 2019). The cash liquidity fund weight is calculated as the holdings in cash of fund i in month t ($Cash_liquidity_{i,t}$).

Investor sophistication is also considered because less sophisticated retail investors are more prone to react adversely to greater concentration due to potentially poor results (Fulkerson and Riley 2019). The institutional ownership dummy ($Institutional_{i,t}$) and the load/no-load fund dummy ($Load_{i,t}$) are included. These dummies are dichotomous variables (yes/no) transformed into numerical dummies. The institutional (load) dummy is equal to 1 when a fund is owned by institutional investors (a fund is a load fund) and 0 otherwise. Institutional ownership could bear a greater fund concentration because institutional investors are more sophisticated and rely more on managers (Barber et al. 2016). Alternatively, no-load fund investors are more sophisticated because they are more informed and better understand managerial decision-making, such as concentration strategies (Zheng 1999).

The crisis dummy ($Crisis_t$) was explained in Sect. "Market overview and data" and controls for instable scenarios. Managers may require greater expected benefits before increasing their concentration during recessions (Fulkerson and Riley 2019). In addition, the fund performance is Carhart's (1997) four-factor alpha because this measure is commonly used in concentration analyses (Choi et al. 2017; Ivkovic et al. 2008; among

⁷ Flows are winsorized at the bottom and top 1% levels of the distribution to ensure that extreme values do not drive the results.

⁸ French's website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Clarify that Applied Quantitative Research (AQR) provides some UK risk factors at www.aqr.com; however, AQR does not provide UK RMW and CMA factors. Thus, the European RMW and CMA factors provided by French's website are used as UK factor proxies.

others).⁹ The alpha is estimated using 36-month return rolling windows; thus, the analyses are restricted to the period from January 2002 to August 2021.

Finally, three skill variables are developed. The stock-picking and market-timing measures of Kacperczyk et al. (2014) are calculated because these measures are unconditional and independent portfolio-style measures. The picking measure (4) determines how fund holdings co-move with the idiosyncratic component of stock returns relative to the market. Skilled managers will underweight (overweight) stocks with regard to the market weights that have subsequently low (high) idiosyncratic returns (Kacperczyk et al. 2014).

$$Picking_t^i = \sum_{j=1}^N (w_{j,t}^i - w_{j,t}^m) (R_{j,t+1} - \beta_{j,t} Rm_{t+1}) \quad (4)$$

where $Picking_t^i$ is the stock-picking skill measure of fund i in month t , $w_{j,t}^i$ is the weight of stock j in fund i in month t (where $j=1, \dots, N$; and N are the total stocks held by fund i in month t), $w_{j,t}^m$ is the weight of stock j in the market portfolio (m) in month t , and $\beta_{j,t}$ measures the covariance between the return of stock j ($R_{j,t}$) and the market return (Rm_t) in month t divided by the variance of the market return.

The market-timing measure (5) indicates how fund holdings co-move with the systematic component of the stock return relative to the market. Skilled managers present timing ability when they overweight/underweight assets with high betas in anticipation of a market increase/decline (Kacperczyk et al. 2014).

$$Timing_t^i = \sum_{j=1}^N (w_{j,t}^i - w_{j,t}^m) (\beta_{j,t} Rm_{t+1}) \quad (5)$$

where $Timing_t^i$ is the market-timing skill measure of fund i in month t , and the remaining variables are defined in (4).

The third skill measure (measure 6) is the return gap developed by Kacperczyk et al. (2008), measuring managerial skills due to unobserved fund trading activity:

$$RG_t^i = RF_t^i - (RH_t^i - Expense_ratio_{i,t}) = RF_t^i - \left(\sum_{j=1}^N w_{j,t-1}^i R_{j,t} - Expense_ratio_{i,t} \right) \quad (6)$$

where RG_t^i is the return gap of fund i in month t , RF_t^i is the net return of fund i in month t , RH_t^i is the holding portfolio return of fund i in month t , $w_{j,t-1}^i$ is the weight of stock j in fund i in month $t-1$ (where $j=1, \dots, N$; and N are the total stocks held by fund i in month $t-1$), $R_{j,t}$ is the return of stock j in month t , and $Expense_ratio_{i,t}$ is the expense ratio of fund i in month t .

The return gap captures unobserved actions between fund-holding disclosure dates, including hidden benefits and hidden costs (trading costs, agency costs, or negative investor externalities). Hidden benefits mainly arise from the interim trades of skilled

⁹ The market size (SMB: small minus big), book-to-market (HML: high minus low), and momentum factors of Carhart (1997) are obtained from the AQR data (www.aqr.com) for funds investing in the UK and from French's data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) for funds investing in Europe, the USA, Japan, other developed markets, and emerging markets.

managers that create value and increase the fund return (RF); however, the return of the disclosed holdings (RH) remains unaffected until the new fund-holding position is disclosed. Kacperczyk et al. (2008) indicated that the return gap is positively/negatively related to hidden benefits/costs and measures the value added/subtracted by the manager.

Table 1 presents the summary statistics of the variables. The HHI ($Top10$) of the SRI and conventional funds are 1.98% and 2.18% (1.19% and 1.32%), respectively. The concentration differences between the SRI and conventional funds are significant, showing higher concentration (HHI and $Top10$) in conventional funds. These figures are consistent with the argument that fund concentration depends on valuable information rather than on the conventional/SRI-fund nature (i.e., $H1$). Furthermore, SRI and conventional fund managers have negative picking, timing, and return gap skills, which is consistent with previous literature (Knigge et al. 2004; Matallín-Sáez et al. 2019, among others).

Empirical findings

This section presents the analyses of the concentration distributions, the difference between the actual fund concentration and the concentration obtained from the asset-allocation solutions of the six optimization models, the concentration determinants, the effect of concentration on performance, and the influence of concentration and skills on performance.

Preliminary concentration analysis

First, a preliminary analysis of the portfolio concentration distributions is conducted with a nonparametric methodology to identify concentration patterns in isolation from other fund variables. This allows for a better understanding of the concentration

Table 1 Summary statistics

	All	SRI funds	Matched conventional	SRI versus matched
HHI	0.0209	0.0198	0.0218	− 0.002***
Top10	0.0126	0.0119	0.0132	− 0.0013***
Sustainability score	0.4221	0.4250	0.4192	0.0058**
Alpha	0.0009	0.0013	0.0005	0.0008***
Return	0.0062	0.0061	0.0062	− 0.0001
Risk	0.0073	0.0083	0.0065	0.0018**
Flows	0.0625	0.0491	0.0716	− 0.0225***
Fund assets (pounds)	2.53*10 ⁷	3.20*10 ⁷	2.25*10 ⁷	9.5*10 ⁶ ***
Age (months)	10.6017	10.2533	10.9226	− 0.6693***
Expense ratio	0.0153	0.0151	0.0155	− 0.0004***
Valuation certain	0.0763	0.0234	0.1278	− 0.1043***
Cash_liquidity	0.0283	0.0276	0.0289	− 0.0012**
Picking	− 0.0096	− 0.0123	− 0.0074	− 0.0049*
Timing	− 0.0127	− 0.0131	− 0.0123	− 0.0008
Return gap	− 0.0137	− 0.0148	− 0.0129	− 0.0019*

This table presents the summary statistics of the monthly fund variables from January 2002 to August 2021 for all SRI and matched conventional pension funds. The last column shows the difference between the SRI-fund and matched conventional-fund variables. The significance levels of the difference in means are based on t-tests. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

differences with regard to the portfolio concentration calculated using the optimization model solutions in the next section (Sect. "Analyzing the deviations from the portfolio optimization models"). The nonparametric methodology detects distribution parameters, such as skewness and kurtosis, and compares distributions better than parametric methods (Abbasi 2022). Table 2 and Fig. 1 present the results.

Panel A of Table 2 shows that conventional funds' *HHI* and *Top10* concentrations are greater than SRI fund concentrations (considering the mean, median, and interquartile range). This evidence is in line with H1: SRI funds do not present more concentrated portfolios than conventional funds. The Kolmogorov–Smirnov and Epps–Singleton tests confirm the existence of differences in the *HHI* and *Top10* distributions of SRI and conventional funds. Figure 1 shows the concentration distributions for further study of these differences.

Graphs 1 and 2 of Fig. 1 illustrate the *HHI* and *Top10* kernel density plots. Both graphs show similar shapes around the mean; however, a few SRI funds exhibit large concentration deviations (greater sharpness). Moreover, the right-skewed conventional-fund distributions show conventional funds with a significantly higher concentration than the average. Graphs 3 and 4 illustrate the cumulative distribution function (CDF) and confirm the lower SRI-fund concentration (CDFs above the diagonal). However, the SRI-fund concentration is greater at the beginning of the function; therefore, Graphs 5–10 illustrate the probability density function (PDF) to determine whether the concentration relation varies over the distribution. Graph 5 confirms that the SRI-fund *HHI* is not lower than the conventional-fund *HHI* in the entire concentration distribution. The SRI-fund *HHI* PDF is significantly larger than the conventional-fund *HHI* PDF in regions higher/lower than the 10%/60% quantile (PDF higher than 1). In contrast, the SRI cohort is underrepresented in regions below 10% and above 60% quantiles (non-significantly

Table 2 Nonparametric analysis of the concentration variables

Panel A. Concentration summary statistics						
	Mean	Standard deviation	Median	Interquartile range	Kolmogorov–Smirnov (p-value)	Epps–Singleton (p-value)
Panel A.1. <i>HHI</i> summary statistics						
SRI	0.0198	0.0086	0.0191	0.0097	0.000***	0.000***
Conv	0.0218	0.0132	0.0218	0.0128		
Panel A.2. <i>Top10</i> summary statistics						
SRI	0.0119	0.0077	0.0101	0.0095	0.000***	0.000***
Conv	0.0132	0.0122	0.0120	0.0108		
Panel B. Divergence measures (%)			Panel C. Polarization indices			
	HHI	Top10		HHI	Top10	
Location	0.4808	−85.2333***	MRP	−0.1449***	−0.0988***	
Shape	99.5193***	185.2333***	LRP	−0.1998***	−0.1945***	
			URP	−0.0902***	−0.0031	

This table is divided into three panels. Panel A presents the summary statistics of *HHI* (panel A.1) and *Top10* (panel A.2) concentration measures for SRI and conventional (Conv.) funds. Panel B shows the divergence measures of SRI-fund and conventional-fund concentration distributions for *HHI* and *Top10* in percentage. Panel C displays the polarization indices of *HHI* and *Top10* concentration distributions between the SRI and conventional funds. MRP, LRP, and URP indicate the median, lower, and upper relative polarization index, respectively. *** indicates significance at the 1% level

