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Sustainable Long-term Investment for Retirement

Jean René Mwizere

*A thesis submitted in fulfillment of the requirements for the degree of
Doctor of Philosophy in Actuarial Science*



Faculty of Actuarial Science and Insurance
Bayes Business School
City St George's, University of London

December 2025

Declaration

I, Jean René Mwizere, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the work.

Supervisor: Dr. Iqbal Owadally
Faculty of Actuarial Science and Insurance
Bayes Business School
City St George's, University of London
London, UK

Co-supervisor: Prof. Andrew Clare
Faculty of Finance
Bayes Business School
City St George's, University of London
London, UK

Examiners: Prof. Carmen Boado-Penas
Department of Actuarial Mathematics & Statistics
Heriot-Watt University
Edinburgh, UK

Prof. Steven Haberman
Faculty of Actuarial Science and Insurance
Bayes Business School
City St George's, University of London
London, UK

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Jean René Mwizere

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Abstract

This research evaluates the integration of environmental, social, and governance (ESG) considerations in long-term retirement planning, with a particular focus on their relevance for retail investors. In chapter 2, we use a historical backtesting approach to demonstrate that sustainable investment approaches can outperform investment in a conventional, market capitalisation-weighted equity portfolio in terms of pension accumulation and overall financial performance. These results therefore support the case for integrating sustainable investment principles into portfolio management.

Integrating Environmental, Social, and Governance (ESG) factors into investment strategies offers a potential way to align sustainability goals with long-term financial performance. Chapter 3 looks at this issue in the context of retirement by evaluating the potential benefits of ESG integration into a retirement portfolio over an extended investment horizon. A long-term investment model is developed incorporating Refinitiv ESG scores under multiple sustainable approaches and comparing their performance with a traditional index tracker across major equity markets (FTSE 100, FTSE 250, and S&P 500). The analysis replicates the asset allocation glide paths of 17 UK Master Trust Funds and 27 US Target Date Funds to capture realistic investment behaviour. The results indicate that ESG-screened approaches can enhance portfolio performance and stability over the long run, although the extent of improvement varies across different integration methods.

Chapter 4 assesses the potential long-term implications of integrating Environmental, Social, and Governance (ESG) scores into retirement portfolios for an individual US investor. We compare the performance of a traditional equity portfolio with two sustainable ESG-screened portfolios: a market-capitalisation-weighted version and an ESG-weighted version. Our main finding is that the traditional approach to investing outperforms both the sustainable portfolios in terms of retirement security. These results imply that there may be a cost to investing sustainably. If an individual is willing to bear that cost, we find that a sustainable portfolio where the weights are derived from the ESG scores provides better future retirement outcomes than one where the weights are determined by the market capitalisation of the ESG-screened constituent stocks.

Finally, in chapter 5, we examine the role of sustainable investing within the frameworks of a finite-horizon life-cycle model as well as the classic Merton consumption–investment

problem. We construct two sustainable versions of the S&P 500 by screening stocks using their ESG score: a market capitalization-weighted sustainable portfolio and an ESG score-weighted sustainable portfolio. Historical time series of returns are constructed by dynamically screening stocks, and geometric Brownian motions are then fitted to the time series. We find that risk-adjusted returns on sustainable portfolios decline significantly only when sustainability requirements are very stringent. Tail risk reduces the more sustainable a portfolio is. In both the life-cycle model and the Merton setting, we find that optimal consumption declines only very slightly as sustainability preferences strengthen, as long as these preferences remain moderate. Wealth accumulation and annuitization remain stable with moderately sustainable portfolios. The ESG-weighted portfolio performs better than the market capitalization-weighted portfolio in terms of consumption and wealth accumulation over the life cycle.

Chapter 1

Introduction

1.1 Problem Statement

Over the past two decades, increasing attention to sustainability has reshaped the global investment landscape. Environmental, Social, and Governance (ESG) factors, once considered a niche concern, have become an essential part of modern financial decision-making. However, despite the rapid growth of sustainable investing among both institutional and individual investors, evidence on whether it delivers superior performance compared to traditional practices remains inconclusive.

In the context of retirement investing, a similar shift is evident. Pension fund managers are increasingly moving away from traditional approaches toward more data-driven and market-responsive strategies, reflecting the growing integration of ESG considerations into investment decision-making and risk management, OECD (2021) and World Bank (2022). This transition is further supported by the long-term nature of pension liabilities, which aligns closely with sustainable investment strategies and the need to deliver stable outcomes for retirees, OECD (2022). At the same time, increasing recognition of climate-related and financial stability risks, alongside evolving regulatory frameworks, is encouraging institutional investors to adopt more responsible and forward-looking practices, IMF (2023). Consequently, the pension industry is progressively incorporating sustainability into portfolio construction, as reflected in the continued expansion of global sustainable investment markets, (Morningstar, 2025; GSIA, 2022).

Pension investments play a crucial role in determining the level of wealth retirees can accumulate to support themselves in retirement. Therefore, the inclusion of Environmental, Social, and Governance (ESG) factors as part of investment decision-making must be carefully evaluated. It is essential to ensure that adopting ESG considerations does not negatively affect pension outcomes. Otherwise, integrating ESG as an investment criterion in portfolio construction would be counterproductive.

The main objective of this research is to examine how the integration of ESG Factors influence retirement investment outcomes, with a particular focus on individual pension

portfolios. This thesis seeks to contribute to the growing but still limited literature on the adoption of ESG principles in retirement investing as an alternative to traditional approaches, while providing empirical evidence on their potential advantages and limitations.

Our study is motivated by this central question:

Does incorporating ESG factors into retirement portfolios improve investment results, and how can these strategies be designed to achieve better long-term outcomes?

This question is of growing importance given the demographic shift toward younger, more sustainability-conscious investors, alongside increasing regulatory and societal expectations for institutions to engage in responsible investment practices. Younger generations are showing a clear preference for investments that align with their environmental and social values, influencing the direction of global capital flows, Morgan Stanley (2021) and GSIA (2022). This trend is also reflected in the broader shift toward stakeholder-oriented corporate frameworks, (World Economic Forum, 2020). At the same time, regulators and policymakers are introducing stricter disclosure requirements and sustainability standards, placing additional pressure on financial institutions to demonstrate accountability and transparency in their investment decisions, European Commission (2019) and FCA (2022).

In order to capture a balanced view, our analysis includes two major financial markets: the United Kingdom, where ESG regulation is well established, and the United States, where ESG practices are more market-driven and evolving. This dual-market comparison enables the assessment of performance outcomes as well as the broader institutional, regulatory, and cultural contexts that drive ESG adoption.

1.2 Origins of ESG

The concept of ESG gained formal recognition in 2004, when the United Nations Global Compact published *Who Cares Wins* (UN Global Compact, 2004), defining ESG as a framework for evaluating non-financial risks and opportunities that could impact corporate performance. Similar practices were previously called Socially Responsible Investment (SRI). The notion of SRI extends back several centuries and can be traced to religious groups such as the Quakers and the Methodist Church in the eighteenth and nineteenth centuries, who avoided investing in industries linked to alcohol, weapons, or slavery. These early practices were guided by moral and ethical principles rather than financial motives.

The modern understanding and formal use of the term Socially Responsible Investment began to emerge in the late 1960s and 1970s, particularly in the United States,

against the era of major social movements, including the civil rights movement, anti-Vietnam War protests, and the rise of environmental activism. A key milestone in this evolution was the establishment of the first SRI mutual fund, the Pax World Fund, in 1971, which allowed investors to exclude companies involved in the Vietnam War. By the 1980s, SRI had gained wider academic and institutional recognition as a distinct investment approach, integrating ethical, social, and environmental criteria into portfolio decisions.

Although the ESG and sustainable investing are often used interchangeably, they differ in both focus and scope. ESG refers to a set of measurable criteria used to assess how companies manage environmental impact, social responsibility, and governance standards. In contrast, sustainable investing is a broader philosophy that aims to align investments with long-term environmental and social goals, often beyond financial performance alone. In this thesis, the two terms are used interchangeably, recognising that ESG investing forms part of the broader concept of sustainable investment.

1.3 The Rise of ESG

As of December 2024, global sustainable funds reached an estimated USD 3.2 trillion, marking an 8% increase from the previous year and a more than fourfold rise since late 2018 (Morningstar, 2025). This sustained growth underscores the expanding role of Environmental, Social, and Governance (ESG) considerations in global capital markets. Europe continues to dominate the sustainable fund landscape, accounting for 84% of global sustainable funds and comprising approximately 5,502 funds (ESMA, 2023). Within Europe, the United Kingdom has 61 funds that have adopted an official sustainability label, representing around USD 35 billion in assets. The United States follows with 612 sustainable funds, representing 11% of the global total, while the remainder of the world now accounts for 2.3%, up from just 0.7% in 2018 (Morningstar, 2025).

The global sustainable fund universe includes both open-end and exchange-traded funds that, according to their prospectuses and regulatory filings, identify sustainability, impact, or ESG integration as key investment objectives. Despite slower fund inflows in 2024 compared to previous years, the total value of sustainable funds still reached a record high, reflecting the growing institutionalization of ESG investing.

Further changes in the composition of the sustainable fund market are expected, particularly following the implementation of new European Union measures aimed at reducing greenwashing. In particular, the European Securities and Markets Authority (ESMA) introduced guidelines on the use of ESG-related terms in fund names, which are being implemented from May 2025 and are expected to significantly influence how funds are labelled and marketed across the region - ESMA (2024). These developments build on broader regulatory frameworks such as the Sustainable Finance Disclosure Regulation

(SFDR), which has strengthened transparency requirements for sustainable investments - European Commission (2019). As a result, a number of funds have begun removing ESG-related terms from their names after reassessing their compliance with the new regulatory thresholds - Morningstar (2025). Similarly, in the United States, the Securities and Exchange Commission (SEC) has introduced stricter naming and disclosure requirements through updates to the “Names Rule,” with compliance deadlines extending into 2025, requiring funds using ESG-related terminology to ensure that a substantial proportion of their assets aligns with such investment strategies - U.S. SEC (2023).

1.4 Regulation, Challenges and Market Divergence

Despite rapid growth, ESG investing continues to face significant challenges, including concerns around greenwashing, inconsistent definitions, and limited comparability of ESG data across providers. In response, regulatory frameworks have evolved substantially, particularly in Europe, where policymakers have taken a leading role in shaping sustainable finance.

The European Union has established a comprehensive and integrated regulatory architecture through its Sustainable Finance Action Plan, which aims to reorient capital flows toward sustainable activities, manage financial risks stemming from climate change, and enhance transparency in financial markets. Central to this framework is the EU Taxonomy Regulation, which provides a classification system defining environmentally sustainable economic activities, thereby reducing ambiguity and limiting greenwashing, European Commission (2020). Complementing this, the Sustainable Finance Disclosure Regulation (SFDR) requires financial market participants to disclose how sustainability risks are integrated into investment decisions, European Commission (2019), while the Corporate Sustainability Reporting Directive (CSRD) expands the scope and depth of non-financial reporting by mandating standardized ESG disclosures for a broad set of companies - European Commission (2022). More recently, the European Securities and Markets Authority (ESMA) has introduced guidelines on the use of ESG-related terms in fund names, with implementation beginning in 2025, further strengthening investor protection and market integrity, ESMA (2024). Collectively, these regulatory initiatives have transformed ESG from a largely voluntary and principles-based approach into a structured and enforceable component of financial markets, significantly shaping investment behaviour and capital allocation across Europe.

Beyond the European Union, global initiatives have also played a critical role in shaping the development of sustainable finance. Building on the global frameworks discussed earlier, including the Paris Agreement and the Sustainable Development Goals, regulatory efforts have increasingly translated these objectives into concrete financial market requirements, encouraging both governments and corporations to align their strategies

with measurable sustainability targets. In parallel, the Principles for Responsible Investment (PRI), launched in 2006, offer a voluntary framework for institutional investors to incorporate ESG factors into investment processes. The rapid growth in PRI signatories, from 100 in 2006 to over 5,261 by March 2025 - representing USD 139.6 trillion in assets under management, illustrates the increasing institutionalization of ESG as part of fiduciary duty rather than a purely ethical consideration (UN PRI, 2025).

In contrast to Europe’s coordinated and centralized regulatory approach, the United States presents a more fragmented and heterogeneous regulatory landscape. As previously discussed, the U.S. Securities and Exchange Commission (SEC) has taken steps toward enhancing ESG-related disclosures at the federal level, including proposed climate disclosure rules and updates to the Investment Company “Names Rule,” which requires funds using ESG-related terminology to ensure that a substantial proportion of their assets aligns with their stated investment objectives, U.S. SEC (2023). However, the implementation of ESG policies varies significantly across states due to political polarization. While some states have actively promoted ESG integration, others have introduced legislation restricting or discouraging its use in public investment decisions, reflecting the contested nature of sustainable finance within the U.S. context.

At global level, institutional investors have been instrumental in driving the adoption of ESG practices. Alongside regulatory developments, increasing standardization in corporate reporting has contributed to greater transparency. For instance, according to KPMG’s “Big Shifts, Small Steps” report, 96% of the world’s 250 largest companies were using Global Reporting Initiative (GRI) standards by 2022, a substantial increase from 45% in the early 2000s (KPMG, 2022). The wider use of these reporting frameworks supports the integration of ESG factors into investment analysis and decision-making. More generally, this reflects a gradual shift in financial markets, where sustainability considerations are increasingly taken into account in both regulation and investment practice, with a growing emphasis on long-term outcomes.

Nevertheless, ESG investing has faced a range of challenges in recent years, reflecting both structural and cyclical factors. Concerns related to greenwashing, inconsistent ESG definitions, and limited data comparability continue to affect investor confidence and complicate the evaluation of sustainable investment strategies (Berg et al., 2022; KPMG, 2025). At the same time, evolving regulatory frameworks while improving transparency have introduced additional compliance requirements and short-term uncertainty for market participants.

Market conditions have also played a role. Periods of higher interest rates have disproportionately affected sectors closely associated with sustainability, such as clean energy and growth-oriented industries, contributing to relatively weaker short-term performance (ECB (2023) and BlackRock (2025)). Despite these challenges, underlying demand for sustainable investing remains resilient. Evidence from global surveys and market data

suggests that investor interest in ESG-aligned investments continues to be strong, particularly among younger and long-term investors (FinTech Global, 2025; Morningstar, 2025; Larcker et al., 2026).

Overall, while short-term market conditions, regulatory adjustments, and political factors may influence the pace of adoption, the longer-term trend indicates a continued integration of sustainability considerations into investment practices.

1.5 ESG Financial Instruments

Nowadays, ESG considerations are incorporated at multiple levels of investment and finance, providing an additional dimension to traditional portfolio construction. In this context, a range of financial instruments has emerged, enabling investors to align capital allocation with sustainability objectives. These instruments differ in structure and transmission mechanisms but collectively expand the opportunity set for sustainable investing. They can be broadly classified into three main categories: sustainable fixed income (debt instruments), sustainable equities, and sustainable private market or alternative investments.

Among the most prominent instruments, green bonds, social bonds, and sustainability-linked bonds have become central to ESG fixed-income markets. Green bonds are structured as conventional debt instruments but allocate proceeds specifically to environmentally beneficial projects, such as renewable energy or low-carbon infrastructure. Social bonds follow a similar structure but target social outcomes, including healthcare, education, and affordable housing. In contrast, sustainability-linked bonds do not restrict the use of proceeds; instead, their financial characteristics are contingent on the issuer's ability to meet predefined ESG performance targets, thereby embedding sustainability incentives directly into financing conditions (World Bank, 2015; ICMA, 2023). In parallel, ESG equity funds integrate sustainability considerations into stock selection through ESG screening and portfolio tilting, while sustainable index funds and exchange-traded funds (ETFs) replicate ESG benchmarks, offering cost-efficient exposure to diversified sustainable assets - UN PRI (2016). Within the sustainable private markets and alternative investments, ESG integration is primarily associated with impact investing, which targets measurable environmental and social outcomes alongside financial returns. This includes instruments such as microfinance and blended finance structures, which support financial inclusion and mobilize capital for sustainable development. More recently, innovative mechanisms such as debt-for-nature swaps have gained traction, particularly in emerging markets, reflecting a more direct and outcome-oriented approach to sustainability.

The growth of these instruments has been substantial over the past decade, reflecting both regulatory support and increasing investor demand. Across asset classes, ESG

investments remain primarily concentrated in public markets. Equity and fixed-income instruments dominate, with broad evidence showing that public equities historically represent the largest share of ESG allocations, followed by fixed income, while private markets remain smaller but expanding (GSIA, 2022; MSCI, 2023). More specifically, survey-based evidence indicates that equities are used by around 80% of investors to gain ESG exposure, compared to approximately 50–60% for fixed income, whereas alternative assets, including impact strategies, remain below 50% but are increasing in importance (Harvard Law School, 2022; LSEG, 2022). This distribution highlights that, while ESG integration initially developed in equity markets, fixed income has become a key area of growth, particularly for institutional investors such as pension funds, with private markets playing a complementary but still developing role (BlackRock, 2024; FTSE Russell, 2024).

For pension funds and long-term investors, ESG instruments are particularly relevant as they match long investment horizons and liability needs. ESG fixed-income instruments provide stable cash flows while supporting environmental and social projects, making them suitable for liability-driven strategies. ESG equity strategies help improve portfolio resilience and reduce exposure to long-term risks, such as transition risks, while also capturing growth opportunities. In addition, passive ESG funds and lifecycle funds offer cost-efficient and scalable ways to integrate sustainability into retirement portfolios. Overall, ESG instruments allow pension funds to combine financial objectives with long-term sustainability considerations.

1.6 ESG in Pensions

Much of the literature on ESG investing has focused on performance comparisons, namely whether ESG investments outperform, underperform, or match traditional benchmarks. While informative, this perspective is less relevant in the context of pension investing, where the primary objective is not short-term outperformance but the provision of stable and adequate income over the retirement lifecycle. Pension funds are inherently long-term investors, and their investment strategies must be aligned with long-dated liabilities and intergenerational risk-sharing (Bikker et al., 2014; Clark, 2006).

In this context, ESG integration is increasingly viewed as part of long-term risk management rather than a purely ethical overlay. Pension funds are exposed to risks that unfold over extended horizons, including climate transition risks, demographic changes, and social factors that can affect economic growth and asset returns (IOPS, 2023; WTW, 2022). As such, incorporating ESG considerations can contribute to the resilience of pension portfolios by addressing risks that may not be captured by traditional financial metrics.

However, the effectiveness of ESG integration in pension portfolios depends critically

on the availability and reliability of ESG data. Differences in methodologies across ESG rating providers can lead to divergent assessments of the same assets, complicating portfolio construction and risk evaluation (Billio et al., 2021; Agosto et al., 2025). These challenges are particularly relevant in a retirement context, where small differences in expected returns or risk can accumulate over time and materially affect retirement outcomes. The design of ESG strategies is therefore central to pension investment.

Recent developments in the pension industry highlight the growing importance of sustainability in strategic asset allocation. Many pension funds have adopted net-zero commitments and incorporated ESG factors into their investment mandates, reflecting both regulatory pressures and beneficiary preferences (IIGCC, 2024; IOPS, 2023).

From a portfolio perspective, sustainable investment strategies can align with the long-term nature of retirement planning by addressing risks that materialize over extended horizons and by supporting more stable long-term outcomes. This alignment is particularly relevant in a pension context, where investment strategies must match the timing and persistence of liabilities while maintaining sufficient long-term return generation (Hammond et al., 2023; Anderson et al., 2025). Such strategies can be integrated within lifecycle portfolio design and dynamic asset allocation frameworks, allowing pension funds to balance sustainability considerations with evolving risk profiles over the retirement horizon.

This thesis contributes to this discussion by analyzing ESG within a lifecycle portfolio framework, explicitly linking sustainability considerations to consumption, wealth accumulation, and welfare over the retirement horizon. In doing so, it evaluates how ESG integration affects both the accumulation and decumulation phases of pension investment, and whether sustainable strategies can be designed to support long-term financial outcomes without compromising retirement objectives.

1.7 Outline of Thesis

An outline of each of the core chapters of this thesis is provided below and Table 1.1 summarises the key modeling features of these chapters.

Chapter 2: A sustainable approach to retirement investing for the long haul

The first chapter looks at the UK market, focusing on the FTSE 100. We explore how applying Environmental, Social, and Governance (ESG) factors changes the pension outcomes of an individual retirement investment portfolio. The analysis covers four main asset classes: equities, fixed income, alternatives, and cash, and draws on ESG data from Refinitiv and RepRisk. The paper covers only the accumulation (pre-retirement) phase, assuming portfolios are rebalanced once a year. Using historical cash flow modeling, we compare the performance of a traditional index-tracking investment with four ESG-screened strategies and also assess how industry-specific ESG screening differs across the

two ESG data providers.

Chapter 3: Sustainable retirement investing: insights from the UK and US markets

The second chapter extends the analysis by maintaining the same historical modeling approach, introducing quarterly rebalancing, and expanding the scope to include additional indices: the FTSE 250 for the UK and the S&P 500 for the US market. Asset allocation incorporates real-world methods from 17 UK master trust funds and 27 US target-date funds, allowing for a cross-country comparison of retirement investment practices under both traditional and ESG-screened frameworks.

Chapter 4: Can retirement portfolios benefit from sustainable investing?

The third chapter focuses exclusively on the US market, using Refinitiv only as the ESG data source. The model adopts quarterly rebalancing and divides the investment horizon into two 20-year phases: accumulation and decumulation. Historical data from 2002 to 2022 are extended to a 40-year period using Monte Carlo simulations based on an estimated Vector Autoregressive (VAR) model. The analysis compares traditional and ESG-screened investment strategies across multiple performance metrics, emphasizing long-term sustainability and retirement income outcomes.

Chapter 5: Optimal long-term sustainable portfolios

The final chapter introduces portfolio optimization to assess how sustainable investing fits within well-established models of optimal investment behaviour. Two optimization models are applied: the Merton consumption-investment model and a finite-horizon life-cycle model, both in the context of the US market and the S&P 500 index. This chapter investigates optimal consumption, portfolio allocation, and welfare outcomes when sustainable portfolios replace a traditional benchmark, offering insights into the role of ESG integration in optimizing retirement welfare.

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Stock market index	FTSE 100	FTSE 100 + 250 + S&P 500	S&P 500	S&P 500
ESG ratings	RepRisk + Refinitiv	Refinitiv	Refinitiv	Refinitiv
Phase of life-cycle	Pre-retirement	Pre-retirement	Lifetime	Lifetime
Portfolio rebalancing frequency	Annual	Quarterly	Quarterly	Continuous + annual
Asset allocation	Glide paths: UK Master Trusts	Glide paths: UK Master Trusts + US Target Date Funds	Glide paths: US Target Date Funds	Decision variable
Saving rate	Fixed	Fixed	Fixed	Decision variable
Salary	Deterministic with historic inflation	Deterministic with historic inflation	Deterministic with stochastic inflation	Stochastic
Asset classes	Stock + bond + cash + property	Stock + bond + cash + property	Stock + bond + cash + property	Stock + risk-free asset + annuity
Modeling	Backtesting	Backtesting	Monte Carlo simulation	Numerical optimization
Data analysis	Student t , Wilcoxon	Student t , Wilcoxon	Vector autoregressive model estimation	Geometric Brownian motion estimation
ESG portfolios	MC-weighted + ESG-weighted + short-selling	MC-weighted + ESG-weighted	MC-weighted + ESG-weighted	MC-weighted + ESG-weighted

Legend: MC-weighted = market capitalization-weighted portfolio,
ESG-weighted = ESG score-weighted portfolio.

Table 1.1: Key modeling features of the core chapters of this thesis.

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Chapter 2

A sustainable approach to retirement investing for the long haul¹

Abstract

This research evaluates the integration of environmental, social, and governance (ESG) considerations in long-term retirement planning, with a particular focus on their relevance for retail investors. We use a historical backtesting approach to demonstrate that four sustainable investment approaches that we examine outperform investment in a conventional, market-capitalization-weighted equity portfolio in terms of pension accumulation and overall financial performance. These results therefore support the case for integrating sustainable investment principles into portfolio management.

2.1 Introduction

Investor interest in sustainable investment has grown significantly in recent years. The heightened focus on sustainability, responsible investing, and ESG scores can be attributed to several advancements, including a growing awareness of environmental and social issues, new regulatory developments, increasing demand from investors for sustainable options, and recognition of the financial materiality of ESG scores - OECD (2021), Friede et al. (2015).

