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EDHEC BUSINESS SCHOOL

Contents

Introduction

I am delighted to introduce the latest EDHEC-Risk Institute special issue of the EDHEC Research Insights supplement to Investment & Pensions Europe, which aims to provide European institutional investors with an academic research perspective on the most relevant issues in the industry today.

We first look at a problem that arises in the decumulation phase of retirement, namely that relatively little is known about the interaction between withdrawal and investment strategies. In research supported by Bank of America, our specific goal is to identify whether some withdrawal strategies are more suitable than others as a function of the level of risk-taking in the investment portfolio. Overall, we found that state-dependent withdrawal strategies that take into account 'bad states of the world' such as poor market performance (low liquid wealth) or high expected time to live display better results than the fixed withdrawal strategy.

Next, when asset managers are criticised for greenwashing, the answer is often that greenwashing is only an issue for passive investments, while active strategies – particularly active ownership – can fix all these problems. We study to what extent institutional investors' ownership affected corporate carbon emissions in 68 countries for the period from 2007 to 2018 and find that institutional investment on average does not appear to lead to any tangible carbon footprint reduction.

We explore the optimal design of personalised performance portfolios for liability-driven investors in research that was supported by FirstRand. Our analysis suggests that investors would benefit from the availability of 'precision investing portfolios' tailored to their specific circumstances, as opposed to being left with portfolios that focus on standalone performance. It helps shift the emphasis away from investment products towards genuine investment solutions.

In research drawn from the Amundi ETF, Indexing and Smart Beta Investment Strategies research chair at EDHEC-Risk Institute, we present the results of the EDHEC European ETF, Smart Beta and Factor Investing Survey 2021, which feature a slowdown in the use of smart beta and factor investing strategies, and a growing interest in the integration of an SRI/ESG component into investment. The 2021 survey shows significant interest in SRI/ESG among respondents, who overwhelmingly answered all questions related to it. Many of them already include this component in their investment, and a large part of those who do not plan to do so in the near future. While their main motivation to incorporate ESG criteria into their investment is to facilitate a positive impact on society, the majority of them do not want this to be done at the expense of performance.

In an article on replicating real estate indices prepared as part of the Swiss Life Asset Managers France research chair on Real Estate in Modern Investment Solutions at EDHEC-Risk Institute, we find that it is possible to track the EDHEC IEIF Commercial Property (France) index with a satisfactory degree of accuracy over long-term horizons by constructing a buy-and-hold and cap-weighted portfolio of 10 to 15 SCPIs, thereby mitigating the liquidity constraints of the French non-listed real estate fund market. Our proposed replication method does not require any modelling or any data-intensive calculation and is therefore expected to be robust.

Finally, we ask whether ESG investing improves risk-adjusted performance. We argue that ESG strategies should be valued for the unique benefits that they can provide, such as making a positive impact on the environment or society, as opposed to being promoted on the basis of disputable claims regarding their outperformance potential.

We hope that the articles in the supplement will prove useful, informative and insightful. We wish you an enjoyable read and extend our warmest thanks to IPE for their collaboration on the supplement.

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Efficient withdrawal strategies in retirement investing

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The investment problem for individuals and households in the decumulation phase can be broadly defined as a combination of consumption and bequest goals, subject to a dollar budget defined in terms of initial wealth. One of the key challenges for financial advisers is to provide personalised advice to individuals as far as their retirement investment decisions are concerned. The original Merton problem (Merton [1969, 1971]) does address the joint optimisation of investment and consumption decisions, but the analysis is cast in an extremely simplified setting and cannot be directly used to develop an actionable decision-making process for individuals in decumulation. On the other hand, many heuristic withdrawal rules exist such as the 3% (or 4%) rule, including more sophisticated rules (see Suri et al [2020]). Relatively little, however, is known about the interaction between withdrawal and investment strategies. Our specific goal is to identify whether some withdrawal strategies are more suitable than others as a function of the level of risk taking in the investment portfolio.

Maeso et al (2021) propose a formal analysis of efficient investment strategies for individuals and households in the decumulation phase of their life cycle. They create for that purpose a comprehensive and flexible framework that can be used to derive optimal investment decisions taking as given a stream of fixed income withdrawal cash flows in the presence of long-term care risk, with a relatively rich menu of investment opportunities that includes balanced funds, target date funds, equity indices but also annuity products, for which they use realistic market quotes. In what follows, we study the introduction of additional, more flexible, withdrawal strategies as an extension of the Maeso et al (2021) initial framework and focus on the joint optimisation of investment and withdrawal decisions.

To study this joint optimisation, we apply the framework to a 65-year-old woman who is already retired (and assumed to have just retired). We assume that if and when she experiences long-term care needs, she will need additional retirement income to secure a semi-private room at a cost of \$90,155 × (1 + 3.10%)^t per year at date *t*, and an annual cost increase of 3.10%.[1] We invite the reader to refer to section 4 of Maeso et al (2021) for more details on how market and longevity risks are modelled.

Figure 1 illustrates the rationale of the framework as our 65-year-old starts her retirement with an initial wealth of \$500,000 and a 4% initial target withdrawal rate. The target withdrawal rate increases by 2% year on year to adjust for cost of living, and we assume for simplicity that no life event occurs. The individual's target withdrawal *TW(t)* at date *t* is equal to the initial target withdrawal rate times initial wealth in real terms. For illustrative purposes, we assume that she invests all her initial wealth in a balanced fund. At each date *t*, if the value of the balanced fund account at date *t* is sufficient, she withdraws her replacement income needs from this account. Otherwise, she withdraws the balance (possibly nothing) of the account.

The welfare function we use to determine the optimal investment strategy is based on two quantities, namely the discounted income deficit (*ID* in short, always negative), which is defined as actual withdrawals minus target withdrawals (given as 4% of initial wealth in the base case) and the discounted bequest (*BS* in short, always positive).

$$ID = \sum_{t=0}^{\tau-1}\left(AW(t) - TW(t)\right)\exp\left(-tR_{0,t}\right)$$

$$BS = W\_(\tau)\exp\left(-\tau R_{0,\tau}\right)$$

Here, *TW(t)* is the target withdrawal level at time *t* (given by 4% of the initial wealth in the base case, plus a possible cost-of-living adjustment), *AW(t)* is the actual withdrawal level at time *t* (which is equal to *TW(t)* where possible given the available wealth, and less than *TW(t)* otherwise), $R_{0,t}$ is the annualised continuously compounded discount rate at time 0 for maturity *t*, *W_(t)* is the wealth available at time *t* before withdrawal, *W(t)* is the wealth available at time *t* after withdrawal, and τ is the uncertain date of death. Figure 1 shows how to calculate these quantities for a given Monte Carlo scenario. We define a welfare function that separates the contribution of the discounted bequest, which corresponds to the term *Median (BS)*, and the contribution of the discounted income deficit,

1 These figures are borrowed from the Genworth Cost of Care Survey 2019.

1. Illustration of the framework rationale

				Balanced fund: $500,000		
Time (t)	Age (x)	Target withdrawal (TW(t))	Balanced fund return r(t)	Value before withdrawl (W–(t))	Actual withdrawal AW(t)	Value after withdrawal W(t)
0	65	$500{,}000*4\%*(1+2\%)^0$		$500,000	min([TW(0), W–(0)])	W–(0) – AW(0)
1	66	$500{,}000*4\%*(1+2\%)^t$	–5%	W(t–1)*(1+r(t))	min([TW(t), W–(t)])	W–(t) – AW(t)
2	67	.	.	.	.	.
3	68	.	.	.	.	.
4	69	.	.	.	.	.
5	70	.	.	.	.	.
6	71	.	.	.	.	.
7	72	.	.	.	.	.
8	73	.	.	.	.	.
9	74	.	.	.	.	.
10	75	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
τ	τ+65	.	.	.	.	.

Discounted income deficit: $\sum_{t=0}^{\tau-1}\left[AW(t)-TW(t)\right]\exp\left(-t\times R_{0,t}\right)$

Bequest: $W\_(\tau)\exp\left(-\tau\times R_{0,\tau}\right)$

This exhibit displays how the main quantities of the framework are computed when the investment universe is made up of a balanced fund and life events are not taken into account.

which is the term $\lambda VaR_{5\%}$ (ID) (strong risk-aversion with respect to income deficits). It is given by:

$$Median\left(BS\right)+\lambda VaR_{5\%}\left(ID\right)$$

Where λ is a parameter that corresponds to the individual's risk aversion.[2]

Description of the withdrawal strategies

We start by introducing notations that will be useful to define the different withdrawal strategies in what follows:

Date 0 – start of decumulation;
$W_t\_$ – investor liquid wealth at time t before withdrawal;
c_t – withdrawal amount in \$ at time t;
$COLA_t$ – percentage cost-of-living adjustment at time t;
WR – withdrawal rate as a percentage of the investor's initial wealth;
$R_{t,i}$ – zero-coupon rate of maturity i years at time t;
LE_t – cost of the life event at time t;
τ^{LE}: date of occurrence of the life event (equal to +∞ if no life event occurs).

We consider a 65-year-old female individual with initial wealth of $500,000. The investment universe is only made up of balanced funds with a X%/(1–X%) equity/bond allocation and annual rebalancing.[3] We account for the presence of life event risk, which means that long-term care needs can occur with unresolved uncertainty with respect to the timing and severity of the event in terms of additional replacement income needs.

In the original version of the framework and in the presence of life events, the withdrawal strategy involves, where possible, withdrawing each year the same fixed withdrawal rate *WR* (say 3%, 4% or 5%) of the initial wealth $W_0\_$ with a 2% COLA component adjustment, which corresponds to the individual's target level of replacement income to meet her expenses between dates *t* and *t+1*:

$$\forall\, t\in\left[0,\tau_0-1\right],\\ \left\{c_t=\min\left[W_0\_\times WR\times\left(1+COLA_t\right)^t+LE_t,W_t\_\right]\right.\\ COLA_t=2\%$$

An attractive characteristic of this withdrawal strategy is that the individual has good visibility of the level of future withdrawals: if her current wealth at time *t* is sufficient, then she will withdraw the same amount of money in real or nominal terms until she dies. On the other hand, a drawback of this strategy is that she could be ruined before her death and consequently no longer able to meet her replacement income needs. This will happen in those scenarios of the Monte Carlo simulations where the portfolio wealth at time *t* is such that:

$$W_t\_<W_0\_\times WR\times\left(1+COLA_t\right)^t+LE_t$$

We will call this withdrawal strategy WS1.

Some authors, such as Bengen (1994), have focused on the maximum withdrawal rate with respect to the initial wealth for which the withdrawal strategy is sustainable for a 30-year time horizon, consistent with the intuition that a meaningful withdrawal strategy should lead to a low probability of the individual outliving her assets.

In addition to withdrawal strategy WS1, we also test two flexible withdrawal strategies, WS2 and WS3, where the individual cannot withdraw more than 4% of her initial wealth $W_0\_$ with a 2% COLA component adjustment but will withdraw less than this amount if her current wealth $W_t\_$ minus the cost of life events LE_t is lower than a certain threshold. The main objective of these other withdrawal strategies is to minimise the probability of the individual outliving her assets by withdrawing less money in 'bad states of the world'. The three withdrawal strategies WS1, WS2 and WS3 can be summarised as follows:

- WS1: where possible, at each date *t* the individual withdraws 4% of her initial wealth $W_0\_$ with a 2% COLA component adjustment:

$$\forall\, t\in\left[0,\tau_0-1\right],c_t\\ =\min\left[W_0\_\times WR\times\left(1+2\%\right)^t+LE_t,W_t\_\right]$$

- WS2: where possible, at each date *t* she withdraws 4% of her current wealth $W_t\_$ minus the cost induced by life events at time *t*. We fixed a cap such that at time *t* she cannot withdraw more than 4% of the initial wealth with a 2% COLA component adjustment:

$$\forall\, t\in\left[0,\tau_0-1\right],c_t\\ =\min\left[\begin{array}{l}\max\left[0,\min\left[4\%\times\left(W_t\_-LE_t\right),4\%\times\left(1+2\%\right)^t\times W_0\_\right]\right]\\ +LE_t,W_t\_\end{array}\right]$$

- WS3: we again consider withdrawal strategy WS1, but add a floor such that, where possible, at time *t* she cannot withdraw less than 2% of her initial wealth $W_0\_$ with a 2% COLA component adjustment:

2 We have chosen to treat lambda risk aversion and equity allocation as two independent degrees of freedom. We acknowledge that we could have refined our analysis by taking into account the fact that a highly risk-averse investor will naturally tend to choose a less aggressive balanced fund than a less risk-averse investor.
3 Here we take a 1% grid step for the possible values of X.

$$\forall\, t \in [0, \tau_0 - 1], c_t = \min\left[\begin{array}{l} \max\left[2\% \times (1+2\%)^t \times W_{0\_}, \min\left[4\% \times (W_{t\_} - LE_t), 4\% \times (1+2\%)^t \times W_{0\_}\right]\right] \\ +LE_t, W_{t\_} \end{array}\right]$$

Accounting for life events in WS2 implies that the individual will be ruined before her death in scenarios of the Monte Carlo simulations where the portfolio wealth at time t is such that $W_{t\_} < LE_t$ (ie, in scenarios where the cost of the life event at time t exceeds the portfolio wealth at time t). WS2 is attractive in so far as, in the absence of life events, it implies a zero probability of the individual outliving their assets, since the amount withdrawn at time t is a percentage of existing wealth. On the other hand, a drawback of this strategy is that it can lead to a high level of uncertainty over withdrawal amounts in dollars over time, depending on the variation of the portfolio wealth. WS3 presents best-of-both-world characteristics – ie, reasonably low volatility in (real or nominal) withdrawal amounts series over time and a reasonably low probability of the wealth process falling to zero before the individual's death. The introduction of a floor does not guarantee that the individual (even in the absence of life events) will not outlive her assets, but at least it limits the amplitude of the variations of the withdrawal amounts over time (the presence of the floor allows the individual to benefit from a minimum level of replacement income) and it also decreases the probability of ruin (the presence of the cap prevents individuals from withdrawing excessive amounts at any given points in time).

In addition to these three withdrawal strategies, we also wanted to test two other withdrawal strategies where the percentage of liquid wealth withdrawn at time t depends on the individual's expected time to live.

Based on Waring and Siegel (2015) and Sun and Webb (2012), we design modular withdrawal strategies where the withdrawal rate at time t is linked to the individual's remaining time to live. The approach we have adopted is the definition of a glidepath of withdrawal rates as in Sun and Webb (2012), who use tables from the Internal Revenue Service (IRS) that correspond to the inverse of the life expectancy factor. These values – or rather the inverse of these values (see figure 2) – can be loosely interpreted as a conservative value for the individual's time to live.

We thus define two additional withdrawal strategies, labelled as WS4 and WS5, where WS4 is defined with a cap and WS5 with a cap and a floor and where for both strategies the amount withdrawn at

2. Glidepath of withdrawal rates

Annual withdrawal percentage following required minimum distribution strategy

Age	%	Age	%
65	3.13	83	6.13
66	3.24	84	6.45
67	3.31	85	6.76
68	3.42	86	7.09
69	3.53	87	7.46
70	3.65	88	7.87
71	3.77	89	8.33
72	3.91	90	8.77
73	4.05	91	9.26
74	4.20	92	9.80
75	4.37	93	10.42
76	4.55	94	10.99
77	4.72	95	11.63
78	4.93	96	12.35
79	5.13	97	13.16
80	5.35	98	14.08
81	5.59	99	14.93
82	5.85	100	15.87

Source: Sun and Webb (2012).