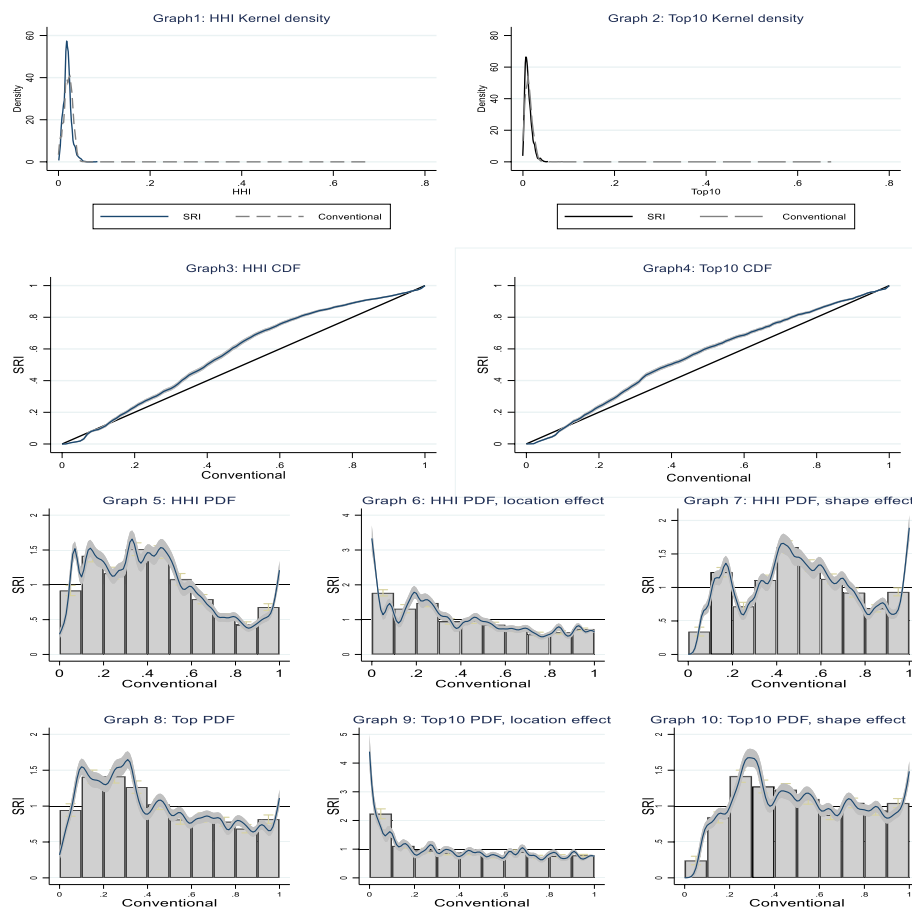


Fig. 1 Concentration distributions in SRI and conventional pension funds. This figure is divided into ten graphs. Graphs 1 and 2 show the kernel density of *HHI* and *Top10* concentration measures for SRI and conventional funds. Graphs 3 and 4 show the cumulative distribution functions (CDF) between SRI and conventional funds for *HHI* and *Top10*, respectively. Graphs 5, 6, and 7 show the probability density function (PDF), the location effect in PDF, and the shape effect in PDF between SRI and conventional funds for *HHI*, respectively. Graphs 8, 9, and 10 show the probability density function (PDF), the location effect in PDF, and the shape effect in PDF between SRI and conventional funds for *Top10*, respectively

different from 1). These differences are further studied by decomposing the PDF into “location” and “shape” effects (Handcock and Morris 1999). Graph 6 illustrates that the bottom-quintile differences in Graph 5 are due to location differences (i.e., mean differences), and Graph 7 illustrates that the middle-top differences are due to outlier-concentrated SRI funds (i.e., differential shape due to dispersion and skewness). Consistent with this evidence, Graphs 8–10 show variability in the *Top10* concentration among SRI funds because this distribution is overrepresented in quantiles higher/lower than 10%/50% (Graph 8), and the differences in the lower/middle quintiles are due to location/shape differences (Graph 9/10).

The location and shape effects are quantified in panel B of Table 2 (Handcock and Morris 1999). The divergence measures indicate a large dispersion in the *HHI* concentration of SRI and conventional funds (significant shape and non-significant location). In contrast, the concentration strategies in the top 10 fund assets differ on average and in dispersion (significant location and shape differences). Additionally, panel C of Table 2

quantifies the degree of inequality between distributions, confirming that the conventional-fund concentration is more unequal than the SRI-fund concentration (negative median, lower, and upper relative polarization indices -MRP, LRP, and URP).

This preliminary concentration analysis shows that SRI and conventional funds develop diverse concentration strategies and conventional funds generally present greater and more varied concentration. Furthermore, the analysis displays the existence of outliers, a feature that should be considered. Specifically, the remaining analyses in Sect. "Empirical findings" are undertaken with the initial *HHI* and *Top10* variables (described in Sect. "Market overview, data, and variables"); however, all analyses are repeated with *HHI* and *Top10* winsorized at the bottom and top 5% and 10% levels. The results obtained using the winsorized concentration measures demonstrate that the findings of the remaining sections are unaffected by outliers.¹⁰

Analyzing the deviations from the portfolio optimization models

This section compares the concentrations obtained using the six optimization-model asset allocations with the fund concentration calculated using actual portfolio holdings. Previous literature has provided a variety of optimization models; however, some models may be difficult to apply by fund managers due to their complexity, assumptions, and sophistication. Moreover, sophisticated optimization techniques do not always provide the best solution in terms of diversification (Oikonomou et al. 2018). Among the existing models, six well-known optimization models are considered because these are widely applied in professional portfolio management (Oikonomou et al. 2018). The first three models (minimum variance, global minimum variance, and optimal portfolio) are based on the traditional mean–variance bases established by Markowitz (1952). The remaining models (naïve diversification, risk-parity, and reward-to-risk timing) are more recent approaches that have less mathematical sophistication and are based on investing intuition (Oikonomou et al. 2018). These six models make it possible to build optimal portfolios on the basis of different premises, representing the primary rationales of optimization techniques among professional managers.

The first model is the minimum variance portfolio; that is, Markowitz's (1952) optimization framework. This model minimizes the portfolio risk (variance) among all feasible portfolios, subject to the following constraints: a required return, the sum of the weights is equal to 1 (normalization of portfolio weights), and the model does not allow short sales. This model assumes that the expected return (μ) and the variance–covariance matrix of asset returns (Σ) are known with certainty. The minimum-variance portfolio problem is expressed as follows:

$$\begin{aligned} \min_w & w' \Sigma w \\ \text{s.t.} & \\ \mu' w & \geq \theta \\ 1' w & = 1 \\ w_j & \geq 0 \quad \forall \quad j = 1, \dots, N \end{aligned} \tag{7}$$

¹⁰ The results with winsorized *HHI* and *Top10* are not included for the sake of brevity and are available upon request.

where $w = [w_{1,t}, w_{2,t}, \dots, w_{N,t}]'$ is the column vector of portfolio weights with N assets in the portfolio at period t , and the purpose is to select a portfolio w that minimizes the variance among all possible portfolios at period t . Σ is the variance–covariance matrix of asset returns, and $\mu = [\mu_{1,t}, \mu_{2,t}, \dots, \mu_{N,t}]'$ is the column vector of asset returns at period t . The constraints are: $\mu'w \geq \theta$, which establishes a lower bound on the portfolio return,¹¹ $1'w = 1$ requires that the portfolio weights sum to one (1 is a vector of ones), and $w_j \geq 0$ is the non-negativity constraint, which discards short selling.

The second model is the global minimum variance portfolio, which is based on the minimum variance portfolio model (7) but does not require a lower bound on the portfolio return, assuming that all stocks have equal expected returns to reduce estimation risks (Ledoit and Wolf 2003; Jagannathan and Ma 2003, among others). Hence, the unique efficient portfolio is the portfolio with the smallest risk (global minimum variance). The optimization problem is expressed as follows:

$$\begin{aligned} \min_w & w' \Sigma w \\ \text{s.t.} & \\ & 1'w = 1 \\ & w_j \geq 0 \forall j = 1, \dots, N \end{aligned} \quad (8)$$

The third model is the optimal or tangency portfolio model. This model provides an optimal and efficient portfolio by maximizing the Sharpe ratio (Sharpe 1966) because the portfolio that maximizes the Sharpe ratio lies on the mean–variance efficient frontier, a point at which the capital market line is tangent to the efficient frontier (Markowitz 1952; Jagannathan and Ma 2003). For this reason, the optimal portfolio is also called tangency portfolio. The optimization problem is expressed as follows:

$$\begin{aligned} \max_w & \frac{w' \mu - R_{f,t}}{\sqrt{w' \Sigma w}} \\ \text{s.t.} & \\ & 1'w = 1 \end{aligned} \quad (9)$$

where $\frac{w' \mu - R_{f,t}}{\sqrt{w' \Sigma w}}$ is the Sharpe ratio and $R_{f,t}$ is the risk-free asset rate at period t . The remaining variables are described in (7).

The fourth model is the naïve diversification with rebalancing. This model assigns a portfolio weight of $1/N$ to each portfolio asset ($w_{j,t} = 1/N$; where $w_{j,t}$ is the portfolio weight of asset j at period t , and N is the total number of portfolio assets considered); therefore, the portfolio is equally weighted. This method is characterized by its simplicity because it does not consider return, risk, or other return moments. However, previous literature points out that this approach is not inferior to mean–variance models

¹¹ The lower bound of the portfolio return (θ) is the minimum positive return of the assets considered because it is assumed that this is the minimum expected return of an investor to accept the investment in a risky portfolio. Nonetheless, Oikonomou et al. (2018) point out that the value assumed of θ is not crucial in this model. Consistent with this argument, the value of θ does not affect the conclusions reached in this study.

or Markowitz-optimization extensions (Bloomfield et al. 1977; DeMiguel et al. 2009). Nonetheless, a rebalancing method is followed to vary $1/N$ weights over time instead of applying a $1/N$ buy-and-hold strategy (Platanakis et al. 2019).

The risk-parity portfolio is the next model, broadly applied by long-term institutional investors, such as pension funds (Anderson et al. 2012). This model requires that each portfolio asset must contribute to the portfolio variance to the same extent. As a result, asset weights are anti-proportional to the variance of each asset (Maillard et al. 2010). The portfolio weights are obtained as follows:

$$w_{j,t} = \frac{1/\sigma_{j,t}^2}{\sum_{j=1}^N (1/\sigma_{j,t}^2)} \quad \forall j = 1, \dots, N \quad (10)$$

where $w_{j,t}$ is the weight of portfolio asset j at period t , and $\sigma_{j,t}^2$ is the variance of the returns of portfolio asset j at period t .