Mandatory ESG reporting has increased significantly in recent years, with support from exchanges and securities market regulators. Recently, the creation of the International Sustainability Standards Board (ISSB), a signatory to the Global Reporting Initiative (GRI), is expected to provide global standards on sustainability reporting and

¹This chapter extends the work in my MSc dissertation which is published in: Owadally, I, Mwizere, J.R. et al (2021). Long-term sustainable investment for retirement. *Sustainability*, 13, 9, 5000.

fast-track the integration of ESG metrics. According to KPMG (2022), 96% of the world's 250 largest companies by revenue used GRI Standards for sustainability or ESG reporting, up from just 45% at the start of the 2000s. The 2024 KPMG Survey on Sustainability Reporting confirms that this figure has remained unchanged.

The sustainability and ESG considerations of investment have become more integrated into mainstream investment practices. As a result, the number of research papers focusing on these topics has increased, covering a wide range of subjects, including: ESG integration in investment decision-making; the impact of sustainability on financial performance; the measurement and reporting of ESG data; investor preferences and behavior; and the development of sustainable investment strategies.

Given the interest in sustainability and ESG, it is likely that research in this field will continue to expand in the coming years, further enhancing our understanding of the relationship between sustainability and investment performance. According to the Financial Conduct Authority ("FCA") in the United Kingdom, investors' appetites and preferences for sustainable investments are increasing, and the sustainable investment funds market is the fastest-growing segment across Europe - FCA (2022)

The increase in interest in sustainable investment can be attributed to three factors. First, recent industry and academic studies suggest that ESG investing is essential for improving risk management and yielding returns that are not inferior to those of existing investment strategies, while being socially responsible - Friede et al. (2015). Second, growing public awareness of the risks associated with climate change, the need for diversity and equality in the workplace, responsible business conduct, and the benefits of globally accepted standards, among others, suggests that these values increase investors' influence and enhance corporate performance - Khan et al. (2016). Third, there is growing momentum among corporations to shift from a short-term perspective of risks and returns to a broader, long-term, and sustainable investment approach - OECD (2021).

Global sustainable investments were estimated at USD 35.9 trillion in 2020, a 55% increase from 2016 (GSIA, 2020). They are expected to comprise a third of global assets under management, estimated at USD 53 trillion by 2025 (Diab et al., 2021). Europe and the USA still represent more than 80% of global sustainable investing assets for the period from 2018 to 2020 (GSIA, 2020; UNCTAD, 2022), with the latter experiencing a growth of 42% for the same period only second to Canada at 48% while the former had a 13% decline probably due to a revision of sustainable investment definitions and methodologies. According to the US Sustainable and Responsible Investment Forum (US SIF), an analysis of SEC filings identified USD 6.5 trillion in assets classified as sustainable or ESG investments in 2024, representing around 12% of total professionally managed assets in the United States (US SIF, 2024). For the EU, ESG assets under management are estimated at approximately EUR 6.6 trillion, accounting for 38% of total assets under management in the region (EPRS, 2024).

The focus of this paper is retirement planning in the United Kingdom. In 2021, the United Kingdom’s road map to sustainable investing within the ESG context involved initiatives such as supporting the Task Force on Climate-related Financial Disclosures (TCFD), developing a green taxonomy, promoting green bonds, and enacting the 2021 Pension Schemes Act. These efforts, aimed at integrating environmental, social, and governance (ESG) considerations into financial decision-making, encourage disclosure of climate-related risks and align investments with a transition to a low-carbon economy - UK Parliament (2021). One of the notable aspects of the Pension Schemes Act 2021 is its focus on climate-related financial risks. It requires pension scheme trustees to assess and report on the financial risks associated with climate change, including how they incorporate climate-related risks into their decision-making processes. This aligns with the broader global trend of integrating ESG considerations into investment decisions, including those made by pension funds.

Researchers have previously studied the performance of socially responsible funds compared to existing conventional funds, primarily over short-term horizons, by examining potential trade-offs between returns and profit for a better public image. Despite employing different research strategies, nearly all present studies reach the same conclusion: there are no significant performance differences between the two types of funds. However, studies specifically related to pension saving remain limited. To this end, this paper aims to investigate whether there is a discernible difference in the long-term performance of conventional and sustainable investments for retirement planning. We evaluate pension value outcomes using data from two ESG providers, namely Refinitiv and RepRisk. The analysis also incorporates methodologies for constructing portfolios based on ESG criteria and draws comparisons between the performance of ESG-screened funds and their counterparts. Additionally, the paper incorporates glide paths currently employed by master trust funds in the United Kingdom for a comprehensive market assessment.

Plan of this chapter. The structure of this paper is as follows: In Section 2.2, we review existing literature on sustainable investment. Section 2.3 outlines our ESG-screened methodologies and research objectives. Section 2.4 employs historical back-testing to evaluate fund performance, presenting results, discussions, and statistical analysis. Finally, in Section 2.5, we draw conclusions based on the findings.

Remark on ESG rating scale. In this chapter, we follow the *RepRisk* convention concerning ESG ratings. ESG scores range **from 100 to 0**:

- stocks with the *lowest* sustainability performance are scored 100,
- stocks with the *highest* sustainability performance are scored 0.

2.2 Literature Review

2.2.1 ESG investing and Investment performance

Early studies on sustainable investment in the 1990s, such as Hamilton et al. (1993), Mallin et al. (1995), Gregory et al. (1997), found no significant difference in investment outcomes when adopting a socially responsible approach. Based on this, researchers argued that investors may as well invest along more sustainable and responsible lines. More recent research has increasingly shown that integrating ESG or sustainability considerations can improve returns and enhance risk-adjusted performance.

Using socially responsible ratings from KLD Research & Analytics for stocks that comprise the S&P 500 and the DS400 indices between 1992 and 2004, Kempf et al. (2007) implemented a trading strategy to assess the impact of investing along sustainable lines. Their approach involved buying stocks with high socially responsible ratings and selling those with low ratings. The study reports significant abnormal returns of up to 8.7% per year, with the strongest results obtained when combining multiple screens, particularly the best-in-class approach and focusing on stocks with extreme ratings. Notably, these abnormal returns remained significant even after accounting for transaction costs.

Amon et al. (2021) examined financial and ESG performance by constructing portfolios based on different passive asset allocation strategies using U.S. and European stock data from 2005 to 2018. They found that ESG-screened strategies consistently outperformed other approaches in both markets. The study also identified a negative correlation between ESG scores and returns, consistent with Ahmad et al. (2021), which they attribute to the size effect: larger-cap stocks, typically associated with higher ESG scores, tend to deliver lower expected returns than smaller-cap stocks. In line with this, the authors observed a positive relationship between company size and ESG scores in both Europe and the U.S.

Krosinsky et al. (2008) also reported a positive correlation between financial returns and sustainable investment. Their study examined 850 SRI portfolios worldwide, narrowing the sample to 135 portfolios with more than USD 100 million in equity under management and at least five years of performance history as of the end of 2007. They define sustainable investment as “an approach to investing driven by the long-term economic, environmental, and social risks and opportunities facing the global economy.” The authors conclude that while no two sustainable portfolios or approaches produce identical results, nor should they, sustainable investment consistently outperformed both ethical fund peers and mainstream indices, regardless of whether portfolios relied on mainstream strategies, hedging techniques, or best-in-class sustainability screens.

Owadally et al. (2021) evaluated the long-term performance of sustainable funds relative to an index tracker fund in the context of retirement investing. Their ESG scenarios

included a passive “Do-It-Yourself” portfolio constructed from FTSE 100 constituents selected based on ESG scores, as well as a set of UK-domiciled actively managed sustainable funds with a 20-year history dating back to 2000. Both ESG-screened approaches generated higher pension wealth than the conventional fund over the investment period. By contrast, a comparative analysis of ESG and conventional funds in Europe and the U.S. from 1994 to 2020 found no significant difference in performance between the two.

Alves et al. (2022) examined the relationship between ESG ratings and stock returns worldwide over a 20-year sample period (2001–2020), using data on 9,253 stocks from 46 countries. Their study is among the few to assess ESG performance across multiple rating providers, namely Refinitiv, MSCI, and Sustainalytics. The authors found no robust relationship between ESG ratings and investment performance. When splitting the sample into two sub-periods (2001–2012 and 2013–2020) to account for the post-2013 boom in ESG ratings, they reported consistent results: stocks with higher ESG ratings did not necessarily generate higher returns in most global markets.

The majority of academic research on ESG investment has focused on public equity markets. Diep et al. (2021), however, examined the influence of ESG on corporate bond performance between 2012 and 2020 and found little evidence of ESG factors enhancing bond returns. Similar conclusions were reached by Slimane et al. (2019), Henke (2016), and Clare et al. (2024), who also reported limited evidence of improved risk-adjusted performance in sustainable bond portfolios. Nonetheless, Clare et al. (2024) echoed the reasoning of early studies in this area: while ESG integration may not boost returns, it does not reduce them either. Therefore, investors who are concerned about the sustainability of business practices might as well incorporate ESG considerations into their fixed-income portfolios.

Using a sample of 116 French SRI mutual funds from 2004 to 2007, Capelle-Blancard et al. (2014) investigated the role of stock screening in sustainable investment. They found that screening at the sector or industry level reduced risk-adjusted returns, suggesting a loss of diversification. By contrast, when broader screening criteria were applied, such as commitment to the UN Global Compact Principles or ILO/Rights at Work, the adverse effects on diversification and financial performance were less pronounced.

While much evidence supports the integration of ESG and sustainability considerations into investment decisions, some studies report less favorable outcomes. Mănescu (2011), Riedl et al. (2017), and Trinks et al. (2017) found that sustainable investments underperformed comparable conventional investments. They attribute this underperformance primarily to negative screening, the exclusion of so-called “sin stocks” in sectors such as tobacco, alcohol, gambling, and military defense, which often involve large corporations that have historically delivered substantial returns.

2.2.2 Risks and ESG credentials

One of the supposed benefits of investing responsibly or more sustainably, using ESG ratings, is that firms with high ratings are less likely to experience, for example, a fine for failing to comply with environmental regulations, damage to their reputation due to poor employment practices, or a negative impact from poor governance. As such, companies with relatively high ESG scores should be more robust during challenging economic environments.

Nakai et al. (2016), and Areal et al. (2010) demonstrated that socially responsible funds performed better than conventional funds during the 2008 financial crisis in the Japanese and US markets, respectively. Nakai et al. (2016) assessed via the Fama–French Three-Factor Model; 2,136 conventional funds and 62 SRI funds for a period from 7 February to 17 September 2008, while Areal et al. (2010) used a Markov-switching conditional CAPM model with the S&P 500 as a benchmark for 51 ethical funds from October 1993 to September 2009.

Arefeen et al. (2020) also investigated the performance and resilience of SRI versus conventional funds listed in the Japan Investment Trust Association during two economic shocks - the U.S. election and Brexit in 2016; only the latter significantly affected conventional fund returns, while overall socially responsible funds exhibited greater resilience and stability during both crises.

Cheema-Fox et al. (2020) looked at the initial stock market reaction to the COVID-19 crisis of 3,023 companies around the globe and found that companies scoring high on a "crisis response" measure were associated with 1.4-2.7% higher stock returns. The study considered a sample of globally listed equities obtained from Truvalue Labs, MSCI, and State Street Corporation with a market capitalization of at least \$1 billion USD as of January 1, 2020, and discerned a positive correlation between crisis response and firm returns.

Using constituents of China's CSI300 index, Broadstock et al. (2021) combined ESG data from SynTao Green Finance with stock prices from the WIND database to assess, over the period 2015–2020, whether ESG credentials were associated with risk mitigation and stock performance. Their findings aligned with those of Cheema-Fox et al. (2020), pointing to a positive relationship. By contrast, Chiappini et al. (2021) examined the performance of sustainable indices in Europe and the U.S. during the COVID-19 lockdowns using an event study approach. They found that, similar to conventional indices, sustainable indices were negatively affected by lockdown announcements and failed to deliver abnormal returns during the pandemic.

2.2.3 ESG ratings

Research on ESG investing has expanded significantly in recent years, with much of the literature, including the studies cited above, focused on assessing the impact of ESG criteria on the risk and return of individual stocks or portfolios. However, findings remain highly sensitive to the quality of ESG ratings, the choice of data source, and the methodologies applied by different rating agencies, each of which adopts its own approach and produces considerable variability in ESG scores.

Brandon et al. (2021) examined the impact of ESG rating disagreement on stock returns using data from seven different ESG providers. They found a positive correlation between stock returns and disagreement in ratings. They noted that divergence was particularly pronounced in the assessment of environmental performance, where differing opinions among rating agencies were most evident.

Berg et al. (2022) measured the differences between six prominent ESG rating agencies. The paper follows early research by Chatterji et al. (2016), which took the lead in decomposing ESG rating divergence by distinguishing two aspects: first, how ESG rating agencies define what they intend to measure, and second, how they conduct the measurement. Their findings indicate that measurement divergence is the primary source of variation in ESG rating, driven by differing ESG definitions and fundamental disagreements over the underlying data.

Dimson et al. (2020) also investigated the discrepancies and diverse weightings attributed to different pillars of ESG ratings by various agencies. The research examines the performance of ESG-screened portfolios and non-screened counterparts. Ultimately, the findings suggest that relying solely on ESG ratings is unlikely to significantly enhance portfolio returns. The study emphasizes that while certain ESG indices, such as FTSE4GOOD and MSCI-ESG, show no signs of underperformance, ESG indices overall did not outperform their conventional counterpart indices over the long term.

Boffo et al. (2020) evaluated the practices, progress, and challenges that comprise ESG investing. Their key finding is that ESG ratings vary significantly depending on the chosen provider, due to qualitative judgments, key indicators and metrics, different frameworks, and the weighting of subcategories.

2.2.4 ESG investing and Pensions

Sievänen et al. (2017) investigated the relationship between sustainable development and financial objectives in pension funds. A survey of over 250 pension funds from 15 European countries is employed, and the study utilizes multinomial logistic regression to examine how pension funds balance responsibility and financial performance. Examining the influence of responsible investing on performance, the findings indicate that funds that integrate sustainability into their strategy frequently attain a balance between financial

and responsible objectives, taking into account not only returns, but also values and motivations.

Alda (2020) compared 22 SRI funds with 20 matched conventional funds drawn from a larger sample of 221 UK domestic equity pension funds, applying linear models to assess how fund characteristics influence ESG scores and to examine the relationship between ESG scores, performance, and flows. The study finds that both conventional and SRI funds share characteristics affecting ESG scores, consistent with features typically associated with SRI. Moreover, greater ESG screening intensity is associated with higher returns and increased fund flows, with SRI funds outperforming their conventional counterparts while maintaining their distinct SRI characteristics. In a related study, Alda (2021) investigated the integration of ESG criteria in both SRI and conventional pension funds using ESG stock scores and panel regressions, along with a nearest neighbor matching method to control for differences in fund characteristics. Analyzing 22 SRI and 221 conventional UK domestic equity pension funds from 2016 to 2018, the findings reveal a substantial overlap in ESG scored holdings between the two fund types, indicating that conventional funds also incorporate certain ESG considerations.

Meins et al. (2021) examined the relevance of Environmental, Social, and Governance (ESG) risks for pension funds, addressing issues such as global ESG reporting practices, the regulatory landscape, the practical application of ESG principles, and trends in climate change litigation. Their study highlights an important outcome: neglecting or failing to account for ESG factors when selecting stocks for pension portfolios can lead to unexpected fluctuations in pension value.

2.2.5 Summary

Overall, the academic literature generally points to potential risk–return benefits from integrating ESG considerations into investment portfolios, with some evidence that strengthening a portfolio’s ESG profile may also help reduce tail risk. At the same time, applying negative screens can weaken performance, particularly when excluded sectors outperform the broader market. In the pension context, where long-term stability and downside protection are critical, these findings underscore both the potential advantages and the trade-offs of incorporating ESG criteria. Despite the lack of standardized ESG metrics and rating methodologies, research in this area continues to expand.

2.3 Research Objectives and Methodologies

In the context of individual pension funds, we analyze differences in performance between pension accumulation achieved through investment in a conventional equity portfolio (proxied by a market-capitalisation-weighted index tracking fund) and portfolios

that integrate sustainable investment techniques. Our model considers a UK-based 45-year-old retail investor who combines salary savings with multi-asset investments from 2000 to 2020, starting with an initial salary of £50,000 projected to grow in line with the UK earnings index published by the Office for National Statistics (ONS, 2020). At the outset (age 45), the investor deposits £50,000 of prior savings into the retirement fund and subsequently contributes 15% of annual salary at the end of each year until retirement at age 65.

We build upon the research conducted by Owadally et al. (2021) by broadening the scope of the modeling analysis. Specifically, we evaluate performance using ESG data from two different providers, thereby capturing potential divergences in rating methodologies. We also assess investments across a broader range of asset classes, equity, fixed income, alternatives, and cash, to reflect the diversified structure of real-world pension portfolios. Furthermore, we incorporate glide-path scenarios that are currently utilized in the United Kingdom (UK), as reported in the 2020 Defined Contribution Investment Forum (DCIF) Master Trust Study, Parkin (2020). Glide-path techniques enable adequate portfolio weighting, with gradual shifts toward less risky asset classes as retirement approaches, thereby reducing exposure to potential market downturns and safeguarding accumulated pension wealth. The use of glide-paths in fund management, both before and during retirement, has been shown to provide growth in the early accumulation phase, mitigate risks in the years leading to retirement, and stability during the decumulation phase (Jang et al., 2022; Pfau et al., 2013; Estrada, 2016; Kobor et al., 2019).

2.3.1 Approach and Portfolio Construction

In our analysis, we evaluate five distinct portfolio construction strategies, four of which explicitly incorporate Environmental, Social, and Governance (ESG) scores as a central criterion for stock selection and portfolio weighting. The objective is to assess whether integrating ESG considerations into the portfolio design has a measurable impact on overall performance. In doing so, we aim to determine whether the inclusion of ESG scores leads to more favorable outcomes, produces results comparable to those of conventional strategies, or results in underperformance.

We will use two ESG data providers, Refinitiv and RepRisk. Refinitiv is one of the leading ESG score providers globally and provides ESG scores for approximately 14,500 public firms and 1,300 private companies, with historical coverage extending back to 2002. The scores are based on publicly disclosed and verifiable ESG information. All scores older than five years are classified as definitive and remain fixed even if firms later restate disclosures or data corrections occur. In contrast, scores for the most recent five years can be revised to account for delayed data releases, corporate events such as mergers, or corrections in reported ESG metrics. Refinitiv does not retroactively adjust

historical ESG scores when methodological changes are introduced. Instead, revisions are limited to the rolling window of non-definitive years, ensuring consistency in the long-term historical series.

As for RepRisk, they provide daily updated ESG risk indicators based on media, NGO, and stakeholder reports rather than company disclosures. Their system screens more than 100,000 media and stakeholder sources across 23 languages, covering over 200,000 public and private entities globally, the historical time series is available from 2007 onward. There is no fixed lookback period after which scores become final; instead, RepRisk maintains a dynamic history where past controversy assessments may be updated if an incident evolves or is reclassified in severity. However, methodological updates at RepRisk do not trigger a full retrospective restatement of historical scores in the way a disclosure-based ESG rating system might. Instead, revisions primarily occur through ongoing incident monitoring, meaning that score changes are driven by new external signals rather than structural recalibration of the database.

Our two ESG data providers apply similar scoring frameworks but with opposite directions. Refinitiv assigns scores on a 0–100 scale, where higher values indicate stronger ESG performance, whereas RepRisk applies the reverse approach, with lower scores reflecting greater sustainability. For consistency and comparability, we adopt the RepRisk convention, such that lower ESG scores represent better performance.

The allocation across the four asset classes remains fixed throughout the investment horizon. Equity exposure is drawn from the FTSE 100, comprising the 100 largest companies by market capitalization listed on the London Stock Exchange. The fixed income component is represented by the M&G Gilt & Fixed Interest Income Sterling A ACC fund, the alternatives allocation by the BlackRock UK Property fund, and the cash allocation by the BlackRock Cash fund. Given the long-term nature of our analysis, we selected funds with continuous data availability over the 2000–2020 period.

The construction of the equity portfolio is carried out as follows:

- **FTSE 100 Tracker:**

Under this strategy, the equity component adopts a conventional passive approach by investing in the HSBC FTSE 100 Index Retail Acc fund, which replicates the performance of the FTSE 100 Index. This approach provides broad market exposure without incorporating ESG considerations. For ease of reference, we designate this strategy as IT (Index Tracker) and use it as the baseline against which ESG-screened strategies are evaluated.

We introduce an alternative approach that incorporates ESG scores into equity portfolio construction, allowing sustainability considerations to influence stock weighting and overall strategy design. To capture heterogeneity in investor sustainability preferences, we construct portfolios using ESG score percentile thresholds denoted by

$[0, \kappa]$, where $\kappa \in 25, 50, 75$. The 100th percentile corresponds to the inclusion of all 100 FTSE constituents, while lower thresholds apply stricter ESG screening, thereby reducing the number of eligible stocks. The parameter κ thus represents the investor’s sustainability preference and serves to assess how different screening intensities affect portfolio performance.

- **Market-cap-weighted:**

Under this strategy, we adopt a dual approach that incorporates both market capitalization and ESG scores in the annual portfolio construction process. ESG scores guide the selection of stocks included in the portfolio, while the weighting method mirrors that of an index tracker, relying on market capitalization.

Stocks with larger market capitalization receive greater portfolio weights, with each stock’s weight determined relative to the total number of stocks in the portfolio:

$$w_i = \frac{M_i}{\sum_{j=1}^n M_j} \tag{2.1}$$

w_i : Weight of stock i in the market-cap-weighted portfolio.

M_i : Market capitalization of stock i .

n : Number of stocks in the portfolio for a given year.

We denote this market-cap-weighted strategy as **MCw**.

- **ESG-weighted:**

We extend the use of ESG scores beyond stock selection to determine weight allocation within the portfolio. Unlike traditional market-capitalization weighting, where larger firms automatically receive greater portfolio weight, this approach emphasizes sustainability by assigning proportionally higher weights to firms with higher ESG credentials, regardless of their market size. The objective is to favor companies demonstrating superior ESG performance, thereby embedding sustainability considerations more deeply into both the composition and the structure of the portfolio.

To achieve this, each stock’s raw ESG score is transformed using a convex exponential decay function:

$$\alpha_i = \exp(-k \cdot \theta_i) \tag{2.2}$$

This transformation ensures that stocks with stronger ESG performance receive proportionally greater importance (weight).

The transformed ESG scores are subsequently employed to determine portfolio weights and to compute portfolio return:

$$w_i^* = \frac{\alpha_i}{\sum_{j=1}^n \alpha_j} \quad (2.3)$$

α_i : Transformed ESG score of stock i .

θ_i : Raw ESG score of stock i .

w_i^* : Weight of stock i in the ESG-weighted portfolio, similar to a softmax function.

k : Positive scaling constant

We denote the ESG-weighted strategy as **ESGw**.

- **ESG Short selling**

We extend our ESG-screened strategies by incorporating short-selling to assess the potential benefits of shorting stocks that exhibit weaker ESG performance. These approaches build directly on the two methods introduced previously (MCw and ESGw), with the addition of short-selling. Specifically, the first strategy relies on market capitalization for weighting while using ESG scores for stock selection, denoted as **MCw Short**. The second applies ESG scores for both weighting and selection, denoted as **ESGw Short**.

$$L_p = \sum_{i: \theta_i \leq \kappa} w_i \quad (2.4)$$

$$S_p = \sum_{i: \theta_i > \kappa} w_i = 1 - L_p \quad (2.5)$$

$$\text{Performance}_i = \begin{cases} \frac{w_i^+}{L_p} \cdot \delta, & \text{if } \theta_i \leq \kappa \quad (\text{long position}) \\ \frac{w_i^+}{S_p} \cdot \sigma, & \text{if } \theta_i > \kappa \quad (\text{short position}) \end{cases} \quad (2.6)$$

L_p : Weight of long positions.

S_p : Weight of short positions.

w_i^+ : Stock weight (given by w_i in MCw or w_i^* in ESGw).

θ_i : Raw ESG score of stock i .

k : Selected ESG percentile threshold.

δ : Exposure to long positions.

σ : Exposure to short positions.

In our modeling, the long position exposure δ is set at 130%, while the short position exposure σ is set at -30%. This reflects a 130/30 strategy structure, which enables an enhanced long position by financing it through short-selling. The allocation between long and short positions is determined by the investor's chosen ESG

preference threshold within a specified percentile range. Stocks with ESG scores equal to or below the chosen percentile threshold are assigned to the long position, whereas the remaining stocks are allocated to the short.

Portfolio returns are measured on an annual frequency

$$R_p = \sum_{i=1}^n w_i R_i \quad (2.7)$$

Where:

R_p : Portfolio return

w_i : Weight of stock i in the portfolio, depending on the strategy

R_i : Return of stock i

n Number of stocks in the portfolio

We account for portfolio dynamics by modeling the growth in pension wealth at time t .

$$\text{Pension}_t = (\text{Pension}_{t-1} + \text{Savings}_t) \times \left[\sum_i (\text{Weight}_{i,t} \times (1 + \text{Net Return}_{i,t})) \right]$$

where i represents asset classes.