This figure reports the withdrawal rates (glidepath) used in Sun and Webb (2012) derived from the IRS tables for required minimum distribution. The percentages correspond to the inverse of the life expectancy factor in the IRS Uniform Lifetime Table. It can be loosely interpreted as a conservative value for the individual's time to live. More details can be found here: https://smartasset.com/retirement/how-to-calculate-rmd

time t is based on this glidepath. Intuitively, the older the individual is, the less time she can expect to live and the higher the percentage she can withdraw from her account without being ruined. With the notations defined above, the withdrawal amount at time t for WS4 is defined as:

$$\forall\, t \in [0, \tau_0 - 1], c_t = \min\left[\begin{array}{l} \max\left[0, \min\left[f(t) \times (W_{t\_} - LE_t), 4\% \times (1+2\%)^t \times W_{0\_}\right]\right] \\ +LE_t, W_{t\_} \end{array}\right]$$

The withdrawal amount for WS5 is:

$$\forall\, t \in [0, \tau_0 - 1], c_t = \min\left[\begin{array}{l} \max\left[2\% \times (1+2\%)^t \times W_{0\_}, \min\left[f(t) \times (W_{t\_} - LE_t), 4\% \times (1+2\%)^t \times W_{0\_}\right]\right] \\ +LE_t, W_{t\_} \end{array}\right]$$

Empirical analysis in a balanced fund universe accounting for life events

To compare the different withdrawal strategies, in addition to the welfare function *Median (BS)* + $\lambda VaR_{5\%}(ID)$, which has no intuitive interpretation, we also report key performance and risk indicators:

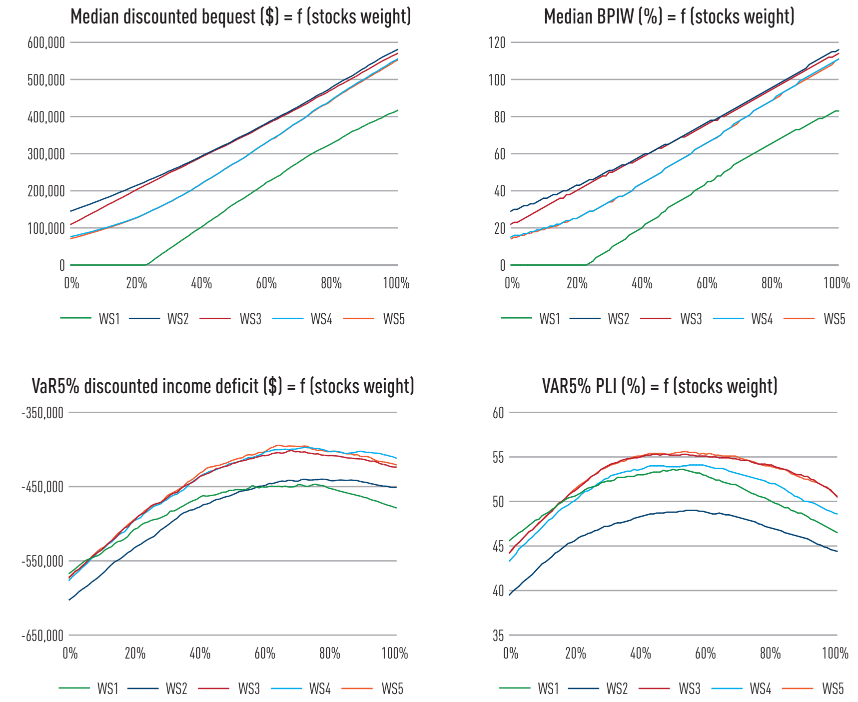
- The additional performance indicator is the Median BPIW (BPIW stands for bequest as percentage of initial wealth), which is the median discounted bequest across all the Monte Carlo scenarios divided by the initial wealth of the individual. This quantity is always positive.
- The additional risk indicator, labelled as 5%VaR PLI (PLI stands for percentage of lifetime income), is the fifth percentile across all the Monte Carlo scenarios of the ratio of the discounted realised withdrawals over the discounted target withdrawals. This quantity is always between 0 and 1 and corresponds to the fifth percentile of:

$$\frac{\sum_{t=0}^{\tau-1} AW(t)\exp(-tR_{0,t})}{\sum_{t=0}^{\tau-1} TW(t)\exp(-tR_{0,t})}$$

Figure 3 shows the median bequest, the fifth percentile of the income deficit, median BPIW and the fifth percentile of the PLI indicators for a universe made up of balanced funds as functions of the weight invested in stocks when considering the five aforementioned withdrawal strategies. Regardless of the equity allocation in the balanced fund, WS2, WS3, WS4 and WS5 display a higher median bequest value than WS1. This result was to be expected since all four strategies systematically involve withdrawal amounts that are lower than or equal to those of the base withdrawal strategy, so it is only logical that they display a higher median bequest compared to withdrawal strategy WS1. More interestingly, when comparing the 5% VaR of the income deficit values of the different strategies, WS3, WS4 and WS5 display better (ie, higher) results than WS2 when the stock weight is higher than or equal to 8%. When we look at the VaR5% PLI chart, we see that (1) WS1 is always the withdrawal strategy with the worst results and (2) WS3 and WS5 are the withdrawal strategies with the best results for a stock weight higher than 15%. Unlike the VaR5% discounted income deficit indicator, which measures in dollars the 5% value-at-risk of the income shortfall, the VaR5% PLI is defined as the fifth percentile value across all scenarios of the ratio between the sum of the individual's discounted actual withdrawals and the sum of the discounted target withdrawals until death.

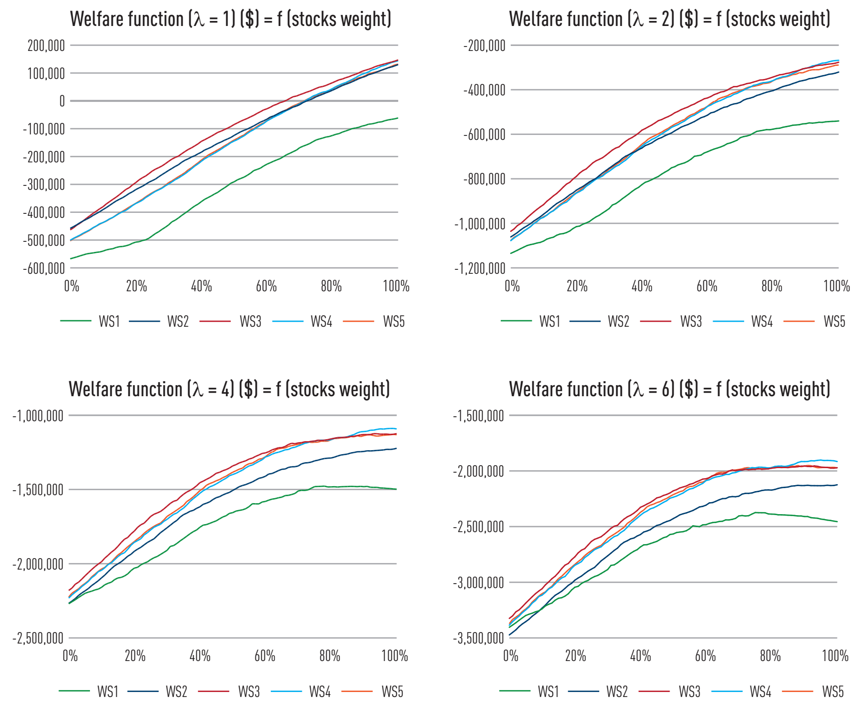
Figure 4 reports the welfare function *Median (BS)* – $\lambda VaR_{5\%}(ID)$ for the five aforementioned withdrawal strategies, for four different values of λ (λ = 1,2,4 and 6) and for a universe made up of balanced funds as functions of the weight invested in stocks. We observe that for all the λ

3. Reporting indicator charts for the balanced fund universe



This figure reports the charts of the median bequest, median BPIW, VaR5% discounted income deficit and VaR5% PLI indicators for a universe made up of balanced funds as functions of the weight invested in stocks with values ranging from 0% to 100%, with a grid step of 1% for the five withdrawal strategies described above. Life events are taken into account.

4. Welfare function charts for the balanced fund universe



This exhibit reports the charts of the welfare function for four different values of λ (λ = 1, 2, 4 and 6) for the five withdrawal strategies detailed above and for a universe made up of balanced funds as functions of the weight invested in stocks with values ranging from 0% to 100%, with a grid step of 1%. Life events are taken into account.

values (except for λ = 6 and a stock weight lower than 8%) and regardless of the stock weight, the welfare function is lower when WS1 is considered. The withdrawal strategy WS3, with both a floor and a cap, appears to be the one that leads to the highest level of investor welfare for most of the possible values of equity allocation in the balanced fund. For a low risk aversion parameter value λ equal to 1, WS3 outperforms WS5 for all stock weights. WS4 and WS5, based on a glidepath that takes into account the individual's expected time to live, do not lead to better results than WS3. We note that whatever the level of risk aversion, when we set the percentage of equity at a low level, the differences between the welfare function value with the fixed withdrawal strategy and those with the other withdrawal strategies are smaller than when we set the percentage of equity at a high level.

Overall, withdrawing less than the 4% target withdrawal with a 2% COLA indexation in cases where the current wealth is below a certain threshold while (1) guaranteeing a minimum absolute level of withdrawal and (2) imposing a maximum absolute level of withdrawal makes it possible to optimise both performance indicators (ie, median bequest) and risk indicators (5%VaR income deficit), which are the building blocks of the welfare function.

Conclusion

The first key result from our analysis is that defining the amount withdrawn from the retirement pot at time t as a constant percentage of the liquid wealth at time t (with a cap and possibly a floor) leads to better results compared to a fixed rule in the balanced fund universe for almost every allocation and risk aversion considered. Secondly, it appears that glidepath withdrawal strategies also display better results than the fixed withdrawal strategy with constant (in real terms) withdrawal amounts but are overall outperformed by the flexible withdrawal strategies with a floor. We also found in an analysis not reported here that these results still hold in universes where annuities are available in addition to balanced funds. Overall, we found that state-dependent withdrawal strategies that take into account 'bad states of the world' such as poor market performance (low liquid wealth) or high expected time to live display better results than the fixed withdrawal strategy. In practice, additional sources of complexity with joint optimisation of investment and consumption decisions in decumulation are the presence of accounts with multiple tax regimes, other sources of income that have an indirect impact on the tax treatment of the managed wealth, and relocation decisions in retirement that may impact the tax efficiency of investment and withdrawal strategies. We leave these questions for further research.

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Active ownership as a tool of greenwashing

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When asset managers are criticised for the vast greenwashing happening in financial markets (EDHEC, 2021), the answer is often that greenwashing is only an issue for passive investments, while active strategies – particularly active ownership – can fix all these problems. Investors preoccupied with climate change can be 'active owners' and influence the carbon footprint of investee companies by voting at shareholder meetings on climate-related issues and by actively engaging with executives and board members. We study to what extent institutional investors' ownership affected corporate carbon emissions in 68 countries for the period from 2007 to 2018 and find that institutional investment on average does not appear to lead to any tangible carbon footprint reduction.

Although national governments have pledged to reduce their greenhouse gas emissions, delivering on their promises will require significant changes in the production and consumption of energy by the sources of these emissions, primarily companies. The financial system is increasingly aware of the risks posed by climate change (Krueger et al [2020]; Bolton and Kacperczyk [2021]) and, accordingly, many financial actors are making investment decisions to reduce their exposure to assets – primarily securities issued by companies – particularly sensitive to climate risks. Because public and private pension schemes, insurance companies, sovereign wealth funds, mutual funds and other institutional asset managers have a long-term investment horizon, the reduction of medium to long-term risks such as climate change is for them of paramount concern (Gibson et al [2021]; Krueger et al [2020]). Moreover, many of those institutional investors also have substantial direct and indirect exposure to sectors that are particularly exposed to climate risks, such as infrastructure and energy.

Initiatives to promote the integration of sustainability into investment decisions are gaining momentum. For example, the vast majority of global institutional investors have now signed the United Nations Principles for Responsible Investment (UNPRI), committing to the integration of ESG factors, including climate change, in their asset management operations. Active ownership is considered an essential ingredient in the implementation of institutional investors' sustainability commitments. In figure 1 we show which tools and activities UNPRI investors declare they are using in relation to climate risks. Investors accounting for about 26% of the total assets under management (AUM) report that they are actively seeking the integration of climate change concerns into the operations of investee companies.

In general, active ownership encompasses both engaging with the management and boards of directors of investee companies and proxy voting on issues concerning governance and performance, including those related to the environmental strategy (Dimson et al [2015, 2019]). Active ownership approaches vary widely across investors and geographies, but they usually involve mobilising public opinion and the media, in particular to bring attention to proxy votes on environmental issues at upcoming shareholders' meetings. Other active ownership initiatives are rolled out behind the scenes and consist of discreet dialogue and interactions between investors and management and/or board directors.

1. Activities and tools used by institutional investors reporting to UNPRI

Panel A: activities undertaken by investors to respond to climate change risk						
	Setting carbon reduction targets for portfolio	Establishing climate change sensitive asset allocation strategy	Targeting low climate resilitent investments	Reducing portfolio exposure to emissions-intensive holdings	Using emssions data or analysis to inform investment decisions	Seeking climate change integration by companies
AUM ($trn)	4.71	6.96	17.79	15.67	18.46	18.51
AUM/total AUM	7%	10%	25%	22%	26%	26%
Panel B: tools used by investors to manage emission risks						
	Carbon footprinting	Scenario testing	Disclosure on emission risk	Target setting for emission risk reduction	Encouraging internal/external portfolio managers to monitor emission risks	Emission risk monitoring/ reporting formalised into contracts when appointing managers
AUM ($trn)	18.03	6.92	9.21	11.27	16.72	4.67
AUM/total AUM	26%	10%	13%	16%	24%	7%

Climate-focused active ownership measures are taken either independently or through collaborative endeavours (Dimson et al [2019]) such as the Carbon Disclosure Project (CDP) and the UNPRI itself. Collaborative engagements aim to encourage companies to disclose their climate change strategies, set emission reduction targets and take action on sector-specific issues such as gas flaring in the oil and gas sector. Examples of objectives in this area include ensuring compensation policies are consistent with environmental targets, and requiring improved disclosure and target setting from companies on their carbon price assumptions.

Whether active engagement by climate-aware investors can actually affect investee companies' carbon footprint is an empirical question with relevant implications for responsible asset management and climate policymaking. In particular, assessing the relationship between climate-aware investors and carbon footprint would shed light on the ability of finance to contribute to the transition towards a low-carbon economy as a complement of, or even as a substitute for, climate policymaking. Importantly, institutional investors own assets that are neither currently nor effectively covered by existing national climate policies. And even in jurisdictions with a carbon taxation mechanism in place, institutional investors are owners of businesses currently not included for instance in cap-and-trade frameworks. Therefore, climate-aware institutional investors can, in many ways, potentially complement or even replace the existing national and international carbon policies.

2. Descriptive statistics

	N	Min	Max	Median	Mean	Standard deviation
Sales ($ '000)	76,530	–	514,000,000	1,392,410	6,351,806	18,800,000
Assets ($ '000)	76,231	–	4,030,000,000	2,777,190	25,000,000	143,000,000
Debt ($ '000)	76,119	–	3,390,000,000	571,887	6,095,393	47,300,000
PPE ($ '000)	74,737	–	272,000,000	450,561	2,907,410	9,605,622
Carbon emissions (tonnes)	46,477	0	34,500,000,000	98,071	3,950,130	225,000,000
Institutional ownership (%)	84,312	0	100	12.3	17.3	17.5
Leverage	76,103	0	0.91	0.21	0.24	0.20
Tobin's Q	72,421	0.1	3.013	1.04	1.29	0.83
Tangibility	74,722	0	0.94	0.19	0.28	0.27
Carbon intensity	46,001	0.0005	329.03	0.039	0.7	8.99

This figure shows full sample descriptive statistics. The first column reports the number of data points for each variable. The second and third columns report the value range. The fourth column reports median values, the fifth reports mean values and the last column reports the standard deviation. Primary variables are from Thomson Reuters ASSET4, Worldscope and Orbis. Secondary variables are derived from primary variables. CI_s is carbon-sales intensity. Leverage is calculated as debt/assets. Tobin's Q is calculated as (market cap + debt)/assets. Tangibility is calculated as PPE/assets. Carbon intensity is calculated as carbon emissions/sales.

Empirical study

To study the actual effect of institutional ownership of climate-aware investors on the climate footprint of investee companies, we obtain firms' annual carbon emissions data from Thomson Reuters ASSET4. Specifically, the data are obtained from all constituent firms of the full ASSET4 universe list for the period 2007 to 2018. This timespan covers all available ASSET4 data and was chosen to maximise the dataset, anticipating that carbon emissions data is relatively unavailable. Thomson Reuters reports scope 1 and 2 carbon emissions data in their disclosed form under variable code ENERDP023. In case a firm does not disclose such emissions data, Thomson Reuters estimates the CO_2 emissions according to various models, reported under variable ENERDP123. This study complements disclosed emissions data with Thomson Reuters' estimates to maximise the number of observations. This yields an initial sample of 7,373 firms. Data on firms' institutional shareholdings is from Orbis. Figure 2 displays the descriptive statistics.

This study adopts an OLS regression model with lagged values for the dependent variable. The regression equation is the following:

$$CF_{it} = \alpha + \beta IO_{it-1} + \gamma' Y_{it-1} + \Lambda + \epsilon_{it}$$

where CF_{it} is the carbon footprint (measured alternatively as CO_2 emissions or as the ratio of CO_2 emissions and revenues) of company i at time t, IO_{it-1} is the institutional ownership of company i at time $t-1$, and Y_{it-1} represents a collection of control variables for firm i at time $t-1$. Λ includes time, country and industry fixed effects.

We investigate whether institutional ownership impacts the carbon footprint (in terms of both emissions and carbon intensity) of investee companies. Figure 3 reports the simplest models estimated using the lagged log of emissions (column

3. Regression results: emissions and carbon intensity

	Log emissions (1) Coeff./se	Log carbon intensity (2) Coeff./se
Institutional ownership	−0.000	-0.001***
	(0.001)	(0.001)
Sales	0.637***	
	(0.010)	
Tobin's Q	−0.011	−0.036***
	(0.007)	(0.007)
Asset tangibility	2.701***	2.740***
	(0.040)	(0.041)
Asset size	0.283***	-0.034***
	(0.014)	(0.010)
Leverage	−0.004	−0.003
	(0.008)	(0.008)
Earnings	−0.014*	−0.017**
	(0.008)	(0.008)
Constant	−1.781	−2.978
	(26010.334)	(21492.527)
Observations	22,114	22,137
R-sq	0.745	0.592
Country	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes

Variables are transformed as indicated to improve data distributional properties. Regression estimates include robust standard errors, clustered at country level. Data are from Thomson Reuters ASSET4; Worldscope and Orbis. Significance levels reported in superscript: *** is significant at 1%; ** is significant at 5%; * is significant at 10%.

4. Regression results: emissions and carbon intensity by quartile

	Log emissions		Log carbon intensity	
	Top 25% emitters Coeff./se	Bottom 25% emitters Coeff./se	Top 25% emitters Coeff./se	Bottom 25% emitters Coeff./se
Institutional ownership	−0.006***	-0.000	−0.004***	0.000
	(0.002)	(0.001)	(0.001)	(0.000)
Sales	0.220***	0.533***		
	(0.042)	(0.020)		
Tobin's Q	−0.054	−0.003	0.050***	−0.031***
	(0.039)	(0.016)	(0.011)	(0.006)
Asset tangibility	1.427***	2.628***	0.182**	2.316***
	(0.144)	(0.082)	(0.073)	(0.037)
Asset size	0.315***	0.388***	0.006	−0.051***
	(0.048)	(0.029)	(0.017)	(0.009)
Leverage	−0.020	0.031	0.121***	0.004
	(0.008)	(0.008)	(0.035)	(0.006)
Earnings	−0.037*	−0.021	−0.011	-0.019***
	(0.020)	(0.017)	(0.013)	(0.007)
Constant	3.940***	0.195	−0.365	−1.689**
	(1.018)	(1.303)	(0.749)	(0.736)
Observations	5,369	16,880	5,309	16,828
R-sq	0.493	0.548	0.282	0.445
Country	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes

Variables are transformed as indicated to improve data distributional properties. Regression estimates include robust standard errors, clustered at country level. Data are from Thomson Reuters ASSET4; Worldscope and Orbis. Significance levels reported in superscript: *** is significant at 1%; ** is significant at 5%; * is significant at 10%.

1) and the log of carbon intensity (column 2). The coefficients should be interpreted as an impact on the percentage of emissions.

First, the table shows that the institutional ownership coefficient has the hypothesised sign. However, considering the emissions volume, there is no statistically significant effect. On the contrary, focusing on carbon intensity, we observe that it decreases by 0.1% for each 1% increase in ownership by institutional investors. Therefore, for one standard deviation in institutional ownership, carbon intensity decreases by −1.75% annually.