Finally, the reward-to-risk timing model proposed by Kirby and Ostdiek (2012) is applied. This model is based on the reward-to-risk ratio (i.e., return divided by variance), mitigating the estimation risk and overcoming the instability of portfolios obtained using Markowitz mean–variance methods (Kirby and Ostdiek 2012). This model provides more stable portfolios with lower transaction costs by overweighting assets with higher return and lower variance; that is, assets with a higher reward-to-risk ratio. This strategy allocates asset weights in proportion to the contribution of each asset's mean–variance ratio to the mean–variance ratio of the universe of assets (Oikonomou et al. 2018). The portfolio weights are obtained as follows:

$$w_{j,t} = \frac{\mu_{j,t}^+/\sigma_{j,t}^2}{\sum_{j=1}^N (\mu_{j,t}^+/\sigma_{j,t}^2)} \quad \forall j = 1, \dots, N, \quad (11)$$

where $\mu_{j,t}^+ = \max(\mu_{j,t}, 0)$ to discard short selling. In the case of all negative asset returns, portfolio assets are equally weighted ($1/N$).

To estimate portfolio weights using the six optimization models over the time period for the 80 SRI and 84 conventional funds studied, it is assumed that the universe of assets in the optimization models is the actual quarterly fund assets in which the SRI and conventional funds invest quarterly. This assumption makes it possible to start from the actual portfolio asset allocation to consider the investment profile of each fund by observing whether the optimization models vary the real portfolio asset weights. The optimization models are estimated quarterly because the real fund-holding weights are quarterly. Nonetheless, the remaining pension-fund data are monthly; thus, quarterly estimated weights are used in the three months of each quarter to obtain monthly weights (Brown et al. 2021). This replicates the process explained with the real fund weights in Sect. "Market overview and data".

Concentration measures (1) and (2) are calculated from the weights obtained from the six optimization models over the study period. Table 3 presents the results. The SRI and conventional funds are less concentrated with the actual holdings than with the holdings of the optimization-model solutions (significantly negative differences), except with the naïve diversification. These results indicate that funds deviate from the optimization

Table 3 Estimated variables with portfolio optimization model solutions

	All	Actual vs optimization variables	SRI	SRI actual vs SRI optimization variables	Conv	Conv actual vs conv optimization variables
HHL minimum variance	0.3564	−0.3355***	0.3567	−0.3369***	0.3562	−0.3344***
HHL global minimum variance	0.4812	−0.4603***	0.4797	−0.4599***	0.4823	−0.4605***
HHL optimal portfolio	0.6820	−0.6611***	0.6808	−0.661***	0.6830	−0.6612***
HHL naïve	0.0195	0.0014***	0.0161	0.0037***	0.0222	−0.0005
HHL risk parity	0.0432	−0.0223***	0.0405	−0.0207***	0.0454	−0.0236***
HHL reward-to-risk timing	0.0879	−0.067***	0.0898	−0.0701***	0.0862	−0.0645***
Top10 minimum variance	0.3568	−0.3442***	0.3586	−0.3467***	0.3554	−0.3422***
Top10 global minimum variance	0.4813	−0.4687***	0.4838	−0.4719***	0.4793	−0.4661***
Top10 optimal portfolio	0.6751	−0.6625***	0.6723	−0.6605***	0.6772	−0.664***
Top10 naïve	0.0071	0.0054***	0.0045	0.0073***	0.0093	0.0039***
Top10 risk parity	0.0367	−0.0241***	0.0339	−0.022***	0.0389	−0.0257***
Top10 reward-to-risk timing	0.0803	−0.0677***	0.0751	−0.0633***	0.0845	−0.0713***
Alpha minimum variance	0.01402	−0.0131***	0.0140	−0.0127***	0.01404	−0.0135***
Alpha global minimum variance	0.00929	−0.0084***	0.00928	−0.0079***	0.0093	−0.0088**
Alpha optimal portfolio	0.0424	−0.0415***	0.0453	−0.0439***	0.0397	−0.0392***
Alpha naïve	0.0060	−0.0051***	0.0067	−0.054***	0.0049	−0.0044***
Alpha risk parity	0.0058	−0.0049***	0.0065	−0.0052***	0.0046	−0.0041***
Alpha reward-to-risk timing	0.0494	−0.484***	0.0497	−0.0484***	0.0488	−0.0483***
Picking minimum variance	0.0228	−0.0324***	0.0199	−0.0322***	0.0251	−0.0325***
Picking global minimum variance	0.0156	−0.0252***	0.0102	−0.0225***	0.0199	−0.0273***
Picking optimal portfolio	0.1053	−0.1148***	0.0983	−0.1105***	0.1109	−0.1183***
Picking naïve	−0.0142	0.0046**	−0.0122	−0.0001	−0.0159	0.0085***
Picking risk parity	−0.0145	0.005**	−0.0142	0.0019	−0.0148	0.0074***
Picking reward-to-risk timing	0.1009	−0.1105***	0.1005	−0.1128***	0.1013	−0.1087***
Timing minimum variance	0.0023	−0.015***	0.0025	−0.0156***	0.0022	−0.0145***
Timing global minimum variance	0.0014	−0.014***	0.0014	−0.0145***	0.0013	−0.0136***
Timing optimal portfolio	0.0142	−0.0268***	0.0193	−0.0324***	0.0100	−0.0223***
Timing naïve	−0.0127	0.0001	−0.0154	0.0023	−0.0105	−0.0018
Timing risk parity	−0.0113	−0.0013	−0.0133	0.0002	−0.0097	−0.0026
Timing reward-to-risk timing	0.0051	−0.0177***	0.0029	−0.016***	0.0070	−0.0192***

This table presents the summary statistics of concentration measures (1) and (2), performance (four-factor alpha), and skill measures (4)–(5) calculated with the weights obtained from the six optimization models applied (minimum variance, global minimum variance, optimal portfolio, naïve diversification, risk parity, and reward-to-risk timing) for all, SRI, and conventional funds. Columns (3), (5), and (7) show the differences between the variables calculated with the actual fund

Table 3 (continued)

weights and the variables obtained from the optimization model solutions. The significance levels of the differences in means are based on t-tests. ** and *** indicate significance at the 5% and 1% levels, respectively

model solutions; hence, H2 cannot be rejected. Additionally, SRI and conventional funds greatly diversify their portfolios and develop asset allocations similar to the naïve diversification. This evidence aligns with multiple studies pointing out that the naïve portfolio selection is a preferred method due to its stability (Fischer and Gallmeyer 2016; Kirby and Ostdiek 2012; among others). This indicates that SRI pension funds do not present problems when diversifying their portfolios due to the limited ESG-asset universe and stricter regulations. Furthermore, the concentration measures from the optimization models illustrate a lower SRI-fund concentration and, consistent with previous literature (DeMiguel et al. 2009; Oikonomou et al. 2018), traditional mean–variance models show poorly diversified portfolios relative to the more recent optimization approaches.

The performance and skill measures (4)–(5)¹² are also calculated from the weights obtained from the six optimization models. Table 3 shows that deviations from the optimization models affect fund performance (lower actual performance than optimization-model performance). Thus, managers should assess the consequences of deviating from some optimization models. Although the optimization skill measures (4)–(5) do not capture real managerial skills because all managers' information regarding future market movements is not included in the optimization models, the optimization models calculate the weights starting from the actual fund assets to consider funds' investment profiles and managers' information signals. Hence, optimization skill measures (4)–(5) make it possible to explore whether optimization models can guide managers to improve their skills. The results indicate that fund managers would have achieved better selectivity and timing skills with the optimized asset allocations, except with the naïve diversification and risk-parity optimizations. Thus, optimization models can help managers in asset allocation decisions to improve performance, picking, and timing skills if managers specify the asset universe in the optimization model.

Concentration determinants

This section studies the determinants of the actual fund concentration to analyze whether funds develop different concentration on the basis of fund characteristics. The concentration determinants using optimization models are not studied because the optimization solutions are subject to model specifications and do not consider fund characteristics. However, actual concentration strategies may depend on fund features, as explained in Sect. "Variables". Accordingly, model (12) is as follows:

$$Conc_{i,t} = \beta_0 + \beta_1 SRI_dummy_{i,t-1} + \beta_2 Sust_score_{i,t-1} + \sum_{j=3}^{13} \beta_j Control_{i,t-1} + FE + \varepsilon_{i,t} \quad (12)$$

¹² The return gaps are not calculated from the optimization solutions because the optimization models do not consider unobserved trading activities between the fund-holding disclosure dates. In other words, optimization models provide a solution for a specific date, and it is necessary to recalculate the model with new information on another date to obtain a new solution. Consequently, the net return (RF_t^1) is the same as the holding portfolio return (RH_t^1) in measure (6) using the optimization model solutions.

where $Conc_{i,t}$ is the fund concentration, either HHI_t^i (measure 1) or $Top10_t^i$ (measure 2), of fund i in month t . $SRI_dummy_{i,t}$ is equal to 1/0 when fund i is an SRI/conventional fund. $Sust_score_{i,t-1}$ is the sustainability score of fund i in month $t-1$.¹³ The control variables are $Return_{i,t-1}$, $Risk_{i,t-1}$, $Assets_{i,t-1}$ (logarithm of TNAs of fund i in month $t-1$), $Flows_{i,t-1}$, $Age_{i,t-1}$ (obtained from the inception and obsolete dates), $Expense_ratio_{i,t-1}$, $Valuation_certainty_{i,t-1}$, $Cash_liquidity_{i,t-1}$, $Institutional_{i,t-1}$, $Load_{i,t-1}$, and $Crisis_{t-1}$. All independent variables are lagged to avoid endogeneity issues (Anantharaman and Lee 2014). FE are time fixed effects to eliminate bias from unobservable factors that change over time and are constant over funds as well as to control for factors differing across funds that are constant over time.¹⁴ Finally, $\varepsilon_{i,t}$ is the error term. Robust standard errors clustered by fund and month are estimated for obtaining standard errors that are robust to heteroskedasticity and within serial correlation, addressing concerns about correlated errors within fund and time dimensions (Newey and West 1987).

Table 4 presents the results of model (12).¹⁵ The significantly negative SRI_dummy in columns (1)–(2) supports H1; that is, SRI funds do not develop more concentrated portfolios than conventional funds. This finding is also consistent with the lower SRI-fund concentration found in the nonparametric analysis (Sect. "Preliminary concentration analysis"). Contrary to previous studies indicating the limited ESG asset universe, this evidence is consistent with the increasing supply and demand of SRIs and the evolution of the SRI from a niche to the mainstream (Revelli 2017). In this line of argument, funds with superior ESG criteria develop less concentrated portfolios (significantly negative $Sust_score$ at 5% and 1% levels in columns 1–2). Therefore, the ESG asset universe is not a limitation.

