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INTRODUCTION

Introduction to the Research for Institutional Money Management supplement in *Pensions&Investments*, April 2022

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t is a great pleasure to introduce the latest "EDHEC Risk Institute" special issue of the Research for International Money Management supplement to *Pensions & Investments*.

In our first article, prepared as part of the Bank of America "Decumulation Investing: Taxonomy, Axiomatic Framework and Financial Engineering Solutions" research chair at EDHEC-Risk Institute, we show how the retirement bond, a dedicated safe asset, can help with retirement planning. The retirement bond allows retirees to calculate how much income they can generate from their retirement pot. The retirement bond itself can be regarded as the risk-free asset for those who want to secure income for a predetermined period, e.g., for the first 10, 20 or 30 years in retirement. For these reasons, the retirement bond and its price appear to be key ingredients in the design of sustainable and efficient spending and investment strategies in decumulation.

We then 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 criticized 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 personalized performance portfolios for liability-driven investors in research that was supported by First Rand Bank. 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 toward genuine investment solutions.

In an article on replicating real estate indexes prepared as part of the Swiss Life Asset Managers France "Real Estate in Modern Investment Solutions" research chair 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 modeling 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 Pensions & Investments for their collaboration on the supplement.

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The Retirement Bond: How a Dedicated Safe Asset Can Help with Retirement Planning

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Decumulation - the process of turning capital into income - has been recognized as a most difficult task, as perhaps best emphasized by strong statements made by two recipients of the Nobel Prize in economics. Richard Thaler describes it as a "more difficult challenge than accumulation," $^{\prime\prime}$ while William Sharpe calls it the "nastiest, hardest problem in finance."² The core difficulty is the tradeoff between current and future consumption: spending more today means saving less and thus reducing future consumption - that is, unless strong portfolio performance makes up for the higher withdrawal. In brief, the decumulation problem is essentially about finding a spending rule and an investment strategy that support the desired lifestyle for as long as needed. Such decisions are complex because they must be made in the face of uncertain future returns on retirement savings and an uncertain planning horizon.

A popular approach to this problem is the so-called "4% rule," which was analyzed by Bengen (1994) and recommends that a retiree should spend an amount equal to 4% of her initial savings plus an inflation adjustment every year. Specifically, Bengen (1994) finds that such withdrawals are sustainable for at least 33 years for individuals holding 50% or 75% of their assets in stocks and the rest in bonds, and regardless of the choice of the retirement date from 1926 to 1976.³ The "Trinity study" by Cooley, Hubbard and Walz (1998) confirms these results and emphasizes that a substantial allocation to equities, greater than 50%, is needed to support a 4% withdrawal rate adjusted for inflation for 30 years. A series of follow-up papers have sought to improve the 4% rule by allowing for flexibility in withdrawals. For instance, Bengen (2001) lets withdrawals increase more slowly than inflation after the age of 75, and Guyton (2006) proposes to forgo adjustment for inflation after a year of negative portfolio performance. These rules allow for higher withdrawals in the early years of retirement than the 4% rule does, at the expense of lower withdrawals in later years.

Spending rules of the "x%" type seem to make retirement planning extremely simple because they establish a one-to-one relationship between a level of income and a level of wealth. For instance, according to the 4% rule, an individual should build a nest egg equivalent to 25 times the targeted real annual income. But as simple as it is, this rule of thumb creates confusion between a wealth goal and an income goal, although the latter is the ultimate objective of retirement investing and the two goals are not equivalent (Merton, 2014). That income is the quantity of interest to savers has recently been acknowledged in the U.S. pension regulation, with the passage of the Setting Every Community Up for Retirement Enhancement (SECURE) Act in 2019. Section 105 requires administrators of defined-contribution pension plans to provide "lifetime income illustrations." Unlike any "x%" rule, the Interim Final Rule published in August 2020 states that these illustrations should be based on an estimate for an annuity price, and it reviews assumptions (including, notably, longevity and interest rates) recommended to calculate that price.⁴

In contrast, the 4% rate is not based on any observed or estimated price for annuities or bonds. While the 4% rule happens to be feasible in backtests based upon U.S. data, it suffers from several severe shortcomings. On the one hand, Scott, Sharpe and Watson (2009) point out that it involves a strong opportunity cost in the sense that it often leads to large final surpluses, suggesting that withdrawals could have been higher. They also show that by purchasing an inflation-indexed bond ladder with 30-year maturity at a 2% yield to maturity, an individual could enjoy a higher withdrawal rate of 4.46% without bearing any shortfall risk or running into a final surplus. On the other hand, Pfau (2010) shows that the 4% policy would have frequently failed in 13 out of 17 developed non-U.S. countries from 1900 to 2008 and guestions its future sustainability in the U.S., arguing that past good equity performance may not repeat itself. Overall, the fact that 4% is too conservative a rate in many 30-year periods and might be too high in some others suggests that an appropriate withdrawal rate should depend on market conditions, as opposed to being a "universal" value supposed to work at any point in time.

To find the maximal withdrawal rate in a given period of specified length (e.g., 20 or 30 years after the retirement date), one can use Scott, Sharpe and Watson's (2009) bond ladder as well as the closely related concepts of "bonds for financial security" developed by Muralidhar, Ohashi and Shin (2016), "retirement SelFIES" (Standard of Living indexed, Forward-starting, Income-only Securities) by Merton and Muralidhar (2017) and "retirement bond" by Martellini, Milhau and Mulvey (2019). The retirement bond is defined as a security that pays an annual cash flow of \$1 (with a possible cost-of-living adjustment) for a predetermined period. As argued below, in the absence of arbitrage opportunities, this definition implies that the maximal spending rate is the reciprocal of the bond price. Since it is a function of interest rates, the maximal rate depends on observable market conditions through the yield curve but avoids any dependency with respect to unobservable or implied parameters such as the volatilities and risk premia of risky assets. The rest of this article presents the retirement bond in more detail and explains how the maximal withdrawal rate is calculated.

The Safe Asset: The Retirement Bond

Conventional financial advice is for retirees to hold a mixture of stocks and bonds, with the aim of diversifying their portfolio and taking advantage of both the lower volatility of fixed income and the stronger performance potential of equities. A look at the equity glide paths of target date funds suggests that the volatility reduction objective is given priority, especially when approaching retirement. According to Morningstar's 2018 Target-Date Fund Landscape, the equity allocation in commercial target-date funds after the target date is less than 50% and can be as low as 20% for the most conservative funds. It can be noted that, according to the results of Cooley, Hubbard and Walz (1998), such allocations do not support a 4% withdrawal rate for 30 years in all scenarios. Indeed, Cooley et al. (1998) show that a portfolio fully invested in bonds has only a 20% chance of supporting a 4% withdrawal rate adjusted for inflation for 30 years, while a portfolio consisting of 75% stocks has the best success rate, at 98%. The problem seems to be exacerbated with a decreasing equity glide path, because Bengen (1996) shows that annual decreases of respectively 2% and 3% in the stock weight will reduce the safe withdrawal rate from 4.14% to 3.81% and 3.29%, respectively.⁵

Whatever the exact percentage of stocks, Scott, Sharpe and Watson (2009) argue that "supporting a constant spending plan using a volatile investment policy is fundamentally flawed." But what would be a non-volatile investment policy in the context of retirement? Merton (2014) warns us that if we reason in terms of income instead of wealth, which is the correct perspective when we think about retirement, then Treasury bills are highly unsafe although they have the lowest volatility across most asset classes. The proper way to find a risk-free portfolio is to start from the cash flows that a retiree would target, and to identify an asset that pays these exact cash flows or, alternatively, to construct a "retirement goal-hedging portfolio" that replicates them.