At a more granular level, figure 4 illustrates the difference between the bottom and top quartiles of the distribution of the emissions and carbon intensity. The results suggest that in the bottom quartile of the distribution institutional ownership makes no difference: the coefficient is not significantly different from zero. If we observe the quartile of 'heavy polluters', we see that the coefficient is negative and significant for both of the dependent variables used in this research. As for emissions, the coefficient (−0.006) suggests that for each 1% increase in institutional ownership, there is a 0.6% decrease in CO_2. One standard deviation increase in ownership leads to a robust decrease of approximately 10.5% in emissions. When carbon intensity is considered, the effect is smaller in magnitude but still statistically significant: an increase of 1% in institutional ownership determines a carbon intensity reduction of 0.4% (one standard deviation increase in institutional ownership leads to a 12.7% decrease in carbon intensity).

Conclusions

We study to what extent institutional investors' ownership affected corporate carbon emissions in 68 countries for the period from 2007 to 2018. The results show that institutional investment on average does not appear to lead to any meaningful reduction in carbon footprint (measured as CO_2 emissions and carbon intensity). However, institutional investors are associated with a limited carbon footprint reduction for the highest polluters in the sample. Thus, responsible investors can help the decarbonisation of investees but are unlikely to play a major role in the low-carbon transition unless their active ownership becomes more effective.

COP26 has disappointingly been a missed opportunity for the planet. Finance was at the very centre of most COP26 discussions and is often identified as a solution to the inaction of governments. Our analysis shows that institutional shareholders do not reduce their investees' carbon footprint in any meaningful way but they do contribute to carbon emission reductions in the most polluting companies. However, even for the highest emitting companies in our sample, the carbon footprint reduction is of a limited magnitude. Therefore, active ownership – as it has been carried out so far – is not a solution in the fight for climate change but, at best, a tool of greenwashing.

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Precision investing:

On the optimal design of personalised performance portfolios for liability-driven investors

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Merton's (1973) fund separation theorem establishes that there are at least two reasons why an investor would want long or short exposure to a given risky asset. The first is the 'speculative motive', which is to maximise the short-term Sharpe ratio of the portfolio, and it drives the introduction of the maximum Sharpe ratio (MSR) portfolio. The second is the 'hedging motive', which is to hedge against unfavourable changes in investment opportunities – eg, interest rates or risk premia. In the presence of liabilities, a third motive exists, which is to hedge against unexpected changes in the value of liabilities (Martellini and Milhau [2012]), so a liability-hedging portfolio (LHP) enters the solution as an additional building block. The introduction of minimum performance constraints, such as a minimum wealth or funding requirement in asset and liability management impacts the allocation decision regarding these funds. For instance, the optimal strategy in the presence of a minimum wealth constraint involves a dynamic allocation between the performance-seeking portfolio (PSP) and a pure discount bond that pays off the desired minimum (which represents the hedging demand against unexpected changes in interest rates), and the outcome of that strategy is a non-linear payoff equal to the payoff of a bond-plus-call strategy. The optimal strategy is thus a form of option-based portfolio insurance (El Karoui, Jeanblanc and Lacoste [2005]). Deguest, Martellini and Milhau (2014) extend this result to asset-liability management by showing that the optimal liability-driven investing strategy in the presence of a minimum funding ratio constraint involves dynamic allocation to the PSP and the LHP.

The above fund separation theorems describe the building blocks and the allocation rule to be used to maximise expected utility, but there are situations in which some of the building blocks and/or the allocation strategy are given and cannot be optimally chosen. This is in particular the case in delegated portfolio management contexts, where each decentralised asset manager is tasked with managing a sub-component of the whole investor portfolio, with a payoff function that is exogenously fixed and not necessarily optimal.[1]

If the PSP is not meant to be used naked but as part of an investment strategy that involves one or more other building block(s), then how should it be constructed? It is unclear whether the standard Sharpe ratio maximisation prescription is optimal for each sub-component of the portfolio even if it is at the overall portfolio level. Besides, even if the manager is in charge of the whole PSP, a pure focus on the expected return and the volatility of the portfolio is only rational in the absence of liabilities. For liability-driven investors, relative risk is a more meaningful objective. Moreover, preferences are not always accurately represented by the simple mean-variance utility function, and other welfare criteria which capture higher-order moments, like expected utility, or explicitly penalise downside risk, like expected shortfall, may be regarded as more appropriate.

To address these questions, this paper provides a characterisation for the optimal PSP for a given welfare function when this PSP is used with another building block in a multi-asset portfolio that may involve rebalancing. As in Merton (1973) and Cox and Huang (1989), we are interested in analytical expressions of optimal portfolios, since these expressions facilitate numerical calculations, hence practical implementation, and they help understand the impact of exogenous param-

1 That the portfolio eventually held by investors is not optimal can be explained by the presence of frictions preventing them from fully revealing their preferences to decentralized asset managers, or by the presence of frictions preventing asset managers from coordinating their actions so as to implement a utility-maximizing payoff.

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eters, such as the PSP's weight in a fixed-mix strategy or the minimum wealth level in an insurance strategy. Fully explicit solutions are not always available in extremely general settings, but in most of the cases presented in this paper, the welfare function can be calculated explicitly, which makes numerical optimisation fast and accurate.

We demonstrate that the optimal PSP can be represented as a combination of several funds, which involves an MSR portfolio plus one or more other fund(s). This result implies that the MSR portfolio alone is in general suboptimal. Among the other funds are the global minimum variance (GMV) portfolio and the 'most liability-friendly' (MLF) portfolio, which maximises the correlation with liabilities. The allocation to the various funds depends on the welfare function and the strategy in which the PSP is used.

This personalised approach to PSP construction is somewhat similar to the precision medicine model, widely regarded as a fundamental breakthrough that will mark the start of a whole new era for medical practice by proposing the customisation (or mass-customisation) of healthcare, with treatments, practices or products being tailored to a subgroup of patients, instead of a one-drug-fits-all model. For this reason, we use the term precision investing to define a personalised investment strategy that is tailored to optimise investor suitability versus standalone risk-adjusted performance.

Optimising the choice of the underlying asset for a convex payoff

Let us start with a two-step investment process in which a centralised decision maker chooses an insurance strategy whose payoff is a convex function of the PSP payoff, and a decentralised asset manager is assigned the task of constructing a PSP. The optimisation problem is to search for the optimal PSP for a given payoff function.

Technical assumptions
Beginning with some initial wealth or asset level A_0 at time 0, the insurance strategy aims to secure minimum wealth level M by time T by investing in a PSP and a pure discount bond that pays $1 at time T. To obtain a closed-form expression for the optimal PSP, we need to make a few stylising assumptions:

- The PSP is invested in risky assets whose prices follow geometric Brownian motions and is a fixed-mix portfolio that is continuously rebalanced towards the weights $\mathbf{w}$;
- The short-term interest rate r is constant;
- The insurance strategy is either constant proportion portfolio insurance (CPPI) with continuous rebalancing or option-based portfolio insurance (OBPI).

OBPI involves purchasing a pure discount bond that pays M at time T, plus n European call options written on a PSP with value S. By imposing that the strike price be equal to M/n, the payoff of this strategy is $A_T = \max[M, nS_T]$. The number of options is then determined by the budget constraint, which states that initial wealth is split between the bond and the options. In those scenarios where the options end in the money, the relative gross return of the insured portfolio with respect to the PSP is $\xi = nS_0/A_0$, a quantity that we call 'access to upside' because it is the fraction of the PSP return that is captured with the insurance strategy. ξ is always less than 1, reflecting the fact that insurance against downside risk has a strictly positive opportunity cost. A noteworthy property of ξ is that it is decreasing in the PSP volatility, as can be seen by rewriting terminal asset value as a bond-plus-call payoff, $A_T = M + [[\xi A_0/S_0] S_T - M]^+$. A lower PSP volatility implies a lower call price for a given spot price, so ξ must increase for the call price to stay constant.

With CPPI, insurance is achieved by taking the dollar allocation to the PSP at each point in time to be a constant multiple m of the risk budget, where the risk budget is defined as the distance between the current portfolio value and the floor. The floor is the discounted value of the minimum target wealth level.

Welfare metrics
The standard optimisation criterion in the academic literature is the expected utility from terminal wealth, that is $E[U(A_T)]$ for some utility function U. The power utility function, $U(x) = x^{1-\gamma}/1-\gamma$, is a standard choice. When the risk aversion parameter γ is set to zero, the welfare metric is risk-neutral and reduces to expected wealth. Unlike the quadratic utility function that is used in mean-variance portfolio analysis, expected power utility captures the impact of higher-order moments (most notably skewness and kurtosis) on welfare.

The value of expected utility has no economic significance, so the agent in charge of constructing the PSP may prefer to use goal-based investing criteria, eg, maximising the probability of reaching a target wealth level or minimising the expected shortfall with respect to that level. Mathematically, the success probability and the expected shortfall given a target wealth N are written as $P[A_T \geq N]$ and $E[[N - A_T]^+]$. It can be noted that minimising the expected shortfall is equivalent to maximising the expectation of a concave function of wealth, so this objective is qualitatively similar to expected utility maximisation.

Under the assumptions of geometric Brownian prices and a fixed-mix PSP, the PSP payoff is log-normally distributed, so all the above welfare metrics can be written as functions $f(e_S, v_S)$ of the expectation and variance of the logarithmic PSP return, respectively denoted by e_S and v_S. This property holds more generally with any welfare criterion that can be written as $E[\phi(S_T)]$ for some function ϕ. Explicit expressions for the function f are given in the appendix.

A two-fund separation result for precision investing
The optimal vector of percentage weights in the risky assets is given by the following proposition.

Proposition 1 (Optimal PSP for non-linear payoff)

Let

$$x = -\frac{\partial f}{\partial e_S} + 2\frac{\partial f}{\partial v_S}$$

and assume that $x \neq 0$ at the optimum. Then, the optimal PSP is

$$\mathbf{w}^* = -\frac{\lambda_{MSR}}{x\sigma_{MSR}}\frac{\partial f}{\partial e_S}\mathbf{w}_{MSR} + \left[1 + \frac{\lambda_{MSR}}{x\sigma_{MSR}}\frac{\partial f}{\partial e_S}\right]\mathbf{w}_{GMV^+}$$

MSR and *GMV* respectively denote the maximum Sharpe ratio portfolio and the global minimum variance portfolio, and λ_{MSR} and σ_{MSR} are the Sharpe ratio and the volatility of the MSR portfolio. All vectors have length equal to the number of constituents.

The two funds that make up the optimal PSP are the standard building blocks of mean-variance analysis, namely the maximum Sharpe ratio (MSR) and global minimum variance (GMV) portfolios, and the weights of these funds depend on the function f, hence on the welfare metrics and the shape of the insured payoff. The representation given by Proposition 1 is not completely explicit because the optimal weight vector is present in the right-hand side through the derivatives of f. But it is an equation that can be numerically solved for $\mathbf{w}^*$, and this numerical routine is fast and accurate thanks to the above analytical expressions.

Numerical illustrations

Methodology

To give concrete examples of optimal PSPs, we consider the problem of optimising the stock portfolio that serves as the underlying asset of an insurance strategy (OBPI or CPPI). Because the manager in charge of the PSP ends up holding two portfolios, namely MSR and GMV, it suffices to assume that she has access to two risky assets, which respectively correspond to the two portfolios. Deguest, Martellini and Milhau (2021) show that the Sharpe ratios (λ), volatilities (σ) and correlation (ρ) of the MSR and GMV portfolios satisfy the equalities

$$\rho_{MSR,GMV} = \frac{\lambda_{GMV}}{\lambda_{MSR}} = \frac{\sigma_{GMV}}{\sigma_{MSR}}$$

We let σ_{MSR} = 20%, σ_{GMV} = 12% and λ_{MSR} = 0.40. These values imply $\rho_{MSR,GMV}$ = 60% and λ_{GMV} = 0.24. Assuming a 1% short-term rate, we obtain expected returns of 9% and 3.88% per year for the MSR and GMV portfolios.

The risk aversion parameter in utility (γ) is set to 10, the investment horizon is one year, and the target wealth in expected shortfall is taken to be $N = \alpha \times A_0 \times \exp[rT]$ with α = 110%. Thus, the target is 110% of the amount of wealth that would be attained by investing in cash. We set the floor as a minimal percentage of that amount, which ranges from 10% to 90%. A 0% floor would correspond to no insurance, and a 100% floor implies that initial wealth is fully invested in cash, so that the choice of the PSP is irrelevant. Optimal PSPs are calculated by numerically maximising expected utility or by minimising the expected shortfall. Analytical expressions for the derivatives of the welfare function are provided to the optimiser to accelerate convergence.

Our benchmark PSP is the MSR portfolio, which would be the default choice for an investor endowed with mean-variance preferences, seeking a portfolio fully invested in risky assets and ignoring the payoff function. The utility gain of the optimal PSP with respect to the MSR portfolio is measured as the 'monetary utility gain', which is the quantity denoted with *MUG* such that investing $A_0 \times [1 + MUG]$ in the insurance strategy with the MSR portfolio delivers the same utility as investing in the strategy with the optimal PSP.

Impacts of floor and multiplier

The numerical results are shown in figures 1 and 2. Although leverage constraints have not been introduced, the chosen parameter values imply long-only allocations in many cases. With the utility criterion, both weights are positive for floors ranging from 10% to 80%, and with expected shortfall, they are positive until a 60% floor level. With both criteria, the optimal share in the MSR portfolio is increasing in the floor: with expected utility and a CPPI multiplier of 3, the MSR allocation is 8.42% for a 10% floor and grows to 16.29% for a 50% floor and to 60.09% for a 90% floor, with the remainder invested in the GMV portfolio. With OBPI, the same qualitative pattern is observed, but the MSR weight ranges within narrower bounds, from 20.00% to 34.78% with utility-based preferences and from 42.93% to 56.13% with shortfall-based preferences. Remarkably, the optimal PSP shows little sensitivity to the floor level while the floor ranges from 10% to 50%: it has 20% in the MSR constituent with expected utility and 42.93% with expected shortfall. This happens because for low floors, the probability for the non-insured PSP to fall short of the minimum is close to zero, so that the coefficient of access to upside, ξ, is almost 1. In these specific circumstances, the optimal PSP coincides with the one that maximises expected utility or minimises expected shortfall, regardless of the non-linear payoff.

Not only is the optimal share of MSR asset increasing in the floor, but it is also decreasing in the multiplier of CPPI strategies, from 167.97% for a multiplier of 1 down to 31.43% for a multiplier of 5 with the shortfall criterion. Therefore, more conservative insurance strategies require a greater share of MSR portfolio to compensate for the larger amount of risk-free asset that is introduced at the asset allocation stage.

1. Utility-maximising performance-seeking portfolios for insured payoffs

Floor (%)	10	20	30	40	50	60	70	80	90
CPPI, *m* = 1									
MSR (%)	22.46	25.42	29.13	33.97	40.62	50.42	66.45	97.61	183.19
GMV (%)	77.54	74.58	70.87	66.03	59.38	49.58	33.55	2.39	−83.19
Monetary utility gain (% of A_0)	6.13	4.31	2.91	1.84	1.04	0.47	0.12	0.00	0.10
CPPI, *m* = 3									
MSR (%)	8.42	10.12	11.83	13.80	16.29	19.69	24.93	34.57	60.09
GMV (%)	91.58	89.88	88.17	86.20	83.71	80.31	75.07	65.43	39.91
Monetary utility gain (% of A_0)	55.72	33.30	22.15	15.05	10.03	6.30	3.49	1.43	0.19
CPPI, *m* = 5									
MSR (%)	6.69	8.23	9.55	10.97	12.65	14.82	17.96	23.37	36.75
GMV (%)	93.31	91.77	90.45	89.03	87.35	85.18	82.04	76.63	63.25
Monetary utility gain (% of A_0)	69.12	41.67	28.49	20.28	14.44	9.96	6.35	3.37	1.01
OBPI									
MSR (%)	20.00	20.00	20.00	20.00	20.00	20.03	20.84	25.07	34.78
GMV (%)	80.00	80.00	80.00	80.00	80.00	79.97	79.16	74.93	65.22
Monetary utility gain (% ofA_0)	8.54	8.54	8.54	8.53	8.41	7.65	5.69	3.09	1.09

This table displays the optimal percentage weights of the MSR and GMV portfolios and the monetary utility gains achieved by switching from the MSR portfolio to the optimal PSP. The floor is defined as $M \times \exp[-rT]/A_0$. Relative risk aversion is set to 10.

2. Expected shortfall-minimising performance-seeking portfolios for insured payoffs

Floor (%)	10	20	30	40	50	60	70	80	90
CPPI, m = 1									
MSR (%)	45.87	49.76	55.07	62.58	73.62	90.58	118.2	167.97	280.74
GMV (%)	54.13	50.24	44.93	37.42	26.38	9.42	−18.20	−67.97	−180.74
Expected shortfall optimal (%)	8.43	8.25	8.11	8.00	7.95	7.95	8.03	8.21	8.58
Expected shortfall MSR (%)	9.18	8.83	8.51	8.24	8.04	7.96	8.06	8.44	9.17
CPPI, m = 3									
MSR (%)	26.46	27.10	27.94	29.10	30.79	33.45	38.24	48.76	80.83
GMV (%)	73.54	72.90	72.06	70.90	69.21	66.55	61.76	51.24	19.17
Expected shortfall optimal (%)	14.23	13.27	12.33	11.41	10.53	9.71	9.00	8.50	8.46
Expected shortfall MSR (%)	18.69	17.21	15.74	14.28	12.85	11.47	10.17	9.06	8.50
CPPI, m = 5									
MSR (%)	22.43	22.73	23.11	23.63	24.36	25.48	27.41	31.43	44.23
GMV (%)	77.57	77.27	76.89	76.37	75.64	74.52	72.59	68.57	55.77
Expected shortfall optimal (%)	21.07	19.36	17.66	15.98	14.32	12.69	11.15	9.76	8.82
Expected shortfall MSR (%)	29.48	26.85	24.23	21.62	19.03	16.46	13.94	11.54	9.49
OBPI									
MSR (%)	42.93	42.93	42.93	42.93	42.93	43.11	49.01	56.13	–
GMV (%)	57.07	57.07	57.07	57.07	57.07	56.89	50.99	43.87	–
Expected shortfall optimal (%)	8.63	8.63	8.63	8.63	8.63	8.63	8.55	7.62	–
Expected shortfall MSR (%)	9.56	9.56	9.56	9.56	9.55	9.45	8.83	7.02	3.93

This table displays the optimal percentage weights of the MSR and GMV portfolios and the expected shortfalls associated respectively with the MSR portfolio and the optimal PSP. For the 90% floor in the OBPI strategy, the numerical calculation did not converge.