Consistent with previous literature, Table 4¹⁶ also shows that a larger fund size may imply information advantages, thus, managers of larger funds increase the fund concentration (Qin and Wang 2021). More expensive funds also present greater concentration (Keim and Madhavan 1997). The concentration in stocks with lower intrinsic value indicates managers' confidence in their information because they have fewer opportunities to diversify valuation errors with higher concentration (Fulkerson and Riley 2019). Additionally, more liquid funds concentrate the portion of noncash portfolio holdings to have sufficient liquidity for liquidity-motivated trades (Fulkerson and Riley 2019). Contrary to previous arguments (Fulkerson and Riley 2019), more sophisticated investors (institutional and no-load) react adversely to concentration (negative $Institutional$ and positive $Load$). Finally, managers take refuge in fewer assets during crises (significantly positive $Crisis$).

¹³ The sustainability score denotes the ESG fund standards of conventional and SRI funds because both SRI and conventional funds consider ESG criteria in their portfolio allocations (Revelli 2017).

¹⁴ The significant results of the test for time-fixed effects show the need to control for these effects. These results are available upon request.

¹⁵ The variance inflation factors (VIFs) do not show multicollinearity problems.

¹⁶ Some coefficients are close to 0 (e.g. $Assets$ or $Valuation_certain$); that is, the impact of these variables on the dependent variable is limited. However, the coefficient magnitudes are monthly, and the annual effect is larger.

Table 4 Influence of fund characteristics on fund concentration

	(1)	(2)
SRI_dummy	−0.0025*** (−11.57)	−0.0022*** (−11.14)
Sust_score	−0.0043** (−2.19)	−0.0064*** (−3.46)
Return	0.0038 (1.57)	0.0037 (1.62)
Risk	0.0016*** (4.02)	0.1598*** (4.26)
Assets	0.0007*** (9.48)	0.0005*** (8.79)
Flows	−0.0002 (−0.54)	−0.0003 (−0.69)
Age	−0.0003*** (−15.38)	−0.0002*** (−15.20)
Expense_ratio	0.2222*** (8.58)	0.2259*** (11.65)
Valuation_certain	−0.0006*** (−3.43)	−0.0009*** (−5.96)
Cash_liquidity	0.0101*** (8.25)	0.0087*** (5.75)
Institutional	−0.0012*** (−3.57)	−0.0007** (−2.49)
Load	0.0009*** (4.12)	0.0008*** (3.78)
Crisis	0.0012*** (4.18)	0.0014*** (5.69)
Constant	0.0129*** (7.7)	0.0064*** (4.36)
R-squared	0.1244	0.1242
VIF	1.18	1.18
No. Obs	4875	4975

This table presents the results of model (12), with *HHI* and *Top10* concentration measures as dependent variables in columns (1) and (2), respectively. All models are estimated with time fixed effects and robust standard errors clustered by fund and month. T-statistics are in parentheses. ** and *** indicate significance at the 5% and 1% levels, respectively

Performance–concentration relationship

This sections examines the influence of concentration on fund performance to test H.3; that is, whether a higher portfolio concentration improves the performance of SRI and conventional pension funds, per the information advantage theory (Van Nieuwergugh and Veldkamp 2010). Model (13) is proposed on the basis of previous concentration studies (Chen and Lai 2015; Fulkerson and Riley 2019):

$$\begin{aligned}
 Performance_{i,t} = & \beta_0 + \beta_1 SRI_dummy_{i,t-1} + \beta_2 Conc_{i,t-1} \\
 & + \beta_3 Sust_score_{i,t-1} + \sum_{j=4}^{13} \beta_j Control_{i,t-1} + FE + \varepsilon_{i,t}
 \end{aligned} \tag{13}$$

where $Performance_{i,t}$ is the four-factor alpha of fund i in month t , $SRI_dummy_{i,t}$ is equal to 1/0 when fund i is an SRI/conventional fund, $Conc_{i,t-1}$ is either HHI_{t-1}^i or $Top10_{t-1}^i$ of fund i in month $t-1$, $Sust_score_{i,t-1}$ is the sustainability score of fund i in month $t-1$, and the control variables are $Risk_{i,t-1}$, $Assets_{i,t-1}$, $Flows_{i,t-1}$, $Age_{i,t-1}$, $Expense_ratio_{i,t-1}$, $Valuation_certainty_{i,t-1}$, $Cash_liquidity_{i,t-1}$, $Institutional_{i,t-1}$, $Load_{i,t-1}$, and $Crisis_{t-1}$. FE are time-fixed effects.

Table 5 presents the results of model (13). Panel A shows that SRI funds outperform conventional funds (significantly positive SRI_dummy), and SRI funds are able to use ESG information to increase concentration and improve performance (positive HHI and $Top10$ in column 2). This result again demonstrates that the ESG asset universe provides investment opportunities. Additionally, the $Top10$ concentration positively affects conventional funds' performance (column 3). These results do not reject H3, indicating that the SRI and conventional funds use information advantages to increase their performance through concentration. However, conventional fund managers have an information advantage in a few stocks ($Top10$); thus, they focus on the stocks in which they enjoy an information advantage to enhance performance (Johnson and Moggridge 2012).

Panels B–G show the results of model (13) with the fund variables calculated from the weights obtained in the optimization models.¹⁷ Unlike the generalized positive concentration–performance relation found in panel A, panels B–G show that the significance of the concentration variables is lower, and the results are mixed, prevailing a generalized negative influence of concentration on performance. The results of panels B–D are consistent with previous studies using traditional optimization models that find lower performance with higher concentration (Gangi and Varrone 2018). Moreover, although the actual fund concentration is similar to the naïve portfolio concentration (see Table 3), panel E indicates that the naïve portfolio concentration has a diverse effect on performance. This shows that the actual fund concentration responds to managers' valuable information, which improves performance (Choi et al. 2017; Fulkerson and Riley 2019; Kacperczyk et al. 2005). It is also noted that the reward-to-risk timing model may help managers exploit informational advantages with concentration to improve performance (panel G). The latter result is due to the idiosyncrasy of this model; that is, out-weighting assets with higher return and lower volatility improves performance with higher concentration.

Importance of managerial skills when developing concentration strategies

Although managers with information advantages can improve performance through concentration strategies, the success of these strategies also depends on managerial skills (Chen and Lai 2015). This section examines the relationship between skills, concentration, and performance.

Skills by concentration level

Table 6 shows skills by concentration level to test H4, H5, and H6 about whether managers of more concentrated funds present superior picking, timing, and return

¹⁷ Control variables are not included and are available upon request.

Table 5 Performance-concentration relation

	HHI as concentration measure			Top10 as concentration measure		
	All	SRI	Conv	All	SRI	Conv
Panel A: Results with the variables calculated from the actual fund weights						
SRI_dummy	0.0022*** (16.33)			0.0023*** (16.55)		
Concentration	0.0291*** (3.39)	0.1109*** (6.67)	0.0149 (1.41)	0.0605*** (5.91)	0.1151*** (6.25)	0.0520*** (4.00)
Sust_score	0.0074*** (6.98)	0.012*** (6.41)	0.007*** (5.81)	0.0076*** (7.29)	0.0121*** (6.56)	0.0072*** (5.94)
Risk	0.2125*** (11)	0.1488*** (5.71)	0.1534*** (6.95)	0.2065*** (10.71)	0.1611*** (6.28)	0.1420*** (6.36)
Assets	−0.0001 (−0.01)	−0.0001* (−1.68)	−0.0002*** (−3.56)	−0.0000 (−0.32)	−0.0001 (−1.42)	−0.0002*** (−3.77)
Flows	−0.0001 (−0.45)	−0.0002 (−0.37)	−0.0001 (−0.3)	−0.0001 (−0.41)	−0.0001 (−0.34)	−0.0001 (−0.23)
Age	−0.00002** (−1.99)	−0.0001*** (−6.93)	0.00003** (2.37)	−0.0000 (−1.62)	−0.0001*** (−7.28)	0.0000*** (3.20)
Expense_ratio	−0.044*** (−2.92)	−0.1076*** (−4.73)	−0.0612*** (−3.37)	−0.0510*** (−3.42)	−0.1235*** (−5.50)	−0.0723*** (−4.01)
Valuation_certain	−0.0044*** (−12.93)	−0.0063*** (−19.97)	−0.0012*** (−4.36)	−0.0044*** (−12.78)	−0.0062*** (−19.70)	−0.0011*** (−4.10)
Cash_liquidity	0.0015* (1.75)	−0.0043 (−1.02)	0.0037*** (5.09)	0.0012 (1.46)	−0.0098** (−2.27)	0.0037*** (5.20)
Institutional	−0.0015*** (−8.12)	−0.0008*** (−4.68)	−0.0015*** (−5.09)	−0.0015*** (−8.14)	−0.0009*** (−5.36)	−0.0014*** (−4.89)
Load	−0.0005*** (−2.92)	0.0017*** (6.68)	−0.0016*** (−7.38)	−0.0005*** (−3.06)	0.0016*** (6.40)	−0.0016*** (−7.48)
Crisis	−0.0032*** (−15.87)	−0.0029*** (−11.33)	−0.0025*** (−10.43)	−0.0032*** (−16.09)	−0.0030*** (−11.57)	−0.0025*** (−10.66)
Constant	−0.0003 (−0.34)	−0.0004 (−0.24)	0.0025** (2.33)	−0.0003 (−0.35)	0.0006 (0.41)	0.0023** (2.09)
R-squared	0.3786	0.6057	0.1962	0.3818	0.6057	0.2009
No. Obs	4874	2063	2811	4874	2063	2811
Panel B: Results with the variables calculated from the minimum variance model solution						
Concentration	−0.0037 (−1.05)	−0.0049 (−0.94)	−0.0018 (−0.39)	−0.0012 (−0.32)	0.0157*** (3.27)	−0.0084 (−1.54)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.1113	0.1978	0.1233	0.1063	0.1997	0.1173
No. Obs	4212	1706	2506	4777	2012	2765
Panel C: Results with the variables calculated from the global minimum variance model solution						
Concentration	0.0010 (0.51)	0.0139*** (5.19)	−0.0088*** (−3.05)	0.0007 (0.38)	−0.0002 (−0.09)	−0.0002 (−0.07)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.1227	0.2402	0.1104	0.1052	0.2144	0.0891
No. Obs	4296	1728	2568	4728	2012	2716
Panel D: Results with the variables calculated from the optimal portfolio model solution						
Concentration	−0.0097* (−1.85)	−0.0214*** (−2.80)	−0.0035 (−0.52)	−0.0014 (−0.22)	−0.0172** (−2.24)	0.0098 (1.04)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.2113	0.5966	0.1523	0.2512	0.5338	0.2819

Table 5 (continued)