At each year, t , the accumulated pension consists of the previous year's balance plus new contributions, compounded by the weighted performance of the portfolio.

Risk-adjusted performance is measured by

$$\text{Sharpe} = \frac{R_p - R_f}{\sigma_p} \quad (2.8)$$

With

$$\sigma_p = \sqrt{\frac{1}{T-1} \sum_{t=1}^T (R_{p,t} - \bar{R}_p)^2} \quad (2.9)$$

Where:

R_p : Portfolio return

R_f : Risk-free rate

σ_p Standard deviation of portfolio returns

$R_{p,t}$: Portfolio return at time t

\bar{R}_p : Mean portfolio return over the period

T : Number of return observations

Fund administration costs exert a significant influence on long-term investment performance. In our pension accumulation model, we assume that portfolios are rebalanced annually, and consider the overall charge figure (OCF) as the only cost. OCF is assumed to remain constant throughout the investment horizon, as reported in Table 2.1, with values sourced from the Morningstar database in February 2023. Further information on financial performance, specifically the total annual returns of asset class funds and FTSE 100 constituents, was retrieved from Refinitiv Datastream.

Fund Name	OCF
HSBC FTSE 100 Index Retail ACC	0.29%
M&G Gilt&Fixed Interest Income Sterling A ACC	0.55%
Blackrock UK Property	0.91%
Blackrock Cash	0.40%

Table 2.1: Annual overall charge figure (OCF). Source: Morningstar database, Feb. 2023.

The objective of this research is to assess whether ESG-screened strategies applied to the FTSE 100 yield performance patterns that diverge from those of a conventional index tracker. By doing so, the paper contributes to the growing discourse on sustainable investment, demonstrating its relevance as a long-term alternative to traditional approaches. It also provides empirical evidence on the performance of sustainable portfolios, highlighting their potential value for retirement planning and their suitability for retail investors seeking passive, cost-efficient investment strategies.

2.4 Historical Back-testing

2.4.1 Investment Approach

In our analysis, we simulate portfolio construction based on historical data and assess the effectiveness of our investment decisions to inform about potential future benefits. The primary objective is to incorporate ESG scores into our sustainable investment strategies for long-term retirement plans and compare their performance to that of a typical index tracker fund. Our ESG-screened portfolio construction strategies can be readily replicated by passive investors, allowing for the early mitigation of pension fund value fluctuations using ESG scores data.

Through back-testing, we identify investment approaches that have historically delivered favorable returns while effectively managing risk. In addition, we assess the sensitivity of portfolio outcomes to ESG score percentile thresholds and alternative investment strategies. By analyzing how asset allocations, portfolio selection methods, and ESG risk

management techniques would have performed historically, we gain deeper insight into the long-term implications of ESG integration for pension fund performance.

Nevertheless, this analysis is subject to several limitations. First, ESG data availability is limited in the early part of the sample period: RepRisk coverage begins only in 2007, while Refinitiv data are available from 2002 onward. To address this gap, we impute missing values for earlier years using the average ESG scores observed in later periods. Second, even in more recent years, ESG scores are not reported for all FTSE 100 constituents, resulting in portfolios that are, at times, constructed from fewer than the full set of 100 stocks. These data limitations should be taken into account when interpreting the results, as they may affect both the composition of the ESG-screened portfolios and their historical comparability.

Finally, the research is further bound by assumptions regarding consistent investor behavior, limited consideration of external influences, and the exclusion of management costs. In sum, past performance should not be construed as an absolute assurance of similar outcomes in the future; instead, it serves as an indicative measure of potential possibilities.

2.4.2 Results and Discussion

In this section, we conduct a comparative analysis of four ESG-screened investment strategies against a conventional index-tracking approach. The evaluation covers a 20-year investment horizon and incorporates glide path variations that align with those currently implemented by UK master trust funds. Particular attention is given to the terminal wealth outcomes of pension portfolios, allowing for an assessment of how ESG integration affects long-term performance across various master trust structures.

In this paper, Refinitiv ESG scores and the 75th percentile threshold serve as the baseline scenario for all ESG-screened strategies. Under this specification, FTSE 100 constituents with ESG scores above the 75th percentile in a given year are excluded from the portfolio. This approach is replicated for the 50th and 25th percentile thresholds in subsequent scenarios.

Figure 2.1 illustrates the comparative performance of six randomly selected master trust funds from the set of seventeen examined glide paths. The results indicate that all ESG-screened strategies - MCw, ESGw, MCw SHORT, and ESGw SHORT - outperform the conventional index tracker (IT). Within these strategies, the ESG-weighted approach consistently yields the highest pension accumulations. Notably, Master Trust 11 (MT#11) achieves the greatest accumulation under the ESG-weighted, whereas Master Trust 15 (MT#15) shows the weakest outcome under the index tracker scenario.

The findings suggest that integrating ESG considerations into pension fund investment strategies can improve financial outcomes compared to a conventional index-tracking

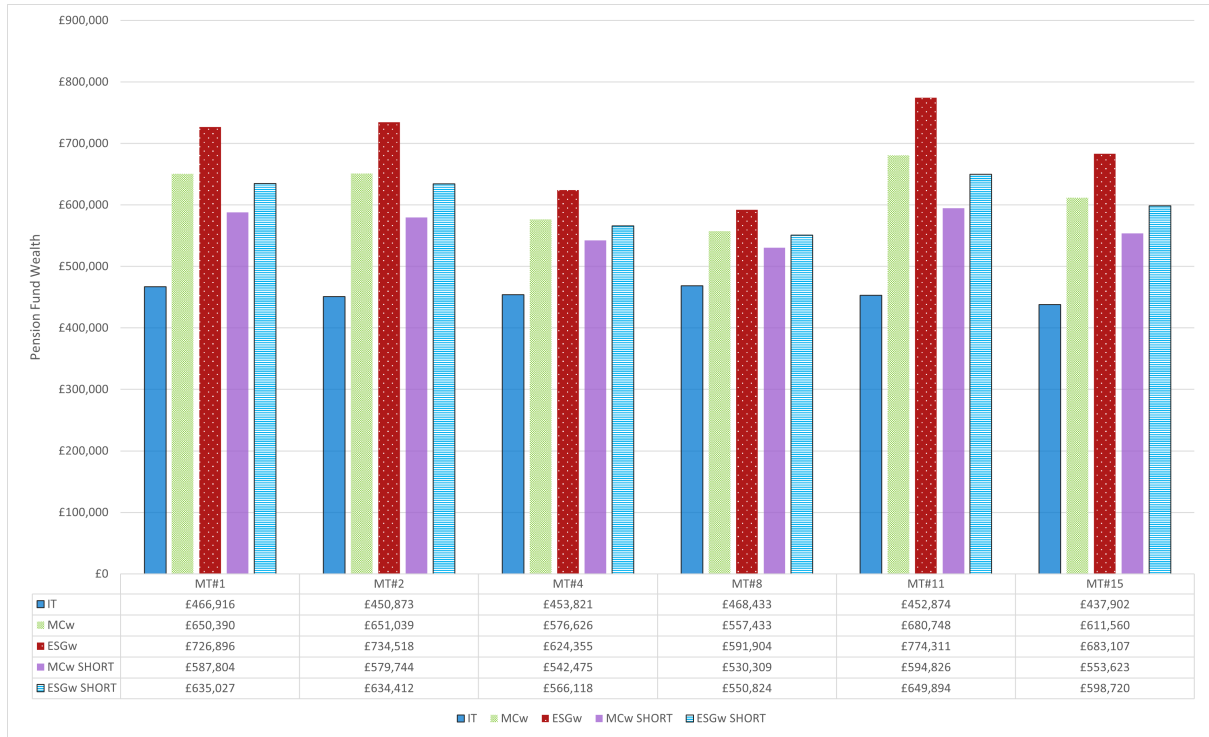


Figure 2.1: Portfolio outcomes of six representative Master Trusts.

approach. Nonetheless, it should be emphasized that the six master trust funds presented in Figure 2.1, together with the additional results reported in Tables 2.22–2.25 of the appendix, represent only a snapshot of performance. Outcomes may differ depending on the choice of asset class funds, glide-path design, investment strategy, stock index selection, ESG data provider, and the specific time period under analysis.

We extend our analysis by examining alternative percentile cut-offs to reflect varying levels of investor ESG preference. ESG scores are employed as metrics of sustainability, covering the Environmental, Social, and Governance dimensions, as well as an Overall ESG score. Table 2.2 and Table 2.3 present the performance variations of the market-cap-weighted and ESG-weighted strategies across the six selected master trusts, accounting for different percentile threshold choices.

Market-cap-weighted Strategy				
Master Trust	Index Tracker	75 th	50 th	25 th
MT#1	£466,916	£650,390	£570,043	£490,065
MT#2	£450,873	£651,039	£568,796	£485,960
MT#4	£453,821	£576,626	£522,549	£468,532
MT#8	£468,433	£557,433	£518,294	£477,527
MT#11	£452,874	£680,748	£578,855	£481,497
MT#15	£437,902	£611,560	£539,077	£466,541

Table 2.2: Percentile variation in retirement wealth under the market-cap-weighted strategy vs index tracker.

ESG-weighted Strategy				
Master Trust	Index Tracker	75 th	50 th	25 th
MT#1	£466,916	£726,896	£676,831	£591,059
MT#2	£450,873	£734,518	£683,714	£594,647
MT#4	£453,821	£624,355	£593,164	£538,914
MT#8	£468,433	£591,904	£569,306	£529,424
MT#11	£452,874	£774,311	£708,298	£599,954
MT#15	£437,902	£683,107	£639,357	£563,057

Table 2.3: Percentile variation in retirement wealth under the ESG-weighted strategy vs index tracker.

The detailed results shed light on the role of ESG scores in portfolio construction and offer a clear baseline against the index tracker strategy. They demonstrate that ESG-screened strategies achieve stronger pension accumulation outcomes, underscoring the importance of ESG integration in pension fund investment design. Exploring different percentile thresholds reveals variations in pension accumulation and provides deeper insight into their impact on portfolio performance. This approach enables investors to tailor their strategies to their sustainability preferences, particularly by applying negative screening to exclude companies with poor ESG performance.

For both the MCw and ESGw strategies, portfolios constructed under the 75th percentile threshold include a larger number of stocks than those based on the more conservative 25th percentile, owing to the exclusion of fewer FTSE 100 constituents. Such differences in portfolio size can influence pension accumulation over the investment horizon. Nevertheless, even at the stricter 25th percentile, ESG-screened strategies consistently outperform conventional index trackers, highlighting the potential benefits of integrating

Market-cap-weighted shorting Strategy				
Master Trust	Index Tracker	75 th	50 th	25 th
MT#1	£466,916	£587,804	£580,999	£640,030
MT#2	£450,873	£579,744	£573,677	£630,406
MT#4	£453,821	£542,475	£532,610	£577,267
MT#8	£468,433	£530,309	£525,102	£554,971
MT#11	£452,874	£594,826	£590,559	£669,913
MT#15	£437,902	£553,623	£543,560	£594,917

Table 2.4: Percentile variation in retirement wealth under the market-cap-weighted shorting strategy vs index tracker.

ESG-weighted shorting Strategy				
Master Trust	Index Tracker	75 th	50 th	25 th
MT#1	£466,916	£635,027	£658,486	£709,027
MT#2	£450,873	£634,412	£666,616	£714,213
MT#4	£453,821	£566,118	£580,530	£613,107
MT#8	£468,433	£550,824	£560,212	£583,474
MT#11	£452,874	£649,894	£679,314	£748,805
MT#15	£437,902	£598,720	£622,931	£663,287

Table 2.5: Percentile variation in retirement wealth under the ESG-weighted shorting strategy vs index tracker.

ESG considerations into investment design.

In the case of short-selling strategies as illustrated in Tables 2.4–2.5, a reversal in dynamics is observed. In the 75th percentile scenario, not only are stocks falling within the 25th percentile excluded from the portfolio, but also subject to short selling, allowing investors to capitalize on both market shifts. Consequently, opting for a lower percentile results in an increased number of shorted stocks, thereby possibly and constantly enhancing pension accumulation.

The portfolio’s performance appears to benefit from the combination of exclusion by ESG percentile threshold, coupled with an increased number of stocks available for shorting. This observation holds significance under our established model conditions, suggesting a potential correlation between portfolio size, short-selling activity, and overall performance. Furthermore, it is notable that ESG-screened strategies, combined with short-selling, also consistently outperform the conventional index tracker.

The performance of the remaining master trusts is illustrated under Tables 2.22–2.25 in the appendix.

2.4.3 Statistical Analysis

Our next undertaking involves conducting a detailed statistical analysis of our findings to assess the presence of notable differences in the portfolio’s performance under various ESG-screened investment strategies and the conventional approach. We aim to substantiate the potential advantages of constructing Do-It-Yourself ESG layered portfolios, which could yield comparable or superior performance when juxtaposed with prevailing conventional fund strategies. The examination of financial and ESG metrics will be pivotal in assessing the notion that incorporating ESG principles into investment strategies can potentially lead to enhanced risk-adjusted returns.

In our pursuit of unbiased and accurate assessments, we deliberately avoid making assumptions about normality regarding the resulting pension fund wealth for the seventeen master trusts over our investment period for each of the investment strategies. To validate the non-normality of certain strategies, we conducted a Shapiro normality test. The results were conclusive, specifically for the IT and MCw SHORT, as indicated in Table 2.6. Recognizing the unsuitability of parametric tests for non-normal data, we opted for the non-parametric Wilcoxon signed rank test, as evidenced in Tables 2.7 and 2.8.

The outcome of each ESG-screened strategy, when compared to the conventional index tracker, is noteworthy. Table 2.8 reveals that for all scenarios, the P-value is less than 0, indicating a statistically significant difference in performance between the ESG strategies and the conventional index tracker. These findings underscore the relevance of ESG considerations in contemporary investment decision-making processes.

Shapiro Normality Test					
Values	IT	MCw	ESGw	MCw SHORT	ESGw SHORT
W	0.7982	0.9525	0.9716	0.8890	0.9354
P-Value	0.0019	0.4968	0.8455	0.0446	0.2674

Table 2.6: Distributional normality of pension accumulation outcomes

T-Test paired				
Values	IT&MCw	IT&ESGw	IT&MCw SHORT	IT&ESGw SHORT
t	-11.38	-12.20	-10.45	-12.14
df	19	18	23	21
P-Value	4.703E-10	4.02E-10	2.847E-10	5.519E-11

Table 2.7: Mean differences in pension accumulation across strategies

Wilcoxon Test				
Values	IT&MCw	IT&ESGw	IT&MCw SHORT	IT&ESGw SHORT
P-Value	8.57E-10	8.57E-10	1.671E-07	8.57E-10

Table 2.8: Non-parametric differences in pension outcomes

We enhance our analysis with an examination of financial performance over the 2000-2020 period, providing insights into the effectiveness of alternative investment strategies. Risk-adjusted returns, measured using the Sharpe ratio, are evaluated across the seventeen DCIF master trust funds.

The Sharpe ratio is a crucial metric, as it measures the excess return of a portfolio relative to its risk, providing insight into its risk-adjusted performance. The best Sharpe ratio is the highest value achieved by an investment or portfolio. A higher Sharpe ratio indicates better risk-adjusted performance, meaning the investment delivers greater returns per unit of risk.

In calculating the Sharpe ratio, we incorporate Risk-Free rates obtained from the Bank of England, considering the official bank rate at the end of each year, and confirmed via Refinitiv DataStream for the 1-year UK Gilt. The comprehensive results are presented in Table 2.9, providing insight into the comparative performance of each strategy. Notably, all ESG-screened strategies consistently outperform the index tracker strategy, demonstrating their potential to deliver superior financial performance. To further strengthen our findings, we conduct a Wilcoxon signed-rank test on the Sharpe ratio results to determine whether there is a significant difference in performance between the four ESG-screened investment strategies and the FTSE 100 index tracker (IT).

The null hypothesis posits that there is no significant distinction between the strategies' performance, while the alternative hypothesis suggests the presence of a significant difference. For all four paired scenarios, the resulting p-values are less than 5% and even close to zero, indicating strong evidence against the null hypothesis. Thus, we find evidence for the alternative hypothesis, leading us to conclude that there is a statistically significant difference in portfolio performance between the four ESG investment strategies and the conventional strategy, as measured by the Sharpe ratios (see Table 2.10-2.12).

Sharpe Ratio					
Master Trust	IT	MCw	ESGw	MCw SHORT	ESGw SHORT
MT#1	0.1186	0.5012	0.6043	0.4130	0.5102
MT#2	0.0823	0.4423	0.5397	0.3597	0.4590
MT#3	0.0933	0.4519	0.5310	0.3691	0.4354
MT#4	0.1439	0.4770	0.5521	0.4151	0.4779
MT#5	0.0962	0.4400	0.5194	0.3641	0.4362
MT#6	0.1024	0.4512	0.5554	0.3808	0.4855
MT#7	0.0522	0.3969	0.5400	0.3372	0.4976
MT#8	0.2237	0.5181	0.5845	0.4587	0.5223
MT#9	0.0805	0.4269	0.5310	0.3577	0.4668
MT#10	0.1725	0.5046	0.5718	0.4265	0.4871
MT#11	0.0872	0.4672	0.5611	0.3630	0.4519
MT#12	0.1459	0.4721	0.5440	0.4097	0.4718
MT#13	0.0879	0.4413	0.5479	0.3682	0.4758
MT#14	0.1069	0.4586	0.5551	0.3899	0.4822
MT#15	0.0756	0.4289	0.5223	0.3548	0.4456
MT#16	0.0610	0.4221	0.5093	0.3343	0.4147
MT#17	0.0993	0.4409	0.5145	0.3683	0.4312

Table 2.9: Sharpe Ratio results under various investment strategies for the seventeen examined master trust funds.

Shapiro Normality Test					
Values	IT	MCw	ESGw	MCw SHORT	ESGw SHORT
W	0.8810	0.9678	0.9522	0.9299	0.9819
P-Value	0.0330	0.7789	0.4927	0.2165	0.9720

Table 2.10: Distributional normality of Sharpe ratios

T-Test paired				
Values	IT&MCw	IT&ESGw	IT&MCw SHORT	IT&ESGw SHORT
t	-25.44	-35.34	-18.90	-27.55
df	30	26	31	28
P-Value	2.20E-16	2.20E-16	2.20E-16	2.20E-16

Table 2.11: Mean differences in Sharpe ratios across strategies

Wilcoxon Test				
Values	IT&MCw	IT&ESGw	IT&MCw SHORT	IT&ESGw SHORT
P-Value	8.57E-10	8.57E-10	7.04E-07	8.57E-10

Table 2.12: Non-parametric differences in Sharpe ratios

2.4.4 The case for ESG rating

The relatively slow adoption of sustainable investment strategies is often attributed to the need for a standardized ESG methodology among ESG data providers. This leads to varying reporting styles, case weighting, and ESG scores, causing challenges for investors seeking uniformity and reliable comparisons. Despite this disparity, multiple studies have investigated the impact of using different ESG data providers on portfolio performance (Brandon et al., 2021; Berg et al., 2022; Chatterji et al., 2016). These studies consistently demonstrate that sustainable funds generally outperform conventional funds, regardless of potential rating divergence.

While the lack of a standard ESG methodology might introduce uncertainty, the overall positive performance of sustainable funds showcases their resilience and attractiveness as viable investment options. Investors are increasingly recognizing the long-term benefits of aligning their portfolios with environmental, social, and governance (ESG) considerations. As sustainable investing gains traction, it becomes crucial for ESG data providers to collaborate on developing a standardized methodology that enhances transparency, consistency, and accuracy in ESG ratings. A unified approach will empower investors to make well-informed decisions based on reliable and comparable data, fostering the growth of sustainable finance and its positive impact.

In our model, we assume annual portfolio rebalancing for simplicity; however, in practice, portfolios are often rebalanced more frequently to optimize returns and adapt to market dynamics, which can potentially impact portfolio performance due to associated costs. Ideally, our annual portfolio would consist of 100 stocks. However, historical data is affected by factors such as company closures, mergers/acquisitions, and missing ESG scores, which can affect information accessibility. Consequently, the number of stocks in most years is below 100. ESG score availability varies by provider; Refinitiv and RepRisk ESG scores are available post-2000 (2002 and 2007, respectively). We use the average of existing ESG scores for the specific intervals, and the annual portfolio size reflects the surviving stocks and ESG score availability from providers, as shown in Table 2.13.

Number of Stock					
Year	RepRisk	Refinitiv	Year	RepRisk	Refinitiv
2000	57	37	2011	58	97
2001	65	43	2012	66	99
2002	71	56	2013	69	98
2003	69	61	2014	69	99
2004	73	78	2015	72	98
2005	71	92	2016	69	98
2006	72	94	2017	71	99
2007	78	95	2018	70	100
2008	34	99	2019	74	98
2009	59	98	2020	72	100
2010	60	99			

Table 2.13: FTSE 100 Constituents with ESG Scores per Provider

In addition to evaluating pension accumulation in ESG-screened portfolios and the FTSE 100 tracker, we analyze the industry-level impact of ESG percentile threshold screening using data from Refinitiv and RepRisk, as shown in Tables 2.14 & 2.15 at the 75th percentile, Tables 2.16 & 2.17 at the 50th and lastly, Tables 2.18 & 2.19 for the 25th percentile scenario. The stock’s classification utilizes the Industry Classification Benchmark (ICB), a global system that categorizes stocks into specific industries based on their primary business activities. Notably, the industries with the highest number of screened-out stocks, regardless of the ESG data provider or chosen percentile threshold, are the Industrial, Financial, and Consumer Services.

The selected ESG percentile threshold determines the number of stocks excluded in a given year. A higher percentile results in fewer exclusions, thereby retaining a broader portfolio. In contrast, a lower percentile leads to the removal of more stocks, producing a more compact portfolio that may offer distinct advantages. This approach may help reduce management costs, particularly while dealing with frequent rebalancing occurrences that often entail higher transaction costs. By selecting an appropriate percentile level, investors can strike a balance between portfolio diversification and cost-effectiveness, optimizing their investment strategy for long-term success.

REFINITIV YEARLY SCREENING											
ICB	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ENERGY	2	2	1	1	0	0	0	0	1	0	0
BASIC MATERIALS	2	3	4	0	1	0	0	1	0	0	0
INDUSTRIAL	6	6	9	8	9	7	7	5	8	8	6
FINANCIAL	10	8	6	9	8	8	7	6	5	4	6
UTILITIES	1	1	0	0	0	1	0	0	1	2	2
TECHNOLOGY	2	1	1	0	0	0	2	2	2	2	3
TELECOMMUNICATIONS	1	0	0	0	0	1	0	0	0	0	0
CONSUMER SERVICES	1	1	1	5	4	4	7	7	7	7	7
HEALTH CARE	0	0	0	0	0	0	0	1	1	0	0
CONSUMER GOODS	0	2	3	2	3	4	2	3	0	2	1
TOTAL	25	24	25	25	25	25	25	25	25	25	25

Table 2.14: Number of FTSE 100 Constituents screened out at a 75th percentile of ESG Scores-Refinitiv Scenario.

REPRISK YEARLY SCREENING											
ICB	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ENERGY	1	3	2	1	1	1	1	1	1	1	1
BASIC MATERIALS	1	1	1	1	1	1	1	2	1	1	2
INDUSTRIAL	4	4	4	5	5	5	5	5	5	5	5
FINANCIAL	4	3	4	4	4	4	4	4	4	4	4
UTILITIES	1	1	1	1	1	1	1	1	1	1	0
TECHNOLOGY	0	0	0	0	0	0	0	0	0	0	0
TELECOMMUNICATIONS	0	0	1	1	1	1	1	1	2	1	1
CONSUMER SERVICES	3	2	2	2	2	3	2	3	3	3	3
HEALTH CARE	0	0	0	0	0	0	0	0	0	0	0
CONSUMER GOODS	1	1	2	2	2	2	2	1	1	3	2
TOTAL	15	15	17	17	17	18	17	18	18	19	18

Table 2.15: Number of FTSE 100 Constituents screened out at a 75th percentile of ESG Scores-RepRisk Scenario.