WELFARE GAINS
The welfare gains from optimising the PSP mechanically increase with the allocation to the PSP, so they are lower at higher floors and with higher CPPI multipliers. For a 70% floor and a multiplier of 3, the monetary utility gain is 3.49% of initial wealth, but it grows to 10.03% for a 50% floor. For a 70% floor and a multiplier of 3, the expected shortfall decreases from 10.17% to 9.00%, and if the multiplier rises to 5, the decrease is from 13.94% to 11.15%.

Introducing liabilities

In theory (Martellini and Milhau [2012]), utility-maximising liability-driven investing (LDI) strategies involve two building blocks, namely the maximum Sharpe ratio portfolio and the portfolio that has the largest squared correlation with liabilities, and the allocation to these funds depends on risk aversion and also on risk budgets (distance to floor) if a minimum funding constraint is imposed. In practice, LDI falls under the class of two-step investment strategies, where a centralised manager decides how much to allocate to a PSP versus a liability-hedging portfolio (LHP), and decentralised managers are in charge of constructing the building blocks, not necessarily by following the Sharpe ratio maximisation and the correlation maximisation prescriptions. The optimisation problem that we address now is the optimal choice of the PSP for a given (and not necessarily optimal) choice of LDI strategy and LHP.

Liability-driven investing strategies
The simplest LDI strategies are of the buy-and-hold or fixed-mix types. They are characterised by a single parameter π, which is the initial percentage weight allocated to the PSP. For mathematical tractability purposes, we assume that fixed-mix portfolios are continuously rebalanced, but we do not assume that the LHP perfectly matches liability returns, and we denote its value with B to make it distinct from L, the present value of liabilities.

Another, more sophisticated, class of LDI strategies is designed to keep the funding ratio above a certain minimum at all times, to comply with the requirements of a third party (eg, a pension plan's sponsor or the regulator) or simply as self-imposed discipline (see Martellini and Milhau [2012] for a derivation of optimal investment policies in the presence of such constraints).

A four-fund separation result
The welfare metrics applied to insurance strategies are still relevant in asset-liability management, but they should now apply to the funding ratio $R = A/L$, as opposed to asset value A. Indeed, the quantity of interest is not the absolute value of assets but the level of assets relative to liabilities. Thus, the expected shortfall is now calculated with respect to a target funding ratio expressed as αR_0, that is a multiple α (greater than 1) of the initial funding ratio.

To derive as many analytical expressions as possible, the assumption of geometric Brownian motion dynamics is extended to the present value of liabilities. Under this condition, the welfare metrics can be written as $f(e_S, v_S, c_{SL}, c_{SB})$, where c_{SL} and c_{SB} are the covariances of the PSP with liabilities and the LHP, respectively. The solution to the optimisation problem is given in the following four-fund separation theorem.

Proposition 2 (Optimal PSP in liability-driven investing)

Let

$$x = -\frac{\partial f}{\partial e_S} + 2\frac{\partial f}{\partial v_S}$$

and assume that we have $x \neq 0$ at the optimum. Then, the optimal PSP is

$$\begin{aligned}\mathbf{w}^* = & -\frac{\lambda_{MSR}}{x\sigma_{MSR}}\frac{\partial f}{\partial e_S}\mathbf{w}_{MSR} - \frac{\beta_{L/MLF}}{x}\frac{\partial f}{\partial c_{SL}}\mathbf{w}_{MLF} - \frac{\beta_{B/MBF}}{x}\frac{\partial f}{\partial c_{SB}}\mathbf{w}_{MBF} \\ & + \left[1 + \frac{\lambda_{MSR}}{x\sigma_{MSR}}\frac{\partial f}{\partial e_S} + \frac{\beta_{L/MLF}}{x}\frac{\partial f}{\partial c_{SL}} + \frac{\beta_{B/MBF}}{x}\frac{\partial f}{\partial c_{SB}}\right]\mathbf{w}_{GMV}\end{aligned}$$

MLF and *MBF* respectively denote the 'most liability-friendly' and the 'most LHP-friendly' portfolios, which maximise the squared correlations with liability returns and LHP returns, respectively. $\beta_{L/MLF}$ is the beta of liabilities with respect to the MLF portfolio, and $\beta_{B/MBF}$ is the beta of the LHP with respect to the MBF portfolio.

When the LHP B perfectly replicates liability returns L, the MLF and MBF portfolios are identical, so Proposition 2 reduces to a three-fund separation result. It should be noted that the MLF portfolio differs from the LHP in that it is invested in the PSP constituents only. Thus, if the PSP universe is formed within an equity universe but liabilities are bond-like, the LHP is typically a duration-matching fixed-income portfolio while the PSP is the most 'bond-like' equity portfolio (see Coqueret, Martellini and Milhau [2014]).

With the expected utility criterion and a fixed-mix strategy, we have a fully explicit expression:

$$\begin{aligned}\mathbf{w}^* = {} & \frac{\lambda_{MSR}}{\gamma\pi\sigma_{MSR}}\mathbf{w}_{MSR} + \left[1-\frac{1}{\pi}\right]\beta_{B/MBF}\mathbf{w}_{MBF} + \frac{1}{\pi}\left[1-\frac{1}{\lambda}\right]\beta_{L/MLF}\mathbf{w}_{MLF} \\ & + \left[1-\frac{\lambda_{MSR}}{\gamma\pi\sigma_{MSR}} - \left[1-\frac{1}{\pi}\right]\beta_{B/MBF} - \left[1-\frac{1}{\pi}\right]\beta_{L/MLF}\right]\mathbf{w}_{GMV}\end{aligned} \tag{1}$$

Numerical illustrations

In the numerical illustration, we assume that liabilities are similar to a long-term bond with an expected return of 2% per year and volatility of 4%. We assume here for simplicity that the LHP perfectly replicates the liabilities, so the manager in charge of the PSP holds the MSR, MLF and GMV portfolios. These portfolios are assumed to be fully invested in equities, with volatilities respectively taken to be 21%, 19% and 17%, and expected returns respectively set at 9.40%, 4.80% and 6.50%. The correlations (in percentage) are set as follows:

	MLF	GMV	Liabilities
MSR	50.00	80.95	3.50
MLF		89.47	7.00
GMV			6.26

Figure 3 displays examples of optimal PSPs for buy-and-hold and fixed-mix LDI strategies, with expected utility or expected shortfall as the welfare criterion. For any combination of an investment policy and a welfare function, the optimal share of MSR decreases as the PSP weight increases, while the MLF portfolio is assigned an increasing weight. The GMV weight tends to increase too, although non-monotonically. This result confirms that a combination of the MLF and the GMV portfolios acts as a (non-perfect) substitute for the LHP.

The weight assigned to the MLF portfolio is low overall, reaching 1.33% at most, but it strongly depends on the assumed correlation with liabilities (see equation 1), which is assumed to be a low 7% here. In additional tests, the results of which are not shown here, we have considered a stock-bond universe for the PSP, in which the MLF has 80% correlation with liabilities, and have found that the optimal share of MLF can exceed 30% when the PSP weight is greater than 50%.

Conclusion

This article introduces a continuous-time framework for portfolio optimization that differs from Merton's (1973) seminal model in two ways. First, optimisation does not apply to the entire portfolio of an investor, but only to the performance-seeking portfolio (PSP) managed in isolation from the remainder of the portfolio, which is invested in other building blocks that are taken as given – eg, cash in portfolio insurance or the liability-hedging portfolio in a liability-driven investing strategy. Also taken as an input is the investment policy combining the PSP with the other building blocks, which ranges from simple buy-and-hold policies to more sophisticated portfolio

3. Optimal performance-seeking portfolios in liability-driven investing strategies

Floor (%)	10	20	30	40	50	60	70	80	90	100
Expected utility – buy and hold										
MSR (%)	177.21	93.72	64.19	49.00	39.64	33.21	28.46	24.74	21.69	19.07
MLF (%)	0.10	0.75	0.98	1.09	1.17	1.22	1.25	1.28	1.31	1.33
GMV (%)	−77.32	5.53	34.83	49.90	59.19	65.57	70.29	73.97	77.00	79.60
Monetary utility gain (% of A_0)	0.05	0.00	0.09	0.29	0.63	1.10	1.73	2.57	3.68	5.21
Expected utility – fixed mix										
MSR (%)	190.48	95.24	63.49	47.62	38.10	31.75	27.21	23.81	21.16	19.05
MLF (%)	0.00	0.74	0.98	1.11	1.18	1.23	1.26	1.29	1.31	1.33
GMV (%)	−90.48	4.03	35.53	51.28	60.73	67.03	71.53	74.90	77.53	79.63
Monetary utility gain (% of A_0)	0.06	0.00	0.09	0.34	0.75	1.31	2.03	2.92	3.98	5.21
Expected shortfall – buy and hold										
MSR (%)	192.40	198.41	204.35	175.43	135.36	103.02	80.39	65.14	54.70	47.28
MLF (%)	−0.01	−0.06	-0.11	0.12	0.43	0.68	0.85	0.97	1.05	1.11
GMV (%)	−92.39	−98.35	-104.24	−75.55	-35.78	-3.70	18.76	33.89	44.25	51.61
Expected shortfall optimal (%)	9.39	8.75	8.06	7.49	7.28	7.38	7.73	8.29	9.02	9.90
Expected shortfall MSR (%)	9.46	8.90	8.31	7.72	7.35	7.38	7.77	8.42	9.29	10.34
Expected shortfall – fixed mix										
MSR (%)	511.09	234.89	143.15	100.91	79.13	66.76	59.05	53.84	50.10	47.28
MLF (%)	−2.48	−0.34	0.37	0.69	0.86	0.96	1.02	1.06	1.09	1.11
GMV (%)	−408.61	−134.54	−43.52	−1.61	20.01	32.28	39.94	45.10	48.81	51.61
Expected shortfall optimal (%)	8.45	8.20	8.08	8.09	8.23	8.46	8.76	9.10	9.49	9.90
Expected shortfall MSR (%)	9.24	8.53	8.14	8.09	8.26	8.56	8.94	9.37	9.84	10.34

This table displays the percentage weights of the MSR, MLF and GMV portfolios in optimal PSPs for liability-driven investing strategies. The optimality criterion is either the maximisation of expected utility from the final funding ratio with a risk aversion of 10, or the minimisation of expected shortfall with respect to a funding ratio of 110%.

insurance strategies. Second, the welfare metric to be maximised is not necessarily the expected utility of the PSP payoff, but can be a general function of the value of assets, which depends on the payoffs of the other building blocks and the multi-portfolio investment policy. If the strategy involves rebalancing, the corresponding terminal asset value is a non-linear function of the PSP payoff – eg, a concave function for fixed-mix policies or a convex one for portfolio insurance strategies. An important area for further research will be to relax the assumption of geometric Brownian motion for the prices of PSP constituents, but this framework already provides interesting insights: optimal PSPs can be written as combinations of the traditional maximum Sharpe ratio and global minimum variance (GMV) portfolios, plus a 'most liability-friendly' (MLF) portfolio, which maximises the correlation with liabilities if welfare is derived from the relative value of assets with respect to liabilities. The optimal share of the proxy for the risk-free asset, which is either the GMV or MLF portfolio, decreases when the investment policy at the asset level gets more conservative.

Additional work is needed to design an operational framework for the practical implementation of optimal PSPs, including the choice of the PSP constituents and a suitable methodology to estimate their risk and return parameters. The analysis conducted in this article suggests that investors would benefit from the availability of such 'precision investing portfolios' tailored to their specific circumstances, as opposed to being left with portfolios that focus on standalone performance. Just as modern healthcare seeks precision medicine tailored to a patient's personal situation, as opposed to using the same treatment for everyone, precision investing departs from the Sharpe ratio maximisation paradigm to seek optimal PSPs that explicitly take into account an investor's preferences and constraints. As such, it helps shift the emphasis away from investment products towards genuine investment solutions.

The research from which this article was drawn was produced as part of the EDHEC-Risk Institute/FirstRand research chair on designing and implementing welfare-improving investment solutions for institutions and individuals.[2]

APPENDIX

The expected utility and expected shortfall of an OBPI strategy are given by the following formulas:

$$E\left[U\left(\frac{A_T}{A_0}\right)\right]=\frac{k^p}{p}\exp\left[prT\right]\Phi\left(\frac{1}{\sqrt{v_S}}\left[\log\frac{k}{\xi}+rT-e_S\right]\right)$$
$$+\frac{\xi^p}{p}\exp\left[pe_S+\frac{p^2}{2}v_S\right]\Phi\left(\frac{1}{\sqrt{v_S}}\left[\log\frac{\xi}{k}+e_S-rT+pv_S\right]\right)$$

$$E\left[\left[N-A_T\right]^+\right]=N\left[\Phi\left(\frac{1}{\sqrt{v_S}}\left[\log\frac{\alpha}{\xi}+rT-e_S\right]\right)-\Phi\left(\frac{1}{\sqrt{v_S}}\left[\log\frac{k}{\xi}+rT-e_S\right]\right)\right]$$
$$-\xi\exp\left[e_S+\frac{v_S}{2}\right]\left[\Phi\left(\frac{1}{\sqrt{v_S}}\left[\log\frac{\alpha}{\xi}+rT-e_S-v_S\right]\right)\right.$$
$$\left.-\Phi\left(\frac{1}{\sqrt{v_S}}\left[\log\frac{k}{\xi}+rT-e_S-v_S\right]\right)\right]$$

In these formulas, Φ denotes the cumulative distribution function of the standard normal distribution*, p is $1-\gamma$, the percentage floor is defined as $k = M \times \exp[-rT]/A_0$ and the percentage target is $\alpha = N \times \exp[-rT]/A_0$.

With a CPPI strategy, the expected shortfall is given by

$$E\left[\left[N-A_T\right]^+\right]=\left[N-M\right]\Phi\left(\frac{1}{m\sqrt{v_S}}\left(\log\frac{\alpha-k}{1-k}-m\left[e_S-rT\right]-\frac{m\left[1-m\right]}{2}v_S\right)\right)$$
$$-\left[A_0\exp\left[rT\right]\right.$$
$$\left.-M\right]\exp\left[m\left[e_S-rT+\frac{v_S}{2}\right]\right]\Phi\left(\frac{1}{m\sqrt{v_S}}\left(\log\frac{\alpha-k}{1-k}-\frac{m\left[1+m\right]}{2}v_S\right)\right)$$

For expected utility, no analytical expression is available, so we employ a Monte-Carlo simulation method to estimate the welfare function $f(e_S,v_S)$.

For a fixed-mix LDI strategy, we have

$$E\left[U\left(\frac{R_T}{R_0}\right)\right]=\frac{1}{p}\exp\left[pe_R+\frac{p^2}{2}v_R\right],$$

$$E\left[\left[\alpha R_0-R_T\right]^+\right]=\alpha R_0\Phi\left(\frac{\log\alpha-e_R}{\sqrt{v_R}}\right)-R_0\exp\left[e_R+\frac{v_R}{2}\right]\Phi\left(\frac{\log\alpha-e_R+v_R}{\sqrt{v_R}}\right),$$

where e_R and v_R are the expectation and variance of the logarithmic change in the funding ratio, that is

$$e_R=\pi\left[e_S-e_B\right]+e_B-e_L+\frac{\pi\left[1-\pi\right]}{2}v_{S/B},$$
$$v_R=\pi^2v_{S/L}+\left[1-\pi\right]^2v_{B/L}+2\pi\left[1-\pi\right]c_{S/L,B/L}$$

The quantities e_B and e_L are the expected log returns of the LHP and liabilities, and $v_{S/B}$ and $v_{S/L}$ are the tracking errors of the PSP with respect to the LHP and of the LHP with respect to liabilities, respectively. $c_{S/B/L}$ is the covariance between the log relative returns of the PSP and LHP with respect to liabilities. The special case where the LHP perfectly replicates liabilities is recovered by letting $v_{B/L} = c_{S/L,B/L} = 0$ and $e_B = e_L$.

For a buy-and-hold strategy with a possibly imperfect LHP, no closed-form expressions for expected utility and expected shortfall are available, so we employ a Monte Carlo simulation technique like for CPPI.

* This function is present in the Black-Scholes formula for the pricing of European options

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2 We are grateful to Albert De Wet for very useful feedback

ESG investing gains momentum

Results from the annual EDHEC European ETF, Smart Beta and Factor Investing Survey

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In 2021, 55% of respondents were investing in SRI/ESG. Of those, 67% were using ETFs to invest in SRI/ESG.

60% of respondents would like to see further developments in SRI/ESG-based ETFs and/or low-carbon ETFs.

80% of respondents plan to increase their portfolio exposure to ESG in the near future.

To facilitate a positive impact on society (64%) is the main reason why respondents incorporate ESG into their investment decisions.

ESG and fixed income are the main expectations for future development of smart beta and factor investing products; respondents would also like more customised smart beta and factor investing solutions to be developed.

Almost every year since 2006, EDHEC has conducted a survey on European professional investors' views and uses of ETFs, as part of the Amundi research chair at EDHEC-Risk Institute on ETF, indexing and smart beta investment strategies. Our survey also investigates investor use of smart beta and factor investing strategies and focuses on investor interest in socially responsible investing (SRI)/environmental, social, governance (ESG) investing, both in the context of ETFs and smart beta and factor investing strategies.

The EDHEC European ETF, Smart Beta and Factor Investing Survey 2021 was conducted between mid-February and the beginning of April 2021, using an online questionnaire addressed to European professionals in the asset management industry. It targeted institutional investors, as well as asset management firms and private wealth managers. Our 202 respondents, of whom 81% are using ETFs, were high-ranking professionals within their organisations (39% belong to executive management and 31% are portfolio managers), with large assets under management (37% of respondents represent firms with assets under management exceeding €10bn). Respondents were distributed across European countries, with 67% from European Union member states, 15% from Switzerland, 13% from the UK and 5% from other countries outside the EU.