	HHI as concentration measure			Top10 as concentration measure		
	All	SRI	Conv	All	SRI	Conv
No. Obs	678	227	451	612	273	339
Panel E: Results with the variables calculated from naïve-diversification model solution						
Concentration	−0.0066 (−0.32)	0.3524** (2.44)	−0.1507*** (−3.63)	0.0190 (0.66)	0.1302 (0.72)	−0.0652** (−2.21)
Control variables	0.0819	0.2758	0.1864	0.0820	0.2144	0.1592
R-squared	1643	913	730	1643	913	730
No. Obs	−0.0066	0.3524**	−0.1507***	0.0190	0.1302	−0.0652**
Panel F: Results with the variables calculated from the risk-parity model solution						
Concentration	0.0084 (1.30)	0.0261 (1.47)	−0.0345*** (−3.33)	0.0128** (2.04)	0.0169 (1.20)	−0.0227** (−2.47)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0523	0.2033	0.1696	0.0533	0.2003	0.1642
No. Obs	1680	947	733	1677	944	733
Panel G: Results with the variables calculated from the reward-to-risk timing model solution						
Concentration	0.0071** (2.52)	−0.0007 (−0.29)	0.0260*** (3.21)	0.0060*** (2.83)	0.0094*** (2.88)	−0.0000 (−0.00)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.2842	0.4335	0.2587	0.2415	0.3921	0.1386
No. Obs	1146	754	392	1671	938	733

This table presents the results of model (13) for all, SRI, and conventional pension funds with the *HHI* and *Top10* concentration measures calculated from the actual fund weights (panel A), the minimum-variance (panel B), the global minimum variance (panel C), the optimal portfolio (panel D), the naïve diversification (panel E), the risk parity (panel F), and the reward-to-risk timing (panel G) optimization-model solutions. All models are estimated with time fixed effects and robust standard errors clustered by fund and month. Control variables are not shown in panels B–G and the results are available upon request. T-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

gaps. Panels A and B show the results obtained using actual fund holdings. The most concentrated funds display significantly better picking, timing, and a larger return gap than the least concentrated funds (Q1 versus Q5). However, panel A shows generalized poor managerial skills (broadly negative picking, timing, and return gap), and the managers of the most concentrated funds are only able to develop one skill correctly (picking in SRI funds and timing in conventional funds). Additionally, the generalized negative return gaps indicate that managers do not have investment ability to create enough value to offset trading costs and other hidden costs with hidden benefits. Thus, H4, H5, and H6 are rejected.

Although no prior studies examined the relationship between concentration and skills, Zambrana and Zapatero (2021) also find differential behaviours between pickers and timers, arguing that the behaviour depends on the information collected and processed by managers. These authors report that pickers rely on firms' information, whereas timers rely on macroeconomic information. Considering these premises, SRI fund managers are specialized in ESG-firm information and develop picking skills considering ESG-firm issues, leading them to leverage their information advantages through concentration (Choi et al. 2017; Fulkerson and Riley 2019; Kacperczyk et al. 2005). In contrast, conventional fund managers process more heterogeneous information and are more exposed to multiple investment objectives, receiving insights into a broad range of macroeconomic

Table 6 Managerial skills by actual and estimated concentration level

	All funds			SRI funds			Conventional funds		
	Picking	Timing	Return gap	Picking	Timing	Return gap	Picking	Timing	Return gap
Panel A. Skills by actual HHI level									
Q1	0.0002	−0.0009	−0.0122	0.0023	−0.0031	−0.0168	−0.0018	0.0015	−0.0121
Q2	0.0025	−0.0028	−0.0129	−0.0167	−0.0077	−0.0135	0.0044	−0.0046	−0.0119
Q3	−0.0054	−0.0016	−0.0151	0.005	0.0144	−0.0114	−0.0002	0.0007	−0.0134
Q4	−0.0095	−0.0109	−0.0121	−0.0195	−0.0094	−0.0109	−0.0035	−0.0205	−0.0153
Q5	−0.0365	−0.0482	−0.0182	−0.0326	−0.0597	−0.022	−0.0372	−0.0405	−0.0154
Q1–Q5	0.0367***	0.0473***	0.0060***	0.0349***	0.0566***	0.0052**	0.0354***	0.042***	0.0034**
Panel B. Skills by actual Top10 level									
Q1	−0.0034	−0.0018	−0.0121	−0.0024	−0.002	−0.014	−0.0044	−0.0016	−0.0121
Q2	0.0019	−0.0035	−0.0112	−0.0081	−0.0118	−0.0132	0.0031	−0.0007	−0.0095
Q3	0.0003	−0.0029	−0.0155	0.0002	0.0105	−0.0147	−0.0008	0.0002	−0.0142
Q4	−0.0112	−0.0027	−0.0138	−0.0176	−0.0108	−0.0127	−0.0032	−0.0087	−0.0152
Q5	−0.0346	−0.0536	−0.0179	−0.0347	−0.0525	−0.0201	−0.0326	−0.0522	−0.0168
Q1–Q5	0.0312***	0.0518***	0.0058***	0.0323***	0.0505***	0.0061**	0.0282***	0.0506***	0.0047**
Panel C. Skills by HHI level calculated with the weights from the minimum variance optimization									
Q1	−0.0029	0.0204		−0.0020	0.0150		−0.0028	0.0257	
Q5	0.0139	0.0299		0.0233	0.0304		0.0073	0.0296	
Q1–Q5	−0.0168***	−0.0094*		−0.0252***	−0.0154		−0.0101*	−0.0040	
Panel D. Skills by HHI level calculated with the weights from the global minimum variance optimization									
Q1	0.0026	0.0166		0.0131	0.0022		−0.0055	0.0256	
Q5	0.0045	0.0234		0.0046	0.0217		0.0040	0.0263	
Q1–Q5	−0.0018	−0.0068		0.0085	−0.0195***		−0.0095	−0.0007	
Panel E. Skills by HHI level calculated with the weights from the optimal portfolio optimization									
Q1	0.0158	0.1040		0.0243	0.1039		0.0083	0.1041	
Q5	0.0172	0.1000		0.0103	0.1082		0.0226	0.0959	
Q1–Q5	−0.0014	0.0041		0.0141	−0.0043		−0.0143	0.0083	
Panel F. Skills by HHI level calculated with the weights from the naive diversification									
Q1	−0.0329	−0.0095		0.0040	0.0032		−0.0518	−0.0161	
Q5	−0.0231	−0.0332		−0.0320	−0.0440		−0.0149	−0.0167	
Q1–Q5	−0.0098	0.0237***		0.0359***	0.0472***		−0.0370***	0.0006	
Panel G. Skills by HHI level calculated with the weights from the risk-parity optimization									
Q1	−0.0129	−0.0230		−0.0032	−0.0178		−0.0182	−0.0325	
Q5	−0.0287	−0.0255		−0.0375	−0.0331		−0.0176	−0.0157	
Q1–Q5	0.0158**	0.0025		0.0343***	0.0153*		−0.0006	−0.0169	
Panel H. Skills by HHI level calculated with the weights from the reward-to-risk timing optimization									
Q1	0.0483	0.1572		0.0375	0.1494		0.0573	0.1636	
Q5	−0.0753	0.0610		−0.0732	0.0600		−0.0707	0.0631	
Q1–Q5	0.1236***	0.0962***		0.1106***	0.0893***		0.1279***	0.1005***	
Panel I. Skills by Top10 level calculated with the weights from the minimum variance optimization									
Q1	0.0114	0.0241		0.0138	0.0256		0.0090	0.0243	
Q5	−0.0095	0.0078		−0.0209	−0.0163		−0.0022	0.0217	
Q1–Q5	0.0210***	0.0164***		0.0347***	0.0419***		0.0113**	0.0025	
Panel J. Skills by Top10 level calculated with the weights from the global minimum variance optimization									
Q1	−0.0017	0.0118		−0.0056	−0.0220		−0.0005	0.0323	
Q5	−0.0081	0.0132		−0.0097	0.0215		−0.0069	0.0068	
Q1–Q5	0.0065	−0.0014		0.0041	−0.0436***		0.0064	0.0255***	
Panel K. Skills by Top10 level calculated with the weights from the optimal portfolio optimization									
Q1	0.0202	0.1320		0.0187	0.1237		0.0220	0.1421	
Q5	0.0393	0.1082		0.0438	0.0879		0.0357	0.1247	
Q1–Q5	−0.0191	0.0238*		−0.0251	0.0359**		−0.0137	0.0173	
Panel L. Skills by Top10 level calculated with the weights from the naive diversification									
Q1	−0.0329	−0.0095		0.0040	0.0032		−0.0518	−0.0161	

Table 6 (continued)

	All funds			SRI funds			Conventional funds		
	Picking	Timing	Return gap	Picking	Timing	Return gap	Picking	Timing	Return gap
Q5	−0.0231	−0.0332		−0.0320	−0.0440		−0.0149	−0.0167	
Q1–Q5	−0.0098	0.0237***		0.0359***	0.0472***		−0.0370***	0.0006	
Panel M. Skills by Top10 level calculated with the weights from the risk-parity optimization									
Q1	−0.0128	−0.0236		−0.0030	−0.0191		−0.0177	−0.0326	
Q5	−0.0327	−0.0255		−0.0374	−0.0318		−0.0218	−0.0174	
Q1–Q5	0.0199**	0.0019		0.0344***	0.0127		0.0042	−0.0152	
Panel N. Skills by Top10 level calculated with the weights from the reward-to-risk timing optimization									
Q1	−0.0005	0.0898		0.0139	0.0977		−0.0103	0.0963	
Q5	−0.0218	0.0726		−0.0317	0.0662		−0.0164	0.0791	
Q1–Q5	0.0212**	0.0172***		0.0456***	0.0315***		0.0061*	0.0173	

This table is divided into fourteen panels. Panels A and B show the stock picking, market timing, and return gap obtained from measures (4)–(6) for all, SRI, and matched conventional pension funds from top (Q1) to bottom (Q5) concentrated funds according to the *HHI* and *Top10* calculated from the actual fund weights, respectively. Panels C–H show the stock picking and market timing obtained from measures (4)–(5) for all, SRI, and matched conventional pension funds in top (Q1) and bottom (Q5) concentrated funds according to the *HHI* calculated from the minimum-variance (panel C), the global minimum variance (panel D), the optimal portfolio (panel E), the naïve diversification (panel F), the risk parity (panel G), and the reward-to-risk timing (panel H) optimization-model solutions. Panels I–N show the stock picking and market timing obtained from measures (4)–(5) for all, SRI, and matched conventional pension funds in top (Q1) and bottom (Q5) concentrated funds according to the *Top10* calculated from the minimum-variance (panel I), the global minimum variance (panel J), the optimal portfolio (panel K), the naïve diversification (panel L), the risk parity (panel M), and the reward-to-risk timing (panel N) optimization-model solutions. Skills from Q2 to Q4 are not displayed in panels C–N and are available upon request. The significance levels of the difference in means of quintiles 1 and 5 (Q1–Q5) are based on t-tests. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

variables. These factors generate informational externalities, enabling them to develop timing skills and exploit macroeconomic-information advantages with concentration. Panel B also shows generalized poor skills for *Top10* quintiles. Picking and timing skills are only positive in the middle-concentrated SRI and conventional funds.