REFINITIV YEARLY SCREENING											
ICB	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ENERGY	4	3	4	3	2	0	0	0	1	0	0
BASIC MATERIALS	5	6	8	2	2	2	3	3	4	2	2
INDUSTRIAL	12	13	15	18	15	9	10	13	11	10	11
FINANCIAL	14	9	8	10	11	14	11	12	11	12	11
UTILITIES	3	4	2	2	3	4	4	4	4	5	4
TECHNOLOGY	3	2	2	1	1	2	3	2	2	2	3
TELECOMMUNICATIONS	1	0	0	0	0	1	1	0	1	1	1
CONSUMER SERVICES	3	4	4	7	8	9	12	9	10	12	11
HEALTH CARE	2	2	2	2	1	2	1	1	2	1	1
CONSUMER GOODS	2	5	4	4	6	6	4	5	4	4	6
TOTAL	49	48	49	49	49	49	49	49	50	49	50

Table 2.16: Number of FTSE 100 Constituents screened out at a 50th percentile of ESG Scores-Refinitiv Scenario.

REPRISK YEARLY SCREENING											
ICB	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ENERGY	3	5	3	3	4	2	2	1	1	2	1
BASIC MATERIALS	2	3	3	2	1	2	3	3	3	3	3
INDUSTRIAL	6	4	7	6	6	6	6	6	6	7	6
FINANCIAL	7	4	6	5	8	9	8	9	6	7	5
UTILITIES	2	3	3	3	3	4	2	1	3	4	3
TECHNOLOGY	0	0	0	0	0	0	0	0	0	0	0
TELECOMMUNICATIONS	1	2	2	1	2	2	1	2	2	2	2
CONSUMER SERVICES	5	5	5	7	5	5	7	7	9	8	10
HEALTH CARE	0	0	0	1	0	0	0	1	0	0	0
CONSUMER GOODS	4	3	4	6	5	6	5	5	5	4	6
TOTAL	30	29	33	34	34	36	34	35	35	37	36

Table 2.17: Number of FTSE 100 Constituents screened out at a 50th percentile of ESG Scores-RepRisk Scenario.

Lower-percentile thresholds, such as the 25th, reflect a conservative approach to portfolio construction, resulting in a narrower and more focused portfolio. The success of this approach heavily relies on the availability and accuracy of ESG scores from data providers. In some cases, the resulting number of stocks may be considerably reduced due to limited ESG data. For example, in 2018, RepRisk provided ESG scores for only 70 of the FTSE 100 constituents, while Refinitiv offered complete coverage. When applying the 25th percentile screening, 75 stocks were excluded under the Refinitiv scenario, resulting in a portfolio of 25 stocks, whereas RepRisk excluded 52 stocks, producing a portfolio of only 18 stocks.

While this strict approach might raise concerns for some investors seeking diversification, it could prove advantageous for short-selling strategies. A more concentrated portfolio can enable short sellers to target specific stocks that are exposed to ESG risks. By capitalizing on the identification of poorly performing companies in terms of ESG criteria, short sellers could potentially profit from the subsequent underperformance of these companies.

However, adopting a lower percentile screening approach requires careful consideration, as stock performance is not determined solely by ESG characteristics. Achieving long-term financial goals while maintaining alignment with sustainability principles depends on balancing diversification with focused investment. Such an approach supports a more resilient and sustainably grounded portfolio strategy that extends beyond short-term performance metrics.

REFINITIV YEARLY SCREENING											
ICB	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ENERGY	4	4	4	3	2	0	0	0	1	0	0
BASIC MATERIALS	7	7	10	5	4	5	4	8	7	8	6
INDUSTRIAL	16	15	18	18	17	13	14	14	14	14	14
FINANCIAL	19	19	15	15	21	18	20	20	19	17	19
UTILITIES	6	6	5	5	5	5	5	5	5	5	5
TECHNOLOGY	3	2	2	2	2	2	3	2	2	2	3
TELECOMMUNICATIONS	2	0	0	1	1	2	1	1	2	1	1
CONSUMER SERVICES	11	12	13	16	14	17	15	14	16	18	18
HEALTH CARE	2	2	2	2	1	3	3	2	2	1	2
CONSUMER GOODS	4	5	5	6	7	8	8	8	7	7	7
TOTAL	74	72	74	73	74	73	73	74	75	73	75

Table 2.18: Number of FTSE 100 Constituents screened out at a 25th percentile of ESG Scores-Refinitiv Scenario.

REPRISK YEARLY SCREENING											
ICB	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ENERGY	5	5	5	4	4	3	2	2	3	2	2
BASIC MATERIALS	3	4	6	3	4	5	5	6	5	5	7
INDUSTRIAL	9	6	10	8	8	8	7	6	7	7	7
FINANCIAL	10	10	6	9	11	11	11	11	11	11	10
UTILITIES	3	3	5	5	5	6	6	6	5	6	4
TECHNOLOGY	0	0	0	0	0	0	0	1	0	0	0
TELECOMMUNICATIONS	2	2	2	2	2	2	2	2	2	2	2
CONSUMER SERVICES	8	8	9	12	10	13	12	11	12	13	14
HEALTH CARE	0	0	1	1	1	0	0	1	0	1	0
CONSUMER GOODS	5	5	5	7	5	6	6	7	7	8	8
TOTAL	45	43	49	51	50	54	51	53	52	55	54

Table 2.19: Number of FTSE 100 Constituents screened out at a 25th percentile of ESG Scores-RepRisk Scenario.

Further detail is provided in Tables 2.20 and 2.21, which report the Top 3 stocks by market capitalization excluded from the annual portfolio between 2010 and 2020 under the two ESG data providers. This analysis demonstrates how percentile screening affects industry-level representation and portfolio construction. The systematic exclusion of certain stocks based on ESG criteria generates distinct portfolio profiles that embody a more sustainability-oriented investment approach.

RepRisk consistently identifies the same set of stocks to be screened out across all examined percentiles, demonstrating a stable and unvarying ESG reporting. On the other hand, Refinitiv exhibits dynamic changes in the excluded stocks, indicating a more fluid and evolving screening process. This distinction highlights the contrasting methodologies employed by the two ESG data providers in stock screening and underscores the importance of understanding the nuances in their respective approaches when making investment decisions.

For Refinitiv, most of the excluded Top 3 stocks are found in the Financial, Consumer Services, and Industrials sectors, while for RepRisk, significant exclusions occur in the Financial, Health Care, and Energy sectors. These differences indicate that the two ESG data providers employ distinct methods for constructing their ESG scores. Refinitiv relies more on reported disclosures and quantitative measures, which may explain why financial and service-based firms are more often excluded. RepRisk, on the other hand, places greater weight on controversies and reputational risks, which can result in more exclusions in consumer-focused sectors and those exposed to environmental issues. Overall, this comparison shows that the choice of ESG data provider can also influence which stocks are excluded, and in turn, affect portfolio construction and investment outcomes.

Investors could gain valuable insights into the alignment of their portfolios with en-

vironmental, social, and governance (ESG) considerations by identifying the industries primarily impacted through percentile screening. With this knowledge, investors can make well-informed decisions, actively supporting companies that excel in ESG performance while balancing their exposure to industries with weaker sustainability practices. This proactive approach enables investors to contribute to positive changes and drive sustainable practices through their investment choices.

REFINITIV YEARLY SCREENING			
YEAR	75th	50th	25th
2010	CNE,ENRC,RR	BG,SAB,NG	HSBA,NWG,BG
2011	SAB,IPR,ANTO	SAB,NG,RKT	HSBA,BG,SAB
2012	MRO,SAB,RR	MRO,SAB,BG	MRO,HSBA,SAB
2013	MRO,SAB,PRU	MRO,LLOY,SAB	MRO,LLOY,SAB
2014	SAB,BAE,EXPN	SAB,PRU,BG	HSBA,SAB,LLOY
2015	SAB,EXPN,OMU	SAB,PRU,NG	HSBA,SAB,RKT
2016	EXPN,OMU,ITV	PRU,BT.A,WPP	DGE,RKT,LLOY
2017	OMU,MCRO,AHT	PRU,NG,CPG	HSBA,PRU,LLOY
2018	MRO,EXPN,HL	PRU,MRO,NG	VOD,LLOY,PRU
2019	MRO,EXPN,AHT	MRO,PRU,NG	RIO,LLOY,MRO,
2020	NG,MRO,FLTR	PRU,NG,MRO	HSBA,RIO,PRU

Legend: AHT = Ashtead Group. ANTO = Antofagasta. BAE = BAE Systems.

BG = BG Group. BT.A = BT Group. CNE = Capricorn Energy. CPG = Compass Group.

DGE = Diageo. ENRC = Eurasian Nat Res Corp. EXPN = Experian. FLTR = Flutter Entertainment. HL = Hargreaves Lansdown. HSBA = HSBC Holdings. IPR = International Power. ITV = ITV. LLOY = Lloyds Banking Group. MCRO = Micro Focus Intl. MRO = Melrose Industries. NG = National Grid. NWG = Natwest Group. OMU = Old Mutual. PRU = Prudential. RIO = Rio Tinto. RKT = Reckitt Benckiser Group. RR = Rolls-Royce Holdings. SAB = Sabmiller. VOD = Vodafone Group. WPP = WPP

Table 2.20: Top three FTSE 100 by market-cap screened out at ESG percentiles (Refinitiv).

REPRISK YEARLY SCREENING			
YEAR	75 th	50 th	25 th
2010	HSBA,BP,GSK.	HSBA,BP,GSK.	HSBA,BP,VOD.
2011	HSBA,BP,GSK.	VOD,HSBA,BP.	VOD,HSBA,BP.
2012	HSBA,BP,VOD.	HSBA,BP,VOD.	HSBA,BP,VOD.
2013	HSBA,VOD,BP.	HSBA,VOD,BP.	HSBA,VOD,BP.
2014	HSBA,BP,GSK.	HSBA,BP,GSK.	HSBA,BP,GSK.
2015	HSBA,BATS,GSK.	HSBA,BATS,GSK.	HSBA,BATS,GSK.
2016	HSBA,BP,RDS.	HSBA,BP,RDS.	HSBA,BP,RDS.
2017	HSBA,BATS,BP.	HSBA,BATS,BP.	HSBA,BATS,BP.
2018	HSBA,BP,RDS.	HSBA,BP,RDS.	HSBA,BP,RDS.
2019	HSBA,AZN,BP.	HSBA,AZN,BP.	HSBA,AZN,BP.
2020	HSBA,GSK,BP.	AZN,HSBA,GSK.	ULVR,AZN,HSBA.

Legend: AZN = AstraZeneca PLC. BATS = British American Tobacco PLC. BP = BP PLC. GSK = Glaxosmithkline PLC. HSBA = HSBC Holdings PLC. RDS = Royal Dutch Shell PLC. ULVR = Unilever PLC. VOD = Vodafone Group PLC

Table 2.21: Top three FTSE 100 by market-cap screened out at ESG percentiles (RepRisk).

2.4.5 Analysis of ESG Components

When constructing portfolios, investors are not limited to considering the overall ESG score; they may instead direct their attention to individual components -Environmental (E), Social (S), or Governance (G) - depending on their specific priorities or preferences. By focusing on specific ESG components, investors can align their portfolios with sustainability priorities that better reflect their values and objectives, thereby enabling a more personalized and targeted approach to sustainable investing. Figure 2.2 illustrates the performance for six of the seventeen examined master trusts under the Environmental (E) component and again demonstrates that the ESG-screened portfolio outperforms the use of a conventional FTSE 100 tracker.

Considering the divergence in reporting of ESG metrics, portfolio performance varies not only based on the chosen investment strategy or percentile threshold, as previously discussed, but also on the specific ESG component under consideration. Figure 2.3 presents the pension accumulation trajectory for Master Trust Eleven (MT#11) over the 20-year investment period, considering only the Environmental (E) component across all investment strategies. This case serves as an illustrative example from the full set of seventeen master trusts. Comparable representations are available for the remaining master trusts and investment strategies, showing consistent performance patterns.

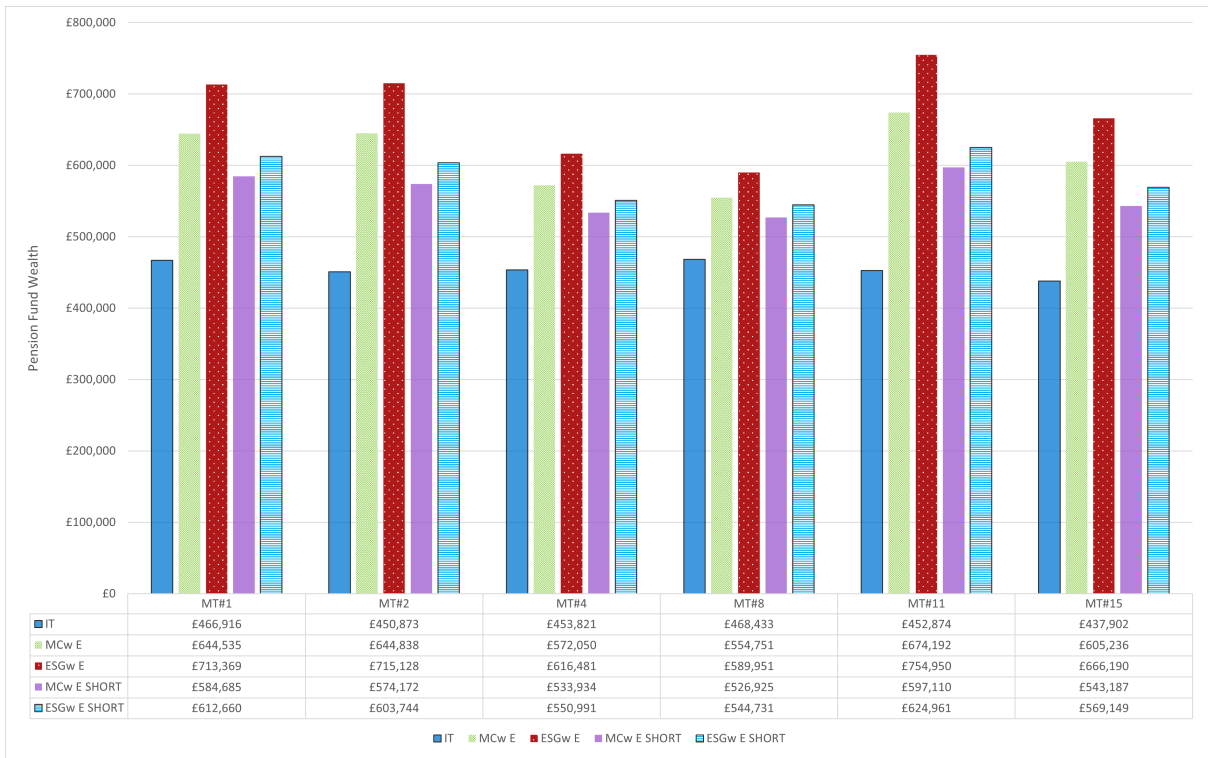


Figure 2.2: Retirement portfolio performance of six representative Master Trusts under the Environmental (E) component.

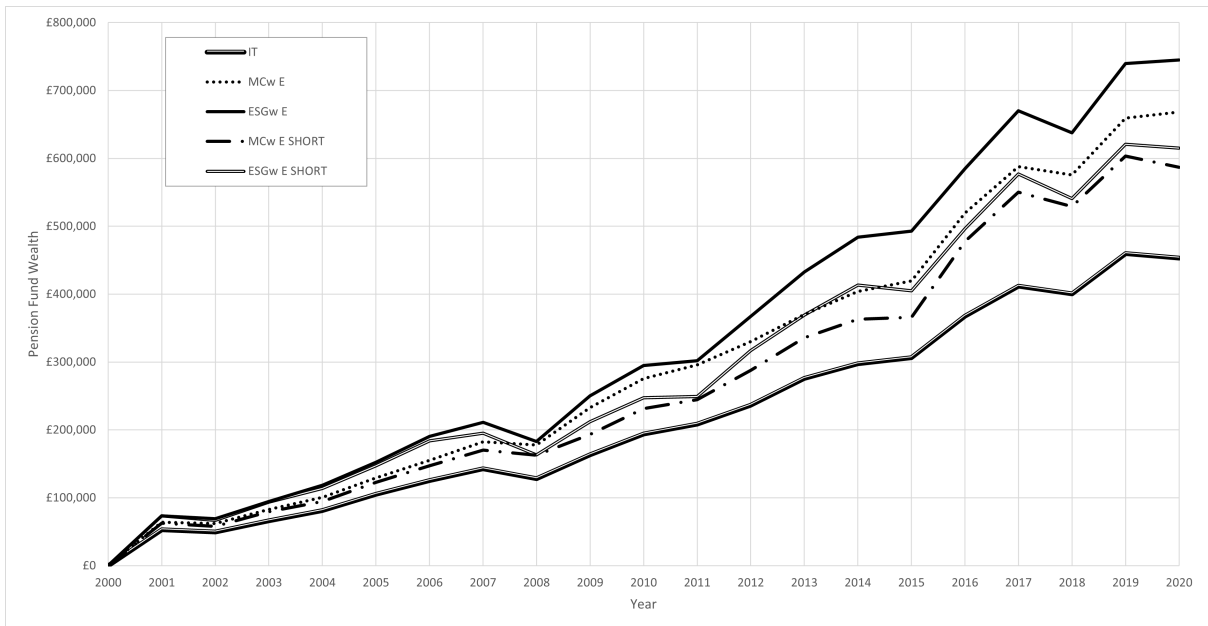


Figure 2.3: Pension wealth trajectories of MT#11 master trust under Environmental (E) component.

A clear pattern emerges from the analysis, indicating that portfolio construction based on individual ESG components, rather than relying solely on overall ESG scores, may yield as well favorable pension accumulations across various investment scenarios. These positive outcomes persist even when compared to the conventional FTSE 100 portfolio or to strategies using the overall ESG score (see Figure 2.4). This finding highlights the importance of examining the aspects of ESG, enabling investors to capitalize on specific sustainability priorities and tailor their portfolios to align with their preferences. By focusing on distinct ESG components - Environment (E), Social (S), or Governance (G) - investors can make better choices and informed decisions, yielding similar or superior financial performance while channeling investments toward companies with strong sustainability performance.

Figure 2.4 shows how a typical master trust pension fund wealth develops over time under different ESG-screened strategies compared to the index tracker. All ESG-screened strategies end with higher wealth than the index tracker, which suggests that applying ESG screening improves long-term pension outcomes. The lines for the overall ESG score and the individual E, S, and G components move very closely together for most of the period, showing that the effect of ESG integration is steady and builds gradually over time.

In the final years, the strategies start to separate more clearly. The S (Social) and G (Governance) strategies produce the highest pension wealth, slightly ahead of the overall ESG strategy. The E (Environmental) strategy performs the weakest among the ESG approaches but still does better than the index tracker. This indicates that, in this sample, social and governance considerations added more value than environmental consideration alone. The visible gap between all ESG strategies and the benchmark by the end of the period highlights the cumulative benefit of ESG integration in a long-term investment context.

Furthermore, this approach is consistent with the broader shift in sustainable investment demand, focusing on striking a balance between financial performance and wider societal and environmental goals. As ESG considerations become increasingly central to investment practices, such a framework will enable investors to integrate sustainability into their decision-making while maintaining financial objectives. In doing so, it contributes to the advancement of more resilient and responsible investment practices.

The performance of other ESG components (Social and Governance) under different Master Trusts is depicted in the appendix in Figures 2.5-2.8.

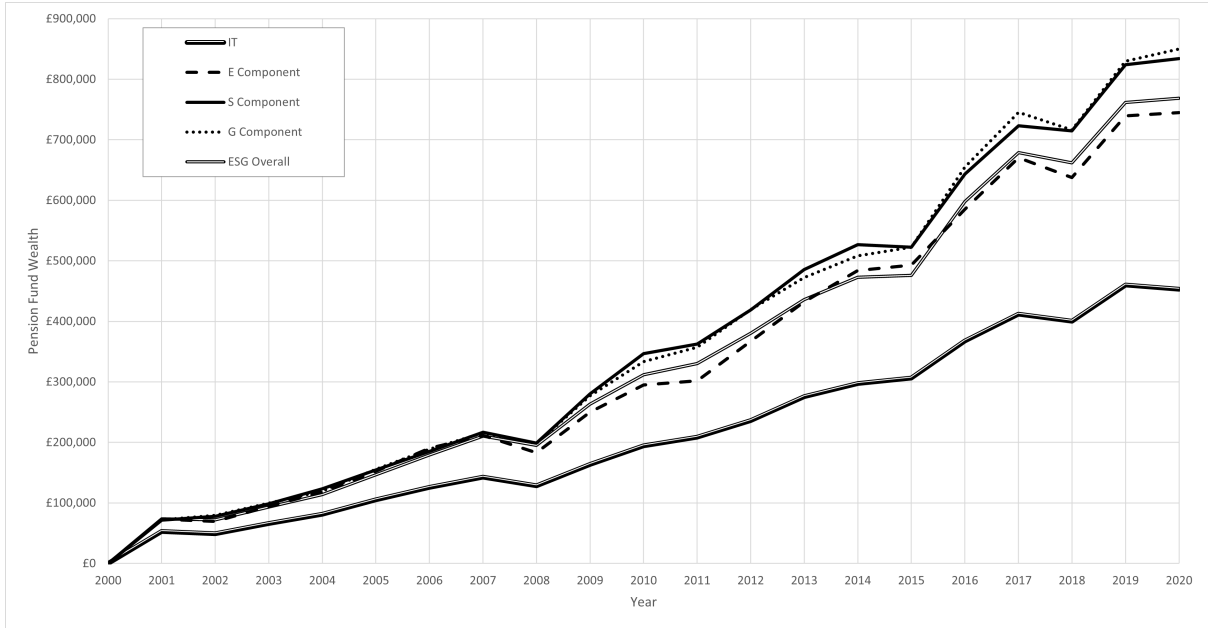


Figure 2.4: Pension wealth trajectories of MT#11 under ESG-weighted strategy for E, S, G, and overall score.

2.5 Conclusion

Our research objectives aim to assess the long-term performance of sustainable retirement investments and determine any variations in performance compared to their conventional counterpart. Our approach integrates a cash flow model that comprises FTSE 100 constituents, with ESG Scores as the primary selection criteria. In addition to a conventional FTSE 100 tracker fund investment approach, we present four distinct ESG-screened portfolio management strategies: market-cap-weighted, ESG-weighted, and two portfolio construction approaches involving short-selling stocks with low ESG performance as outlined in section 2.3.1. To provide a comprehensive view, we evaluate the results over a 20-year investment period using data from two ESG data providers, RepRisk and Refinitiv.

The numerical valuation of our pension fund at retirement, along with the subsequent statistical analysis by investment strategy, highlights the potential benefits of integrating ESG factors into the existing considerations for portfolio construction. This is evidenced by its sustained performance over the investment period, independent of the selected ESG data provider or the self-constructed ESG-screened investment strategy. Crucially, each of our ESG-screened strategies significantly outperforms the conventional index tracking approach across all examined 17 master trust funds, whether considering overall ESG scores or the individual ESG components (Environment, Social, and Governance).

Throughout our diverse examination of various ESG-screened portfolio comparisons, percentile choices, and ESG component evaluations, we consistently find that considering ESG scores significantly impacts performance. As investors strive to secure their finan-

cial future during retirement, integrating ESG metrics into their investment decisions is likely to result in favorable outcomes. This strengthens the notion that integrating ESG considerations into investment decisions can lead to positive outcomes, aligning financial returns with sustainable principles.

While our research offers valuable insights, it has limitations, including challenges with comprehensive ESG data availability and potential survivorship bias. We have also not fully considered the momentum effects of major financial crises. Additionally, in the ESG-weighted approach, a transformation function with scaling parameter k is used to determine portfolio weights and, consequently, performance. The results may vary under alternative functional forms, different values of the scaling parameter, or alternative definitions of screening thresholds. Future research could also involve expanding ESG data sources, addressing survivorship bias, making timely adjustments for market changes, and exploring the impact of financial crises on portfolio performance across diverse indices and regions.

New numerical results presented here are derived from ESG scores provided by Refinitiv. Notably, Owadally et al. (2021) previously conducted a comparable analysis using RepRisk ESG scores. Despite variations in ESG-screened strategies, glide paths, and asset fund selections, our results align consistently with theirs.

In conclusion, our paper underscores the importance of ESG scores in investment decision-making for retirement planning. We emphasize the potential benefits of incorporating ESG metrics in portfolio construction, leading to sustainable and responsible investment outcomes. As responsible investing continues gaining traction in the financial landscape, continuous evaluation and research of ESG-screened strategies are vital to guide investors toward achieving their financial objectives and contributing to a more sustainable future.

Appendix for Chapter 2

2.A Additional Results

Supplementary material is provided here in the form of additional tables and figures that expand on the analysis presented in the main text.

The first set of tables (Tables 2.22–2.25) reports pension value outcomes for the remaining master trusts across all investment strategies, with results presented under varying percentile thresholds.