The notable results of this year's survey were a slowdown in the use of smart beta and factor investing strategies, and a growing interest in the integration of an SRI/ESG component into investment. Here we provide the key highlights of the survey.

How investors use ETFs and their expectations of future developments

Over the years, our surveys have shown a wide adoption of ETFs to invest in the main asset classes, with 93% of respondents using ETFs to invest in equities in 2021, 68% in corporate bonds and 67% in government bonds. Such levels have been observed for more than a decade. For other investments, such as SRI/ESG and smart beta and factor investing, the use of ETFs has developed more recently. These two asset classes deserve a special focus in the analysis of the survey results, as we note that the first is expanding while the second is stagnating or even declining in popularity among European investors.

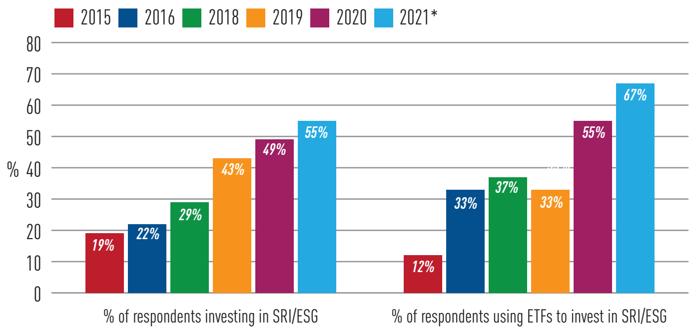
SRI/ESG ETFs

In 2015, only 19% of respondents were investing in SRI/ESG, compared to 55% of respondents in 2021, of whom 67% used ETFs to invest in SRI/ESG in 2021, whereas the figures were only 12% in 2015 and 33% in 2019 (see figure 1). From figure 1, we see that consideration of SRI/ESG within investment has been growing since 2019 especially and that the use of ETFs has particularly developed from 2020. Aggregating the results, we find that 37% of all ETF users were using ETFs based on SRI/ESG in 2021, compared to only 2% in 2015. In terms of assets under management (AUM), 27% of investment in SRI/ESG was made through ETFs in 2021, versus 39% in 2020. This decrease in intensity may be explained by the arrival of new users whose share invested in SRI/ESG may be lower than that of investors present in this market segment for longer.

Smart beta and factor investing ETFs

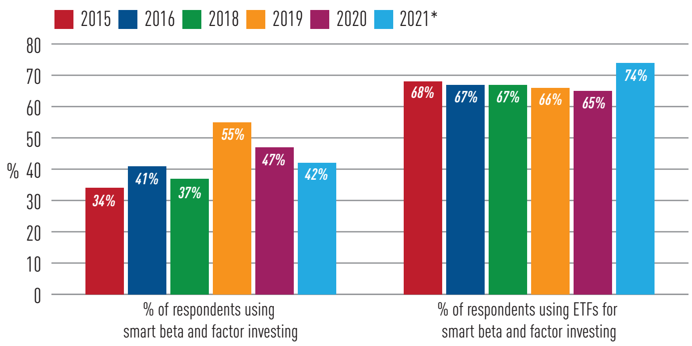
If we look at the proportion of respondents investing in this asset class, we see that a decline began in 2020. In 2021, 42% of respondents were investing in smart beta and factor investing strategies, compared to 47% in 2020 and 55% in 2019, the highest level over the period (see figure 2). However, ETFs remain an appealing instrument for this asset class. 74% of respondents were using ETFs to invest in smart beta and factor investing in 2021, versus 65% in 2020. In terms of AUM, 33% of investment in smart beta and factor investing was made through ETFs in 2021, versus 47% in 2020.

1. SRI/ESG ETF usage



* *No survey in 2017*

2. Smart beta and factor investing ETF usage



* *No survey in 2017*

The role of ETFs in the asset allocation process
Our survey results clearly indicate that the current usage of ETFs is dominated by a truly passive investment approach. Despite the possibilities that ETFs offer for implementing tactical changes, due to their liquidity and low costs, they are mainly used for long-term exposure. Some 66% of respondents use ETFs for buy-and-hold investments, while only 37% use them for tactical bets. Moreover, achieving broad market exposure remains the main focus of ETFs for 74% of users, compared with 53% of respondents using ETFs to obtain specific sub-segment exposure.

Cost and quality of replication are the two main drivers for selecting ETF providers (90% and 84% of respondents, respectively), related to the main motivations for using ETFs, namely reducing investment costs while tracking the performance of the index. Qualitative criteria considered by investors are breadth of the range and the long-term commitment of the provider (42% and 41% of respondents, respectively).

Future development of ETFs
In 2021, 49% of investors planned to further increase their use of ETFs in the future, despite the already high maturity of this market and high adoption rates. Lowering investment costs is the primary driver behind investors' future adoption of ETFs (85% of respondents). In addition, investors are not only planning to increase their ETF allocation to replace active managers (65% of respondents) but are also seeking to replace other passive investing products through ETFs (46% of respondents).

The top priority for 48% of respondents is currently the further development of SRI/ESG ETFs. In second position, 39% of respondents called for more development of low-carbon ETFs. Additionally, for ETFs related to smart beta indices, 29% of respondents called for further developments (see figure 3). The demand for ETFs based on single-factor indices or multi-factor indices lags far behind (20% and 18%, respectively).

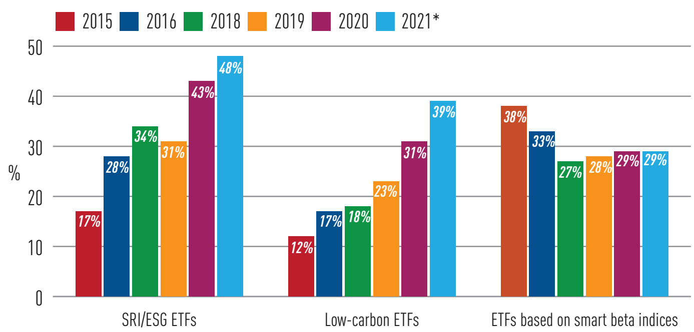
If we aggregate the responses concerning SRI/ESG and low-carbon ETFs, we see that 60% of respondents would like to see further developments in at least one of the two categories, compared with 50% in 2020 and 38% in 2019. In the same way, if we aggregate the responses concerning smart beta indices with demand for ETFs based on single-factor and multi-factor indices, we see that 45% of respondents would like to see further developments in at least one category related to smart beta equity or factor indices, compared with 43% in 2020 and 45% in 2019. It is interesting to see that since 2020, the demand for further development of ETFs based on SRI/ESG and low-carbon indices took the lead ahead of the demand for further development of smart beta and factor indices ETFs.

Present and future investor approach to ESG

In view of the significant development of ESG integration in ETFs, it was interesting to further investigate investors' position with regard to ESG. First, we note that the proportion of respondents investing in SRI/ESG is a little higher among the 81% of respondents that use ETFs than in the overall sample of respondents (55% versus 51%). Of those that do not yet integrate ESG considerations into their investment, 68% are considering doing so in the near future.

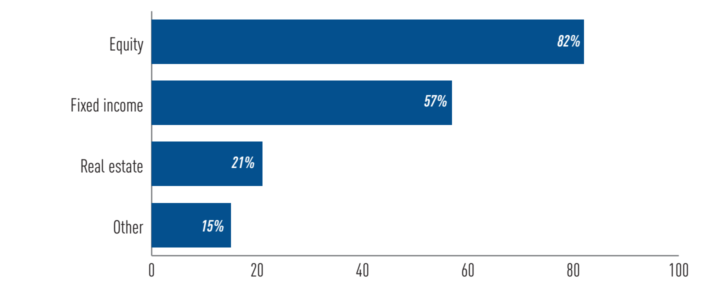
Respondents mainly include ESG concerns in the equity (82%) and fixed-income (57%) asset classes. Some 21% also consider ESG in the real estate asset class and 15% in other asset classes, including

3. Type of ETF products to be further developed in future

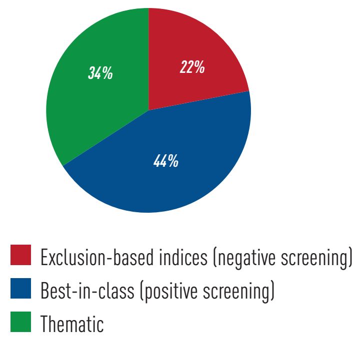


* *No survey in 2017*

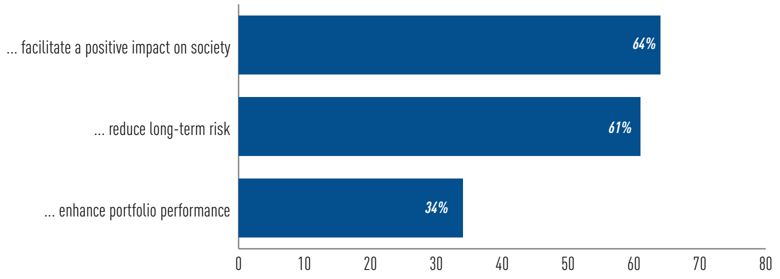
4. Asset classes in which ESG is considered



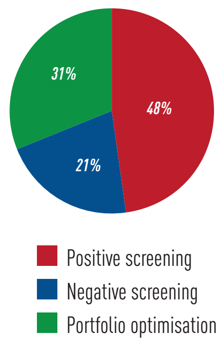
5. Preferred approach to ESG



6. Incorporating ESG considerations is important in investment decisions to ...



7. Best approach to reduce a portfolio's carbon footprint



private equity (5%) and infrastructure (4% – see figure 4).

Respondents were asked to indicate their preferred approach to ESG. Figure 5 shows that the best-in-class (ie, positive screening) approach comes far ahead of the other two, with 44% of respondents preferring it, compared with 34% for the thematic approach and 22% for the negative screening approach.

Respondents were asked about the reasons they find it important to incorporate ESG into investment decisions. The two main reasons given were to facilitate a positive impact on society (64%) and to reduce long-term risk (61% – see figure 6).

Interestingly, figure 6 shows that only a third (34%) think that incorporating ESG will serve to enhance portfolio performance. However, when respondents were asked if they were willing to accept lower performance in exchange for a better ESG score, almost two-thirds (65%) said they were not. It will therefore be important to find the right balance between this score and portfolio performance.

Respondents were also asked about the approach they consider to be the best for aligning their investments with the objective of a 1.5°C temperature rise under the Paris Agreement. Some 48% of them consider the best approach to be positive screening. Portfolio optimisation comes in second position (31% of respondents). Lastly, only 21% of respondents consider negative screening as the best approach (see figure 7).

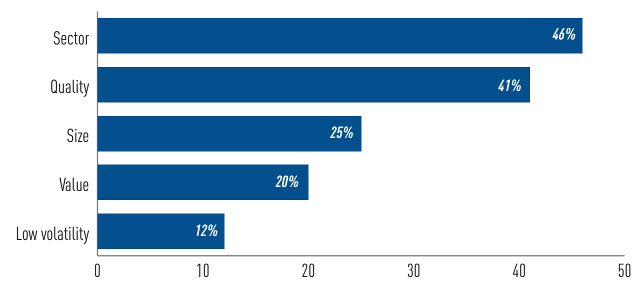
Some 44% of respondents consider ESG as a factor, while 46% do not and 10% have no opinion. Respondents say they observe factor biases when incorporating ESG into their portfolio, mainly sector bias (46% of respondents) and quality bias (41% – see figure 8). As a result, 61% of them think that sector or neutrality constraints are appropriate when using an ESG filter.

Respondents indicate they intend to use ETFs in their portfolio, first to improve its overall sustainability (48%) and second to incorporate ESG across the passive allocation (45%). Incorporating innovative ESG exposures came in last position, with 30% of respondents citing an intention to do so (see figure 9).

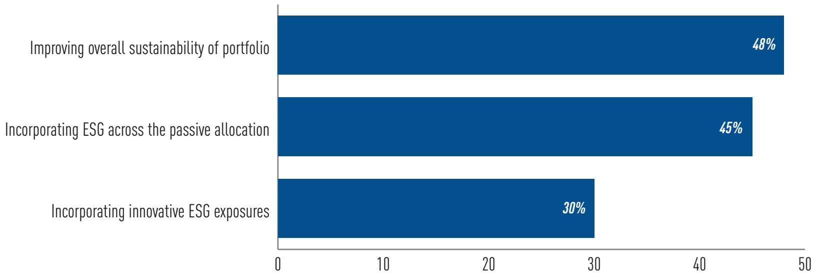
Some 71% of respondents include ESG considerations in more than 20% of their assets and 21% in more than 80% of their assets (see figure 10), which shows the significant place that ESG holds in investment for those who already consider ESG.

In addition, 80% of respondents plan to increase their portfolio exposure to ESG in the near future. It should be noted that two respondents declared that their portfolio was already almost entirely invested according to ESG criteria and that they therefore did not foresee an increase of their ESG exposure.

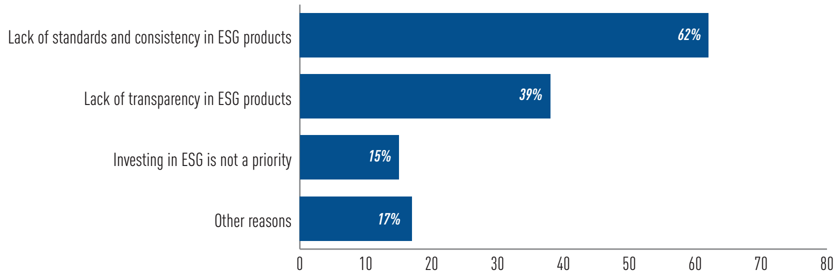
8. ESG factor biases



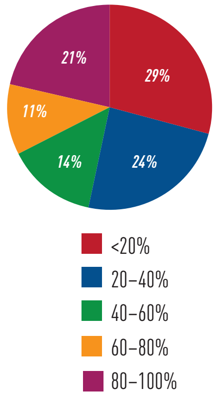
9. Use of ETFs to incoporate ESG into the portfolio



11. Reasons for not developing the use of ESG



10. Percentage of overall assets incorporating ESG



Some 62% of respondents indicate that the main reason preventing them from developing their use of ESG is the lack of standards and consistency in ESG products, while 39% cite a lack of transparency in ESG products. Only 15% of respondents do not see investing in ESG as a priority.

Not surprisingly, 78% of respondents believe that improvements in ESG regulation across Europe will enable them to make better ESG allocations.

Key objectives driving the use of smart beta and factor investing strategies

Survey participants were also invited to give their opinion on smart beta and factor investing strategies beyond their use through ETFs.

Use of smart beta and factor investing strategies

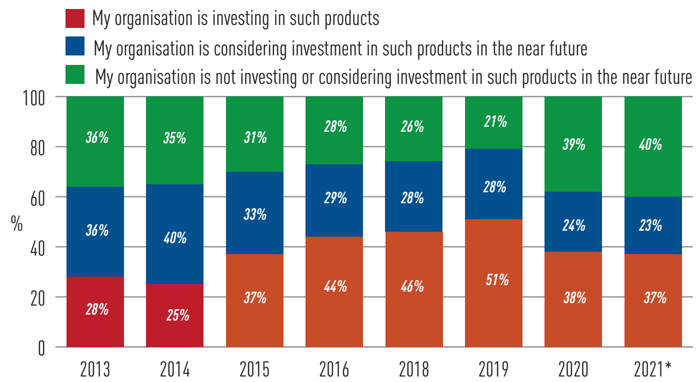
The main motivation behind the adoption of smart beta and factor investing strategies is to improve performance. Managing risk is also considered an important criterion. Some 37% of participants currently rely on smart beta and factor investing strategies; 23% do not but are considering adopting such strategies in the future (see figure 12). We note that the proportion of respondents adopting smart beta and factor investing strategies is a little higher among respondents who use ETFs (42%), as displayed in figure 2, than among the overall sample of respondents (37%), as displayed in figure 12. We see a significant decrease in the share of respondents that use smart beta and factor investing solutions in 2020. Thus, while only about one-fifth of investors were not investing or considering investment in such products in the near future in 2019, they now represent two-fifths in 2021.

Smart beta and factor investing solutions also typically make up only a small fraction of portfolio holdings among those respondents who have adopted these strategies. Almost three-quarters of respondents (73%) allocate less than 20% of their total investments to smart beta and factor investing strategies, and only 10% of respondents allocate more than 40%. However, 37% of respondents are planning an increase of more than 10% in terms of assets in their use of smart beta and factor investing products in the near future, while only 10% indicate a planned decrease.

Implementation of smart beta and factor investing strategies

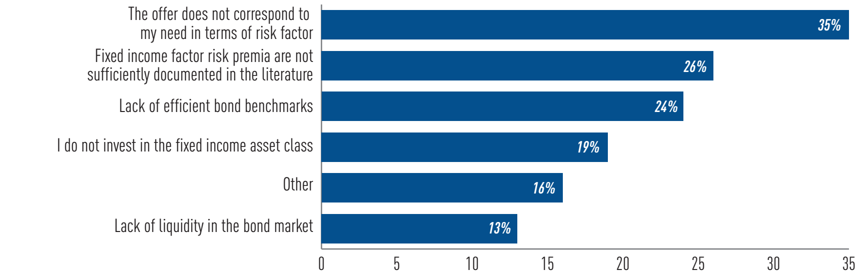
Our survey generates several insights into how investors implement their smart beta and factor investing strategies. Slightly more respondents are using discretionary smart beta and factor investing strategies (61%) than replicating strategies (57%). In terms of the actual product wrapper used for smart beta and factor investing exposure, respondents currently favour passive funds that replicate smart beta and factor investing indices (64% of respondents), ahead of active solutions, ie,

12. Use of smart beta and factor investing solutions



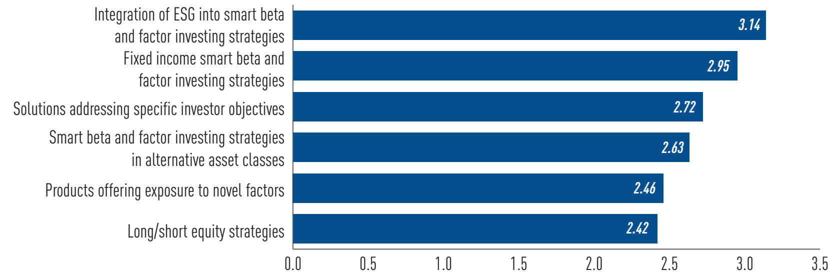
* No survey in 2017; totals not exact due to rounding

13. Main reasons for not using fixed income smart beta and factor investing products



14. Type of solutions requiring further developments in future

On a scale from 0 = not required to 5 = strong priority



approaches including a significant amount of discretion (47% of respondents). Respondents most frequently use smart beta/factor-based exposures to harvest long-term premia (as opposed to tactical use).