Cash Flow Schedule for the Retirement Bond

Consider an individual who is 10 years away from retirement and wants to secure fixed replacement income for the first 20 years in retirement. A 20-year period is chosen here because it approximately matches the life expectancy of a 65-year-old American. The risk-free asset for that goal is a bond ladder with equal annual payments, normalized to \$1, for 20 years, beginning 10 years from now. We call this bond ladder a "retirement bond," and its cash flows are depicted in Figure 1. It has two key characteristics: (1) a deferred start date for payments and (2) fully amortizing annual installments of equal size, achieved

- ³ Because his dataset ended in 1992, Bengen used average stock and bond returns and an average inflation rate for subsequent years.
- ⁴ The SECURE Act requires two values of income to be provided. One is obtained by converting savings into a single life annuity, and the other by converting them into a joint and survivor annuity.

¹ Thaler, R., 2019. Financial Advisors and Retirement: The Decumulation Dilemma. PIMCO Insight, October 28, 2019.

² Sharpe, W., 2017. Tackling the "Nastiest, Hardest Problem in Finance". Bloomberg Opinion, June 5, 2017.

⁵ But Bengen (1996) finds that a 1% annual decrease in the equity allocation has no material impact on the safe withdrawal rate, which remains slightly greater than 4%.

by progressive redemption of principal combined with interest payments. This amortization scheme is familiar to the many households that purchase real estate through a mortgage with fixed monthly payments.

Despite the name "fixed-income security," it is important to emphasize that a straight bond does not deliver such constant cash flows. As illustrated in Figure 1, if the individual purchases a regular coupon-paying bond maturing at the end of the first 20 years of retirement, she receives coupon payments while still in accumulation when she does not need replacement income. Besides, the periodic payments are much smaller than the final one, which includes both the last coupon and the principal. As a result, there is a profound mismatch between the cash flows served by the bond and those the individual needs.

Inflation Indexation

The illustration in Figure 1 assumes cash flows fixed in nominal terms, of \$1 per year. It is important to emphasize that over a retirement planning period that spans several decades, the impact of inflation on the purchasing power of replacement income is severe. With an average inflation rate of 2% per year – the target of the Federal Reserve and the European Central Bank – the purchasing power of \$1 is cut by one-third after 21 years (1- $1.02^{-21} \approx 0.34$).

Protection against inflation can be introduced either through indexation of cash flows on realized inflation, as is done for Treasury inflation-protected securities (TIPS), or via a fixed cost-of-living adjustment (COLA), e.g., 2% per year. These options have different implications for the construction of a goal-hedging portfolio with existing government bonds, because the former requires the use of TIPS, while the latter can be implemented with nominal bonds, which have the advantage to offer higher capacity and liquidity.

Measuring the Purchasing Power of Savings in Terms of Replacement Income

Retirement Bond Pricing

Just like a regular bond, a retirement bond can be priced by calculating the sum of discounted future cash flows. For cash flows fixed in nominal terms, the (dirty) price at time *t*, excluding the cash flow paid at that time, is given by

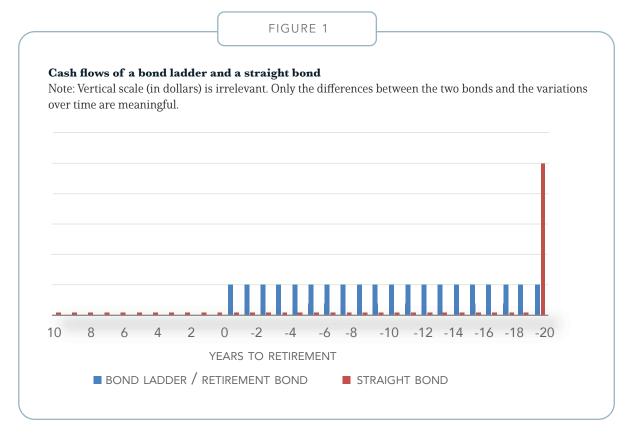
⁽¹⁾
$$\beta_t = \sum_{t_i > t} CF_{t_i} \exp[-[t_i - t]y(t, t_i - t)],$$

where summation is taken over all cash flow dates after time *t*, CF_{t_i} is the cash flow of time t_i and $y(t,t_i - t)$ is the continuously compounded nominal zero-coupon rate of maturity $t_i - t$ prevailing at time *t*. This formula holds both in accumulation, i.e. before retirement, and in decumulation, i.e. after retirement. Cash flows are normalized at \$1, or \$1 plus a fixed compounded COLA π , in which case we have

$$CF_{t_i} = [1 + \pi]^{t_i - t_0},$$

where t_0 is a reference date for indexation.

When cash flows are indexed on realized inflation, the bond price at the reference date for indexation, t_0 , is



still given by Equation (1), but nominal zero-coupon rates must be replaced with real rates.

Maximum Replacement Income

In the absence of arbitrage opportunities, the maximal replacement income that one can finance with the wealth level W_t accumulated at time t, is

$$ri_t = \frac{W_t}{\beta_t}.$$

By letting t = 0, where date 0 conventionally denotes the retirement time, it can be seen that the reciprocal of the bond price is the maximum withdrawal rate that can be sustained for 20 or 30 years, or whatever payment period is specified for the retirement bond.

Unlike any "x%" spending rule, where x is a percentage determined from historical analysis combined with a given stock-bond investment policy, the strategy that fully invests in the retirement bond and every year withdraws an amount equal to ri_0 (plus inflation or a COLA) has no risk of exhausting wealth before the bond maturity. Moreover, it makes efficient use of savings in that it leaves no unspent surplus after all scheduled withdrawals have been made. In contrast, a fixed universal rate is necessarily unsafe in some market conditions and too conservative in others. Bengen's (1994) results show that a 5% rate is often feasible for 30 years with 50% in stocks and 50% in bonds, but there are a few periods in which it covers only 20 years of expenses,⁶ so prudence calls for a 4% rate, even though 5% is likely to succeed.

To avoid incurring the opportunity cost of decreasing spending from 5% to 4%, it would obviously be desirable for the freshly retired person to know if she is at the start

of a period where equity and bond returns and inflation will support 5%, or if she must make do with 4%. Since future returns and inflation are unknown, she could run Monte-Carlo simulations, taking current market conditions as initial conditions, e.g., by looking at the dividend yield to try and assess whether equities are cheap or expensive. Such simulations, however, are contingent upon assumptions about risk premia, and the corresponding estimate for the withdrawal rate will be prone to large errors. In contrast, the reciprocal of the retirement bond price provides a withdrawal rate that depends on current market conditions through discount rates but does not involve unobservable parameters such as risk premia and volatilities. The zero-coupon curve is observable, at least up to the estimation of zero-coupon rates from the market prices of Treasury securities. Gürkaynak, Sack and Wright (2007) developed an efficient estimation procedure, and their dataset is available from the website of the Federal Reserve, which we use for the calculations below.

Numerical Examples

Since it is an increasing function of discount rates, the withdrawal rate has substantially reduced over the past 40 years. As evidenced in Figure 2, today's retirees can finance much less income than those of the early 1980s per dollar saved.⁷ Individuals retiring from July 1981 to July 1982 could withdraw an amount equivalent to more than 15% of their savings every year (see the "20 years; 0%" line), while those retiring in January 2022 should consume at the lower rate of 6% per year. This reduction is due to the decrease in interest rates, which can be seen for the 10-year sovereign yield in Figure 2. Note that the withdrawal rate has always been greater than the 10-year yield, and the gap between the two lines has been widening over time. One explanation is

⁶ See his Figure 1(c).

⁷ That withdrawal rates have been decreasing does not imply that today's retirees have less income from their savings than those who retired in the early 1980s because, owing to inflation effects, the nest egg may be bigger today.

that while the yield can, in principle, fall to zero, the 20year withdrawal rate must be greater than 1/20 = 5% as long as discount rates are positive.