Panels C–N show the skills in the top and bottom concentrated portfolios (Q1 and Q5) obtained from the optimization model solutions¹⁸ to analyze whether the optimization models can help managers obtain differential skills by concentration level. Panels C–E show that the greater skills with higher concentration, as observed in panels A–B, are not sustained with optimization models. In contrast, managers achieve superior picking in the least concentrated funds (panel C) and superior timing in the least concentrated SRI funds (panel D). This evidence is consistent with the diversification assumptions of traditional optimization models (Markowitz 1952). Nonetheless, more modern models (panels F–H) provide some significantly positive Q1–Q5 differences, indicating superior skills in the top concentrated funds. The greater similarity of the latter results with those found in panel A aligns with the rationality of these models; that is, more modern models are based on managers' investing intuition (Oikonomou et al. 2018). Panels I–N also show mixed results for *Top10* quintiles, confirming no rationalization between concentration and skills in the optimization models because concentration and skills are not included among the model premises.

¹⁸ The skills of the remaining quintiles are not shown for the sake of brevity but are available upon request.

The influence of skills on concentration

This section presents the results of the influence of skills on concentration because the analyses in Sect. "Skills by concentration level" reveal distinct skills according to the level of the actual fund concentration. Skill measures (4)–(6) are included in model (12) to obtain model (14) as follows:

$$\begin{aligned} Conc_{i,t} = & \beta_0 + \beta_1 SRI_dummy_{i,t-1} + \beta_2 Sust_score_{i,t-1} \\ & + \beta_3 Picking_{t-1}^i + \beta_4 Timing_{t-1}^i + \beta_5 RG_{t-1}^i \\ & + \sum_{j=5}^{15} \beta_j Control_{i,t-1} + FE + \varepsilon_{i,t} \end{aligned} \quad (14)$$

where $Picking_{t-1}^i$ is the stock-picking skill of fund i in month $t-1$, $Timing_{t-1}^i$ is the market-timing skill of fund i in month $t-1$, and RG_{t-1}^i is the return gap of fund i in month $t-1$. The remaining variables are described in model (12).

Panel A of Table 7 displays the results of model (14),¹⁹ which align with Table 4's findings; that is, SRI funds have a lower concentration than conventional funds. Additionally, managers with better picking and timing exploit their skills by increasing fund concentration (significantly positive timing at 5% and 10% in columns 1 and 2). In contrast, managers with a larger return gap diminish fund concentration. Although the latter conduct is not consistent with that found in Table 6, it shows that managers aim to address the negative return gaps by reducing concentration to offset hidden costs.

Skills, concentration, and performance

This last section examines the joint effect of concentration and skills on performance to test H7. Kacperczyk et al. (2014) found that skills can predict performance, and Choi et al. (2017) pointed out the interaction effect of skills and concentration strategies on performance. Skill measures (4)–(6) and skill–concentration interaction variables ($Skill_{t-1}^i * Con_{i,t-1}$) are included in model (13) to obtain model (15). Model (15) allows the analysis of the specific effect of picking, timing, and return gap skills on performance and the joint effect of skills and concentration on performance as follows:

$$\begin{aligned} Performance_{i,t} = & \beta_0 + \beta_1 SRI_dummy_{i,t-1} + \beta_2 Conc_{i,t-1} \\ & + \beta_3 Sust_score_{i,t-1} + \sum_{j=4}^6 \beta_j Skill_{t-1}^i \\ & + \sum_{j=7}^9 \beta_j Skill_{t-1}^i * Con_{i,t-1} + \sum_{j=10}^{19} \beta_j Control_{i,t-1} + FE + \varepsilon_{i,t} \end{aligned} \quad (15)$$

where $\sum_{j=4}^6 \beta_j Skill_{t-1}^i$ represents the picking, timing, and return gap measures (4)–(6) of fund i in month $t-1$, and the interaction terms $\sum_{j=7}^9 \beta_j Skill_{t-1}^i * Con_{i,t-1}$ allow to study the impact of concentration according to picking, timing, and return gap on the performance of fund i in month $t-1$, respectively. The remaining variables are described in model (13).

Panel B of Table 7 presents the results of model (15). Comparing these results with those shown in panel A of Table 5, the persistent and superior evidence of the positive concentration–performance relationship after controlling for skills indicates that

¹⁹ The control-variable results are available upon request and are in line with the findings presented in Table 4.

Table 7 Relation between skills, concentration, and performance

Panel A. Concentration determinants						
	HHI			Top10		
SRI_dummy	− 0.0027***			− 0.0022***		
	(− 12.4)			(− 11.43)		
Sust_score	− 0.0037*			− 0.0060***		
	(− 1.91)			(− 3.23)		
Picking	0.02***			0.0086***		
	(9.54)			(5.90)		
Timing	0.0015**			0.0007*		
	(2.34)			(1.73)		
Return gap	− 0.0055***			− 0.0047***		
	(− 3.34)			(− 2.89)		
Control variables	Yes			Yes		
R-squared	0.1607			0.1340		
No. Obs	4867			4867		
Panel B. Influence of concentration and skill on performance						
	Panel B.1. HHI as concentration measure			Panel B.2. Top10 as concentration measure		
	All	SRI	Conv	All	SRI	Conv
SRI_dummy	0.0023***			0.0023***		
	(16.45)			(16.65)		
Concentration	0.0417***	0.116***	0.0293***	0.0736***	0.1194***	0.0663***
	(4.58)	(6.65)	(2.65)	(6.85)	(6.09)	(4.92)
Sust_score	0.0072***	0.0118***	0.007***	0.0075***	0.0120***	0.0073***
	(6.82)	(6.31)	(5.89)	(7.13)	(6.53)	(5.95)
Picking	− 0.0028**	0.0057	− 0.0058***	− 0.0023	0.0212***	− 0.0101***
	(− 2.21)	(1.51)	(− 4.15)	(− 1.23)	(3.51)	(− 4.97)
Timing	− 0.0002	− 0.0029	− 0.0008**	− 0.0000	− 0.0008	− 0.0015***
	(− 0.56)	(− 1.12)	(− 2.49)	(− 0.09)	(− 0.23)	(− 2.77)
Return gap	− 0.0043	− 0.01	− 0.007**	− 0.0090**	− 0.0232**	− 0.0085**
	(− 1.39)	(− 1.38)	(− 2.01)	(− 2.39)	(− 2.41)	(− 1.98)
Picking*Conc	− 0.0045	− 0.3694**	0.3582***	− 0.0017	− 0.0642***	0.0359***
	(− 0.06)	(− 2.31)	(4.19)	(− 0.25)	(− 3.76)	(4.59)
Timing*Conc	− 0.0125	0.0269	0.1154***	− 0.0010	− 0.0047	0.0084***
	(− 0.36)	(0.25)	(2.93)	(− 0.36)	(− 0.48)	(2.78)
Return_gap*Conc	0.3512***	0.5927*	0.4284***	0.0370***	0.0762**	0.0338***
	(3.2)	(1.71)	(3.59)	(3.65)	(2.57)	(3.20)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.3836	0.6097	0.2058	0.3880	0.6133	0.2104
No. Obs	4874	2063	2811	4859	2060	2799

This table is divided into two panels. Panel A shows the results of model (14) with the actual fund variables. The concentration variable is *HHI* in column (1) and *Top10* in column (2). Panel B shows the results of model (15) with the actual fund variables. The concentration variable is *HHI* in panel B.1 and *Top10* in panel B.2. All models are estimated with time fixed effects and robust standard errors clustered by fund and month. Control variables are not shown and the results are available upon request. T-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

managers exploit information advantages with concentration. The negative impact of conventional fund skills (picking, timing, and return-gap) on performance relates to the poor skills found in Sect. "Skills by concentration level". Furthermore, the scarce influence of SRI managers' skills on performance is also explained by the poor SRI fund skills. The predictive margins of the significant interaction terms are presented in Appendices B–C to understand the results better because interaction terms are formed of non-dummy variables (concentration and skills).

The graphs in Appendix B/C show the relationship between the *HHI/Top10* and the performance for three skill levels (maximum, average, and minimum). Graphs B.1–B.2 of Appendix B show increasing SRI-fund performance with greater *HHI* concentration for all picking and return gap levels. Moreover, managers with the maximum picking/return gap level achieve higher/lower performance levels than the managers with the minimum picking/return-gap level. Hence, SRI-fund managers with superior picking skills can exploit this ability using concentration strategies to enhance fund performance. However, more skilled traders do not achieve the performance level of less skilled traders using concentration strategies. This evidence is consistent with the generalized negative return gap found in Table 6, revealing estimation errors in the marginal benefit with regard to the marginal cost of increasing concentration (Fulkerson and Riley 2019; Kacperczyk et al. 2005).

Graphs B.3–B.5 show increasing performance with greater *HHI* for all skill levels in conventional funds. Nevertheless, managers with the maximum/minimum skills achieve the lowest/highest performance. Furthermore, Graph B.4 shows that more skilled timers develop more concentrated portfolios to achieve the same performance as less skilled timers. This evidence indicates that the positive timing of the most concentrated conventional funds does not translate into better performance. Chen and Lai (2015) found a negative relationship between performance and concentration due to overconfidence; that is, a human bias that causes individuals to overestimate their skills, misjudge the accuracy of their private information, and overestimate the value of assets (Fellner-Röhling and Krügel 2014). These results indicate that conventional-fund managers are overconfident in their information signaling and timing skills, affecting their performance.

Graphs C.1–C.2 in Appendix C show higher performance with greater *Top10* concentration in SRI funds, and the SRI managers with the maximum picking (return gap) level achieve the highest (lowest) performance level. Graphs C.3–C.5 also display a positive *Top10*-performance relationship in conventional funds, and managers with the maximum/minimum skill levels achieve the lowest/highest performance level.