Market-cap-weighted Strategy				
Master Trust	Index Tracker	75 th	50 th	25 th
MT#3	£454,039	£674,541	£574,742	£481,045
MT#5	£430,417	£568,252	£508,038	£448,743
MT#6	£454,068	£602,795	£543,865	£481,699
MT#7	£390,215	£478,493	£448,091	£411,527
MT#9	£442,902	£589,974	£532,261	£471,778
MT#10	£463,967	£598,693	£537,825	£477,615
MT#12	£458,393	£582,093	£528,708	£475,483
MT#13	£455,582	£626,739	£557,866	£485,505
MT#14	£443,797	£571,740	£518,808	£464,154
MT#16	£439,536	£698,018	£584,349	£477,692
MT#17	£457,407	£665,887	£573,029	£485,336

Table 2.22: Retirement wealth under market-cap-weighted strategy with percentile variation for remaining Master Trusts.

ESG-weighted Strategy				
Master Trust	Index Tracker	75 th	50 th	25 th
MT#3	£454,039	£763,290	£700,925	£598,433
MT#5	£430,417	£620,827	£585,137	£524,440
MT#6	£454,068	£664,759	£628,947	£564,610
MT#7	£390,215	£518,999	£501,858	£465,441
MT#9	£442,902	£651,236	£616,322	£553,496
MT#10	£463,967	£649,838	£613,511	£551,947
MT#12	£458,393	£629,174	£598,585	£545,323
MT#13	£455,582	£701,580	£659,298	£582,447
MT#14	£443,797	£623,695	£592,863	£537,216
MT#16	£439,536	£805,339	£732,591	£611,787
MT#17	£457,407	£749,020	£692,064	£597,113

Table 2.23: Retirement wealth under ESG-weighted strategy with percentile variation for remaining Master Trusts.

Market-cap-weighted Shorting Strategy				
Master Trust	Index Tracker	75 th	50 th	25 th
MT#3	£454,039	£600,848	£590,051	£672,374
MT#5	£430,417	£523,199	£514,761	£563,154
MT#6	£454,068	£553,986	£546,571	£584,900
MT#7	£390,215	£452,707	£447,712	£458,687
MT#9	£442,902	£543,729	£536,046	£574,852
MT#10	£463,967	£556,840	£550,936	£603,378
MT#12	£458,393	£546,944	£537,587	£582,360
MT#13	£455,582	£568,179	£559,719	£599,678
MT#14	£443,797	£533,245	£525,917	£564,902
MT#16	£439,536	£603,822	£594,363	£677,717
MT#17	£457,407	£600,544	£587,270	£662,291

Table 2.24: Retirement wealth under market-cap-weighted shorting strategy with percentile variation for remaining Master Trusts.

ESG-weighted shorting Strategy				
Master Trust	Index Tracker	75 th	50 th	25 th
MT#3	£454,039	£644,501	£673,862	£739,588
MT#5	£430,417	£553,930	£569,029	£605,835
MT#6	£454,068	£595,203	£616,390	£648,520
MT#7	£390,215	£483,844	£500,967	£509,599
MT#9	£442,902	£585,281	£606,409	£638,514
MT#10	£463,967	£583,324	£598,167	£639,583
MT#12	£458,393	£571,329	£586,219	£618,401
MT#13	£455,582	£616,292	£643,759	£676,716
MT#14	£443,797	£564,248	£582,653	£612,386
MT#16	£439,536	£661,065	£701,438	£769,590
MT#17	£457,407	£639,744	£667,485	£725,379

Table 2.25: Retirement wealth under ESG-weighted shorting strategy with percentile variation for remaining Master Trusts.

A broader overview of the composition of the glide paths used in the analysis is also provided below. To illustrate this, six representative master trusts are randomly selected, with their glide path structures reported in Tables 2.26–2.31. These examples serve to highlight the variation in asset allocation strategies across different master trusts and to contextualize the pension value results presented in the main analysis.

YEAR	EQUITY	ALTERNATIVE	FIXED INCOME	CASH
2000-2001	78.60%	5.70%	15.60%	0.00%
2002-2004	72.70%	5.80%	21.40%	0.00%
2005-2007	66.50%	6.00%	27.60%	0.00%
2008-2010	60.40%	6.10%	33.40%	0.00%
2011-2013	54.50%	6.10%	39.40%	0.00%
2014-2016	49.50%	5.10%	45.40%	0.00%
2017-2019	44.00%	4.00%	51.90%	0.00%
2020	36.00%	4.00%	60.10%	0.00%

Table 2.26: MT#1 Glide-path for the four asset classes across the investment period.

YEAR	EQUITY	ALTERNATIVE	FIXED INCOME	CASH
2000-2005	90.00%	10.00%	0.00%	0.00%
2006	83.88%	10.00%	5.88%	0.24%
2007	77.76%	10.00%	11.76%	0.48%
2008	71.64%	10.00%	17.64%	0.72%
2009	65.52%	10.00%	23.52%	0.96%
2010	59.40%	10.00%	29.40%	1.20%
2011	56.70%	9.70%	32.40%	1.20%
2012	54.00%	9.40%	35.40%	1.20%
2013	51.30%	9.10%	38.40%	1.20%
2014	48.60%	8.80%	41.40%	1.20%
2015	45.90%	8.50%	44.40%	1.20%
2016	44.10%	8.30%	46.40%	1.20%
2017	42.30%	8.10%	48.40%	1.20%
2018	40.50%	7.90%	50.40%	1.20%
2019	38.70%	7.70%	52.40%	1.20%
2020	36.90%	7.50%	54.40%	1.20%

Table 2.27: MT#2 Glide-path for the four asset classes across the investment period.

YEAR	EQUITY	ALTERNATIVE	FIXED INCOME	CASH
2000-2010	55.47%	13.46%	26.58%	4.49%
2011	50.88%	12.75%	30.73%	5.64%
2012	46.29%	12.03%	34.87%	6.79%
2013	41.71%	11.32%	39.02%	7.94%
2014	37.12%	10.61%	43.16%	9.09%
2015	32.53%	9.90%	47.31%	10.24%
2016	27.94%	9.18%	51.45%	11.38%
2017	23.35%	8.47%	55.60%	12.53%
2018	18.77%	7.76%	59.74%	13.68%
2019	14.18%	7.04%	63.89%	14.83%
2020	9.59%	6.33%	68.03%	15.98%

Table 2.28: MT#4 Glide-path for the four asset classes across the investment period.

YEAR	EQUITY	ALTERNATIVE	FIXED INCOME	CASH
2000	40.60%	27.09%	32.31%	0.00%
2001-2009	37.82%	28.36%	33.82%	0.00%
2010-2014	32.74%	25.27%	40.87%	1.12%
2015-2019	20.40%	18.82%	52.01%	8.78%
2020	13.20%	14.65%	57.46%	14.69%

Table 2.29: MT#8 Glide-path for the four asset classes across the investment period.

YEAR	EQUITY	ALTERNATIVE	FIXED INCOME	CASH
2000-2002	85.00%	0.00%	15.00%	0.00%
2003	83.50%	0.00%	16.50%	0.00%
2004	80.50%	0.00%	19.50%	0.00%
2005	77.50%	0.00%	22.50%	0.00%
2006	74.50%	0.00%	25.50%	0.00%
2007	71.50%	0.00%	28.50%	0.00%
2008-2017	70.00%	0.00%	30.00%	0.00%
2018	64.17%	0.00%	27.50%	8.33%
2019	58.33%	0.00%	25.00%	16.67%
2020	52.50%	0.00%	22.50%	25.00%

Table 2.30: MT#11 Glide-path for the four asset classes across the investment period.

YEAR	EQUITY	ALTERNATIVE	FIXED INCOME	CASH
2000-2005	82.00%	5.50%	11.00%	1.50%
2006	78.80%	5.40%	14.20%	1.60%
2007	75.60%	5.30%	17.40%	1.70%
2008	72.40%	5.20%	20.60%	1.80%
2009	69.20%	5.10%	23.80%	1.90%
2010	66.00%	5.00%	27.00%	2.00%
2011	59.80%	4.80%	33.30%	2.10%
2012	53.60%	4.60%	39.60%	2.20%
2013	47.40%	4.40%	45.90%	2.30%
2014	41.20%	4.20%	52.20%	2.40%
2015	35.00%	4.00%	58.50%	2.50%
2016	33.25%	3.80%	55.58%	7.37%
2017	31.50%	3.60%	52.65%	12.25%
2018	29.75%	3.40%	49.73%	17.12%
2019	28.00%	3.20%	46.81%	22.00%
2020	26.25%	3.00%	43.88%	26.87%

Table 2.31: MT#15 Glide-path for the four asset classes across the investment period.

As discussed in Section 2.4.5, we present the performance of our constructed sustainable portfolios versus the FTSE 100 index tracker for the remaining ESG components. The Social component is illustrated in Figures 2.5 & 2.6, which present results for the six representative master trusts as well as an example of pension accumulation trajectories for Master Trust Eleven (MT#11). Corresponding figures for the Governance component are provided in Figures 2.7 & 2.8.

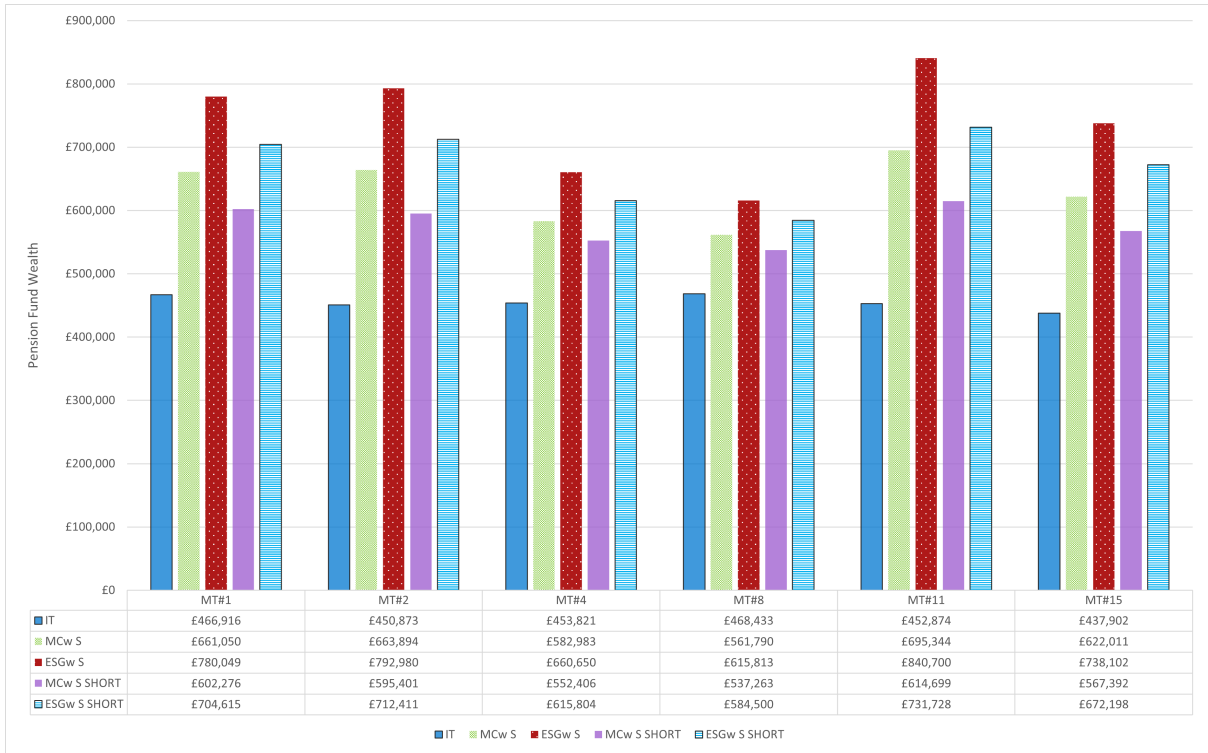


Figure 2.5: Retirement portfolio performance of six representative Master Trusts under the Social (S) component.

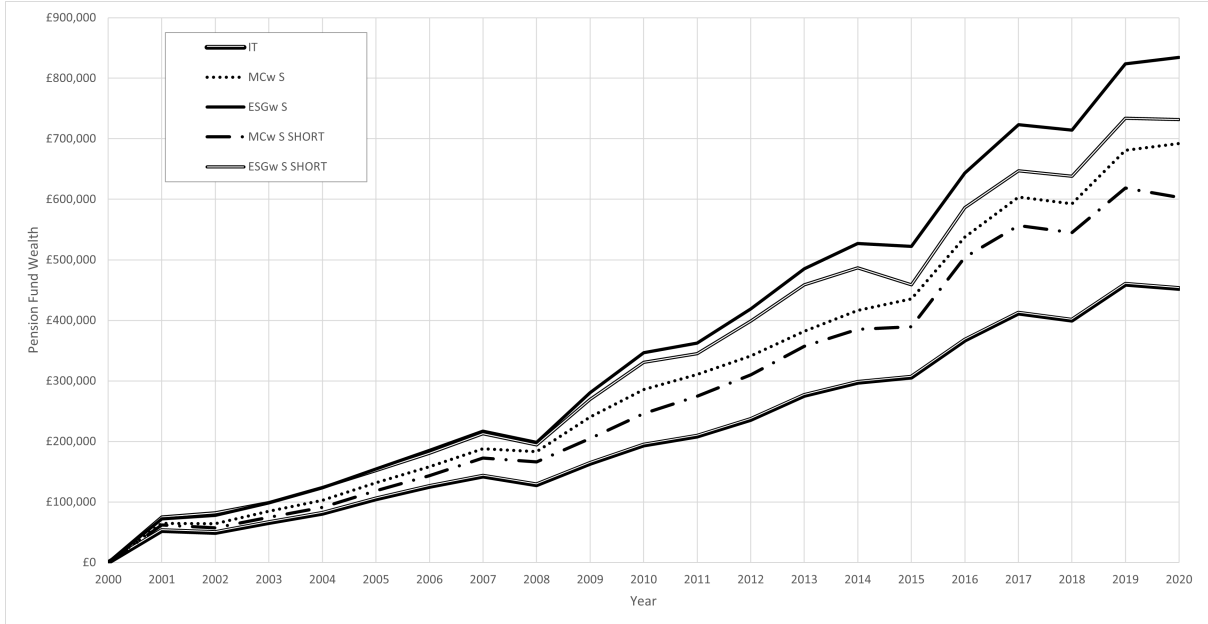


Figure 2.6: Pension wealth trajectories of MT#11 master trust under the Social (S) component.

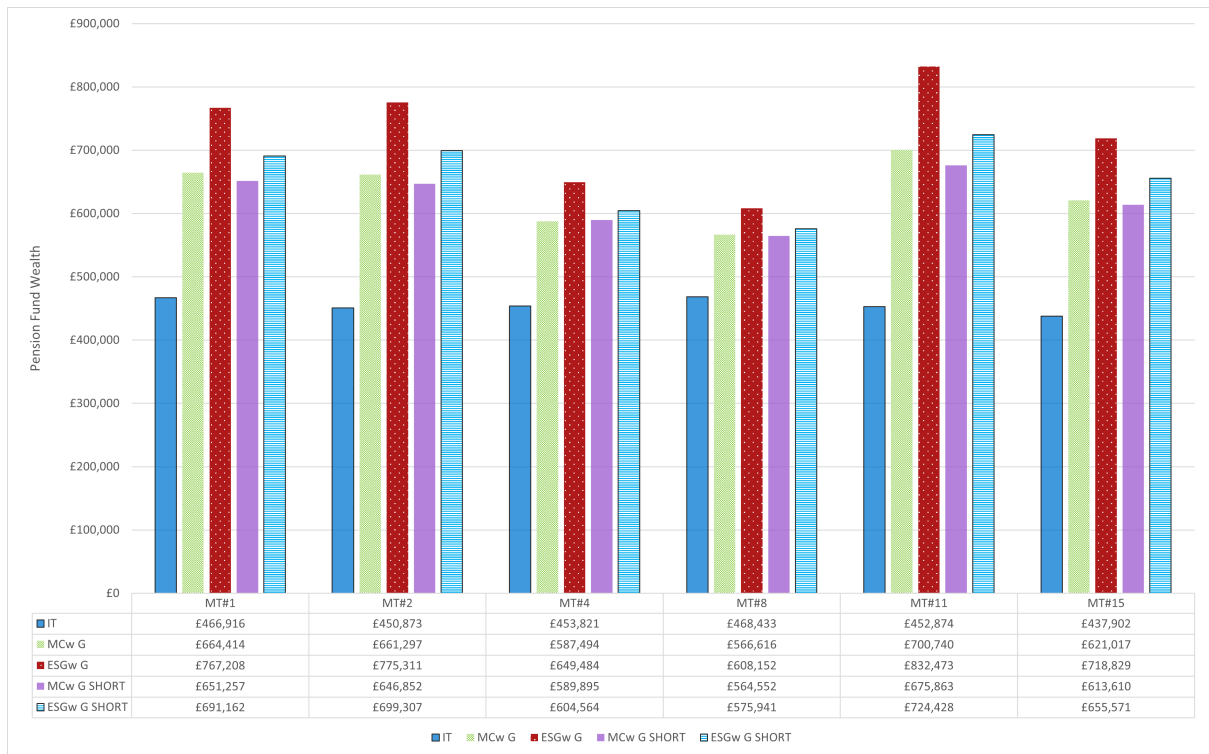


Figure 2.7: Retirement portfolio performance of six representative Master Trusts under the Governance (G) component.

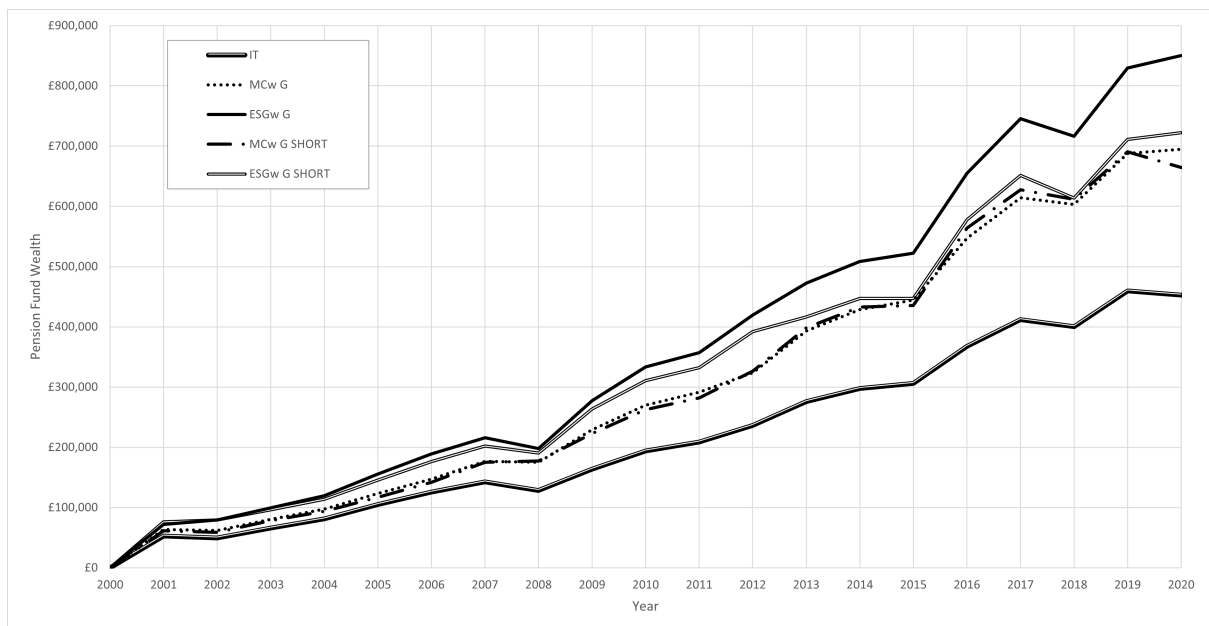


Figure 2.8: Pension wealth trajectories of MT#11 master trust under the Governance (G) component.

Resulting risk-adjusted performance under the RepRisk ESG provider is illustrated in Table 2.32, while performance outcome for the six representative master trusts is represented in Figure 2.9.

Sharpe Ratio					
Master Trust	IT	MCw	ESGw	MCw SHORT	ESGw SHORT
MT#1	0.1186	0.6462	0.4770	0.5604	0.5882
MT#2	0.0823	0.5691	0.4081	0.5068	0.5280
MT#3	0.0933	0.5950	0.4403	0.5221	0.5858
MT#4	0.1439	0.5766	0.4330	0.5113	0.5460
MT#5	0.0962	0.5451	0.4202	0.5063	0.5606
MT#6	0.1024	0.5621	0.4049	0.4958	0.4971
MT#7	0.0522	0.4607	0.2930	0.3973	0.3317
MT#8	0.2237	0.5538	0.4907	0.5632	0.5947
MT#9	0.0805	0.5117	0.3845	0.4897	0.4945
MT#10	0.1725	0.5900	0.4879	0.5581	0.6116
MT#11	0.0872	0.6220	0.4732	0.5477	0.6025
MT#12	0.1459	0.5636	0.4305	0.5093	0.5438
MT#13	0.0879	0.5651	0.3945	0.4899	0.4913
MT#14	0.1069	0.5636	0.4067	0.4978	0.5092
MT#15	0.0756	0.5534	0.3893	0.4842	0.5107
MT#16	0.0610	0.5465	0.4145	0.5107	0.5655
MT#17	0.0993	0.5579	0.4203	0.5087	0.5605

Table 2.32: Sharpe Ratio results under various investment strategies for the seventeen examined master trust funds - RepRisk.

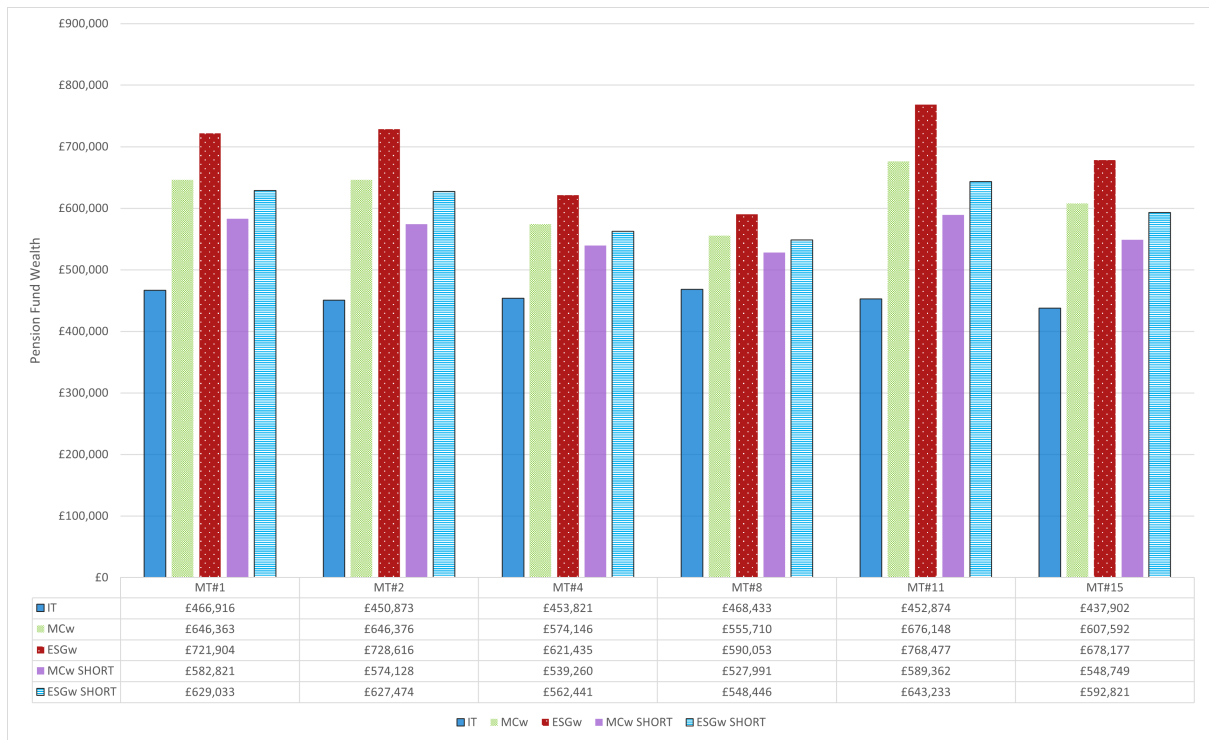


Figure 2.9: Retirement portfolio performance of six representative Master Trusts - RepRisk.

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Chapter 3

Sustainable Retirement Investing: Insights from the UK and US Markets

Abstract

Integrating Environmental, Social, and Governance (ESG) factors into investment strategies offers a potential way to align sustainability goals with long-term financial performance. This paper looks at this issue in the context of retirement by evaluating the potential benefits of ESG integration into a retirement portfolio over an extended investment horizon. A long-term investment model is developed incorporating Refinitiv ESG scores under multiple sustainable approaches and comparing their performance with a traditional index tracker across major equity markets (FTSE 100, FTSE 250, and S&P 500). The analysis replicates the asset allocation glide paths of 17 UK Master Trust Funds and 27 US Target Date Funds to capture realistic investment behaviour. The results indicate that ESG-screened approaches can enhance portfolio performance and stability over the long run, although the extent of improvement varies across different integration methods.