Impact of Cost-of-Living Adjustment

If she requires a cost-of-living adjustment, a retiree must accept a lower initial withdrawal rate. In January 2022, the rate including an adjustment of 2% per year is 4.91%, versus 6% for the unadjusted version. Because 0.0491×1.02=5.01%, the adjustment implies a substantial cut in spending in the first year, but after 10 years, adjusted withdrawals exceed the unadjusted ones, as can be seen from Figure 3. Therefore, applying a cost-of-living adjustment is essentially equivalent to sacrificing some consumption in the early stage of retirement for higher consumption in later years. It is up to individuals to decide whether or not their relative preference for short-term vs. long-term consumption justifies such an adjustment.

Comparison with the 4% Rule

The withdrawal rates in Figure 2 cannot be directly compared with the popular 4% rate because Bengen (1994) determined this value by requiring a minimum payment period of 30 years as well as inflation-indexed retirement income cash flows. For a fairer comparison, let us consider a payment period of 30 years and apply an adjustment to proxy for expected inflation. With these parameters and a 2% annual adjustment, the maximal withdrawal rate for a person retiring on Jan. 3, 1994, at the start of the year in which Bengen's original paper was published, is 6.24%. This value is much greater than 4%, but one might wonder whether the adjustments for realized inflation prescribed by the 4% rule eventually lead to greater withdrawals than the 2% adjustment. Figure 4 shows that this is not the case - at least for the 27 years for which inflation data is available to date - and also that the withdrawals with the retirement bond dominate those made under the 4% rule. Even by requiring a 5% annual growth in payments, which decreases the maximal withdrawal rate from 6.24% to 4.32%, the withdrawals with the retirement bond remain greater than those of the 4% rule. Therefore, the 4% rule led individuals who retired in the mid-1990s (at the time the paper was published) to underspend.

On the other hand, a withdrawal rate of 4% may not be sustainable for 30 years with certainty in the market conditions of January 2022. With a cost-of-living adjustment of 2% per year, the maximal rate for an individual retiring on Jan. 3, 2022, is indeed only 3.33%. We can also take advantage of a real discount curve now being available to calculate the price of a retirement bond with inflation-indexed cash flows of \$1 in real terms.⁸ The maximal withdrawal rate for a retiree requiring indexed cash flows is 3.05%, which is still less than 4%. This does not mean that the savings of an individual withdrawing 4% plus inflation every year beginning in January 2023 will necessarily be exhausted before the 30 years are up, but these withdrawals will only be feasible in some scenarios for equity returns and inflation. In other words, a 4% rate is literally "unsafe" in current market conditions.

As evidenced in Figure 5, which shows the maximal withdrawal rate for an individual who targets 30 years of inflation-adjusted withdrawals, this situation has prevailed since August 2011 with a maximal rate that has ranged from 3% to 4%. Before August 2011, it used to be greater than 4%, so the 4% rule was then too conservative. In conclusion, there is simply no "universal"

FIGURE 2

Maximal withdrawal rate

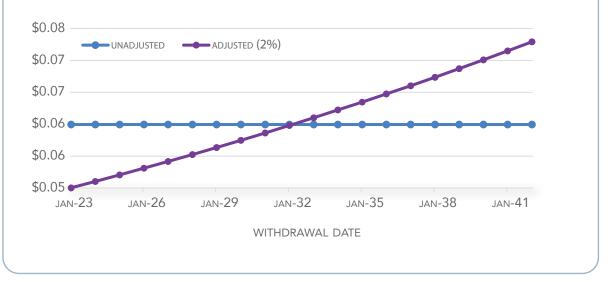
Note: The maximal withdrawal rate is the percentage of wealth at retirement that can be withdrawn every year for 20 years beginning one year after the retirement date. Annual withdrawals are either constant in nominal terms – which corresponds to a 0% adjustment – or subject to a 2% annual adjustment for the cost of living. The 10-year yield is the market yield on U.S. Treasury securities at 10-year constant maturity from the Federal Reserve.



FIGURE 3

Adjusted vs. non-adjusted withdrawals for \$1 of savings on Jan. 3, 2022

Note: The retirement date is Jan. 3, 2022. Unadjusted withdrawals are equal to 6% of savings at the retirement time. Adjusted cash flows are equal to 4.91% of savings at the retirement time, plus a 2% annual growth rate, which starts accruing at the retirement time.



safe withdrawal rate that is valid at any time and in any market conditions.

Today's retirees might be disappointed that the maximal withdrawal rate for a 30-year period and inflation-adjusted withdrawals is less than the supposedly universal 4% level. This situation is due to the current environment with negative real interest rates, which makes 4% spending an aspirational goal in the terminology introduced by Deguest et al. (2015). To maximize their chances of achieving that goal, retirees must take some risk and invest part of their savings in an asset class, typically equities, that is expected to outperform the retirement bond. However, risk should be taken with caution in order not to put the retiree's lifestyle at risk. Recent research by Martellini and Milhau (2020) suggests that the retirement bond is a helpful building block, leading to more efficient spending of investors' risk budgets, in the context of goal-based investing strategies designed for the pre-retirement phase. Extension to the decumulation phase is the focus of ongoing research.

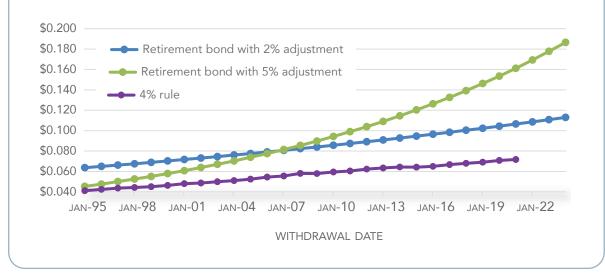
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⁸ We use the real zero-coupon yield curve estimated by Gürkaynak, Sack and Wright (2010). The updated dataset is available from the Federal Reserve website. Zero-coupon rates are available for maturities ranging from two to 20 years, but we need to discount cash flows with maturities ranging from one to 30 years, so we extrapolate the one-year rate to the left and the 20-year rate to the right.

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FIGURE 4

Withdrawals with retirement bond vs. withdrawals with 4% rule for \$1 of savings on Jan. 3, 1994 Note: The retirement date is Jan. 3, 1994. With the retirement bond, withdrawals are equal to 6.24% of savings at the retirement time, plus a 2% annual growth rate, which starts accruing at the retirement time. With the 4% rule, withdrawals are equal to 4% of savings at the retirement time, plus cumulative inflation since that time. Inflation is the growth in the Consumer Price Index for All Urban Consumers and All Items, seasonally adjusted.





Maximal withdrawal rate with inflation-adjusted withdrawals and a 30-year decumulation period

Note: The maximal withdrawal rate is the percentage of savings at the retirement time that can be withdrawn every year for 30 years beginning one year after the retirement date. Annual withdrawals grow at the realized inflation rate.



CONCLUSION

While the 4% spending rule and its variants have proved to be sustainable in historical backtests, there is no guarantee that they will be successful for individuals retiring now or in the future. Moreover, their sustainability is achieved at the cost of underspending in many scenarios where the retiree is left with a surplus at the end of the planning period. In this article, we argue that a sustainable and efficient withdrawal rate should be a function of market conditions, and we show that a meaningful withdrawal rate is given by the reciprocal of the price of a "retirement bond," defined as a bond ladder that pays \$1 (possibly adjusted for inflation or the cost of living) per year for the planning period. The retirement bond price can be calculated from the observable yield curve and does not involve any subjective assumption about risk premia or the retiree's tolerance for risk. It enables retirees to calculate very easily how much income they can generate from their retirement pot. The retirement bond itself can be regarded as the risk-free asset for those who want to secure income for a predetermined period, e.g., for the first 10, 20 or 30 $\,$ years in retirement. For these reasons, the retirement bond and its price appear to be key ingredients in the design of sustainable and efficient spending and investment strategies in decumulation.