Consistent with the information-advantage principles, this section demonstrates that the SRI and conventional funds employ concentration strategies to leverage informational advantages and improve performance. However, the generalized poor skills do not allow managers to exploit concentration strategies, affecting performance. Only superior SRI-fund pickers can exploit the selectivity skills with concentration, improving performance. Hence, H7 is rejected. It is noteworthy that conventional-fund managers can improve performance with higher concentration, but skilled conventional-fund managers cannot exploit their skills with concentration. This evidence shows that conventional managers make estimation errors about the marginal benefit relative to the marginal cost of increasing concentration, and present managerial overconfidence in their skills

Table 8 Relation between skills, concentration, and performance obtained from the optimization-model solutions

	HHI as concentration measure			Top10 as concentration measure		
	All	SRI	Conv	All	SRI	Conv
Panel A: Results with the variables calculated from minimum variance optimization						
Concentration	−0.0016 (−0.42)	0.0010 (0.20)	−0.0030 (−0.61)	−0.0023 (−0.62)	0.0192*** (3.99)	−0.0094* (−1.69)
Picking	0.0202 (1.57)	0.0372** (2.26)	0.0061 (0.31)	−0.0467*** (−4.56)	−0.0662*** (−6.83)	0.0286 (1.31)
Timing	−0.0036 (−0.43)	−0.0400** (−2.05)	0.0125 (1.10)	−0.0163 (−1.55)	−0.0254* (−1.78)	−0.0137 (−1.08)
Picking*Conc	−0.0253 (−0.71)	−0.0897* (−1.95)	0.0403 (0.72)	0.1739*** (6.18)	0.2236*** (7.56)	−0.0224 (−0.40)
Timing*Conc	0.0089 (0.45)	0.1161* (1.88)	−0.0285 (−1.08)	0.0456 (1.48)	0.0692* (1.66)	0.0396 (1.04)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.1328	0.2102	0.1618	0.1426	0.2469	0.1594
No. Obs	4178	1677	2501	4741	1983	2758
Panel B: Results with the variables calculated from global minimum variance optimization						
Concentration	0.0000 (0.01)	0.0123*** (4.55)	−0.0077*** (−2.65)	0.0016 (0.85)	−0.0002 (−0.07)	−0.0005 (−0.19)
Picking	0.0024 (0.20)	−0.0107 (−1.17)	0.0396** (2.29)	−0.0102 (−0.99)	−0.0132 (−1.61)	0.0076 (0.62)
Timing	−0.0070 (−0.80)	0.0100 (0.77)	0.0117 (0.87)	−0.0086 (−1.26)	−0.0296*** (−3.32)	0.0175*** (2.91)
Picking*Conc	0.0267 (1.15)	0.0336* (1.87)	−0.0251 (−0.70)	0.0589*** (2.93)	0.0499*** (3.06)	0.0435* (1.71)
Timing*Conc	0.0153 (0.88)	−0.0170 (−0.77)	−0.0209 (−0.71)	0.0168 (1.18)	0.0641*** (3.67)	−0.0405*** (−3.28)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.1481	0.2454	0.1634	0.1388	0.2288	0.1508
No. Obs	4262	1699	2563	4692	1983	2709
Panel C: Results with the variables calculated from optimal portfolio optimization						
Concentration	−0.0161*** (−2.98)	−0.0424*** (−4.78)	−0.0040 (−0.59)	0.0050 (0.78)	−0.0168** (−2.02)	0.0184** (2.18)
Picking	−0.0346*** (−2.86)	−0.0755*** (−4.55)	0.0055 (0.24)	0.0569*** (3.28)	0.0101 (0.76)	0.0943*** (4.15)
Timing	−0.0141 (−1.40)	0.0781** (2.00)	−0.0146 (−1.27)	0.0369*** (3.02)	0.0617* (1.96)	0.0164 (1.55)
Picking*Conc	0.0803*** (3.86)	0.1315*** (5.26)	0.0329 (0.97)	−0.0674*** (−2.65)	−0.0114 (−0.56)	−0.1041*** (−2.88)
Timing*Conc	0.0199 (1.46)	−0.1150** (−2.11)	0.0221 (1.43)	−0.0484*** (−2.68)	−0.1057* (−1.95)	−0.0184 (−1.23)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.2871	0.6682	0.2482	0.3098	0.5396	0.4053
No. Obs	678	227	451	612	273	339
Panel D: Results with the variables calculated from naive diversification						
Concentration	−0.0116 (−0.54)	0.3497** (2.46)	−0.1616*** (−3.32)	0.0066 (0.24)	0.1466 (0.84)	−0.0752** (−2.11)
Picking	0.0079 (1.45)	0.0289* (1.90)	0.0043 (0.82)	0.0075** (2.37)	0.0253** (2.49)	0.0042 (1.27)

Table 8 (continued)

	HHI as concentration measure			Top10 as concentration measure		
	All	SRI	Conv	All	SRI	Conv
Timing	−0.0016 (−1.11)	−0.0080 (−1.44)	−0.0001 (−0.05)	−0.0009* (−1.66)	−0.0015 (−0.40)	−0.0005 (−0.82)
Picking*Conc	−0.2129 (−1.45)	−0.7588 (−0.97)	−0.1126 (−0.80)	−0.5427** (−2.41)	−1.8824 (−0.82)	−0.2725 (−1.16)
Timing*Conc	0.0384 (0.81)	0.9297** (2.14)	−0.0190 (−0.30)	0.0429 (1.03)	2.7503* (1.89)	0.0028 (0.06)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0850	0.2920	0.1902	0.0868	0.2336	0.1631
No. Obs	1643	913	730	1643	913	730
Panel E: Results with the variables calculated from risk-parity optimization						
Concentration	0.0105 (1.62)	0.0351* (1.84)	−0.0365*** (−3.15)	0.0145** (2.22)	0.0246 (1.54)	−0.0231** (−2.32)
Picking	0.0027 (1.57)	0.0247* (1.85)	0.0015 (0.97)	0.0026 (1.58)	0.0216** (2.25)	0.0014 (0.93)
Timing	−0.0001 (−0.22)	0.0105 (1.14)	−0.0001 (−0.08)	−0.0001 (−0.18)	0.0106 (1.46)	−0.0001 (−0.21)
Picking*Conc	−0.0168 (−1.47)	−0.2213 (−0.56)	−0.0090 (−0.85)	−0.0160 (−1.45)	−0.1714 (−0.47)	−0.0071 (−0.69)
Timing*Conc	0.0016 (0.18)	−0.0987 (−0.31)	−0.0032 (−0.32)	0.0015 (0.20)	−0.1434 (−0.42)	−0.0013 (−0.16)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0533	0.1730	0.1676	0.0542	0.1688	0.1621
No. Obs	1643	913	730	1640	910	730
Panel F: Results with the variables calculated from reward-to-risk timing optimization						
Concentration	0.0080 (1.57)	0.0099* (1.89)	0.0235* (1.80)	0.0069*** (3.10)	0.0350*** (5.24)	0.0004 (0.14)
Picking	0.0172*** (3.75)	0.0356*** (4.56)	0.0026 (1.54)	0.0056*** (2.63)	0.0564*** (5.02)	0.0013 (1.47)
Timing	−0.0010 (−0.75)	−0.0017 (−0.13)	−0.0010 (−1.03)	−0.0013 (−1.49)	0.0446*** (2.76)	−0.0009 (−1.37)
Picking*Conc	−0.0171 (−0.33)	−0.1702*** (−3.26)	0.0493 (0.39)	−0.0132* (−1.80)	−0.1526*** (−2.73)	0.0044 (1.35)
Timing*Conc	0.0015 (0.34)	0.3043** (1.99)	0.0035 (0.31)	0.0016 (0.61)	−0.1828*** (−4.25)	0.0038* (1.93)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.3140	0.4991	0.2582	0.2647	0.5024	0.1482
No. Obs	1131	741	390	1634	904	730

This table presents the results of model (15) with the *HHI* and *Top10* concentration measures calculated from the minimum-variance (panel A), global minimum variance (panel B), optimal portfolio (panel C), naïve diversification (panel D), risk parity (panel E), and reward-to-risk timing (panel F) optimization-model solutions for all, SRI, and conventional funds. All models are estimated with time fixed effects and robust standard errors clustered by fund and month. Control variables are not shown and the results are available upon request. T-statistics are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively

and information signals in developing concentration strategies (Chen and Lai 2015; Fulkerson and Riley 2019; Kacperczyk et al. 2005).

Table 8 shows the results of model (15) with the variables calculated from the optimization model solutions. The results confirm the diverse effects of concentration on performance found in panels B–G of Table 5. Skills from traditional optimization-model solutions also affect performance in different ways (panels A–C). However, the picking skills from modern optimization-model solutions positively influence SRI-fund performance (panels D–F). The predictive margins of the significant interaction terms²⁰ show that only some models provide higher performance with superior skills and higher concentration, differing between the SRI and conventional portfolios. Specifically, the asset allocation from the reward-to-risk timing model helps SRI funds exploit picking and timing skills. In contrast, the asset allocation from the optimal portfolio model helps conventional funds exploit picking skills, presenting higher performance with superior skills and greater concentration. Additionally, results from the optimal portfolio (reward-to-risk timing) models show lower performance with superior skill levels and a higher concentration in SRI (conventional) funds. The discrepancy between the same models for the SRI and conventional funds is because the models must calculate asset weights from actual fund holdings to consider the investment profile of the SRI and conventional funds. Consistent with previous literature, these results indicate that the best optimization models differ between the SRI and conventional funds because SRI portfolios usually present higher uncertainty (Oikonomou et al. 2018).

Conclusions

This study analyzes whether the limited universe of ESG assets can lead SRI pension funds to deviate from the asset allocations of six well-known portfolio optimization models (minimum variance, global minimum variance, optimal portfolio, naïve diversification, risk-parity, and reward-to-risk timing), presenting higher concentration and lower performance than their conventional peers. Unlike previous research, this study considers that SRI-fund concentration strategies may be related to informational advantages. In addition, this study overcomes previous studies on simulated SRI portfolios because the analyses consider the actual investment profiles of funds in the optimization models. Hence, this study also demonstrates whether optimization models can guide managers to improve their skills, concentration strategies, and performance.

The results indicate that the concentration of UK SRI equity pension funds is lower than the concentration of UK conventional equity pension funds. Moreover, pension funds largely diversify their portfolios, showing a concentration similar to the naïve diversification. Thus, the actual fund concentration is lower than the concentration calculated with the optimization-model solutions (except with the naïve diversification). This finding contributes to the SRI literature by demonstrating that the ESG asset universe is not an endemic SRI fund restriction and can provide investment opportunities.

In addition, greater fund concentration improves the performance of SRI and conventional funds, which is consistent with the principles of the information-advantage

²⁰ Predictive margin graphs of the significant interaction terms in Table 8 are available upon request.

theory. However, accomplishing concentration strategies also depends on managerial skills, and the results indicate poor stock-picking, market-timing, and unobserved trading skills. Only superior SRI-fund pickers can achieve higher performance than less skilled SRI pickers for a particular concentration level. Skilled conventional managers cannot achieve higher performance than less skilled managers for a specific level of concentration, revealing overconfidence in their information signal and skills. These results indicate that managers should know that deviating from the optimization models may damage pension fund participants. Moreover, some optimization models can help managers improve performance and skills through better asset-allocation decisions, such as the reward-to-risk timing model in SRI funds. Nonetheless, managers may be motivated to depart from optimization models because these models provide static solutions, and constantly recalculating models to adapt to market movements may be costly and subject to each model's idiosyncrasy.