The existence of factor risk premium, ease of implementation and academic evidence are the primary concerns when it comes to smart beta and factor investing strategy factors.

Smart beta and factor investing strategies in fixed income

The results of our survey show that 15% of the overall sample of respondents currently use smart beta and factor investing for fixed income. However, about two-thirds (67%) of this sub-sample of respondents do so with less than 20% of their total investment. The additional 85% of respondents say they do not invest in smart beta and factor investing products for fixed income mainly because the offer does not correspond to their needs in terms of risk factor (35%), because risk premia are not sufficiently documented in the literature (26%) and because there is a lack of efficient bond benchmarks (24% – see figure 13).

All respondents, including those who already invest in smart beta and factor investing for fixed income, and those who do not yet invest, show a rather significant interest in it. However, they are mitigated in their plans to increase their use of smart beta and factor investing for fixed income in the future, because they have doubts about the maturity of the research results for fixed income strategies.

Some 52% of respondents indicate that smart beta and factor investing bond solutions are useful in performance-seeking portfolios for harvesting risk premia; 46% think that the best solution to achieve efficient harvesting is to use factor investing – ie, selecting bonds according to rewarded attributes (value, momentum, credit, liquidity). Some 58%, 54% and 49% of respondents respectively believe that the three typical factors of the credit risk market, namely slope of the yield curve, carry/level of the yield curve and credit, are the most relevant rewarded factors in fixed income markets.

Future development of smart beta and factor investing strategies

ESG, fixed income, solutions addressing specific investor objectives, and alternative asset classes are the main expectations for the future development of smart beta and factor investing products (see figure 14).

Conclusion

The 2021 survey shows significant interest in SRI/ESG among respondents, who overwhelmingly answered all questions related to it. Many of them already include this component in their investment, and a large part of those who do not plan to do so in the near future. While their main motivation to incorporate ESG criteria into their investment is to facilitate a positive impact on society, the majority do not want this to be done at the expense of performance. We note that the proportion of respondents investing in SRI/ESG is a little higher among respondents who use ETFs than among those who do not. The same result is observed for the use of smart beta and factor investing strategies. While ETFs are widely used to invest in popular asset classes, such as equities and fixed income, we can see that they also facilitate the integration of SRI/ESG and the adoption of smart beta and factor investing strategies.

The research from which this article was drawn was produced as part of the Amundi ETF, Indexing and Smart Beta Investment Strategies research chair at EDHEC-Risk Institute.

Replication of real estate indices

Evidence from the French property investment market

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The shift from active to passive investing has been a broad and defining trend of the investment management industry over the last decade. According to Morningstar, assets of US passive equity funds represented more than half of the overall assets of equity funds at the end of 2020. This compares to approximately 20% at the end of 2010. Index tracking has therefore become a priority for asset managers and ultimately for investors, who expect passive strategies to replicate an index in a reliable and cost-efficient way. Index strategies are now commonly available to investors not only in the equity asset class but also in fixed income, credit and indirect real estate, via exchange-traded funds or mutual funds invested in listed (equity) real estate investment trusts (REITs).

However, the design of representative and investable direct property indices has historically raised a number of issues related to the heterogeneity and indivisibility of real estate assets, the procyclicality of transaction volumes, the relative lack of investability (the index components are generally not available for sale), the appraisal-based valuation process, as well as more subtle effects such as temporal aggregation (see for example Geltner [2015] and EDHEC [2009] for further details on all the issues mentioned). Nevertheless, investable passive strategies tracking the direct real estate market could serve two important purposes. First, they could help deliver systematic exposure to the asset class without the unwanted short-term volatility (primarily the result of a liquidity tradeoff) that typically accompanies REITs, thus providing investors with an important source of diversification and risk-adjusted performance inside their multi-asset portfolios; second, the bond-like nature of the asset class makes passive real estate strategies promising building blocks (alongside traditional fixed income) for the construction of income-generating investment solutions in retirement.[1]

The EDHEC IEIF Commercial Property (France) index (EDHEC IEIF index) addresses some of the issues mentioned above, in the context of the French commercial real estate market (see EDHEC [2009] for more details) by using publicly registered non-listed funds known as Société Civile de Placement Immobilier (SCPI). Put simply, the EDHEC IEIF index is a market capitalisation-weighted portfolio of commercial SCPIs that satisfy a minimum liquidity requirement. It is investable by design, which makes it an appropriate benchmark for investors seeking passive exposure to French commercial real estate, whether it is to improve the risk-adjusted return of a multi-asset portfolio or to enrich a goal-hedging (retirement) portfolio.

In practice, however, an investor willing to track the EDHEC IEIF index would likely not consider a 'full replication' approach (ie, at all times holding every component in the exact proportion prescribed by the index) because of the transaction costs generally associated with SCPIs and the limited liquidity of some index components. Interestingly, prior research on SCPIs (see Guedj et al [2021]) shows investors can actually construct efficient and diversified SCPI portfolios with a limited number of constituents. In this context, this article analyses the practical implementation of a passive SCPI strategy tracking the EDHEC IEIF index; our study also considers the ability of an SCPI portfolio to help replicate the underlying direct real estate investment market, namely the MSCI France Annual Property index (MSCI index). We conclude the article with an assessment of the impact of smoothing on tracking error estimations. Our analysis relies on the same 2003–19 historical dataset (including 53 commercial SCPIs) as that used by Guedj et al (2021), which was kindly provided by the Institut de l'Epargne Immobilière et Foncière (IEIF), the leading independent research organisation covering the French real estate investment market. At any point during the 2003–19 period, our dataset covers at least 80% of the total market capitalisation of the EDHEC IEIF index universe.

Index tracking when full replication is impractical

The academic literature has extensively tackled the problem of index tracking when full (ie, perfect) replication cannot be implemented (because of operational and/or transaction costs), formalising it as a complex constrained optimisation problem[2] whereby one seeks a suitable subset of the index portfolio that mimics the full index as closely as possible.

1 For more details on goal-based retirement investing, see L. Martellini and V. Milhau (2021). *Advances in Retirement Investing*. Cambridge University Press.

2 See K. Benidis, Y. Feng and D. P. Palomar (2018). Optimization Methods for Financial Index Tracking: From Theory to Practice. *Foundations and Trends in Optimization* 3(3): 171–279.

Sophisticated replication methods are data-intensive and more suited to liquid asset classes like equities. Less liquid asset classes like real estate may be handled with simpler heuristics, such as a two-step approach where the selection of index components and the portfolio allocation (weighting) across the selected components are handled separately.

Our approach involves designing selection and allocation processes that account for the specific features and constraints of the index replication problem at hand, and then testing alternative approaches to assess the robustness of our results. We consider four specific features and/or constraints. First, the relative scarcity of data (long-dated individual SCPI performance available on a semi-annual basis only) leads us to favour heuristic methods over optimisation-based methods, although the latter are considered in robustness checks. Second, given the low liquidity of SCPIs, we aim for a limited number of constituents in the portfolio and seek to avoid holding positions in the smallest SCPIs since these usually have the lowest liquidity. Third, the significant transaction costs incurred by SCPI investors make dynamic rebalancing impractical, so we favour a buy-and-hold approach when designing the replicating portfolio; the portfolio is therefore constructed on day one and held static for the entire investment period. Finally, both the EDHEC IEIF index and the MSCI index follow a cap-weighted portfolio allocation, which precisely requires a buy-and-hold approach (since, in the absence of corporate actions, price fluctuations fully explain market cap fluctuations); this is therefore another reason to favour a buy-and-hold portfolio construction.

Based on the considerations mentioned above, we propose to test the following replication methodology on our historical SCPI dataset:

- ***Two-step approach:*** we first select a set of SCPIs and then determine the portfolio allocation.
- ***Portfolio size:*** we set a fixed number (N) of SCPIs, eg, N = 10.
- ***Selection process:*** we retain the N largest SCPIs (ranked by market capitalisation), subject to the same liquidity filter as that used in the EDHEC IEIF index (see EDHEC [2009]).
- ***Allocation process:*** we set the weights to be proportional to market capitalisation (ie, a 'cap-weighted' allocation).
- ***Rebalancing:*** we opt for a buy-and-hold approach, so there is no rebalancing once the initial portfolio has been established.

Our results cover 10 overlapping historical backtesting periods (December 2003–December 2019, December 2004–December 2019, ..., December 2012–December 2019) and five different portfolio sizes (N = 5, 10, 15, 20, 25). All our results are based on gross total returns, both for the indices and the SCPI portfolios.[3] For each backtest, we compute two indicators to assess the quality of the replication, the annualised mean excess return (*MER*) and the annualised tracking error (*TE*), which we define as follows:

$$MER = \frac{1}{n}\sum_{t=1}^{n}\left(r_t^P - r_t^I\right) \times M$$

$$TE = \sqrt{\frac{1}{n-1}\sum_{t=1}^{n}\left(r_t^P - r_t^I - MER\right)^2} \times \sqrt{M}$$

where r_t^P and r_t^I are respectively the replicating portfolio return and the index return at period t, and M is the number of periods in a year.

We use semi-annual returns (M = 2) when attempting to replicate the EDHEC IEIF index, and annual returns (M = 1) when attempting to replicate the MSCI index.

Our robustness tests aim to assess the sensitivity of our results with respect to a change in the methodology, and we therefore consider alternative selection methods (eg, segmentation) and/or allocation methods (eg, equal weights, *TE*-minimising weights).

Replication of the EDHEC IEIF index

Our proposed methodology naturally leads to potential replication error, due to two primary causes. First, our selection of SCPIs (at the time of investment) only represents a subset of the full EDHEC IEIF index universe. Second, our buy-and-hold portfolio does not keep track of changes in the index universe, ie, the portfolio does not change when SCPIs get added to or removed from the index. Our replicating portfolio therefore differs from the index on day one, and potentially diverges away from the index over time.

Figure 1 reports the replication results (*MER* and *TE*) for the EDHEC IEIF index. We see that the quality of replication improves as we increase the number of SCPIs in the replicating portfolio: we observe a *MER* closer to zero (on average) and a lower *TE* for a portfolio of 25 SCPIs than for a portfolio of five SCPIs. This is in line with expectations since increasing the number of SCPIs mechanically mitigates the first cause of replication error mentioned previously. Additionally, we note that the empirical *MER* monotonically increases as we add SCPIs to the portfolio, indicating that smaller SCPIs may be a source of outperformance. This is consistent with the findings of Guedj et al (2021) related to the 'fund size' attribute, namely that small SCPIs have outperformed their larger counterparts by a statistically significant amount (approximately 2% per annum) over the 2003–19 period. The monotonic relationship between *MER* and number of SCPIs in the portfolio may also be linked to the performance difference empirically observed by Guedj et al (2021) between surviving and non-surviving SCPIs (since non-survivors historically fall inside the lower size quartiles of the population) although this difference is not statistically significant.

From a quantitative standpoint, the low level of *TE* (between 0.4% and 1.3%) displayed in figure 1 is comparable to levels previously reported by the literature related to investable passive index-tracking strategies. For example, Lee (2014) analyses the performance and tracking error of UK real estate funds and identifies a group of 'pure index' funds whose *TE* is between 2% and 4% depending on the property fund benchmark selected. Additionally, publications related to other asset classes report that 'passive' equity funds are those with a *TE* of 1% or less[4], and that it is possible to use a sampling-based approach to replicate one investment grade index and one high-yield corporate bond index with *TE* levels of 0.9% and 2.6% respectively.[5] Note that the comparison with other asset classes should be interpreted with caution since SCPI data, unlike equity or bond data, is often subject to significant smoothing (see the last section of the article for an assessment of smoothing effects on *TE*).

We conclude this section with a review of the robustness tests presented in figure 2. Because the SCPI universe comprises both open-end and closed-end vehicles, we enrich the selection method with a common form of segmentation (stratified sampling) based on the capital type of SCPIs, ensuring that the replicating portfolio is consistent, at the time of its construction, with the overall mix (% of open-end versus % of closed-end) of the EDHEC IEIF index. Our tests also include

3 We follow Guedj et al (2021): gross total return for an SCPI does not include subscription fees and is defined as

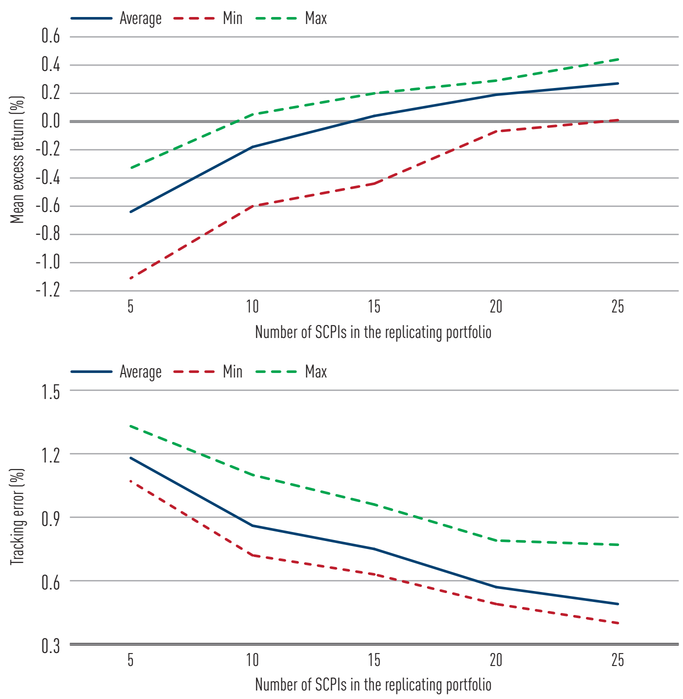
$$\ln\left(\frac{S_{t+1} + D_{t,t+1}}{S_t}\right)$$

where S_t and $D_{t,t+1}$ are respectively the reported subscription price at time t and the gross dividend amount paid between $]t,t+1]$.

4 A. Alford, R. C. Jones and K. D. Winkelmann (2003). A Spectrum Approach to Active Risk Budgeting. *Journal of Portfolio Management* 30(1): 49–60.

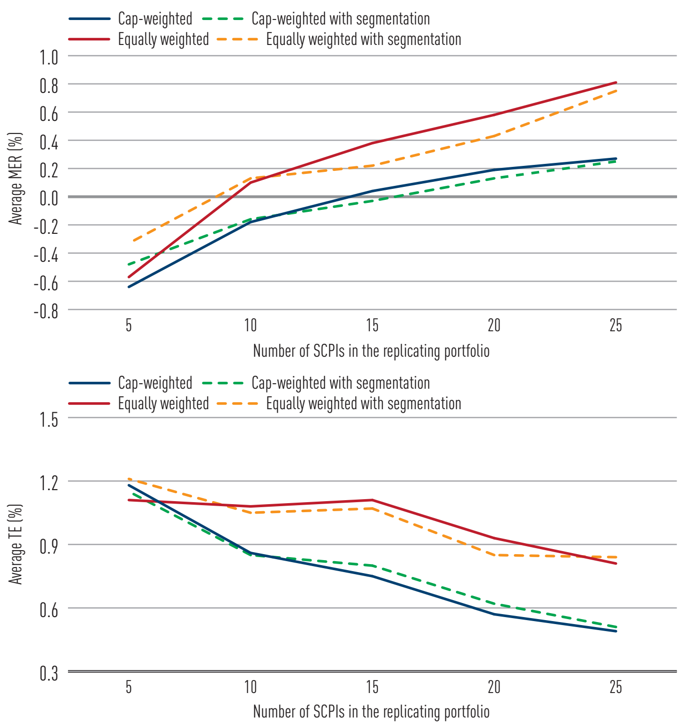
5 L. Gouzilh, M. de Jong, T. Lebaupain and H. Wu (2014). The Art of Tracking Corporate Bond Indices. Amundi Working Paper.

1. Mean excess return and tracking error, EDHEC IEIF index



The top (respectively bottom) diagram displays the average (solid blue line), minimum (dashed red line) and maximum (dashed green line) values of mean excess return (respectively of tracking error) across the 10 overlapping historical backtesting periods for the replication of the EDHEC IEIF index, as a function of the number of SCPIs in the replicating portfolio.

2. Robustness tests – mean excess return and tracking error, EDHEC IEIF index



The top (respectively bottom) diagram displays the average value of mean excess return (respectively of tracking error) across the 10 overlapping historical backtesting periods for the replication of the EDHEC IEIF index, as a function of the number of SCPIs in the replicating portfolio. The base methodology (solid blue line) is a cap-weighted allocation applied to the *N* largest SCPIs; the alternative methodologies (robustness tests) include amending the allocation to equal weights (solid red line), amending the selection by including segmentation based on capital type (dashed green line), or amending both allocation and selection (dashed orange line).

an alternative allocation method based on equal weights at the time of investment without any rebalancing (ie, still a buy-and-hold approach). We find in figure 2 that the qualitative features detailed above remain unchanged: average *MER* increases and average *TE* decreases with the number of SCPIs in the portfolio. We note that segmentation has very little impact on results and that an equal-weighted allocation unsurprisingly magnifies the positive impact of small SCPIs on performance (resulting in higher MER levels overall) and reduces the benefit of adding new SCPIs in a portfolio attempting to replicate a cap-weighted index (resulting in higher TE levels overall).

Replication of the MSCI index

Unlike the EDHEC IEIF index, the MSCI index is not designed to be investable for it measures the unlevered performance of directly held property investments from one appraised valuation to the next. Indeed, the real estate assets included in the index universe are generally not available for sale, they are not carved up into small identical and tradeable pieces of equity ownership, and their actual selling price is not necessarily equal to their appraised value, making the MSCI index difficult to replicate in practice.