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Retirement Investing: Identifying Efficient Withdrawal Strategies

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INTRODUCTION

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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 personalized advice to individuals as far as their retirement investment decisions are concerned. The original Merton problem (Merton, 1969, 1971) does address the joint optimization 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 cashflows in the presence of long-term care risk, with a relatively rich menu of investment opportunities that includes balanced funds, target date funds, equity indexes 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 Maeso et al.'s (2021) initial framework and focus on the joint optimization of investment and withdrawal decisions.

To study this joint optimization, 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%.¹⁰ 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.

Exhibit 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).

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

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 annualized 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. Exhibit 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, which is the term <code>lVaR5%(ID)</code> (strong risk-aversion with respect to income deficits). It is given by:

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

where λ is a parameter that corresponds to the individual's risk aversion.¹¹

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 *W*₀.
- *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.¹² 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:

$$\forall t \in [0, \tau_0 - 1]], \begin{cases} c_t = \min \left[W_{0-} \times WR \times (1 + COLA_t)^t + LE_t, W_t\right] COLA_t = 2\% \end{cases}$$

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 $W_{t-} < W_{0-} \times WR \times (1+CO-LA_t)^{t} + LE_t$. 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 W_{0} 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 minimize 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 summarized as follows:

¹⁰ These figures are borrowed from the Genworth Cost of Care Survey 2019.

¹¹ 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.

 $^{^{12}}$ Here we take a 1% grid step for the possible values of X.

• WS1: where possible, at each date t the individual withdraws 4% of her initial wealth *W*₀₋ with a 2% COLA component adjustment:

[WS1]: $\forall t \in [[0, \tau_0 - 1]], c_t = min [W_{0-} \times WR \times (1 + 2\%)^t + LE_t, W_t-]$

• 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 W_{0-} with a 2% COLA component adjustment:

 $[WS2]: \forall t \in [[0, \tau_0 - 1]], _{C_t}$

=min [max [0,min [4% × (W_t-LE_t), 4% × (1+2%)^t × W_{0-}]] + LE_t, W_t-]

• 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:

 $[WS3]: \forall t \in [[0,\tau_0 - 1]],_{C_t}$ =min [max $[2\% \times (1+2\%)^t \times W_{0-}, min [4\% \times (W_{t-} - LE_t), 4\% \times (1+2\%)^t \times W_{0-}]] + LE_t, W_{t-}]$

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 $W_{t^-} < LE_t$ (i.e., in scenarios where the cost of the life event at time t exceeds the portfolio wealth at time t). WS2 is attractive insofar 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, i.e., 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 Exhibit 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 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:

 $[WS4]: \forall t \in [[0, \tau_0 - 1]], C_t$ =min [max [0, min [$f(t) \times (W_t - LE_t),$ $4\% \times (1+2\%)^t \times W_0$ -]] + LE_t, W_t -]

The withdrawal amount for WS5 is:

$$\begin{split} & [\text{WS5}]: \forall \ \mathbf{t} \in [[0, \tau_0 - 1]], C_t \\ & = \min \left[\max \left[2\% \times (1 + 2\%)^t \times W_{0-}, \min \left[f(t) \times (W_{t-} - LE_t), 4\% \times (1 + 2\%)^t \times W_{0-} \right] \right] \\ & \quad \times W_{0-} \left[\right] + LEt, \ W_{t-} \right] \end{split}$$

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, labeled 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 realized withdrawals over the discounted target withdrawals. This quantity is always between 0 and 1 and corresponds to the fifth percentile of

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

Exhibit 3 shows the median bequest, the fifth percentile of the income deficit, median BPIW and the fifth percentile of the percentage of lifetime income (PLI in short) 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 (i.e. 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.

Exhibit 4 reports the welfare function $Median(BS)+\lambda$ - $VaR_{5\%}$ (ID) for the five aforementioned withdrawal strategies, for four different values of $\lambda(\lambda = 1, 2, 4 \text{ and } 6)$ and for a universe made up of balanced funds as functions of the weight invested in stocks. We observe that for all the $\boldsymbol{\lambda}$ values (except for $\lambda = 6$ 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 optimize both performance indicators (i.e. 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 optimization 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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EXHIBIT 1

Illustration of the Framework Rationale

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. Initial Wealth: \$500 000

Initial Targe	et Withdrawal Rate 4%		\$500 000		
			Balanced Fund		
Age (x)	Target Withdrawal (TW(t))	Balanced Fund Return r(t)	Value before Withdrawall (W-(t))	Actual Withdrawal AW(t)	Value After Withdrawal W(t)
65	500 000*4%*(1+2%) ^0		\$500 000	min([TW(0), W-(0)])	W-(0)-AW(0)
66	500 000*4%*(1+2%)^t	-5%	W(t-1)*- (1+r(t))	min([TW(t), W-t)])	W-(t)-AW(t)
67	-	-	-	-	-
68	-	-	-	-	-
69	-	-	-	-	-
70	-	-	-	-	-
71	-	-	-	-	-
72	-	-	-	-	-
73	-	-	-	-	-
74	-	-	-	-	-
75	-	-	-	-	-
tau+65					
come Deficit	$ \sum_{t=1}^{\tau-1} \left[AW(t) - T\right]$	W(t) lexp $(-t)$	$(\mathbf{R}_{0,i})$ Bec	quest W	$(\tau)exp (-\tau R_{0\tau})$
	Age (x) 65 66 67 68 69 70 71 72 73 74 75 tau+65	$(TW(t))$ 65 500 000*4%*(1+2%)^0 66 500 000*4%*(1+2%)^t 67 - 68 - 69 - 68 - 69 - 70 - 71 - 72 - 73 - 74 - 75 - tau+65 $r-1$	Age (x) Target Withdrawal (TW(t)) Balanced Fund Return r(t) 65 $500\ 000^*4\%^*(1+2\%)^{\Lambda}0$ -5% 66 $500\ 000^*4\%^*(1+2\%)^{\Lambda}t$ -5% 67 - - 68 - - 69 - - 70 - - 71 - - 72 - - 73 - - 74 - - 75 - - tau+65 - -	Age (x) Target Withdrawal (TW(t)) Balanced Fund Return r(t) Balanced Fund Value before Withdrawall (W-(t)) 65 500 000*4%*(1+2%) ^0 \$500 000 66 500 000*4%*(1+2%) ^1 -5% W(t-1)*- (1+r(t)) 67 - - - 68 - - - 68 - - - 69 - - - 70 - - - 71 - - - 72 - - - 73 - - - 74 - - - 75 - - - tau+65 - - -	Age (x) Target Withdrawal (TW(t)) Balanced Fund Return r(t) Value before Withdrawall (W-(t)) Actual Withdrawal AW(t) 65 500 000*4%*(1+2%)^0 \$500 000 min([TW(0), W-(0)]) 66 500 000*4%*(1+2%)^t -5% W(t-1)*- (1+r(t)) min([TW(t), W-t)]) 67 - - - - 68 - - - - 69 - - - - 70 - - - - 71 - - - - 73 - - - - 74 - - - - 75 - - - -

EXHIBIT 2

Glidepath of Withdrawal Rates

This exhibit reports the withdrawal rates (glidepath) used in Webb and Sun (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

Age	%	Age	%
65	3.13	83	6.13
66	3.22	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