The results of this study offer managers, market regulators, and fund participants a better understanding of concentration patterns in the UK SRI and conventional equity pension funds, identifying the benefits and limitations of concentration strategies and the consequences of deviating from optimization models. Additionally, managers can be aware of the risks of overconfidence and their real capabilities in concentration strategies. Managers can also understand each optimization model's complexity, assumptions, and limitations to incorporate upcoming information to adapt to market movements and rebalance portfolios. Moreover, fund participants can better understand the impact of concentration decisions on their pension fund savings. Thus, market regulators should pursue transparency and provide reliable information about concentration strategies to improve the decision-making process of fund participants.

Nevertheless, some limitations should be highlighted, and further research should be conducted. First, although the UK pension fund industry is the second most important worldwide, some concentration patterns may differ in less developed markets and/or markets influenced by distinct demographic patterns, such as population aging. Further research that considers demographics in other countries will address the possible limitations related to country-oriented analyses. Second, SRI fund data limitations result from the continuing growth of the SRI pension fund niche. Furthermore, the analyses are restricted to six optimization models, and the study of additional optimization models will complete the findings. In this sense, the assumption that optimization models consider actual fund asset allocations might also constrain investment alternatives. Moreover, the results are limited to the time horizon of the study; thus, it is necessary to consider that investors' ESG concerns evolve over time and that the rapid expansion of ESG issues in society also influences the ESG asset diffusion. The analysis of other institutional investors may also expand the knowledge about concentration strategies.

Appendix A: Note on *HHI* and *Top10* concentration measures

To illustrate the calculation of *HHI*, suppose Fund A and Fund B with the following portfolio holdings at period t . Fund A invests in four stocks and the weights are: 25%, 25%, 25%, and 25%. Fund B invests in four stocks and the weights are: 70%, 20%, 5%, and 5%.

$$HHI \text{ of Fund A} = 0.25^2 + 0.25^2 + 0.25^2 + 0.25^2 = 0.25.$$

$$HHI \text{ of Fund B} = 0.70^2 + 0.20^2 + 0.05^2 + 0.05^2 = 0.535.$$

Although Funds A and B have the same number of stocks at period t , the higher HHI of Fund B shows greater portfolio concentration because of the larger investment in two assets (70% and 20%) and Fund A is equally weighted. HHI is recalculated with the new weights and holdings of Funds A and B at period $t+1$, and so on as long as the funds do not disappear.

The calculations can be extrapolated to funds with diverse number of holdings; in fact, the funds analysed in this paper hold, on average, 141.8 stocks per quarter (130 stocks and 151.6 stocks in SRI and conventional funds, respectively).

In addition, to illustrate the calculation of $Top10$, suppose two funds. Fund A invests in twenty stocks at period t and is equally weighted (the weight of each stock is 5%). Fund B invests in twenty stocks and the weights of the ten stocks with the highest weights are: 20%, 20%, 15%, 15%, 10%, 5%, 2%, 1%, 1%, 1% (the remainder stocks have weights of 1%).

$Top10$ of Fund A = $0.05^2 + 0.05^2 + 0.05^2 + 0.05^2 + 0.05^2 + 0.05^2 + 0.05^2 + 0.05^2 + 0.05^2 + 0.05^2 = 0.025$, and HHI of Fund A is 0.05.

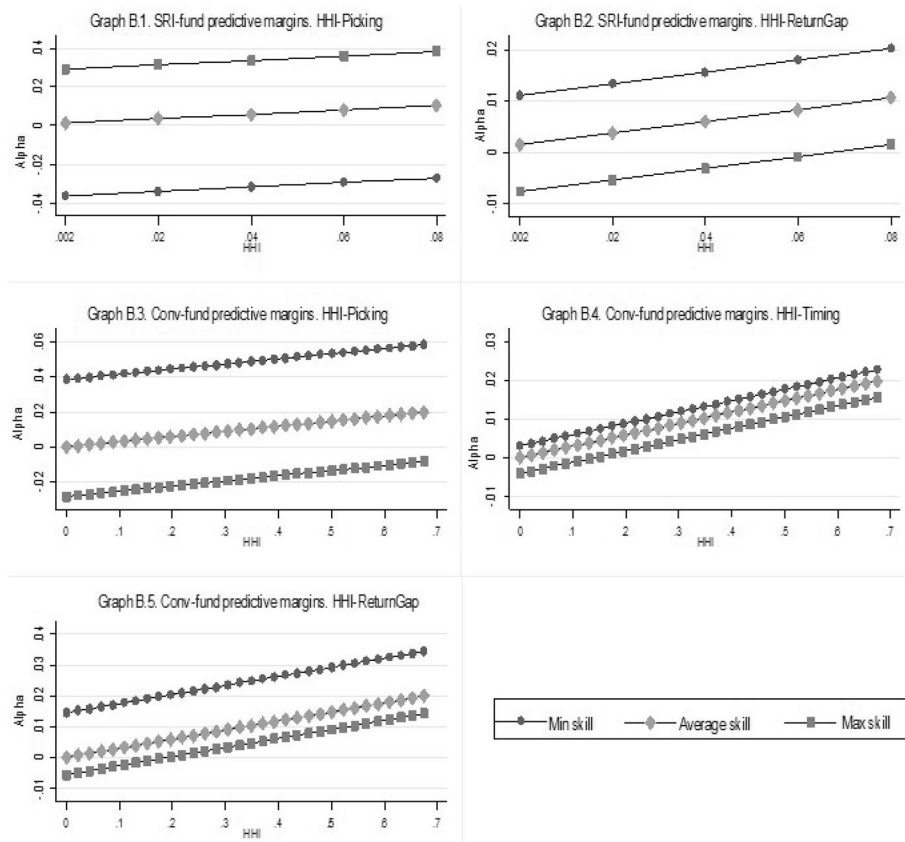
$Top10$ of Fund B is 0.1382, and HHI of Fund B is 0.1392.

HHI and $Top10$ indicate that Fund B is more concentrated than Fund A, and $Top10$ is closer to HHI in Fund B than in Fund A because of the larger importance of a few stocks with regard to the remaining holdings. These results show the interest of including $Top10$ as additional concentration measure when a small number of portfolio holdings are overweighted. $Top10$ will be recalculated for Funds A and B with the new weights and holdings at period $t+1$, and so on as long as the funds do not disappear.

In addition, HHI and $Top10$ are equal in funds holding ten or less assets.

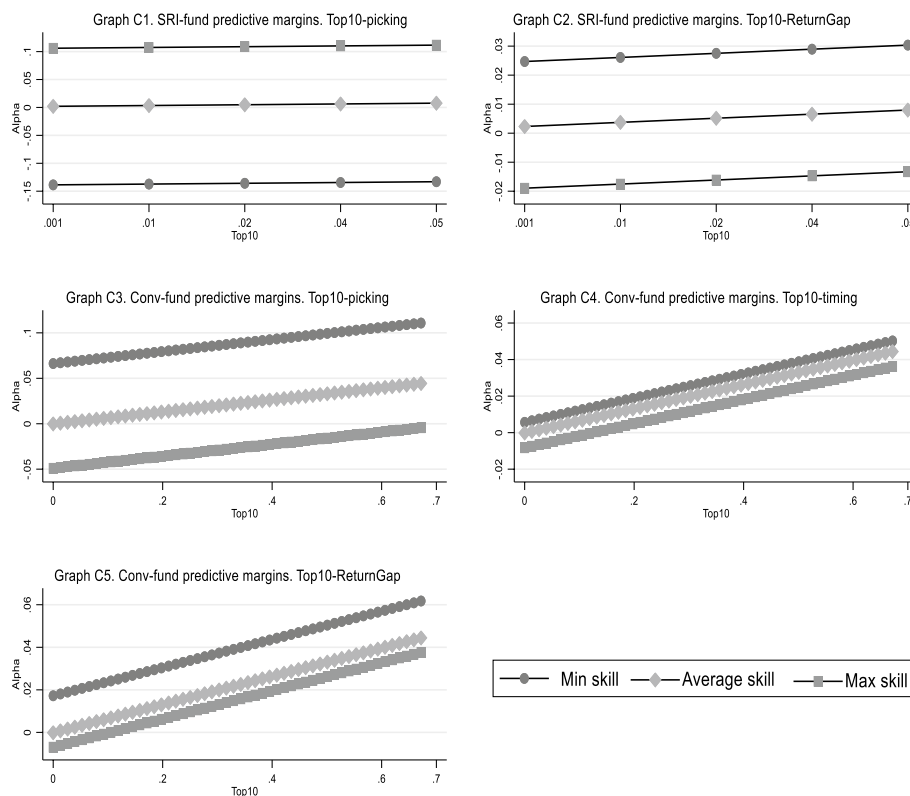
Appendix B: Predictive margins of significant HHI-skill interaction terms in SRI and conventional funds

Graphs B.1–B.5 show the predictive margins of the significant picking-concentration, timing-concentration, and ReturnGap-concentration interaction terms of SRI and conventional funds in panel B.1 of Table 7. The y-axis shows the performance (alpha) and the x-axis shows the HHI concentration.



Appendix C: Predictive margins of significant Top10-skill interaction terms in SRI and conventional funds

Graphs C.1–C.5 show the predictive margins of the significant picking-concentration, timing-concentration, and ReturnGap-concentration interaction terms of SRI and conventional funds in panel B.2 of Table 7. The y-axis shows the performance (alpha) and the x-axis shows the *Top10* concentration.



Abbreviations

AQR	Applied Quantitative Research
CDF	Cumulative distribution function
CMA	Conservative minus aggressive in the investment factor
ESG	Environmental, social, and governance
FE	Fixed effects
FTSE	The Financial Times Stock Exchange
HHI	Herfindahl–Hirschman fund concentration index
HML	High minus low in the book-to-market factor
LRP	Lower relative polarization
MRP	Median relative polarization
OECD	The Organization for Economic Cooperation and Development
PDF	Probability density function
RMW	Robust minus weak in the profitability factor
SMB	Small minus big in the size factor
SRI	Socially responsible investment
TNA	Total net assets
Top10	Concentration of the top-10 fund holdings
UK	The United Kingdom
URP	Upper relative polarization
USA	The United States of America
VIF	Variance inflation factor

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Availability of data and materials

Due to the nature of the research, supporting data is not available.

Declarations

Competing interests

The author declares that she has no competing interests.

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