We nevertheless have at our disposal two classes of French real estate investments that allow investors to indirectly purchase (at least partially) the assets making up the MSCI index: non-listed real estate funds (SCPIs) and the French equivalent of listed REITs, Sociétés d'Investissement Immobilier Cotées (SIICs). A representative and investable index for SIICs is the Euronext IEIF SIIC France index. Schoeffler (2012) indicates that the EDHEC IEIF index is a better proxy than the Euronext IEIF SIIC index for the underlying direct real estate market, while Delfim and Hoesli (2019) report, in a US context, that non-listed funds are a better substitute for direct investments than REITs. We therefore view SCPI portfolios as natural candidates for the replication of the MSCI index, and we take further comfort from the fact that the SCPI universe and MSCI index have similarly broad exposure (respectively 60% and 62% as of the end of 2019) to the office sector, which contrasts with the traditionally large retail bias in the SIIC universe.

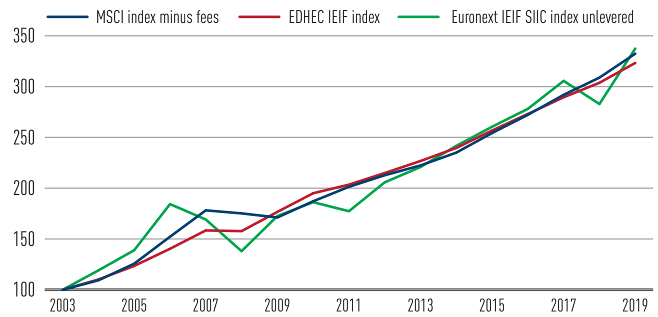
However, one may be tempted to try and include some SIIC exposure in a portfolio seeking to replicate the MSCI index because the latter represents a pool of assets that is approximately three times larger than the SCPI market capitalisation, and because recent research covering several countries including France (see Hoesli and Oikarinen [2021]) has provided evidence that REITs do behave like direct real estate over mid to long-term periods once leverage is adjusted for. Figure 3 visually confirms our intuitions: the EDHEC IEIF index closely tracks the MSCI index once we adjust for fees, and the unlevered Euronext IEIF SIIC index seems to help explain some of the volatility specifically observed in the MSCI index; we also note that the overall performance in 2003–19 is very similar for all three indices, respectively 7.9%, 7.6% and 7.8% compound annual growth rates over the period.

We attempt to quantitatively confirm our expectations with a linear regression (without any adjustment) of the total returns of the MSCI index against those of the two other indices. We obtain a relatively low adjusted R^2 of 35% and note that only the EDHEC IEIF index has explanatory power (p-values of 1.4% and 52% respectively for EDHEC IEIF index and Euronext IEIF SIIC index). However, when replacing the listed real estate index with its 'one-year lagged' version, we see the adjusted R^2 increase to 70% and find evidence of explanatory power for the lagged Euronext IEIF SIIC index variable (p-values now respectively 1.5% and 0.2%). We observe a similar pattern when attempting to replicate the MSCI index with a portfolio combining the two other indices, as shown in figure 4. We find that adding 10% of SIICs to the portfolio increases the *TE* for every investment horizon, while adding 10% of 'lagged SIICs' decreases the *TE* for longer investment horizons as well as on average across all horizons. This behaviour is consistent with the smoothing effect generally observed in appraisal-based indices and the resulting time lag against market-based (listed) counterparts (see Geltner [1993] for an introduction to the issue of lagged/smoothed data in the context of real estate investments). Implementing lagged exposure in a replicating portfolio is not straightforward and we therefore limit ourselves to SCPI portfolios going forward and follow the same replication methodology as that used for the EDHEC IEIF index.

The replication results presented in figure 5 are consistent with expectations. While we continue to see the positive impact of smaller SCPIs on performance (with negative average MER levels in line with the typical management fees applied by SCPIs), the MSCI index property universe is too large (compared to the assets held by SCPIs) for us to observe a decline in *TE* as we increase the number of SCPIs in the portfolio. The *TE* levels achieved (between 3% and 4% on average, and no greater than 5% overall) are consistent with past results reported by the industry over a comparable period[6] (5–6% *TE* when attempting to replicate a pan-European version of the MSCI index with 10 to 20 non-listed real estate funds).

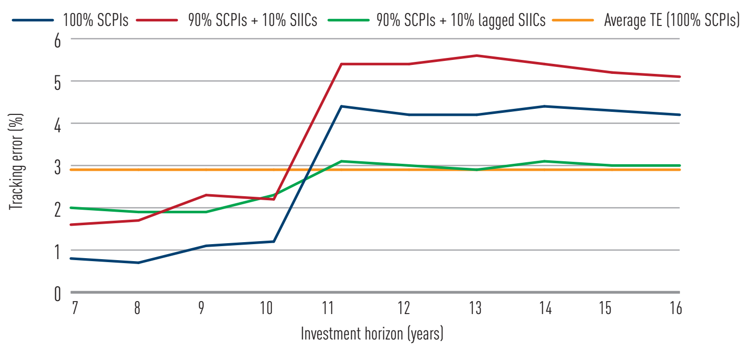
The robustness tests presented in figure 6 include the usual equal-weighted allocation method as well as the in-sample allocation that minimises *TE* (Min *TE* allocation) over each historical backtesting period. Unlike for the EDHEC IEIF index replication, the equal-weighted allocation does not lead to worse average *TE* levels compared to the cap-weighted allocation, despite the cap-weighted nature of the MSCI index. This is most likely again because of the much larger size of the MSCI index property universe: when the selection process is largely imperfect because only a small subset of the index components is captured in the portfolio, the allocation process becomes less relevant and the allegedly 'aligned' weighting scheme no longer dominates the other schemes. In the context of an SCPI-based replication of the MSCI index it therefore seems preferable, subject to liquidity considerations, to opt for an equal-weighted allocation and save 30–40bps of annual

3. Total return performance of MSCI index minus fees, EDHEC IEIF index and Euronext IEIF SIIC index unlevered, 2013–19



This figure displays the 2003–19 total return performance of the MSCI index adjusted for management fees (blue line), the EDHEC IEIF index (red line) and the unlevered Euronext IEIF SIIC index (green line), with all indices rebased at 100 as of 31 December 2003. Management fees (80bps) and unlevering adjustments follow Hoesli and Oikarinen (2021).

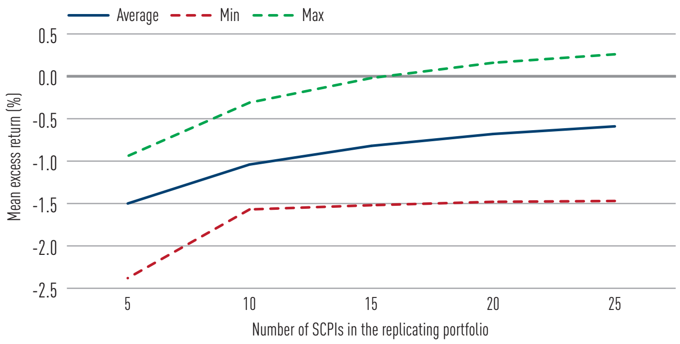
4. Impact of SIICs on tracking error, MSCI index

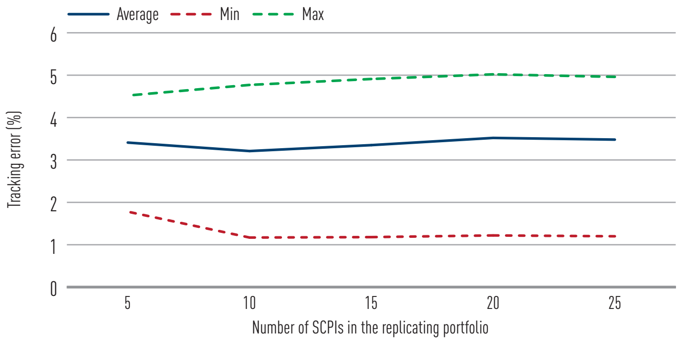


This figure displays the historical tracking errors experienced when replicating the MSCI index with three respective portfolios, as a function of the investment horizon. Each investment horizon corresponds to one of the 10 overlapping backtesting periods (2003–19 = 16 years, 2004–19 = 15 years, etc). The three replicating portfolios are i) a portfolio allocated 100% to the EDHEC IEIF index (blue line), ii) a portfolio allocated 90% to the EDHEC IEIF index and 10% to the Euronext IEIF SIIC Index (red line), and iii) a portfolio allocated 90% to the EDHEC IEIF index and 10% to the one-year lagged Euronext IEIF SIIC index (green line). The orange line represents the average tracking error value across all 10 investment horizons for the EDHEC IEIF index portfolio (100% SCPIs).

6 INREV (2014). The Investment Case for Core Non-Listed Real Estate Funds. Working paper, INREV Research and Market Information.

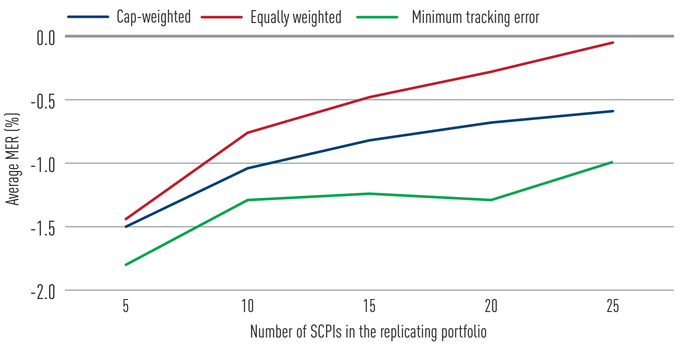
5. Mean excess return and tracking error, MSCI index

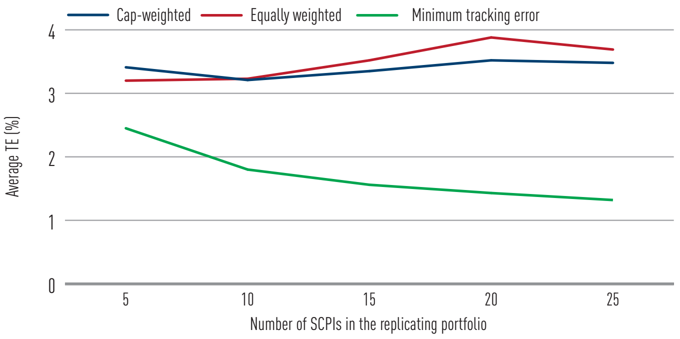




The top (respectively bottom) diagram displays the average (solid blue line), minimum (dashed red line) and maximum (dashed green line) values of mean excess return (respectively of tracking error) across the 10 overlapping historical backtesting periods for the replication of the MSCI index, as a function of the number of SCPIs in the replicating portfolio.

6. Robustness tests – mean excess return and tracking error, MSCI index





The top (respectively bottom) diagram displays the average value of mean excess return (respectively of tracking error) across the 10 overlapping historical backtesting periods for the replication of the MSCI index, as a function of the number of SCPIs in the replicating portfolio. The base methodology (blue line) is a cap-weighted allocation applied to the N largest SCPIs; the alternative methodologies (robustness tests) include an equal weight allocation (red line), and an allocation that minimises tracking error over the investment horizon (green line).

underperformance while keeping a similar level of *TE*.

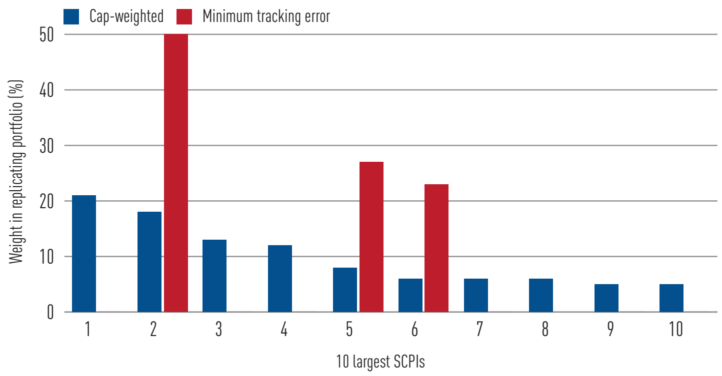
We conclude this section with a review of the results of the Min *TE* allocation (see figure 6) that effectively provides a theoretical, in-sample, lower bound in terms of *TE*. Of course, such an allocation cannot be implemented since it requires an in-sample minimisation, but it is nevertheless informative. Indeed, we note that a full look-ahead bias would allow us to approximately halve the *TE* (down to about 1.5% on average) but at the expense of *MER*, with an underperformance 'cost' of 50–100bps per annum compared to the equal-weighted allocation. This trade-off seems even less compelling when looking at figure 7, which shows one example of a Min *TE* allocation with 10 SCPIs in the portfolio. The high concentration in the optimal portfolio (only invested in assets 2, 5 and 6) is indeed an indication of data overfitting and likely out-of-sample sub-optimality and instability. We would therefore recommend avoiding such an optimised allocation, especially in the presence of material transaction costs.

Accounting for smoothing in the tracking error estimation

Given the presence of smoothing effects in our data, the goal of this final section is to examine the potential impact of smoothing on our *TE* results. More specifically, we wish to know whether our *TE* estimates could be severely underestimated due to smoothing, the same way estimates of non-listed or direct real estate volatility can sometimes be materially underestimated. As a reference, Guedj et al (2021) report that the volatility of open-end SCPIs doubles on average after correcting for smoothing effects.

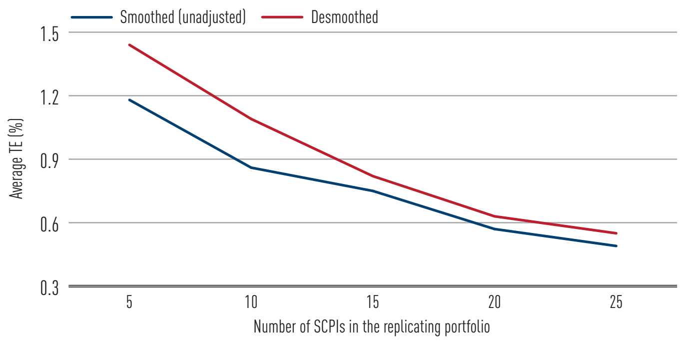
We apply the standard desmoothing technique (see Geltner [1993] for a general description, and Guedj et al [2021] for a direct application to SCPIs) to the excess returns of the replicating portfolio with respect to its target index. This leads us to a desmoothed estimate of the standard deviation of excess returns, ie, a desmoothed estimate of *TE*. Figure 8 presents some results for the EDHEC IEIF index replication. The average desmoothed *TE* is only moderately higher (between 1.09x and 1.26x) than the average smoothed (unadjusted) *TE*. We also report that the maximum *TE* observed across all portfolios and all backtesting periods is 1.8%, so it appears that smoothing only has a modest impact on the estimation of *TE* for the EDHEC IEIF index replication. We report results for the MSCI index replication in figure

7. Robustness tests – cap-weighted versus minimum tracking error allocation with 10 SCPIs, MSCI index



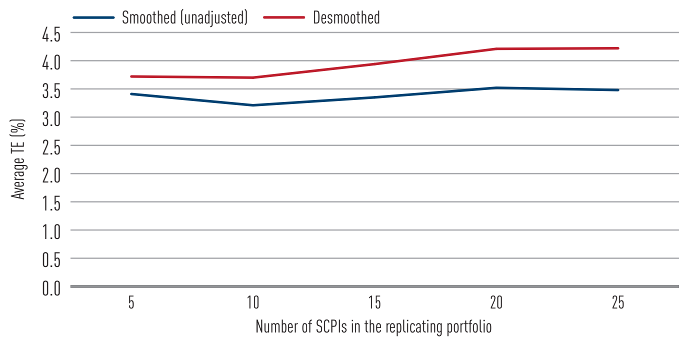
This figure displays the allocation of a replicating portfolio (for the MSCI index) constructed in December 2003 using the 10 largest SCPIs at the time and following a cap-weighted approach (blue bars) and a TE-minimising approach (red bars), where TE is optimised in-sample over the December 2003–December 2019 period. The height of each bar represents the weight of the corresponding SCPI in the replicating portfolio.

8. Desmoothing of tracking error, EDHEC IEIF index



The figure displays the average value of tracking error across the 10 overlapping historical backtesting periods for the replication of the EDHEC IEIF index, as a function of the number of SCPIs in the replicating portfolio. Two calculations of tracking error are reported: unadjusted, ie, smoothed (blue line), and desmoothed (red line).

9. Desmoothing of tracking error, MSCI index



The figure displays the average value of tracking error across the 10 overlapping historical backtesting periods for the replication of the MSCI index, as a function of the number of SCPIs in the replicating portfolio. Two calculations of tracking error are reported: unadjusted, ie, smoothed (blue line), and desmoothed (red line).

9. The average desmoothed *TE* is between 1.09x and 1.21x higher than the average smoothed (unadjusted) *TE*, indicating again that smoothing does not materially distort *TE* estimates. The maximum *TE* observed across all portfolios and all backtesting periods is 6.4% (compared to 5.0% before correcting for smoothing), which seems modest considering the annualised volatility estimate of the MSCI index increases by 1.7x (from 5.4% to 9.4%) when corrected for smoothing.

Conclusions

We find that it is possible to track the EDHEC IEIF Commercial Property (France) index with a satisfactory degree of accuracy (based on mean excess return and tracking error) over long-term horizons by constructing a buy-and-hold and cap-weighted portfolio of 10 to 15 SCPIs, thereby mitigating the liquidity constraints of the French non-listed real estate fund market. Our proposed replication method does not require any modelling or any data-intensive calculation and is therefore expected to be robust.

Additionally, our analysis shows that a buy-and-hold and equal-weighted portfolio of 10 to 15 SCPIs can be seen as a reasonable proxy of the MSCI France Annual Property index. We also confirm that French listed real estate companies (SIICs) have the potential to complement SCPIs to further improve the replication of the MSCI France Annual Property index, although the exact portfolio implementation will likely require a model for the smoothing effect embedded in appraised valuations.

Our work could naturally be extended by including more specific liquidity constraints and criteria in either the selection or the allocation process.