Annual withdrawal percentages

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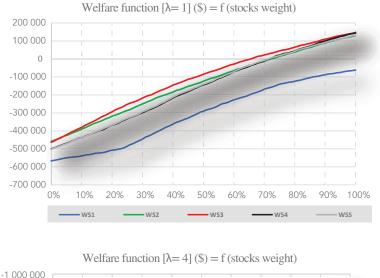
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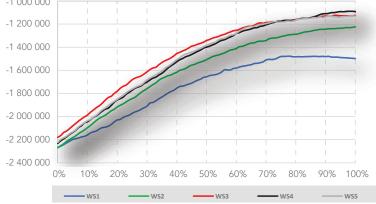
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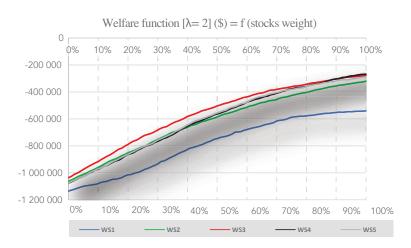


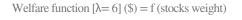
Welfare Function Charts for the Balanced Fund Universe

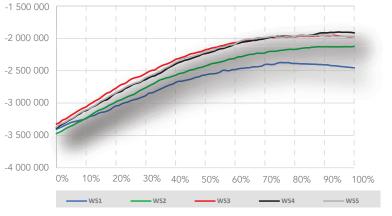
This exhibit reports the charts of the welfare function for four different values of λ ($\lambda = 1, 2, 4$ and 6) for the five withdrawal strategies detailed above and for a universe made up of balanced funds as functions of the weight invested in stocks with values ranging from 0% to 100%, with a grid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











Active Ownership as a Greenwashing Tool Rather than a Climate Change Solution

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When asset managers are criticized 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.

Introduction

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, into their asset management operations. Active ownership is considered an essential ingredient in the implementation of institutional investors' sustainability commitments. In Table 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 mobilizing 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.

Climate-focused active ownership measures are taken either independently or through collaborative endeavors (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 toward 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 & trade frameworks. Therefore, climate-aware institutional investors can, in many ways, potentially complement or even replace the existing national and international carbon policies.

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 maximize 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 CO₂ emissions according to various models, reported under variable ENERDP123. This study complements disclosed emissions data with Thomson Reuters' estimates to maximize the number of observations. This yields an initial sample of 7373 firms. Data on firms' institutional shareholdings is from Orbis. Table 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*, 10_{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. Table 3 reports the simplest models estimated using the lagged log of Emissions (column 1) and the log of Carbon intensity (column 2). The coefficients should be interpreted as an impact on the percentage of emissions.

First of all, the table shows that the institutional ownership coefficient has the hypothesized 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, Table 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 guartile of the distribution the 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).

CONCLUSION

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 decarbonization 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 center 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.

Panel A: Act	ivities undertake	n by investors to resp	ond to climate cha	nge risk		
	Setting carbon reduction targets for portfolio	Establishing climate change sensitive asset allocation strategy	Targeting low climate resilient investments	Reducing portfolio exposure to emissions-intensive holdings	Using emissions data or analysis to inform investment decisions	Seeking climate change integratio by companies
AuM (USD Trillion)	4.71	6.96	17.79	15.67	18.46	18.51
AuM/ Total AuM	7%	10%	25%	22%	26%	26%
Panel B: Too	ls used by investo	ors to manage emission	on risks			
С	arbon footprinting	g Scenario testing	Disclosure on emission risk	Target setting for emission risk reduction	Encouraging internal/external portfolio managers to monitor emission risks	Emissions risks monitoring/ reporting are formalized into contracts when appointing managers
AuM (USD Trillion)	18.03	6.92	9.21	11.27	16.72	4.67
	uM 26%	10%	13%	16%	24%	7%

TABLE 1

TABLE 2

Descriptive statistics

This table 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. CIs 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.

	Ν	Min	Max	Median	Mean	St. Dev.	
Sales (\$000)	76530	-	514,000,000	1,392,410	6,351,806	18,800,000	
Assets (\$000)	76231	-	4,030,000,000	2,777,190	25,000,000	143,000,000	
Debt (\$000)	76119	-	3,390,000,000	571,887	6,095,393	47,300,000	
PPE(\$000)	74737	-	272,000,000	450,561	2,907,410	9,605,622	
Carbon Emissions (Tonnes)	46477	0	34,500,000,000	98,071	3,950,130	225,000,000	
Institutional Ownership (%)	84312	0	100	12.3	17.3	17.5	
Leverage	76103	0	0.91	0.21	0.24	0.2	
Tobin's Q	72421	0.1	3.013	1.04	1.29	0.83	
Tangibility	74722	0	0.94	0.19	0.28	0.27	
Carbon Intensity	46001	0.0005	329.03	0.039	0.7	8.99	

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TABLE 3

Regression results: emissions and carbon intensity

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 & Orbis. Significance levels reported in superscript: *** is significant at 1%; ** is significant at 5%; * is significant at 10%.

	Log Emissions (1) Coefficient/se	Log Carbon Intensity (2) Coefficient/se
Institutional Ownership	-0.000 (0.001)	-0.001*** (0.001)
Sales	0.637*** (0.010)	
Tobin's Q	-0.011 (0.007)	-0.036*** (0.007)
Asset Tangibility	2.701*** (0.040)	2.740*** (0.041)
Asset Size	0.283*** (0.014)	-0.034*** (0.010)
Leverage	-0.004 (0.008)	-0.003 (0.008)
Earnings	-0.014* (0.008)	-0.017** (0.008)
Constant	-1.781 (26010.334)	-2.978 (21492.527)
Observations	22114	22137
R-sq	0.745	0.592
Country	YES	YES
Year	YES	YES
Industry	YES	YES

TABLE 4

Regression results: emissions and carbon intensity by quartile

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: a is significant at 1%; b is significant at 5%; c is significant at 10%.

	Top 25% Emitters Log Emissions	Bottom 75% Emitters Log Emissions	Top 25% Emitters Log Carbon Intensity	Bottom 75% Emitters Log Carbon Intensity
	Coefficient/se	Coefficient/se	Coefficient/se	Coefficient/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 ,	(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	(0.039)	(0.031)	(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	5369	16880	5309	16828
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

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Precision Investing: How to Design Optimal Personalized 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 maximize 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 unfavorable changes in investment opportunities, e.g., 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 maximize 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 decentralized 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.¹³

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 maximization 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 their 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 penalize downside risk, like expected shortfall, may be regarded as more appropriate.

To address these questions, this paper provides a characterization 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 parameters, 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 optimization 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 maximizes 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 personalized 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 customization (or mass-customization) of healthcare, with treatments, practices or products being tailored to a subgroup of patients, instead of a one-drugfits-all model. For this reason, we use the term precision investing to define a personalized investment strategy that is tailored to optimize investor suitability vs. standalone risk-adjusted performance.

Optimizing the Choice of the Underlying Asset for a Convex Payoff

Let us start with a two-step investment process in which a centralized decision maker chooses an insurance strategy whose payoff is a convex function of the PSP payoff, and a decentralized asset manager is assigned the task of constructing a PSP. The optimization 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 stylizing assumptions:

- The PSP is invested in risky assets whose prices follow geometric Brownian motions and is a fixed-mix portfolio that is continuously rebalanced toward the weights 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 $\boldsymbol{\xi}$ 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 optimization 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, $U(x) = x \frac{1-\gamma}{1-\gamma}$, 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, e.g., maximizing the probability of reaching a target wealth level or minimizing 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 [$A_T > N$] and E [[$N - A_T$]⁺]. It can be noted that minimizing the expected shortfall is equivalent to maximizing the expected shortfall is equivalent to maximizing the expectation of a concave function of wealth, so this objective is qualitatively similar to expected utility maximization.

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.

¹³ 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.