3.1 Introduction

The term “ESG” was first officially defined in 2004 by the United Nations Global Compact report entitled “Who Cares Wins” (UN Global Compact, 2004) as an approach for accounting for the impact of non-financial risks on a company’s performance. However, similar investment approaches, some of which were known as socially responsible investing (SRI), can be traced back to the 1970s with exclusions of sin stocks or the 1980s with the anti-South African apartheid divestment campaigns. Although ESG is often regarded as synonymous with the broader concept of “sustainable investment,” the

two are not entirely equivalent. Sustainable investment encompasses a broader range of approaches grounded in diverse principles of sustainability, ethical conduct, and corporate responsibility.

Two major global developments are widely identified as catalysts for the mainstreaming of ESG: the Paris Agreement adopted under the United Nations Framework Convention on Climate Change (UNFCCC) - UNFCCC (2015), and the United Nations Sustainable Development Goals - UN SDGs (2015), which call on nations to address challenges related to poverty, inequality, climate change, and peace by 2030. These initiatives have helped transition ESG from a largely conceptual discussion into a framework that can be systematically measured through national progress and corporate sustainability performance, supported by the development of standardized reporting frameworks and increasing integration into financial markets(OECD (2020); Eccles et al. (2019)).

Regions differ in their adoption of ESG or sustainability investment more generally; in 2022, global sustainable investment assets were estimated at USD 30.3 trillion, with Europe accounting for 46%, while the US market was almost at its half at 28% (GSIA, 2022). However, according to Morningstar Direct (2025), when focusing specifically on global sustainable funds (open-end and exchange-traded funds that apply ESG criteria), Europe accounts for 84% of the USD 3.2 trillion in assets at the end of 2024, representing an 8% increase from the previous year.

Despite several challenges, such as "greenwashing" and a lack of common terminology, the EU's sustainable finance action plan and similar regulations in place have been the most comprehensive globally. They are attributed to being the reason behind Europe's leading position and adoption of sustainable investing (EUROSIF, 2022). The regulations aim for an increase in transparency and clarity in ESG reporting alongside a reoriented focus on sustainable investment in capital allocation. In contrast, the US market lags behind and is in transition from voluntary reporting to a more standardized regulatory framework. The US SEC (Securities and Exchange Commission) rules are scheduled to set ESG common reporting similar to those in Europe; however, due to the structure of US federalism, the acceptance of ESG varies from state to state, with dozens of states having passed pro- or anti-ESG bills (U.S. SEC, 2022), US SIF Foundation (2023).

In the context of both UK & US markets, as the basis of this study, a PWC (2022) study found that 92% of large U.S. companies and 72% of large U.K. firms are using ESG metrics in their incentive plans. The number of ESG rating companies has increased, driven by heightened investor demand; however, the sector still faces challenges related to regulation and data availability. The latter is expected to improve as the Artificial Intelligence (AI) revolution advances, enhancing accuracy and facilitating timely monitoring of ESG factors - World Bank (2021). Although the shift toward stakeholder considerations of non-financial metrics existed well before COVID-19, the pandemic revealed flaws in the company's top-down governance and its inherent overlapping interests,

sparkling awareness and the need for collaboration to achieve a more sustainable economy.

Plan of this chapter. The structure of the paper is as follows. Section 3.2 discusses the existing body of literature, and Section 3.3 details the methodological approach to sustainability. Sections 3.4 and 3.5 report the empirical findings and offer concluding observations.

Relationship to previous chapter. In this chapter, we expand the analysis geographically by introducing the FTSE 250 and the S&P 500, alongside the FTSE 100, which enables a cross-market comparison between the UK and the US. The number of examined strategies is also reduced from five to three by excluding short-selling extensions and focusing only on Index Tracker, MCw, and ESGw portfolios. Furthermore, only Re-finitiv ESG data is retained, simplifying the data scope, while the rebalancing frequency changes from annual to quarterly. Overall, the model becomes simpler and more focused, comparing markets using consistent methods rather than exploring numerous strategy types.

Remark on ESG rating scale. In this chapter, we follow the *RepRisk* convention concerning ESG ratings. ESG scores range **from 100 to 0**:

- stocks with the *lowest* sustainability performance are scored 100,
- stocks with the *highest* sustainability performance are scored 0.

3.2 Related Literature

3.2.1 Performance and Risk Characteristics of ESG Investments

Research focusing on the impact of ESG considerations tends to analyse returns, highlighting differences in the performance of investments adhering to ESG versus traditional strategies. Edmans (2023) in his paper entitled “The End of ESG” argues that ESG is not any different from any other intangible metrics that create long-term financial and social returns. Hence, it should not be given special treatment because ESG investing is just investing for anyone who cares about more than just financial returns. Jégourel et al. (2010) examine the financial performance of socially responsible investment (SRI) funds compared to conventional funds using a traditional CAPM model with time-varying volatility and a multi-factor Carhart-Fama-French model. The study assesses weekly data from Datastream International covering 71 European SRI equity mutual funds, from March 1998 to April 2008, 10 years. The authors find a negative correlation between the intensity of negative screening and both the alpha and beta.

Alessandrini et al. (2020) study ESG scores from the MSCI ACWI Index over the period 2007–2018 and find no significant difference in risk-adjusted performance through the measurement of the impact of negative screening on both passive investments and smart beta strategies. The over-performing attribute of ESG strategies, as evidenced by data from Refinitiv and MSCI, is also disputed by Demers et al. (2020) for the US market in 2020, during the Covid-19 pandemic, with share price resilience attributed to investments in intangible assets rather than following ESG strategies.

Pokou et al. (2023) approached the importance of ESG through an empirical analysis of three categories of ESG preferences. From best-in-class to worst MSCI ESG ratings-based portfolios, 39 assets from different industries for each category were examined for a period from January 2, 2015, to August 31, 2022. Both univariate (GARCH and GJR-GARCH) and multivariate (DCC-GARCH, Copula, and Vine Copula) models were performed, and results proved that the average-middle ranked portfolio empirically provided the highest return and lowest risks against the benchmark and compared to the best and worst in class. Kumar et al. (2016) perform a risk-adjusted analysis of ESG factors in 809 companies representative of average market performance and an extra 157 companies listed on the Dow Jones Sustainability Index to statistically account for volatility from 1 January 2014 to 31 December 2015. Among the 12 industries examined, ESG-listed stocks registered the lowest stock return volatility, on average by 28.67% less. Risk differences also vary across industries, with the energy sector registering a 50.75% difference between ESG and non-ESG. Similarly, the banking, materials, and technology sectors exhibit substantial differences, whereas the food and beverage sector shows only a 6.10% difference.

Gougler et al. (2020) also find that for a value-weighted strategy, low-rated portfolios exhibit negative abnormal returns using the ESG dataset from the Inrate sustainability rating agency for firms listed on the MSCI ACWI for a period from October 2013 to May 2017. Bertelli et al. (2024) empirically assess three hypotheses based on Bloomberg ESG disclosure scores over the period 2007–2021, the superiority of the ESG-screened portfolio against a benchmark (Euro Stoxx) in the long run, lack of over-performance in the short run, and ESG-screened over-performance in financial distress. The authors find distinctive traits between negatively and positively screened portfolios, mainly that negatively screened portfolios significantly outperform in terms of the Sharpe ratio compared to the benchmark over the long term. At the same time, the lack of diversification significantly affects positively screened portfolios. In the short term, neither of the two approaches can produce performance greater than the benchmark, while there is only marginal over-performance during the COVID-19 pandemic.

Spiegeleer et al. (2020) investigate the risk and return characteristics of ESG portfolios using two specific measures: ESG ratings and greenhouse gas (GHG) emission intensity metrics obtained from MSCI ESG Research. The empirical analysis based on a standard

mean-variance allocation framework adjusted for positive and negative screening examines assets in the STOXX Europe 600 and the Russell 1000 indices from December 2009 to December 2019. The study reveals periodical performance variability across the analyzed period, with poor ESG performers generating higher cumulative returns from 2009 to 2010. In contrast, later years show better performance for good ESG performers, starting in early 2019 in Europe and mid-2017 in the US.

3.2.2 ESG Ratings, Methodological Divergence, and Portfolio Construction

The divergence among ESG ratings leads to a low agreement among ESG information providers on ratings. Billio et al. (2021) evaluate the implication of such disagreement on ESG portfolios' performance through the assessment of the definitions, attributes, and standards of ESG criteria from various ESG rating agencies (MSCI, Vigeo-Eiris, Refinitiv, Sustainalytics, ISS Oekom, RobecoSAM, ECPI, Bloomberg, and FTSE Russell) and the impact on resulting investment universes. ESG indices construction is significantly impacted because their component selection relies on metrics from a specific ESG rating provider. Regarding the financial performance of ESG agreements and non-ESG portfolios from 2000 to 2019, the study finds no significant impact of ESG effects on performance, despite existing differences in ESG rating methodologies.

Escrig-Olmedo et al. (2019) investigate the evolution of ESG rating agencies and their assessment criteria from 2008 to 2018. The study finds growth in the sustainability market due to rising demand. Still, despite the integration of new criteria into their assessment models, a persisting lack of commonality and weighting of certain of the basic metrics resulted in diverging ratings. Windolph (2011) classifies the causes of diverging ratings as lack of standardization, lack of credibility of information, bias, trade-offs, lack of transparency, and lack of independence. Avetisyan et al. (2017) study based on four agencies (MSCI, EIRIS, Vigeo, SAM) in the U.S., U.K., France, and Switzerland, respectively, finds negative effects of mergers and acquisitions, which are frequent among ESG rating companies, as partly responsible for a return to old financial values and weakens the SRI movement's goal of change.

3.2.3 ESG Considerations in Pension Funds

Global Top 300 pension funds accounted for USD20.6 trillion AuM in 2023, with 45.6% of the assets in North America, 26.4% in Asia-Pacific, and 24.1% in Europe - Thinking Ahead Institute (2023). The sustainability of pension schemes has become a critical concern, driven by global demographic shifts and increasing stakeholder awareness. Alda (2020) examines the impact of ESG factors on traditional pension funds, focusing on

Morningstar Direct data of the UK's domestic equity pension funds between January 2016 and December 2018 from a sample of 22 socially responsible investing (SRI) funds, and 221 conventional funds. Through nearest-neighbor matching methodology to create a balanced comparison between SRI and non-SRI funds, the study concludes that both SRI and conventional funds share some similar characteristics influencing ESG scores, such as age, turnover, and expenses; however, SRI funds outperform, and a higher ESG score positively influences returns.

According to Saraiva et al. (2024), Lachance et al. (2023), Lewis et al. (2024), Steinbarth et al. (2018), ESG issues fall within the fiduciary duty of a pension manager to consider any substantial factor that might financially impact the pension fund performance. However, the materiality of ESG factors varies by industry and region. Additionally, this fiduciary duty may sometimes impede the integration of ESG considerations into pension funds, as the primary objective remains to secure financial returns. Historically, long-term sustainability has been more emphasized in public pension funds, though private pension funds have recently begun to place greater importance on ESG criteria.

Aubry et al. (2020) note that since the mid-1990s, the Department of Labor (DOL), which regulates pension funds in the U.S., has frequently shifted its stance on considering ESG factors. These factors were sometimes seen as tie-breakers or non-financial considerations, particularly if alternative investments offered comparable risks and expected returns. However, the most recent guidance in 2020 discourages the use of non-pecuniary factors, as this approach typically involves sacrificing financial returns for social objectives, which conflicts with the Employee Retirement Income Security Act of 1974 (ERISA). Aubry et al. (2020) examine 176 public plans obtained from 2001-2018 through the Center for State and Local Government Excellence, and National Association of State Retirement Administrators, of which two-thirds have an ESG policy or social investing mandate. Under OLS regression, the analysis found a negative relationship between investment returns and both state mandates and ESG policies. However, only the state mandates' impact was statistically significant. The fixed-effects model revealed that both state mandates and ESG policies reduced annual returns by 70 to 90 basis points, with the effect of ESG policies being only marginally significant at the 10-percent level.

On the other hand, a study by Alda (2019) provides the reverse effect of Socially Responsible pension funds on private firms' adherence to ESG practice. A sample of 197 UK SR pension funds is obtained from Morningstar Direct, and ESG metrics are acquired through DataStream for their 1,253 distinct stock investments from 2002 to 2018. Three hypotheses are examined with a bivariate Granger causality test, namely, SR pension funds' positive influence on corporate sustainability and the firm's value. The findings support the first hypothesis that SR pension funds influence a firm's corporate responsibility by promoting ESG practices. The second and third hypotheses are not unanimously supported on all 31 ESG factors studied; the case being that ROA is affected

by neither SR pension funds nor ESG variables. Additionally, ESG practices have a limited impact on the firm's value and short-term profitability.

3.2.4 Research Gap and Contribution

Despite the growing body of research on ESG investing, most existing studies primarily focus on short-term horizons and mutual fund performance, with limited attention to the long-term implications for pension funds. The empirical evidence about whether ESG integration enhances or compromises financial performance remains mixed and often context-dependent, varying by region, time period, and methodological approach. Moreover, the literature tends to emphasize cross-sectional performance comparisons or event-driven analyses, offering little insight into the cumulative effects of ESG considerations on long-term retirement outcomes.

There is, therefore, a clear gap in our understanding of how ESG factors influence the risk-adjusted performance and sustainability of pension funds over extended investment horizons. This paper addresses this gap by providing new empirical evidence on the long-term impact of ESG integration within pension portfolios in both the UK and US markets. By examining performance dynamics across different market conditions, the study contributes to the ongoing debate on whether ESG alignment can serve as a viable alternative to traditional investment strategies without compromising long-term returns.

3.3 Sustainability Considerations

Our sustainability framework builds on the analytical foundation of Owadally et al. (2021), who examined pension accumulation under traditional index-tracking and ESG-screened portfolio strategies within the UK. While their work focused on the comparative outcomes of adopting ESG criteria, our study extends the analysis toward understanding how sustainability considerations can be systematically embedded into long-term portfolio design.

In this context, we refine the methodology for constructing ESG-screened portfolios by incorporating an additional ESG data provider, adjusting the portfolio rebalancing frequency, and broadening the investment universe to include multiple regional markets. These enhancements enable a more comprehensive evaluation of the consistency and robustness of ESG effects across diverse economic and regulatory environments.

Rather than revisiting the general debate on the financial merits of ESG integration, this section focuses on how sustainability principles are translated into practical investment decisions within our model framework. By linking ESG screening methods to pension fund dynamics, we provide a structured approach to assess how varying sustainability criteria, data sources, and geographic contexts interact to shape long-term wealth

accumulation outcomes.

3.3.1 Refinitiv Dataset

Our ESG data was acquired from Refinitiv through Datastream and fits our investment horizon from 2002 to 2022. ESG Scores are acquired on a quarterly basis from the overall ESG metrics to each of the components or sub-scores related to Environmental (E), Social (S), and Governance (G). ESG scores' availability varies per period and is reflected in our portfolio construction choices, favoring index constituents with recorded scores at the time of construction, as highlighted in Table 3.18 of the appendix.

Refinitiv ESG databases (Refinitiv, 2023) provide one of the most comprehensive sources of environmental, social, and governance metrics with coverage of over 90% of the global market capitalization, available since 2002. This extensive dataset includes ratings for over 15,500 public and private companies worldwide, through more than 630 different ESG metrics. These scores reflect the relative performance of companies within their sector for environmental and social factors, and their country of incorporation for governance factors.

Environmental metrics include resource use, emissions, and innovation; social metrics cover workforce, human rights, community, and product responsibility; while governance metrics encompass management, shareholders, and corporate social responsibility (CSR) strategy. The weight allocation varies per industry for the environmental and social components, while remaining unchanged across all industries for the governance component. The scores are normalized to percentages ranging from 0 to 100 and are available for either the overall ESG score or for individual components, allowing investors to select investments based on the overall score or specific components. In our paper, we will interpret a lower score as indicating better performance on ESG metrics.

3.3.2 Investment scenarios

To explore the global perspective and impact of ESG factors on retirement investing, our paper will focus on two distinct regions. The United Kingdom (UK) will serve as a representative of the European market, noted for its progressive adoption of sustainability practices through regulations and public acceptance. Additionally, we will analyze the United States of America (US), a major player in global finance, to provide a comprehensive understanding of ESG investing across different market environments.

We will consider the evolution of retirement savings for a retail investor aged 45 in 2002, who is set to retire in 2022. At inception, salary income is estimated at £50,000 and \$50,000 with annual growth reflected by the UK's Office for National Statistics (ONS) earnings index (ONS, 2020) and average wage index (AWI) provided by the Social Security Administration (SSA) for the US Market (SSA, 2022). We also assume a 15% annual

saving rate from the salary, along with an additional lump sum payment of £50,000 and \$50,000 from previously accumulated savings.

We will compare a traditional investment strategy using an index tracker against two distinct ESG-screened investment scenarios.

1. **Index tracker (IT)**: This strategy invests in an equity index tracker fund. For each market, a well-established index tracker ETF is selected, based on the availability of consistent data over the investment period.
2. **Market-cap-weighted (MCw)**: This strategy integrates both market capitalization and ESG scores in constructing the portfolio. ESG scores are used to screen and select the eligible stocks, whereas portfolio weights are assigned in proportion to each firm's market capitalization, consistent with a passive index-tracking approach. This design enables the analysis of how sustainability screening interacts with firm size in shaping portfolio outcomes.

For the chosen stocks, the weight of each constituent is calculated relative to the total market capitalization of the eligible portfolio:

$$w_i = \frac{M_i}{\sum_{j=1}^n M_j} \quad (3.1)$$

w_i : Weight of stock i in the market-cap-weighted portfolio.

M_i : Market capitalization of stock i .

n : Number of eligible stocks in the portfolio.

3. **ESG-weighted (ESGw)**: This strategy integrates ESG scores in both the selection and weighting of portfolio constituents. Unlike market capitalization-based approaches, where larger firms naturally dominate the portfolio, this method embeds sustainability directly into the weighting process, thus favoring companies with superior ESG characteristics irrespective of their size.

In the weighting scheme, each firm's raw ESG score is transformed through a convex exponential decay function:

$$\alpha_i = \exp(-k \cdot \theta_i) \quad (3.2)$$

where better ESG scores correspond to larger transformed values, ensuring that firms with stronger sustainability profiles receive proportionally more influence in the portfolio.

The transformed ESG scores are then normalized to derive portfolio weights:

$$w_i^* = \frac{\alpha_i}{\sum_{j=1}^n \alpha_j} \quad (3.3)$$

w_i^* : Weight of stock i in the ESG-weighted portfolio.

α_i : Transformed ESG score of stock i .

θ_i : Raw ESG score of stock i .

k : Positive scaling constant controlling the sensitivity of weight adjustments to ESG performance.

n : Number of eligible stocks in the portfolio.

To reflect differences in ESG screening intensity, we form portfolios based on distinct ESG score percentiles, represented as $[0, \kappa]$, where $\kappa \in \{25, 50, 75\}$. The 100th percentile includes all index constituents, while lower thresholds apply progressively stricter ESG exclusion criteria. Accordingly, the number of selected firms declines as the ESG percentile threshold becomes more restrictive. Comparing the three ESG screening levels allows us to assess how varying degrees of sustainability preference, ranging from strict to moderate to broad, affect pension portfolio performance.

Apart from annual salary growth, our portfolio construction and associated metrics are considered on a quarterly basis. This includes portfolio rebalancing, saving rates, market capitalization, ESG scores, portfolio returns, asset returns, and glide paths or target date asset weighting strategies.

3.3.3 Asset Allocation

Our pension strategy for asset selection and allocation follows what is commonly referred to as a glide path in the UK and as a target date approach in the US; both terms will be used interchangeably in this paper. The strategy adjusts investments in various asset classes over different stages of the retirement timeline, with the weightings reflecting the investor's anticipated retirement date. As the retirement date approaches, the strategy becomes more conservative to minimize exposure to potential losses. In contrast, initially, the strategy focuses on growth by investing in riskier assets expected to yield higher returns.

The strategy broadens our analysis beyond the traditional 60-40 equity-to-bond ratio to explore a variety of market-based scenarios. This includes utilizing 17 glide paths from master trust funds currently operating in the UK, as documented in the 2020 Defined Contribution Investment Forum (DCIF) (Parkin, 2020) report on master trust strategies, and 27 target date funds available in the US market, as gathered from MorningStar Direct. Details appear in Table 3.17 in Appendix 3.A. The numbering of the Master Trust and Target Date funds in the provided results is random and does not correspond to the alphabetical order presented in the table.

In the UK, master trust funds mainly invest in four categories of assets: Equities, Fixed Income, Alternative, and Cash. We replicate this approach for each asset class by selecting consistently available instruments from 2002 to 2022. The equity investments for

the FTSE 100 tracker strategy will be the "HSBC FTSE 100 Index Fund Retail Accumulation" and the "HSBC FTSE 250 Index Fund CLS Retail Accumulation" for the FTSE 250 analysis. For our ESG-screened strategies, the equity allocation will be constructed based on the index constituents, but its exact composition will vary depending on the chosen ESG percentile threshold. For the other asset classes, all strategies will rely on an identical set of ETFs. The Fixed Income portion is invested in "MG Gilt Fixed Interest Income Sterling A ACC." The Alternative category is represented by "BlackRock UK Property," while the Cash component is invested in "BlackRock Cash."

Similarly, in the US market, the primary focus and majority weighting are allocated to US and non-US equities and fixed income. The asset allocation weighting for the 27 target date funds used in our analysis was sourced from Morningstar and their respective prospectuses as of July 2024. The available information provides a 5-year window between different target dates, and requires an adjustment through linear interpolation to reflect asset weighting for each year of our investment horizon. We also made a minor adjustment by reclassifying and redistributing the asset weights to align with our four primary asset classes - Equity, Fixed Income, Alternative, and Cash - for consistency and ease of comparison. Instruments falling outside these categories were reallocated among the existing classes using weighted averages. Under the fixed income portion, we use the "Vanguard Total Bond Market Index Fund," and for the alternative, the "Vanguard Real Estate Index Investor" is utilized, while the cash component is represented by the "T. Rowe Price Cash Reserves Fund." In terms of equity investments, the traditional approach utilizes the "Vanguard 500 Index Fund" to depict the S&P 500 performance. Similar to the UK context, ESG-screened strategies will be adjusted to reflect set ESG preferences.

Fund selections in both the US and UK markets are based on three main characteristics: popularity, size, and continuity over the 20-year investment horizon. The primary goal is to compare the performance of ESG-screened strategies with traditional index-tracking investments, evaluate any differences, and assess their impact on investment decisions. Our analysis uses historical data, necessitating certain assumptions about the effective cost of investment. We exclude any costs associated with dealing charges or platform management fees and focus solely on the Overall Charge Figure (OCF). We assume that the OCF remains constant throughout the investment period and accurately reflects the total cost of investing in the fund.

Fund Name	Overall Charge Figure (OCF)
UK Market	
HSBC FTSE 100 Index Retail ACC	0.29%
HSBC FTSE 250 Index Fund CLS Retail Accumulation	0.40%
M&G Gilt&Fixed Interest Income Sterling A ACC	0.55%
Blackrock UK Property	0.91%
Blackrock Cash	0.40%
US Market	
Vanguard 500 Index Fund	0.14%
Vanguard Total Bond Market Index Fund	0.15%
Vanguard Real Estate Index Investor	0.27%
T Rowe Price Cash Reserves Fund	0.40%

Source: Morningstar database as of July 2024

Table 3.1: Annual OCF applied throughout the investment period.

3.4 Empirical Results

3.4.1 UK Market: FTSE 100 & FTSE 250

Our analysis begins by using the FTSE 100 as the basis for constructing the ESG-screened portfolio. We obtain quarterly data on index constituents and their corresponding ESG scores from Refinitiv Datastream. We then evaluate pension accumulation outcomes under three investment strategies - Index tracker versus two ESG-screened - allowing for differences in glide paths used by UK master trust funds and varying ESG preferences. The details of our portfolio construction approach are outlined in Section 3.3.2. This assessment is designed to examine the effectiveness of integrating ESG criteria into investment strategies within the context of a prominent benchmark index such as the FTSE 100.