In conclusion, it appears that investors looking for passive exposure to the French commercial real estate asset class, either to enhance the risk-adjusted return of their multi-asset portfolios or to construct a multi-asset retirement goal-hedging portfolio, can potentially gain access to a simple and investable solution.

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Does ESG investing improve risk-adjusted performance?

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From a theoretical point of view, ESG-constrained strategies should display lower risk-adjusted performance because a more constrained optimum is ex-ante dominated by a less constrained optimum.

Asset pricing models also suggest that in equilibrium a negative premium (lower expected performance) should be associated with ESG filters.

From the empirical standpoint, a review of papers on risk-adjusted performance with ESG criteria shows contrasted results including both positive and negative impacts.

Outperformance of ESG investing can be shown to be largely driven by sector/factor biases, and a negative alpha is obtained after accounting/correcting for these biases.

ESG outperformance can possibly be generated by filtering on changes in ESG scores, suggesting the existence of an ESG momentum effect.

While most investors are increasingly concerned with integrating environmental, social and governance (ESG) criteria when constructing their portfolios, it is important to recognise that there are competing motivations for doing so. On the one hand, integration of ESG criteria reduces non-financial risks, such as reputation, political and regulatory risks. Companies which do not consider ESG criteria expose themselves to risks of consumer boycotts, environmental disasters or reputation scandals. Other motives include aligning portfolios with investors' values and norms, making a social impact by pushing companies to act responsibly, reducing exposure to risks faced by ESG laggards, such as climate or litigation risk, and generating outperformance by favouring ESG leaders.

In a survey conducted in 2021 by EDHEC among European investment professionals (see Le Sourd and Martellini [2021]), where respondents could give more than one answer, the two main reasons indicated by respondents for incorporating ESG into their investment decisions were to facilitate a positive impact on society (64%) and to reduce long-term risk (61%). About a third (34%) thought that incorporating ESG would serve to enhance portfolio performance. At the same time, more than a third of respondents (35%) said they were willing to accept a lower performance in exchange for a better ESG score.

ESG investing is indeed often presented as a source of outperformance, and ESG fund providers are fond of endorsing this perception. In this context, it is particularly important to provide a qualified assessment of such beliefs and claims, given that they are central to the understanding of the tradeoffs involved in ESG investing. After all, if ESG investing reduces risk and generates outperformance in addition to enhancing social welfare, then motives for doing good and motives for doing well would be perfectly aligned.

In this article, we analyse whether there is formal empirical support for ESG investment motivations, including most importantly risk and performance motivations. We first analyse the question from a theoretical perspective, and then discuss the empirical findings.

Theoretical insights on the link between ESG constraints and risk-adjusted performance

ESG-constrained strategies should display a lower risk-adjusted performance because a more constrained optimum is ex-ante dominated by a less constrained optimum

From a theoretical point of view, achieving portfolio optimisation using a constrained universe should lead to a

lower risk-adjusted performance than when using a non-constrained universe. Thus, imposing a certain level of ESG constraints on investment decisions creates an opportunity cost with a possible increase in risk and reduction in performance, compared to a portfolio optimally derived without ESG considerations.

To quantify this trade-off, Pedersen et al (2021) propose to compute an ESG-efficient frontier that serves to identify both potential costs and benefits from integrating ESG considerations in portfolio selection. It involves solving a classic efficient frontier problem as defined by Markowitz, but with an additional constraint on an ESG score level. Solving the optimisation problem consists in finding the portfolio with the highest Sharpe ratio (SR) for a chosen ESG score. If one considers both the efficient frontier with no constraints on the portfolio ESG score and the one including only the assets with an ESG score over a defined level, the latter efficient frontier will necessarily stand below the former, as it is obtained by excluding some assets, and is therefore sub-optimal. This creates an opportunity cost, as the discarded assets may be profitable ones. For each ESG score, Pedersen et al (2021) show that it is possible to compute the portfolio with the highest attainable Sharpe ratio and thus define the ESG-SR frontier. If investors do not take ESG into account, they will choose the portfolio with the highest Sharpe ratio, whatever its ESG score. In the same way, Chang and Witte (2010) observe that ESG investing produces lower average returns and lower Sharpe ratios than unscreened investing.

Martellini and Vallée (2021) obtain a similar result in the context of sovereign bond portfolio construction and regarding country ESG scores. In particular, they find that higher environmental scores for developed countries and higher social scores for emerging countries are associated with lower costs of borrowing for issuers and consequently with lower yields for investors.

Asset pricing models also suggest that in equilibrium a negative premium (lower expected performance) should be associated with ESG filters

According to asset pricing theory, if we consider that ESG scores can be viewed as proxies for assets' underlying risk factors, a positive risk premium should be expected for holding stocks with poor ESG scores, compared to stocks with good ESG scores (see Martellini and Vallée [2021] for a similar argument at the sovereign bond level). However, we should also consider that excluding assets with bad performance can have a positive impact (Coqueret [2021]). In what follows, we provide an overview of the academic insights regarding ESG investing in market equilibrium models.

It is often argued that ESG investing generates both lower risk and higher performance, which seems at odds with the key prescription from finance theory. According to asset pricing theory, systematic risk is remunerated and assets that tend to have a low payoff in 'bad' states of the world where marginal utility of consumption is high should have a higher expected return in equilibrium. In this context, riskier stocks with poor ESG scores should earn a higher return, and ESG filters aimed at improving the ESG score of the portfolio should therefore lead to a loss in performance.

To analyse these questions, several authors have shown how ESG can be formally integrated into market equilibrium models. In a recent paper, Pastor et al (2021) derive an equilibrium model taking into account ESG considerations. The model is based on a three-fund separation model including the risk-free asset, the market portfolio and an ESG portfolio. In this model, investors with no specific considerations for ESG will simply hold the market portfolio, while investors with special appetite for green stocks will largely deviate from the market portfolio and overweight green stocks and underweight brown stocks. Alternatively, investors with weaker interest for ESG will deviate from the market portfolio in the opposite way. The authors confirm that the preference of investors for firms with higher ESG scores lower the firms' costs of capital, as investors want to pay more for these firms. Assets with higher ESG scores have negative CAPM alphas, whereas assets with lower ESG scores have positive alphas. Consequently, agents with stronger ESG preferences earn lower expected returns.

In a related effort, Avramov et al (2021) derive a CAPM model taking into account the level of ESG uncertainty both in alpha and beta. In this model the market beta is replaced by the effective beta, which differs from the market beta in the following way. The CAPM beta is based on the covariance and variance of actual returns; the effective beta consider that both the market and individual stock returns integrate a random additional component based on ESG, positive for a green asset and negative otherwise. Thus, the effective beta is computed using the covariance and variance of ESG-adjusted returns. As for alpha, if the CAPM model does not take into account ESG uncertainty, we will observe negative values as the willingness to hold green stocks will not be related to pecuniary benefits. On the contrary, if ESG uncertainty is taken into account, the equilibrium alpha will increase with ESG uncertainty. This model differs from that of Pastor et al (2021) in the following way. Pastor et al (2021) take into account the possibility that ESG investors will disagree about a firm's ESG profile. However, they consider that the ESG score is certain for each investor and that investors can observe other investors' perceived ESG values. On the other hand, Avramov et al (2021) study the implications of uncertainty about the corporate ESG profile. In their model, the investors agree that the ESG scores are uncertain and they also agree on the underlying distribution of the uncertain scores. Taking into account ESG uncertainty modifies equity premium, as well as the alpha and beta components of stock return.

Depending on the models used, different conclusions can be reached in terms of the value added by ESG constraints, and we refer the reader to Coqueret (2021) for a comprehensive review of papers considering the asset pricing model in the context of ESG investing.

After discussing the individual investment decisions and market equilibrium implications of ESG investing from a theoretical standpoint, we now turn to an analysis of the results provided by empirical studies on the subject.

Empirical evidence on the link between ESG constraints and risk-adjusted performance

From the empirical standpoint, a review of papers on risk-adjusted performance with ESG criteria shows contrasted results including both positive and negative impacts

The performance of ESG investment appears to be a controversial topic between those who predict a performance reduction compared to non-ESG, and those who anticipate the opposite result. The first group argues that using ESG screens will necessarily reduce the investment universe and thus lead to poor diversification (Rudd [1981]; Barnett and Salomon [2006]; Renneboog, ter Horst and Zhang [2008]), as per the theoretical argument presented before. Reducing the investment universe appears to be similar to an investment constraint that leads to efficiency losses (Adler and Kritzman [2008]). In addition, restricting portfolios to companies that fulfil ESG criteria tends to create more exposure to specific risk (eg, industry biases, style biases; see Rudd [1981]; Kurtz [1997]; DiBartolomeo and Kurtz [1999]). On the contrary, ESG proponents argue that extra-financial aspects of investments are part of the investment decisions even though they may be hard to define, hard to quantify and often specific to each particular investment (Teoh and Shiu [1990]; Bassen and Kovacs [2008]).

In terms of risks, several empirical studies have established that stocks with a high ESG rating have a lower total risk than stocks with the same systematic risk but a lower ESG rating (Boutin-Dufresne and Savaria [2004]; Bauer, Derwall and Hann [2009]; Lee and Faff [2009]). Hoepner (2010) argues that using ESG screens reduces portfolio risk, due to the lower total risk and lower specific risk of stocks with a high ESG rating. Over the 2007–12 period, De and Clayman (2015) evidenced a strong negative relationship between stock ESG rating and stock volatility, with higher ESG ratings being correlated with lower volatility. This relationship was even stronger during periods of especially high volatility, such as the 2008 financial crisis. Stocks with high ESG ratings tend to be in the low-volatility group, and stocks with low ESG ratings tend to be in the high-volatility group. Cornell and Damodaran (2020) also discuss the link between risk and company ESG scores. Companies with low ESG scores are exposed to reputational and disaster risks, either in human or financial terms, with long-term consequences. Karpoff, Lott and Wehrly (2005) find that firms that violate environmental standards suffer significant market value losses but that these losses are roughly equivalent to the legal penalties imposed. They find no evidence of additional losses from reputational damage.

While there is relative consensus on the risk reduction benefits of ESG investing, the large collection of empirical studies that have investigated ESG investment performance can be divided into three distinct groups: those which show an outperformance of ESG (Consolandi et al [2009]; Renneboog et al [2008], among others), those which show that ESG brings neither underperformance nor outperformance (Naffa and Fain [2021]; Hartzmark and Sussman [2019]; Managi et al [2012], among others), and finally those which conclude that ESG leads to underperformance (Adler and Kritzman [2008]; Berlinger and Lovas [2015], among others). Kanuri (2020) also finds that, in the long run, conventional funds outperform ESG funds (in terms of average returns and Sharpe ratio), even though ESG funds sometimes perform better.

In more detail, Statman and Glushkov (2009) find that stocks with high ESG ratings outperformed stocks with low ESG ratings over the period from 1992 to 2007. De and Clayman (2015) also find a significantly positive correlation between stock ESG rating and risk-adjusted return over the 2007–12 period. They also observe that this correlation can be further improved by excluding stocks with the lowest ESG ratings. This result may be related to the low-volatility effect described in the literature (Haugen and Baker [1991]; Jagannathan and Ma [2003]; Ang et al [2006]), showing the outperformance of low-volatility stocks. In addition, the authors also identify a positive ESG effect, independent of the low-volatility anomaly. Cornell and Damodaran (2020) find no evidence of higher ESG ratings being associated with greater risk-adjusted returns.

Alternatively, Fabozzi, Ma and Oliphant (2008), Hong and Kacperczyk (2009), and Statman and Glushkov (2009) report that stocks in industries involved in alcohol, tobacco, gambling, firearms, military or nuclear operations (the ‘sin’ stocks) outperform stocks in other industries. Pedersen, Fitzgibbons and Pomorski (2021), using their ESG-efficient frontier model, also find a sin stock premium, but smaller than the one estimated by Hong and Kacperczyk (2009). According to Statman and Glushkov (2009), if positive screening (selection of top ESG rating stocks) is associated with negative screening (exclusion of sin stocks), their effects will offset each other, such that ESG indexes will perform comparably to traditional indexes. In a similar register, namely that virtue does not always pay, Bolton and Kacperczy (2021a, 2021b) identify a risk premium related to high carbon emissions, ie, high-emitting firms outperform low-emitting firms.

Lioui and Tarelli (2021) use an ESG factor constructed from the various ESG ratings and find that ESG investing has generated positive alpha over recent decades, with an accumulated alpha above 1% per year for the E and S pillars. These results support the argument that “firms can do well by doing good” as suggested by Edmans (2011), Ostergaard et al (2016) and Gong and Grundy (2019), among others. However, Lioui and Tarelli (2021) identify a downward sloping pattern in the outperformance.

Brammer et al (2006), Lee and Faff (2009), Becchetti et al (2018), Lioui et al (2018), Lioui (2018a, 2018b), Ciciretti et al. (2019), Boermans and Galema (2020), Hübel and Scholz (2020) and Lucia et al (2020) all find that the rewarded ESG factors go long irresponsible firms and short responsible ones. Similarly, Luo and Balvers (2017) find that a portfolio that goes long sin stocks and short non-sin stock earns a monthly average return of 1.33%.

Friede, Busch and Bassen (2015) compiled 2000 empirical studies from 1970 to 2014 and found a non-negative impact of ESG on risk-adjusted performance. Coqueret (2021) also provides a review of empirical studies about ESG performance. Complementary results can be found in Bruno, Esakia and Goltz (2022); Lee, Fan and Wong (2021); Franco (2020); Yue et al (2020); Brunet (2018); Hvidkjaer (2017); Trinks and Scholtens (2017); and Kumar et al (2016), among others.

Reconciling the theoretical and empirical findings

Outperformance of ESG investing can be shown to be largely driven by sector/factor biases, and a negative alpha is obtained after accounting/correcting for these biases

The question arises as to how to reconcile the theoretical prediction of a negative risk premium associated with ESG investing and the contrasted results from empirical studies. First of all, a lack of robustness in empirical findings can explain the contrasted results that may be observed depending on periods and countries. For example, Bauer et al (2005) find evidence of underperformance for German and US ethical funds compared both to ethical indices and conventional funds, while they observe a slight outperformance for UK ethical funds. However, none of these differences were found to be statistically significant after controlling for factors such as size, book-to-market and momentum. In addition, they observe the results from different sub-periods. It appears that German and US ethical funds show a significant underperformance in the beginning of the 1990s, while their performance was comparable to that of conventional funds during the 1998–2001 period. They also observe an age effect. Funds that were set up before 1998 significantly outperformed those launched after 1998. Finally, the older funds end up with a performance close to that of conventional funds, while funds that were launched recently still underperform conventional funds.

Using factor models to correct for factor effects, Di Bartolomeo and Kurtz

(1999) conclude that the outperformance of the Anno Domini index compared to the market was due to factor and industry tilts rather than social responsiveness. Similarly, Bruno, Esakia and Goltz (2022) find that most of the outperformance of ESG strategies can be explained by their exposure to equity style factors that are mechanically constructed from balance sheet information. This result is robust across different multifactor models. Furthermore, the ESG strategies tested show large sector biases. Removing these biases also removes outperformance.

Alternatively, Derwall, Guenster, Bauer and Koedijk (2005) found that the higher returns generated by companies that are more eco-efficient cannot be explained by investment style or industry factors.

Past ex-post outperformance can be explained by an increase in demand effect, which is not inconsistent with a lower expected return from an ex-ante perspective

Cornell and Damodaran (2020) explain that market prices may adjust to a new equilibrium integrating ESG considerations. As the market adjusts, the discount rate for highly rated ESG companies will fall and the discount rate for low rated ESG companies will rise. Due to the changes in the discount rates, the relative prices of highly rated ESG stocks will increase and the relative prices of low ESG stocks will fall. Consequently, during the adjustment period the highly rated ESG stocks will outperform the low ESG stocks. Once the market is in equilibrium, the value of highly rated ESG stocks will be greater, but their expected returns will be lower.

For example, Bebchuk, Cohen and Wang (2013) report the disappearance of a return premium associated with highly rated corporate governance during an earlier period. Due to this process of adjustment, the link between the performance and the stock rating will be dependent on the sample period. During adjustment periods, highly rated stocks will outperform, while low-rated stocks will underperform. Alternatively, after that, when markets are in equilibrium, highly rated stocks will have lower average returns. According to an analysis based on the theory of Fama and French, it appears that preference for highly rated ESG stocks will cause lower average excess returns for these stocks. Again, this conclusion is not in accordance with current declarations concerning ESG, such as that of BlackRock CEO Larry Fink (2020), who stated, “Our investment conviction is that sustainability and climate integrated portfolios can provide better risk-adjusted returns to investors.”

ESG outperformance can possibly be generated by filtering on changes in ESG scores with the existence of an ESG momentum effect

ESG does not really provide a positive risk premium, but rather a negative risk premium, once the performance is explained by the various risk factors and investment sectors. However, ESG can generate positive returns in certain conditions, using ESG momentum. The argument for the outperformance of stocks with high ESG scores is that stock markets underreact to ESG information, and so stocks from firms with a positive ESG impact may be undervalued. The ESG momentum strategy thus consists in overweighting stocks that have improved their ESG rating over recent time periods (see Nagy et al [2016]; Bos [2017]; Kaiser and Schaller [2019] for evidence of outperformance of ESG momentum strategies).

On a somewhat related note with a focus on the intersection between financial momentum and ESG scores, Kaiser (2020) argues that stocks with low ESG scores can be assumed to have more potential for momentum. According to Hillert et al (2014), momentum is related to strong media coverage. Thus, high-momentum stocks are less concerned with their ESG performance and can exhibit lower average ESG ratings, whereas stocks that are currently showing a downward trend in returns need to increase their ESG performance to send a positive signal to the market. However, Kaiser (2020) argues that the proportion of stocks showing both strong momentum patterns and a high ESG performance is likely to increase due to requirements to include such firms in investor portfolios.

Conclusion

While the promoters of ESG investing often argue that this type of investment strategy makes it possible to obtain better performance with lower risk, the situation is not so simple either from a theoretical point of view or from an empirical perspective. The quest for better performance should not be the only reason for ESG investing. We argue that ESG strategies should be valued for the unique benefits that they can provide, such as making a positive impact on the environment or society, as opposed to being promoted on the basis of disputable claims regarding their outperformance potential.

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