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)

$$x = -\frac{\partial f}{\partial e_{\rm s}} + 2\frac{\partial f}{\partial v_{\rm s}},$$

Let

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 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 optimizing 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

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

TABLE 1

We let $\sigma_{MSR} = 20\%$, $\sigma_{GMV} = 12\%$ and $\lambda_{MSR} = 0.40$. These values imply $p_{MSR, GMV} = 60\%$ and $\lambda_{GMV} = 0.24$. 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 maximizing expected utility or by minimizing the expected shortfall. Analytical expressions for the derivatives of the welfare function are provided to the optimizer 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

Utility-maximizing performance-seeking portfolios for insured payoffs

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.

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 (% of A ₀)	8.54	8.54	8.54	8.53	8.41	7.65	5.69	3.09	1.09

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 A_0 in the strategy with the optimal PSP.

Impacts of Floor and Multiplier

The numerical results are shown in Tables 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 maximizes expected utility or minimizes 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.

Welfare Gains

The welfare gains from optimizing 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-maximizing 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 centralized manager decides how much to allocate to a PSP versus a liability-hedging portfolio (LHP), and decentralized managers are in charge of constructing the building blocks, not necessarily by following the Sharpe ratio maximization and the correlation maximization prescriptions. The optimization 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 characterized 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 (e.g., 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).

TABLE 2

Expected shortfall-minimizing performance-seeking portfolios for insured payoffs

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.

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
Exp. Short. Opt. (%)	8.43	8.25	8.11	8.00	7.95	7.95	8.03	8.21	8.58
Exp. Short. MSR (%)	9.18	8.83	8.51	8.24	8.04	7.96	8.06	8.44	9.17
CPPI, <i>m</i> = 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
Exp. Short. Opt. (%)	14.23	13.27	12.33	11.41	10.53	9.71	9.00	8.50	8.46
Exp. Short. 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
Exp. Short. Opt. (%)	21.07	19.36	17.66	15.98	14.32	12.69	11.15	9.76	8.82
Exp. Short. 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	-
Exp. Short. Opt. (%)	8.63	8.63	8.63	8.63	8.63	8.63	8.55	7.62	-
Exp. Short. MSR (%)	9.56	9.56	9.56	9.56	9.55	9.45	8.83	7.02	3.93

A Four-Fund Separation Result

Let

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_o , 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 optimization problem is given in the following four-fund separation theorem.

Proposition 2 (Optimal PSP in Liability-Driven Investing)

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

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

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

To derive as many analytical expressions as possible, the assumption of geometric Brownian motion dynamics is extended to the present value of liabilities. *MLF* and *MBF* respectively denote the "most liability-friendly" and the "most LHP-friendly" portfolios, which maximize 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 $\beta_{L/MBF}$ 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:

$$\mathbf{w}^{*} = \frac{\lambda_{MSR}}{\gamma \pi \sigma_{MSR}} \mathbf{w}_{MSR} + \left[1 - \frac{1}{\pi}\right] \beta_{B/MBF} \mathbf{w}_{MBF} + \frac{1}{\pi} \left[1 - \frac{1}{\gamma}\right] \beta_{L/MLF} \mathbf{w}_{MLF}$$
(1)
+ $\left[1 - \frac{\lambda_{MSR}}{\gamma \pi \sigma_{MSR}} - \left[1 - \frac{1}{\pi}\right] \beta_{B/MBF} - \frac{1}{\pi} \left[1 - \frac{1}{\gamma}\right] \beta_{L/MLF} \right] \mathbf{w}_{GMV}.$

TABLE 3

Optimal performance-seeking portfolios in liability-driven investing strategies

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 maximization of expected utility from the final funding ratio with a risk aversion of 10, or the minimization of expected shortfall with respect to a funding ratio of 110%.

Initial PSP weight (%)	10	20	30	40	50	60	70	80	90	100
Expected utility – E	Buy and hold	1								
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
Mon. Ut. G. (% 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 – F	-ixed 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
Mon. Ut. G. (% 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 h	old								
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
Exp. Short. Opt. (%	6) 9.39	8.75	8.06	7.49	7.28	7.38	7.73	8.29	9.02	9.90
Exp. Short. MSR (%	6) 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
Exp. Short. Opt. (%	6) 8.45	8.20	8.08	8.09	8.23	8.46	8.76	9.10	9.49	9.90
Exp. Short. MSR (%	6) 9.24	8.53	8.14	8.09	8.26	8.56	8.94	9.37	9.84	10.34

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							

Table 3 displays examples of optimal PSPs for buyand-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, optimization 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, e.g., 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 insurance strategies. Second, the welfare metric to be maximized 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, e.g., 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 portfolio" (MLF), which maximizes 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 like 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 maximization 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 toward aenuine 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.¹⁴

Appendix

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

$$\begin{split} E\left[U\left(\frac{A_T}{A_0}\right)\right] &= \frac{k^p}{p} \exp\left[prT\right] \Phi\left(\frac{1}{\sqrt{v_s}}\left[\log\frac{k}{\xi} + rT - e_s\right]\right) \\ &\quad + \frac{\xi^p}{p} \exp\left[pe_s + \frac{p^2}{2}v_s\right] \Phi\left(\frac{1}{\sqrt{v_s}}\left[\log\frac{\xi}{k} + e_s - rT + pv_s\right]\right), \\ E\left[[N - A_T]^+\right] &= N\left[\Phi\left(\frac{1}{\sqrt{v_s}}\left[\log\frac{\alpha}{\xi} + rT - e_s\right]\right) - \Phi\left(\frac{1}{\sqrt{v_s}}\left[\log\frac{k}{\xi} + rT - e_s\right]\right)\right] \\ &\quad - \xi \exp\left[e_s + \frac{v_s}{2}\right] \left[\Phi\left(\frac{1}{\sqrt{v_s}}\left[\log\frac{\alpha}{\xi} + rT - e_s - v_s\right]\right)\right] \\ &\quad - \Phi\left(\frac{1}{\sqrt{v_s}}\left[\log\frac{k}{\xi} + rT - e_s - v_s\right]\right)\right]. \end{split}$$

In these formulas, Φ denotes the cumulative distribution function of the standard normal distribution,¹⁵ p is 1- γ , 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 .

Wit h a CPPI strategy, the expected shortfall is given by

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

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

we have

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

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

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

$$e_R = \pi [e_S - e_B] + e_B - e_L + \frac{\pi [1 - \pi]}{2} v_{S/B},$$

$$v_R = \pi^2 v_{S/L} + [1 - \pi]^2 v_{B/L} + 2\pi [1 - \pi] c_{S/L,B/L}.$$

The quantities e_B and e_L are the expected log returns of the LHP and liabilities, and $v_{S/B}$ and $v_{B/L}$ are the tracking errors of the PSP with respect to the LHP and of the LHP with respect to liabilities, respectively. $c_{S/L,B/L}$ 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. REFERENCES

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¹⁴ We are grateful to Albert De Wet for very useful feedback.

¹⁵ This function is present in the Black-Scholes formula for the pricing of European options.

Replication of Real Estate Indexes – 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 U.S. 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, namely via exchange-traded funds or mutual funds invested in listed (equity) real estate investment trusts (**REITs**).

However, the design of representative and investible direct property indexes 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 investibility (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, investible 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 trade-off) 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. ¹⁶

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 ED-HEC IEIF Index is a market capitalization-weighted portfolio of commercial SCPIs that satisfy a minimum liquidity requirement. It is investible 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 (i.e., 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 Lionel Martellini Professor of Finance EDHEC Business School Director, EDHEC-Risk Institute

and diversified SCPI portfolios with a limited number of constituents. In this context, this article analyzes 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 2003-2019 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 organization covering the French real estate investment market. At any point during the 2003-2019 period, our dataset covers at least 80% of the total market capitalization 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 (i.e., perfect) replication cannot be implemented (because of operational and/or transaction costs), formalizing it as a complex constrained optimization problem¹⁷ whereby one seeks a suitable subset of the index portfolio that mimics the full index as closely as possible. 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 favor heuristic methods over optimization-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 favor 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 favor a buy-and-hold portfolio construction.