Table 3.2 offers a comparative view of six sampled master trust funds, analyzing them through the 25th, 50th, and 75th percentiles and across the three investment strategies. The results demonstrate a wide range of performance levels between the index tracker approach and the two ESG-screened strategies. Overall, the ESGw strategy yields the highest performance, indicating a potential correlation between ESG performance and fund returns. Notably, the glide path utilized by #MT16 achieves the highest values, while #MT7 consistently shows lower values across all percentiles and strategies. These findings also highlight the critical role of well-designed glide paths in guiding asset allocation throughout the retirement investment horizon, in line with previous literature on

efficient pension asset weighting.

The comparison across the three investment strategies provides a clear view of how ESG considerations and the selected ESG percentile thresholds influence investment outcomes. Among the two ESG-screened strategies, only the ESGw approach consistently outperforms relative to the index tracker. However, for both ESG-screened strategies, performance declines as the ESG percentile threshold becomes more restrictive. This pattern further highlights that the design of the ESG integration approach plays a crucial role, as reflected in the superior performance of the ESGw strategy compared to the MCw strategy across all ESG percentile thresholds. The weaker performance observed at lower percentile thresholds may be explained by the reduced number of eligible stocks, which makes the portfolio resemble a traditional exclusionary ESG strategy, such as sin stock removal.

The appendix (Table 3.14) provides the full set of results for the Master Trust Fund glide paths assessed in the UK market context with reference to the FTSE 100.

Master Trust	25 th		50 th		75 th		Index Tracker
	MCw	ESGw	MCw	ESGw	MCw	ESGw	
#MT1	£299,952	£377,023	£326,070	£415,804	£345,394	£433,456	£365,675
#MT5	£297,446	£360,690	£318,531	£390,799	£335,145	£404,891	£352,668
#MT7	£217,870	£247,823	£227,255	£259,403	£232,815	£264,236	£240,000
#MT11	£314,689	£418,164	£348,762	£472,785	£374,960	£497,954	£401,601
#MT14	£297,045	£354,786	£315,516	£380,296	£329,091	£391,993	£344,219
#MT16	£305,821	£419,570	£339,428	£476,393	£365,807	£503,440	£394,687

Table 3.2: Master Trust Funds vs. FTSE 100 Tracker across Percentiles and Scenarios

We extend our analysis to the FTSE 250 to examine the role of ESG screening within the mid-cap segment. A common assumption in the literature and industry practice is that ESG considerations are most relevant for large-cap firms, while their influence on mid-caps is limited due to lower disclosure standards and reduced investor scrutiny. This study provides an opportunity to assess this assumption empirically. By comparing ESG effects across both large-cap and mid-cap indices, we aim to evaluate the applicability and effectiveness of ESG criteria in the mid-cap space, thereby contributing to a more comprehensive understanding of sustainable investing across different market segments.

Table 3.3 presents the pension accumulation outcomes for the three investment strategies based on the FTSE 250. In contrast to the FTSE 100 results, the performance of the ESG-screened strategies declines even at higher ESG percentile thresholds, and the ESGw strategy no longer outperforms the index tracker across several glide paths. We

could, however, still confirm differences in performance across the ESG-screened strategies. These findings further emphasize the critical role of the chosen ESG integration method and highlight how asset allocation decisions, shaped through ESG percentile thresholds, directly influence performance outcomes.

Master Trust	25 th		50 th		75 th		Index Tracker
	MCw	ESGw	MCw	ESGw	MCw	ESGw	
#MT2	£305,697	£418,345	£372,191	£474,835	£434,158	£494,898	£482,732
#MT7	£222,700	£274,329	£246,721	£294,224	£268,428	£301,822	£280,522
#MT9	£322,347	£415,245	£377,879	£460,719	£429,556	£476,970	£465,939
#MT13	£292,244	£380,751	£346,001	£424,625	£394,892	£440,122	£428,847
#MT16	£310,258	£441,558	£400,749	£518,600	£489,829	£545,833	£563,466
#MT17	£311,946	£416,795	£389,869	£480,100	£466,948	£502,196	£527,258

Table 3.3: Master Trust Funds vs. FTSE 250 Tracker across Percentiles and Scenarios

The results of all examined Master Trust Funds glide paths for the UK market under FTSE 250 considerations are represented in Table 3.15 of the appendix.

3.4.2 US Market: S&P 500

To assess regional variations in ESG adoption and performance within retirement investing, we extend the analysis to the S&P 500. A similar investment model to that of the UK context is constructed using the S&P 500 constituents on a quarterly basis. Focusing on the US market, the largest and most liquid equity market globally, enables an extended comparative assessment of ESG strategies relative to traditional approaches in a highly developed and diversified market, offering further insight into the role of sustainable investing in retirement planning.

Table 3.4 presents a sample of pension accumulation outcomes for the six asset allocation weightings used by target date funds in the US market. Across all ESG percentile thresholds, the ESGw strategy consistently produces higher values than the MCw strategy. The performance of the Index Tracker generally lies between the two ESG-screened strategies, often closer to ESGw. Moving from lower to higher ESG percentile thresholds results in higher accumulation values across all target date funds and strategies, with the increase being more pronounced under the ESGw than under MCw.

The asset allocation approach of $\tilde{T}D9$ consistently delivers the highest pension accumulation across all ESG percentile thresholds and strategies, indicating strong overall performance. In contrast, $\tilde{T}D5$ and $\tilde{T}D26$ record the lowest accumulations, especially in the MCw strategy, although they still perform comparably to, or in some cases better

than, the index tracker when using the ESGw specification. These results suggest that ESG-screened strategies can generate pension outcomes similar to or exceeding those of traditional index tracking, especially when ESG preference is not as restrictive and combined with well-designed target date fund allocation structures.

The results of all examined target date funds for the US market under S&P 500 considerations are represented in Table 3.16 of the appendix.

Target Date	25 th		50 th		75 th		Index Tracker
	MCw	ESGw	MCw	ESGw	MCw	ESGw	
$\tilde{T}D3$	\$373,633	\$500,537	\$456,829	\$586,266	\$515,615	\$615,284	\$594,198
$\tilde{T}D5$	\$359,551	\$446,263	\$411,988	\$496,848	\$448,532	\$513,166	\$496,960
$\tilde{T}D9$	\$482,407	\$672,279	\$608,025	\$804,948	\$697,953	\$850,259	\$819,917
$\tilde{T}D17$	\$379,740	\$516,684	\$471,137	\$611,866	\$536,060	\$644,336	\$622,792
$\tilde{T}D21$	\$374,116	\$505,829	\$460,045	\$594,651	\$521,156	\$624,635	\$603,215
$\tilde{T}D26$	\$342,641	\$458,269	\$419,756	\$537,444	\$474,274	\$564,331	\$546,364

Table 3.4: Target Date Funds vs. S&P 500 Tracker across Percentiles and Scenarios

3.4.3 Investment shift to ESG Components (Environmental, Social and Governance)

In this section, we extend the analysis by examining portfolio performance when screening is applied to a single ESG component rather than the overall ESG score. In practice, investors may prioritise specific dimensions of ESG differently; historically, the Environmental (E) component has attracted the most attention, while interest in the Social (S) dimension has increased more recently. We will compare the performance of portfolios screened on individual ESG components against a traditional index tracker to assess whether targeting a specific pillar can also generate improved outcomes.

The analysis covers both the UK market (FTSE 100 and FTSE 250) and the US market (S&P 500). The equity component of the portfolio is constructed by selecting stocks based on their respective E, S, or G scores, depending on the ESG pillar under examination. All other asset classes remain unchanged and are allocated according to the funds detailed in Section 3.3.3. The glide paths and target date fund methodologies for the UK and US markets are also kept consistent with the earlier framework. For this extension, we focus only on the 75th percentile threshold and compare the top-performing (+) and bottom-performing (−) asset allocation methods for each ESG component scenario against the index tracker.

The Environmental Component

Refinitiv’s Environment Pillar Score is a weighted average rating that evaluates a company’s environmental performance. This score is derived from three environmental category ratings: resource use, emissions, and innovation.

Figures 3.1 to 3.3 illustrate the pension accumulation paths for an investor allocating exclusively to the best-scoring Environmental (E) stocks at the 75th percentile, compared with a traditional index tracker for the FTSE 100, FTSE 250, and S&P 500, respectively. The difference in performance is more pronounced under the FTSE 100, Figure 3.1, where the top-performer path for ESGw E+ significantly outperforms the index tracker in terms of pension accumulation, while the MCw E closely matches the index’s movement and performance. The difference between strategies is minimal for the bottom-performing asset allocation method.

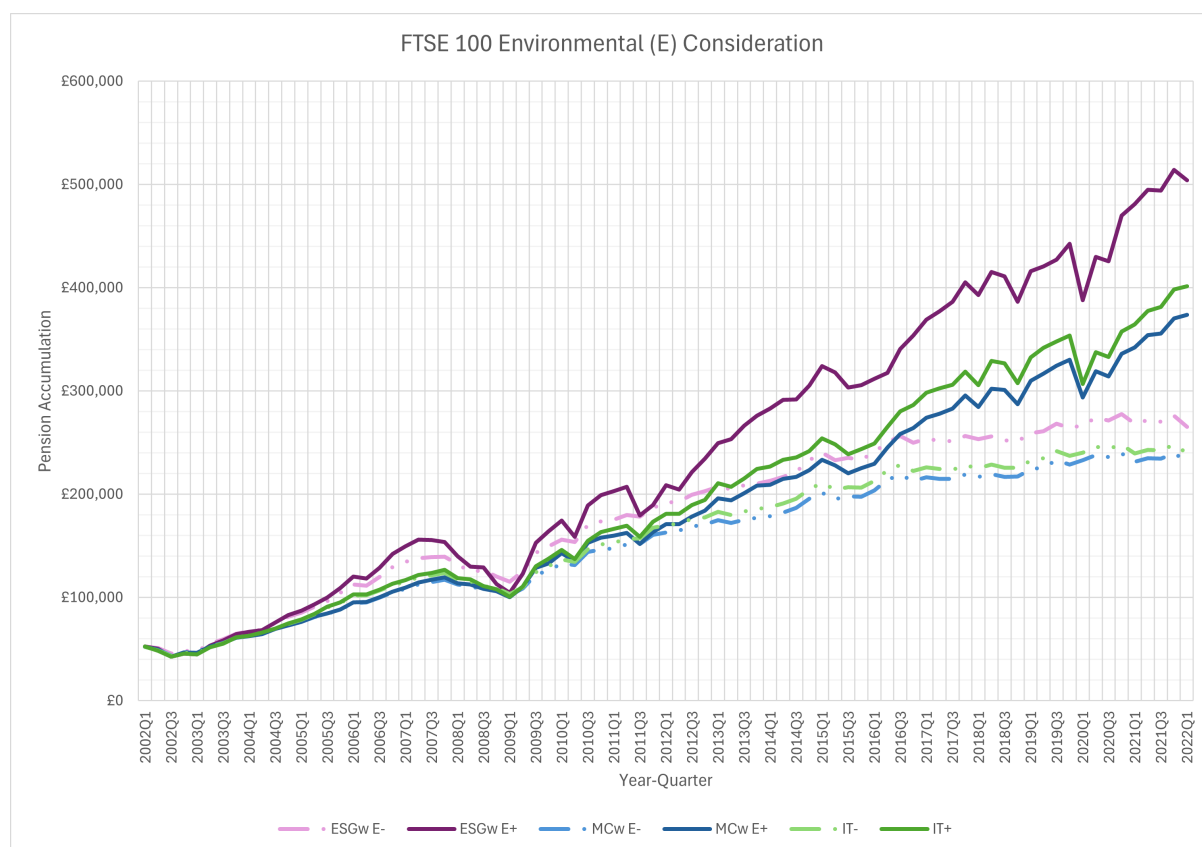


Figure 3.1: Evolution of pension investments under Environmental (E) considerations vs FTSE 100 Index

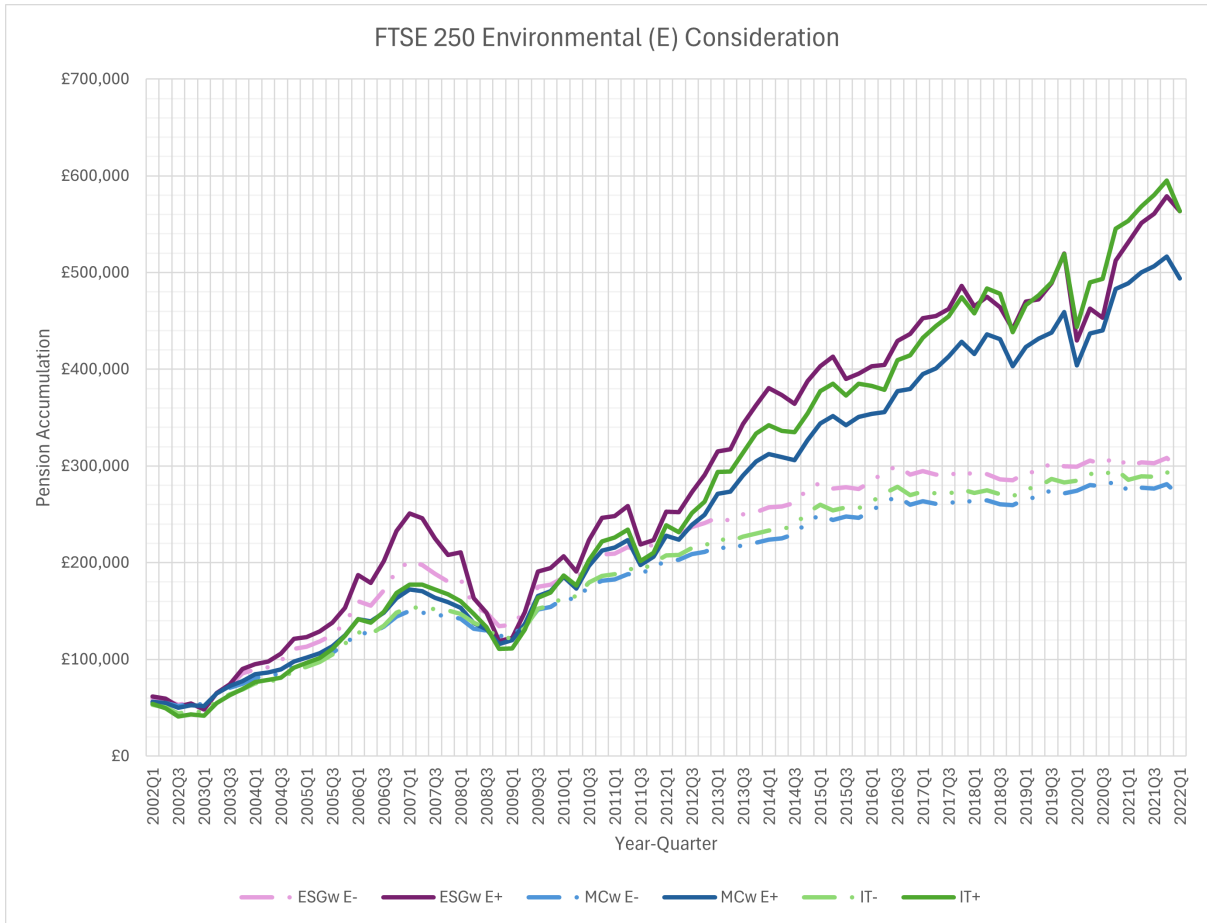


Figure 3.2: Evolution of pension investments under Environmental (E) considerations vs FTSE 250 Index

The performance differences between the top and bottom-performing asset allocation methods widen under the FTSE 250 setting (Figure 3.2), indicating greater sensitivity of mid-cap portfolios to Environmental screening. Although all three strategies follow broadly similar trajectories, the index tracker begins to outperform the two environmentally focused portfolios within the top-performing allocation approach from around 2018 onward. In contrast, under the bottom-performing allocation method, the ESGw E portfolio maintains a consistent lead over both the MCw E portfolio and the index tracker, suggesting that ESG integration can provide relative resilience even when overall performance levels are lower. This divergence suggests that the benefits of environmental screening are not uniform, but rather depend on the interaction between ESG methodology and the underlying glide path design, particularly in less liquid and more volatile segments such as the FTSE 250.

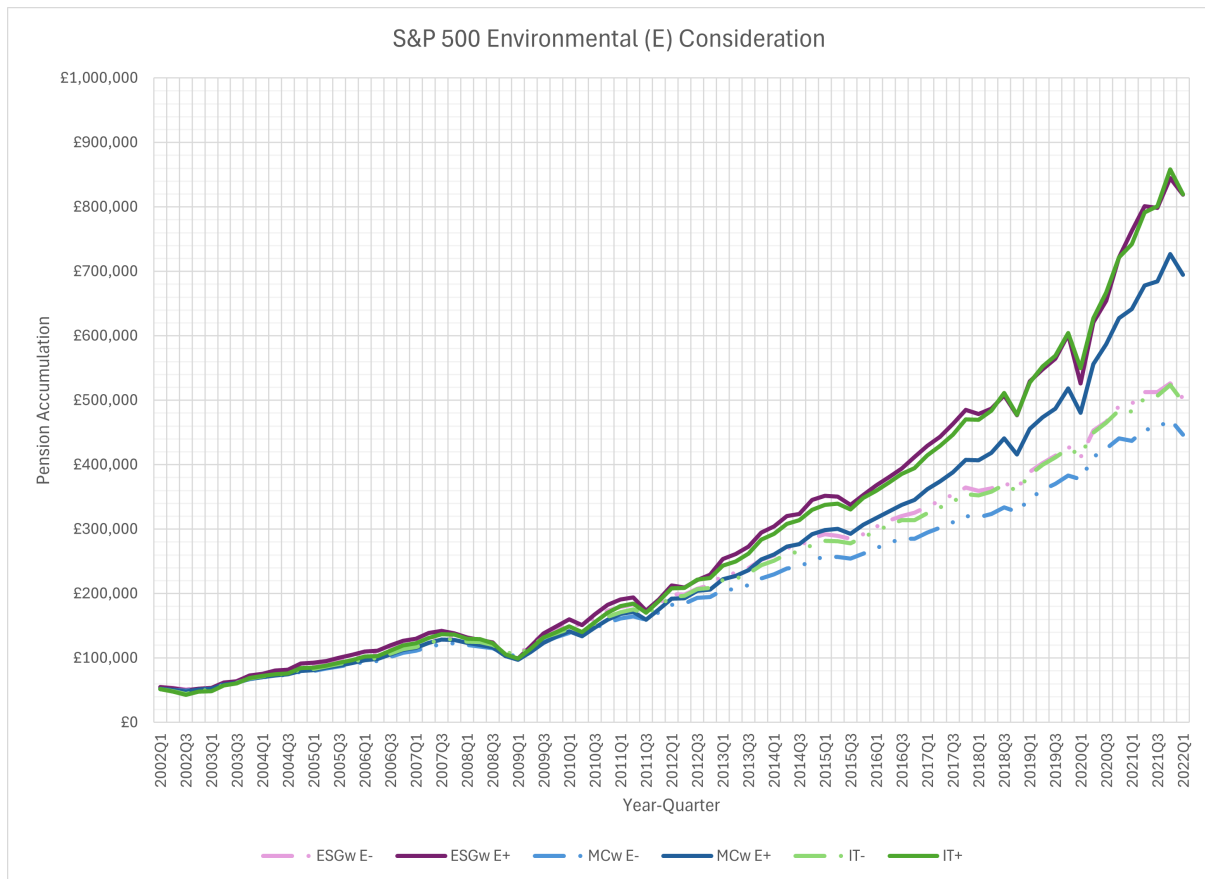


Figure 3.3: Evolution of pension investments under Environmental (E) considerations vs S&P 500 Index

Under the S&P 500 setting (Figure 3.3), portfolios screened on the Environmental component closely mirror the performance of the index tracker under both the top and bottom-performing target date fund allocation structures. In particular, the ESGw E strategy tracks the index almost identically, resulting in near-identical pension accumulation outcomes across the entire investment horizon. This suggests that in a large, highly liquid, and well-diversified market such as the S&P 500, the application of environmental screening does not materially distort portfolio performance.

Social

For the Social pillar, Refinitiv's score reflects a firm's performance based on a weighted aggregation of reported social metrics. The score is constructed from four underlying categories: Workforce, Human Rights, Community Engagement, and Product Responsibility. This structure captures both internal stakeholder treatment and broader societal impact, allowing for a more granular assessment of a firm's social performance within the ESG framework.

Figures 3.4–3.6 shows pension accumulation trajectories for an investor whose preference leans towards the social component. The trend for the FTSE 100, Figure 3.4,

demonstrates that the performance trend for the FTSE 100 aligns with that observed under the environmental consideration, where the ESG-weighted strategy consistently outperforms, followed by the index tracker. In contrast, the performance for the FTSE 250 using the social component, as illustrated in Figure 3.5, diverges from the environmental trends. The ESGw S strategy distinctly outperforms the index tracker throughout the investment horizon. Similarly, the identical movement between the S&P 500 tracker and the ESG-weighted strategy also shifts under the social aspect, with the ESGw S, Figure 3.6, outperforming the index tracker for both the top and bottom asset allocation methods.

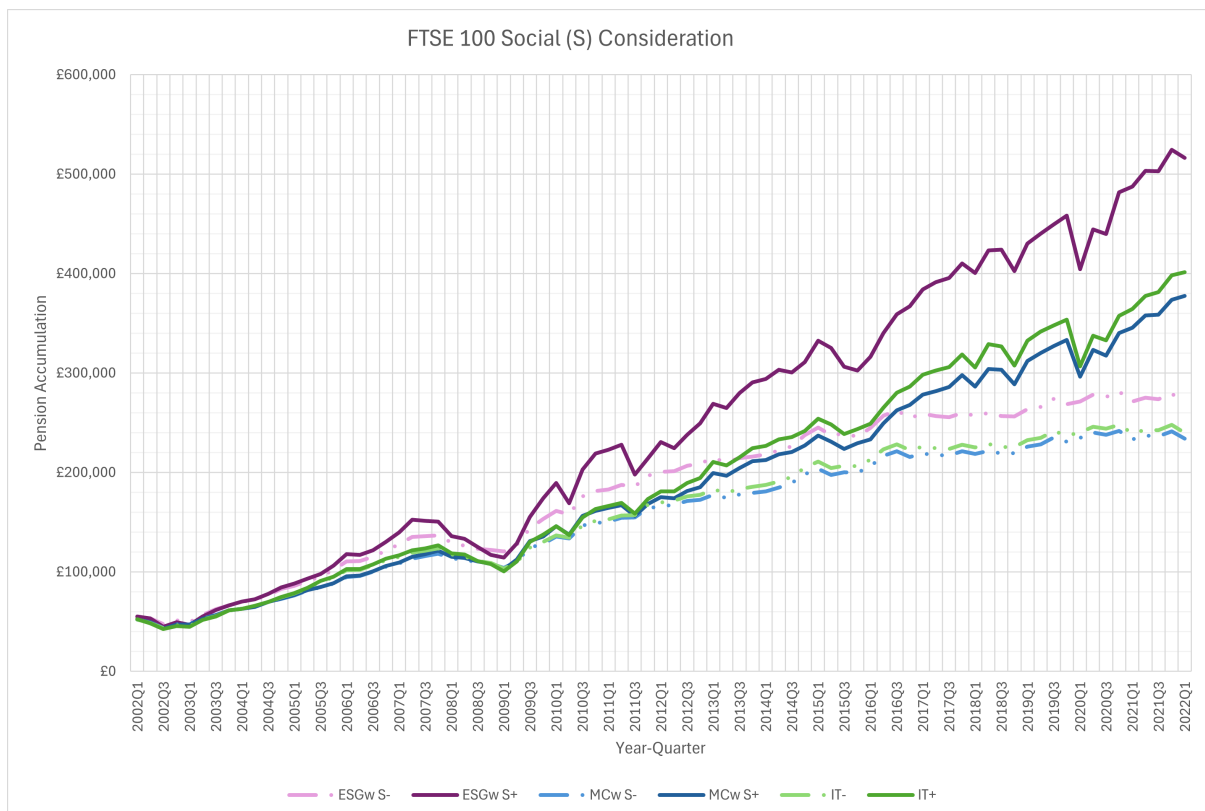


Figure 3.4: Evolution of pension investments under Social (S) considerations vs FTSE 100 Index