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

- (1) **Two-step approach:** we first select a set of SCPIs and then determine the portfolio allocation.
- (2) Portfolio size: we set a fixed number (N) of SCPIs, e.g., N = 10.
- (3) Selection process: we retain the N largest SCPIs (ranked by market capitalization), subject to the same liquidity filter as that used in the EDHEC IEIF Index (see EDHEC, 2009).
- (4) Allocation process: we set the weights to be proportional to market capitalization (i.e., a "cap-weighted" allocation).
- (5) **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 (Dec. 2003–Dec. 2019, Dec. 2004–Dec. 2019, etc., up to Dec. 2012–Dec. 2019) and five different portfolio sizes (N = 5, 10, 15, 20, 25). All our results are based on gross total returns, both for the indexes and the SCPI portfolios.¹⁸ For each backtest, we compute two indicators to assess the quality of the replication, the annualized Mean Excess Return (**MER**) and the annualized Tracking Error (**TE**), which we define as follows:

Mean Excess Return (**MER**) =
$$\frac{1}{n} \sum_{t=1}^{n} (r_t^P - r_t^I) \times M$$

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

where r_t^p and r_t^l 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 (e.g., segmentation) and/or allocation methods (e.g., equal weights, *TE*-minimizing 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

¹⁶ For more details on goal-based retirement investing, see Martellini, L. and V. Milhau (2021), Advances in Retirement Investing. Cambridge University Press.

¹⁷See Benidis, K., 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.

¹⁸ 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].

of changes in the index universe, i.e., 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 SC-PIs 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 5 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 Guedi 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 2003-2019 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.

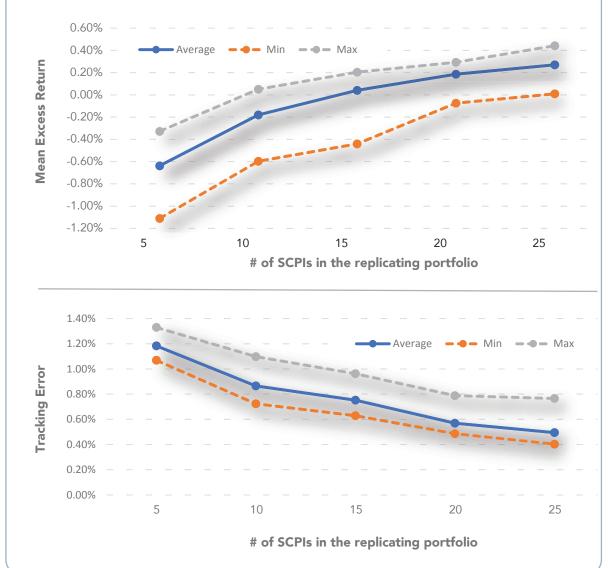
From a quantitative standpoint, the low level of TE (between 0.4% and 1.3%) displayed in Figure 1 is comparable to levels previously reported by the literature related to investable passive index-tracking strategies. For example, Lee (2014) analyzes the performance and tracking error of U.K. real estate 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 19 , 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.²⁰ 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 vs % of closed-end) of the EDHEC IEIF Index. Our tests also include an alternative allocation method based on equal weights at the time of investment without any rebalancing (i.e., 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).

FIGURE 1

Mean Excess Return and Tracking Error (EDHEC IEIF Index)

The top (respectively bottom) diagram displays the average (solid blue line), minimum (dashed orange line) and maximum (dashed grey 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.



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 indextracking strategies.

¹⁹ Alford, A., R. C. Jones and K. D. Winkelmann (2003). A Spectrum Approach to Active Risk Budgeting. Journal of Portfolio Management 30(1), 49–60.

²⁰ Gouzilh, L., M. de Jong, T. Lebaupain and H. Wu (2014). The Art of Tracking Corporate Bond Indices. Amundi Working Paper.

²¹ INREV (2014). The Investment Case for Core Non-Listed Real Estate Funds. Working paper, INREV Research and Market Information

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.

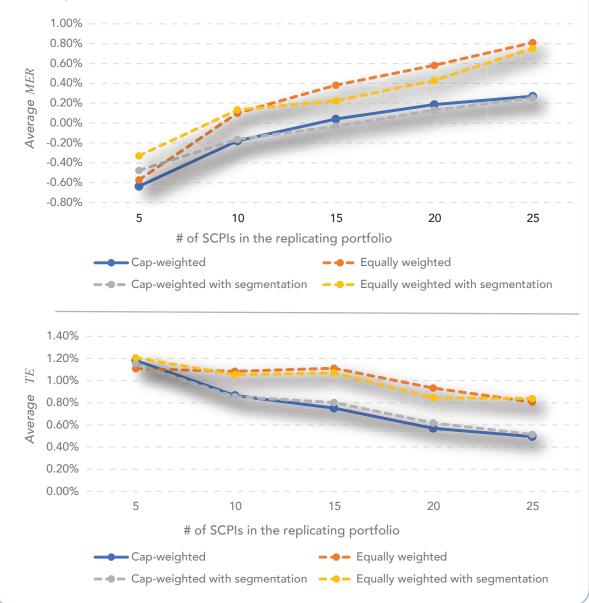
We nevertheless have at our disposal two classes of French real estate investments that allow investors to indirectly purchase (at least partially) the assets making up the MSCI Index: non-listed real estate funds (SCPIs) and the French equivalent of listed REITs, called Sociétés d'Investissement Immobilier Cotées (SIICs). A representative and investable index for SIICs is the Euronext IEIF SIIC France Index (Euronext IEIF SIIC 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 U.S. 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 capitalization, 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 2003–2019 is very similar for all three indexes, 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 indexes. We obtain a relatively low Adjusted R² 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 by its "1-year lagged" version, we see the Adjusted R² 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 indexes, 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 behavior is consistent with the smoothing effect generally observed in appraisal-based indexes 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). ImpleFIGURE 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 (dashed orange line), amending the selection by including segmentation based on capital type (dashed grey line) or amending both allocation and selection (dashed yellow line).



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. menting 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 period²¹ (5–6% *TE* when attempting to replicate a pan-European version of the MSCI Index with 10 to 20 non-listed real estate funds).

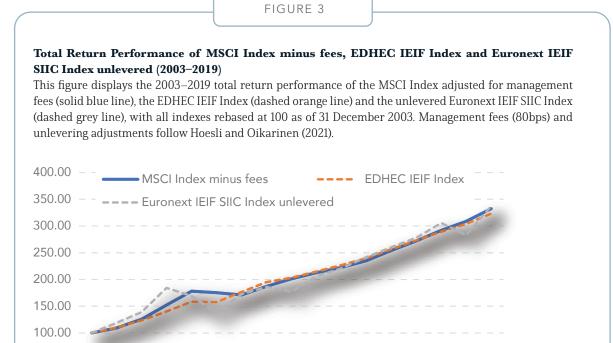
The robustness tests presented in Figure 6 include the usual equal-weighted allocation method as well as the in-sample allocation that minimizes TE (Min TE allocation) over each historical backtesting period. Unlike for the EDHEC IEIF Index replication, the equal-weighted allocation does not lead to 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 30-40 basis points of annual 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 minimization, 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 optimized 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 Tracking Error (*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



50.00 50.00 50.01 50.02 50.02 50.02 50.03 50

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 (2003–2019 = 16 years, 2004–2019 = 15 years, etc.). The three replicating portfolios are i) a portfolio allocated 100% to the EDHEC IEIF Index (solid blue line), ii) a portfolio allocated 90% to the EDHEC IEIF Index and 10% to the Euronext IEIF SIIC Index (solid orange line), and iii) a portfolio allocated 90% to the EDHEC IEIF Index and 10% to the *1-y* lagged Euronext IEIF SIIC Index (solid grey line). The dashed yellow line represents the average Tracking Error value across all 10 investment horizons for the EDHEC IEIF Index portfolio (100% SCPIs).

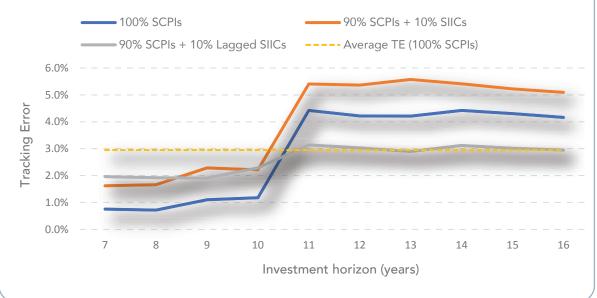


Figure 3 visually confirms our intuitions – The EDHEC IEIF Index closely tracks the MSCI Index once adjusted for fees.

of the standard deviation of excess returns, i.e., 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 back-testing 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 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 annualized volatility estimate of the MSCI Index increases by 1.7x (from 5.4% to 9.4%) when corrected for smoothing.

CONCLUSION

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.

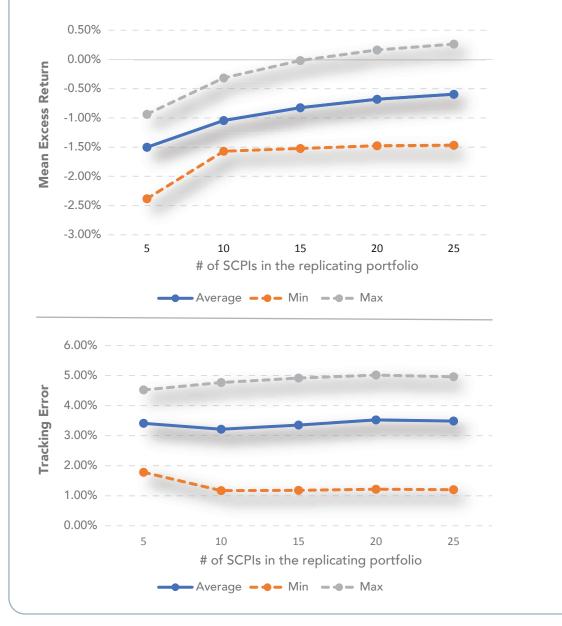
In conclusion, it appears that investors looking for passive exposure to the French commercial real estate asset class, either to enhance the risk-adjusted return of their multi-asset portfolios or to construct a multi-asset retirement goal-hedging portfolio, can potentially gain access to a simple and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

The research from which this article was drawn was produced as part of the Swiss Life Asset Managers France "Real Estate in Modern Investment Solutions" research chair at EDHEC-Risk Institute.

Mean Excess Return and Tracking Error (MSCI Index)

The top (respectively bottom) diagram displays the average (solid blue line), minimum (dashed orange line) and maximum (dashed grey 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.

FIGURE 5



The replication results presented in Figure 5 are consistent with expectations. While we continue to see the positive impact of smaller SCPIs on performance, the MSCI Index property universe is too large for us to observe a decline in TE as we increase the number of SCPIs in the portfolio. FIGURE 6

Robustness Tests: Mean Excess Return and Tracking Error (MSCI Index)

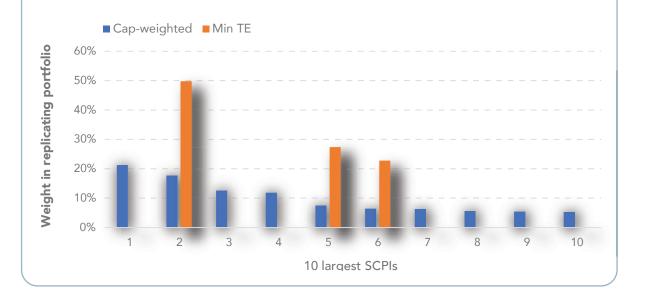
The top (respectively bottom) diagram displays the average value of Mean Excess Return (respectively of Tracking Error) across the 10 overlapping historical backtesting periods for the replication of the MSCI Index, as a function of the number of SCPIs in the replicating portfolio. The base methodology (solid blue line) is a cap-weighted allocation applied to the N largest SCPIs; the alternative methodologies (robustness tests) include an equal weight allocation (dashed orange line), and an allocation that minimizes Tracking Error over the investment horizon (dashed grey line).



The robustness tests presented in Figure 6 include the usual equal-weighted allocation method as well as the in-sample allocation that minimizes TE (Min TE allocation) over each historical backtesting period.

FIGURE 7

Robustness Tests: "Cap-weighted" vs "Min *TE***" allocation with 10 SCPIs (MSCI Index)** This figure displays the allocation of a replicating portfolio (for the MSCI Index) constructed in Dec. 2003 using the 10 largest SCPIs at the time and following a cap-weighted approach (solid blue bars) and a *TE*-minimizing approach (solid orange bars), where *TE* is optimized in-sample over the Dec. 2003–Dec. 2019 period. The height of each bar represents the weight of the corresponding SCPI in the replicating portfolio.

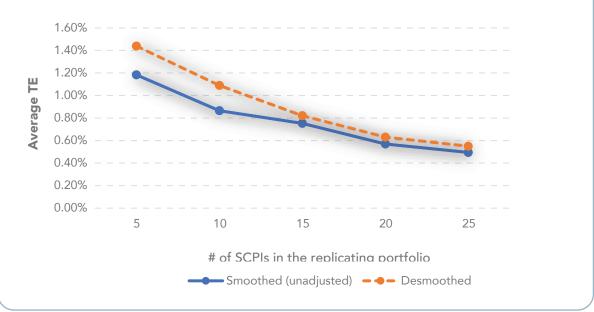


This trade-off seems even less compelling when looking at Figure 7, which shows one example of a Min TE allocation with 10 SCPIs in the portfolio. Figure 8 presents some results for the EDHEC IEIF Index replication.

Desmoothing of Tracking Error (EDHEC IEIF Index)

The diagram 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, i.e., smoothed (solid blue line), and desmoothed (dashed orange line).

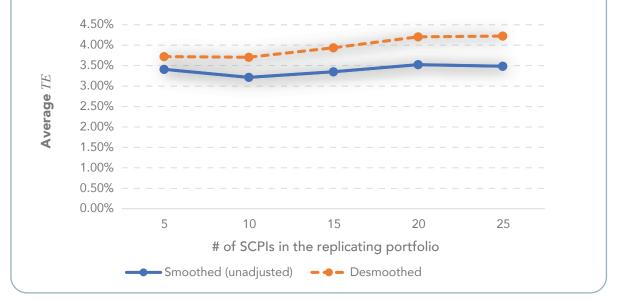
FIGURE 8



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. FIGURE 9

Desmoothing of Tracking Error (MSCI Index)

The diagram 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, i.e., smoothed (solid blue line), and desmoothed (dashed orange line).



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Does ESG Investing Generate Outperformance?

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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 recognize 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 favoring 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 of them (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 analyze whether there is formal empirical support for ESG investment motivations, including most importantly risk and performance motivations. We first analyze 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 optimization 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 optimization 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 analyze 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 (e.g., 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 2007-2012 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 that show an outperformance of ESG (Consolandi et al., 2009; Renneboog et al., 2008, among others), those that 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 that 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 2007–2012 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 Kacperczyk (2021a, 2021b) identify a risk premium related to high carbon emissions, i.e., 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; 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 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 U.S. ethical funds compared both to ethical indexes 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 like size, book-to-market and momentum. In addition, they observe the results from different sub-periods. It appears that German and U.S. 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 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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