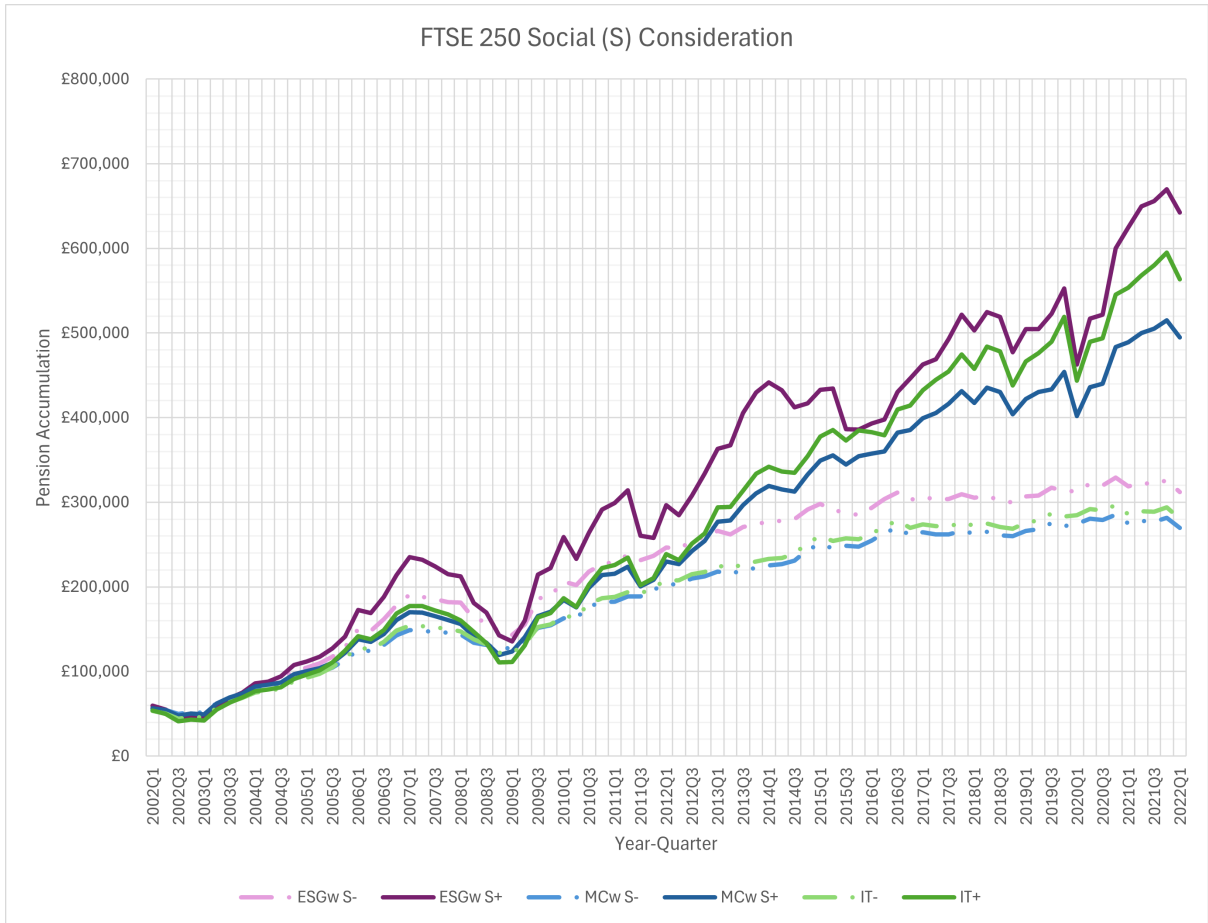


Figure 3.5: Evolution of pension investments under Social (S) considerations vs FTSE 250 Index

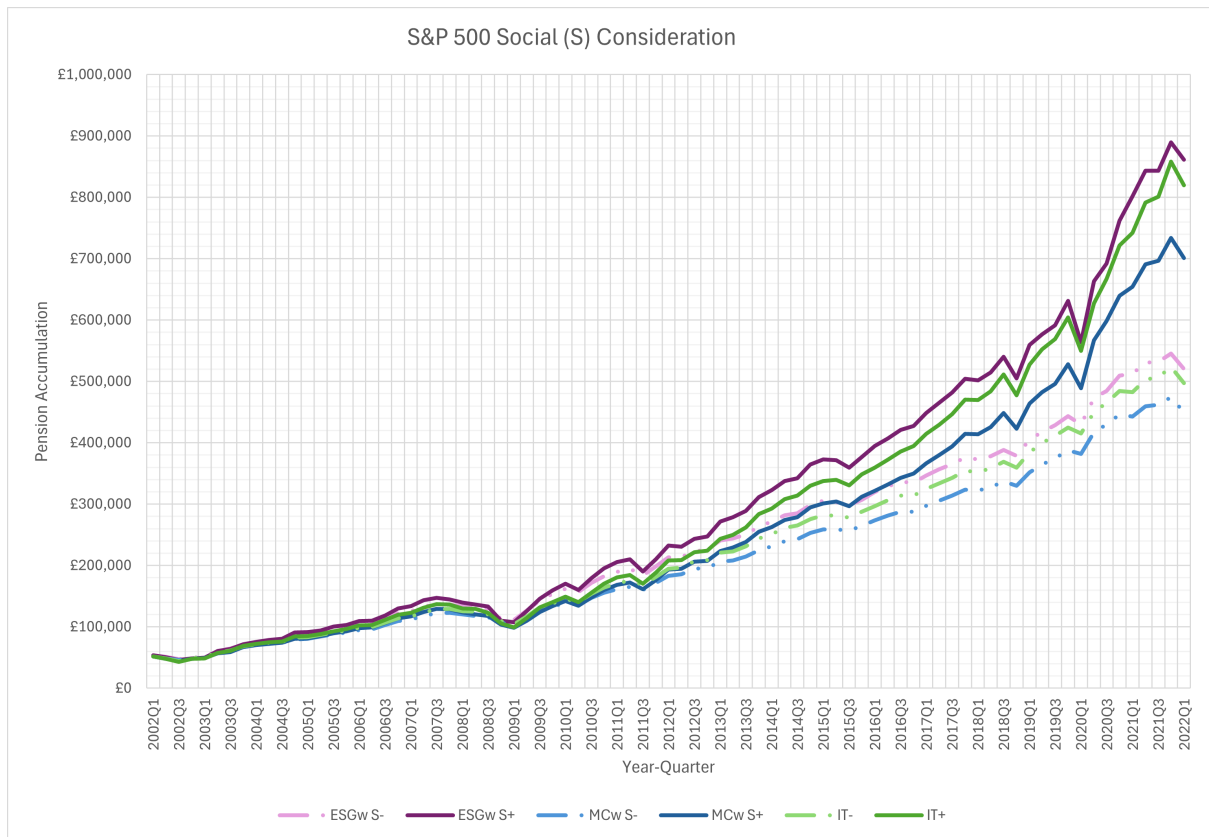


Figure 3.6: Evolution of pension investments under Social (S) considerations vs S&P 500 Index

Governance

The Governance pillar score is calculated as a weighted average of governance-related indicators derived from three key categories: Management, Shareholders, and Corporate Social Responsibility (CSR) Strategy. Unlike the Environmental and Social scores, which are benchmarked against sector peers, the Governance score is assessed relative to the firm’s country of incorporation. This distinction reflects the view that governance practices are more closely shaped by national regulatory frameworks and institutional environments than by industry-specific dynamics.

Figures 3.7 to 3.9 show the evolution of pension accumulation for an investor focused solely on the Governance (G) component of the ESG metrics. Under the FTSE 100 setting (Figure 3.7), the three strategies follow similar trajectories over time, with differences emerging primarily in later stages rather than in the overall pattern. Throughout the investment horizon, the ESG-weighted governance strategy (ESGw G) consistently outperforms both the index tracker (IT) and the market-cap-weighted governance approach (MCw G).

The FTSE 250 scenario, Figure 3.8, presents a distinctive pattern in the governance-focused allocation. From 2007 onward, the ESGw G strategy applied to the bottom-performing asset allocation method begins to outperform the top-performing for both

the index tracker and the MCw G, with this reversal persisting until the typical ranking order is re-established around 2013. During the 2008–2009 period, both the top and bottom index tracker approaches recorded the weakest performance, reflecting heightened sensitivity to governance factors during the financial crisis. While similar deviations are observed under the Environmental and Social components for the FTSE 250, the divergence in the governance case is notably more pronounced. In the latter stages of the investment horizon, particularly from late 2019 onward, the performance of the ESGw G and index tracker strategy converges, indicating a reduced performance gap.

For the S&P 500, consideration of the governance component (Figure 3.9) reveals a pattern consistent with the Environmental and Social cases. The performance of the index tracker and the ESG-weighted governance strategy (ESGw G) closely track one another throughout the investment period.

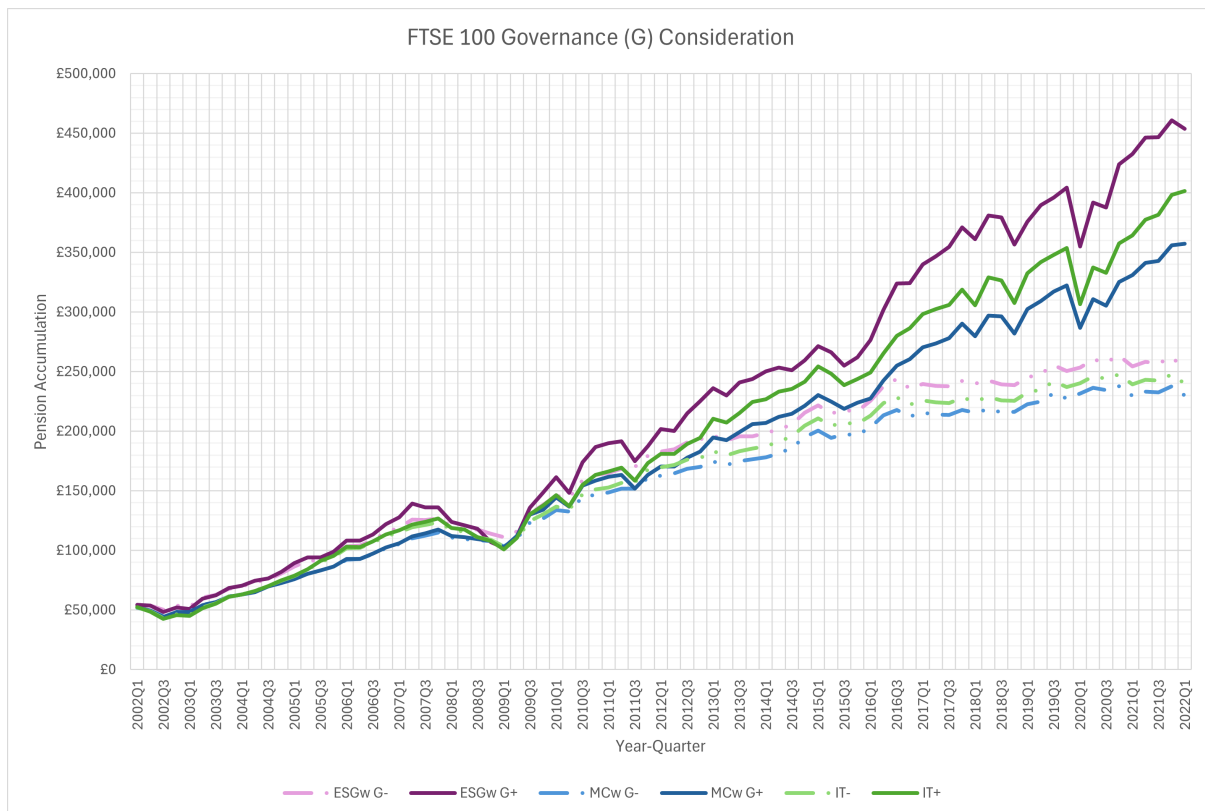


Figure 3.7: Evolution of pension investments under Governance (G) considerations vs FTSE 100 Index

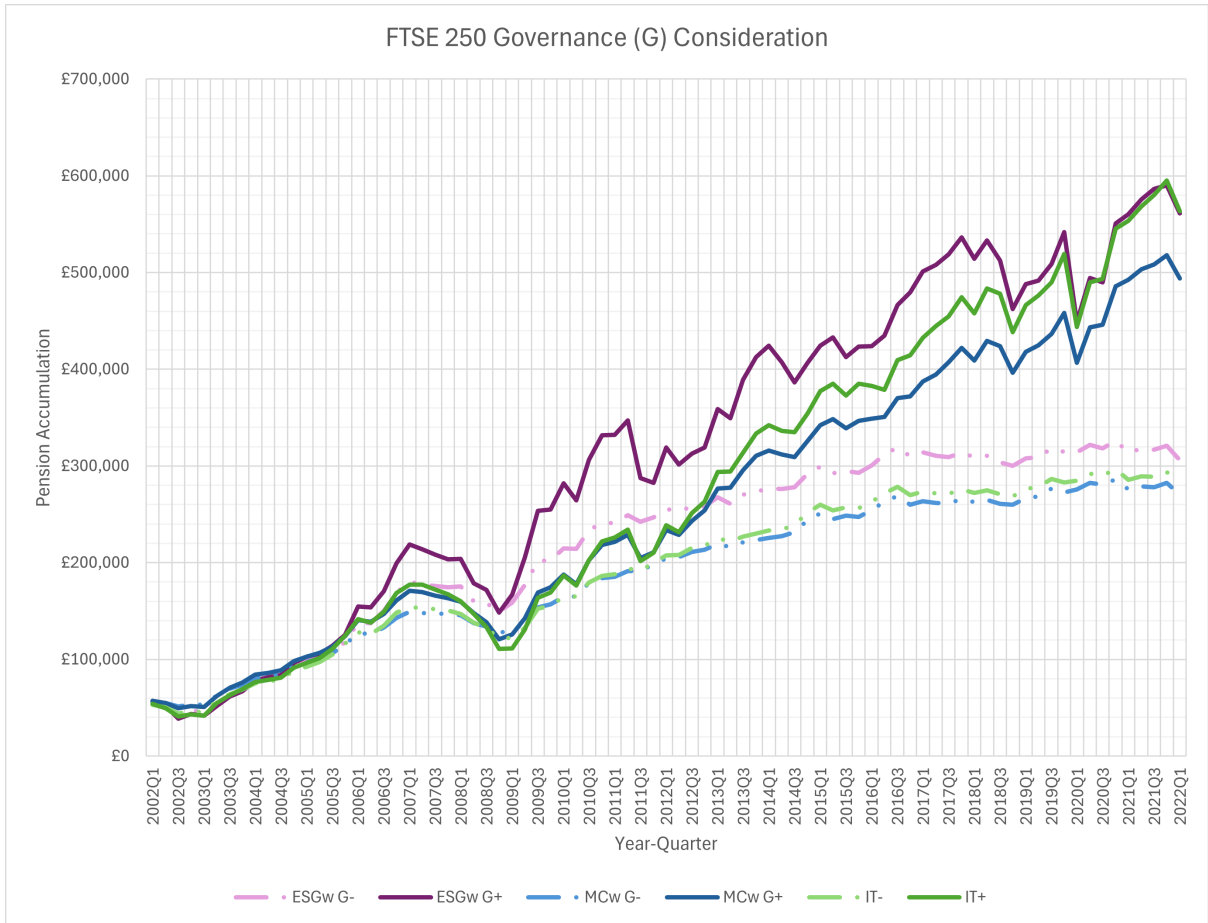


Figure 3.8: Evolution of pension investments under Governance (G) considerations vs FTSE 250 Index

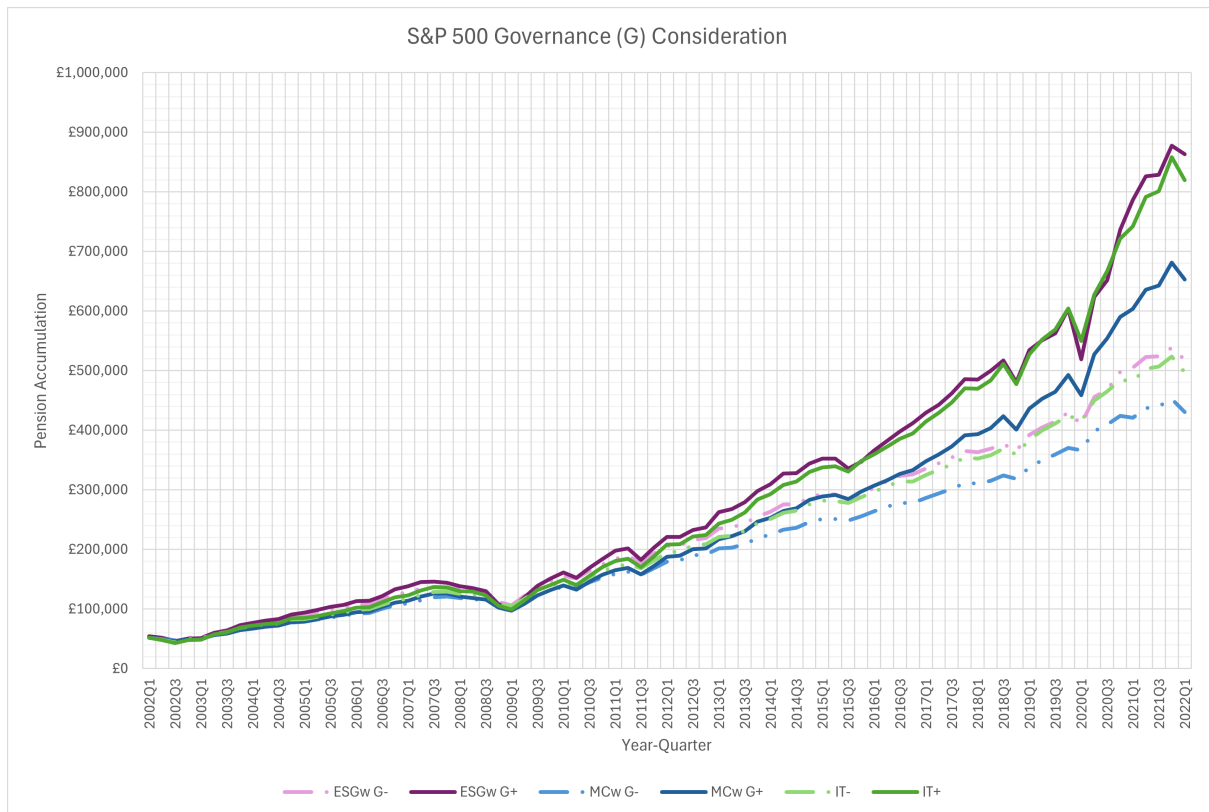


Figure 3.9: Evolution of pension investments under Governance (G) considerations vs S&P 500 Index

In summary, the analysis of pension accumulation across the individual ESG components reveals distinct performance dynamics. For the Environmental pillar, the ESGw E strategy outperforms the index tracker in both the FTSE 100 and FTSE 250 under the top and bottom-performing asset allocation methods. However, the performance advantage narrows in mid-cap allocations and becomes negligible in the S&P 500, where ESGw E closely tracks the index. For the Social component, the ESGw S strategy consistently exceeds the index tracker across both the UK and US markets, with the FTSE 100 showing the widest performance gap in favour of Social integration. For Governance, the ESGw G strategy generally exceeds the performance of both the index tracker and MCw G in the FTSE 100, while the FTSE 250 shows a temporary reversal in performance rankings during the 2007–2013 period, particularly around the financial crisis, followed by a convergence in later years. In the S&P 500, the governance screening results in performance that closely mirrors the index, reflecting limited deviation. Overall, the ESG-weighted strategies demonstrate strong performance relative to index trackers, though the magnitude of outperformance varies across indices and ESG components.

3.4.4 Statistical Testing

To ensure a more thorough evaluation of the three investment strategies, we perform statistical tests on both pension accumulation outcomes (IT, MCw, and ESGw) and risk-adjusted performance, measured through Sharpe ratios (IT-SH, MCw-SH, and ESGw-SH). A Shapiro-Wilk test is first applied to evaluate the normality of the distributions. Given that several results do not satisfy the normality assumption, we employ the Wilcoxon Signed-Rank Test as a non-parametric alternative to the paired t-test. The analysis is conducted using portfolios screened on the overall ESG score at the 75th percentile.

For the FTSE 100 (Tables 3.5–3.7), the decision to apply a non-parametric test is justified by the non-normality of the IT and MCw distributions. The Wilcoxon results yield p-values well below conventional significance thresholds, indicating a statistically significant difference in pension accumulation and Sharpe ratios between the ESG-screened portfolios and the index tracker.

Shapiro Normality Test						
Values	IT	MCw	ESGw	IT-SH	MCw-SH	ESGw-SH
W	0.809	0.767	0.916	0.959	0.951	0.969
P-Value	0.003	0.001	0.126	0.615	0.467	0.795

Table 3.5: Results of the Shapiro-Wilk Normality Test for the FTSE 100 Scenario

T-Test Paired				
Values	IT vs MCw	IT vs ESGw	IT-SH vs MCw-SH	IT-SH vs ESGw-SH
t	1.637	-3.899	2.165	-1.777
P-Value	0.112	0.001	0.038	0.085

Table 3.6: Results of the Paired T-Test for the FTSE 100 Scenario

Wilcoxon Test				
Values	IT vs MCw	IT vs ESGw	IT-SH vs MCw-SH	IT-SH vs ESGw-SH
P-Value	1.52588E-05	1.52588E-05	1.52588E-05	1.52588E-05

Table 3.7: Results of the Wilcoxon Test for the FTSE 100 Scenario

Tables 3.8–3.10 present the corresponding statistical analysis for the FTSE 250. The Shapiro-Wilk results (Table 3.8) indicate normality for all strategies, as all p-values ex-

ceed the 0.05 threshold. Consequently, a paired t-test is applied, showing no significant difference between IT and ESGw in terms of pension accumulation, while a significant difference emerges between the index tracker and MCw. Additionally, both ESG-screened strategies differ significantly from the index tracker in terms of Sharpe ratios. The Wilcoxon test provides a non-parametric confirmation of these results, serving as a robustness check should the normality assumption be challenged.

Shapiro Normality Test						
Values	IT	MCw	ESGw	IT-SH	MCw-SH	ESGw-SH
W	0.934	0.902	0.946	0.963	0.965	0.953
P-Value	0.254	0.073	0.397	0.690	0.732	0.509

Table 3.8: Results of the Shapiro-Wilk Normality Test for the FTSE 250 Scenario

T-Test Paired				
Values	IT vs MCw	IT vs ESGw	IT-SH vs MCw-SH	IT-SH vs ESGw-SH
t	2.118	0.183	2.901	2.270
P-Value	0.043	0.856	0.007	0.030

Table 3.9: Results of the Paired T-Test for the FTSE 250 Scenario

Wilcoxon Test				
Values	IT vs MCw	IT vs ESGw	IT-SH vs MCw-SH	IT-SH vs ESGw-SH
P-Value	1.52588E-05	0.352874756	1.52588E-05	1.52588E-05

Table 3.10: Results of the Wilcoxon Test for the FTSE 250 Scenario

Under the S&P 500 scenario, the normality test reveals differing outcomes between pension accumulation and Sharpe ratios. The Sharpe ratio results show p-values above 0.05, indicating no significant deviation from normality, while pension accumulation displays mixed normality behaviour. Accordingly, both the paired t-test and the Wilcoxon test are applied to assess performance differences. The two tests are broadly consistent in their conclusions, with the exception of the ESGw pension accumulation relative to the index tracker, where the significance levels diverge.

However, given that the Shapiro-Wilk test indicated non-normality in the ESGw pension accumulation distribution, greater weight is placed on the Wilcoxon results. Based

on this non-parametric evidence, we conclude that a statistically significant difference exists between the ESG-screened strategies and the traditional index-based approach.

Shapiro Normality Test						
Values	IT	MCw	ESGw	IT-SH	MCw-SH	ESGw-SH
W	0.878	0.831	0.877	0.929	0.933	0.931
P-Value	0.004	0.000	0.004	0.065	0.082	0.071

Table 3.11: Results of the Shapiro-Wilk Normality Test for the S&P 500 Scenario

T-Test Paired				
Values	IT vs MCw	IT vs ESGw	IT-SH vs MCw-SH	IT-SH vs ESGw-SH
t	5.612	-1.281	8.113	-4.522
P-Value	0.000	0.206	0.000	0.000

Table 3.12: Results of the Paired T-Test for the S&P 500 Scenario

Wilcoxon Test				
Values	IT vs MCw	IT vs ESGw	IT-SH vs MCw-SH	IT-SH vs ESGw-SH
P-Value	1.49012E-08	1.49012E-08	1.49012E-08	1.49012E-08

Table 3.13: Results of the Wilcoxon Test for the S&P 500 Scenario

Across both the UK and US markets, the statistical tests conducted on the FTSE 100, FTSE 250, and S&P 500 confirm meaningful differences between ESG-screened strategies and their traditional index-tracking counterpart. For the FTSE 100, non-parametric testing was required due to violations of normality assumptions for IT and MCw. The Wilcoxon results indicate significant differences in both pension accumulation and Sharpe ratios between ESG-screened portfolios and the index tracker.

In the FTSE 250, all strategies met the normality criteria, enabling the use of paired t-tests. The results indicate that ESGw delivers similar pension accumulation to the index tracker, while significant differences emerge between the index tracker and MCw. In terms of risk-adjusted performance, both ESG strategies differ significantly from the index tracker. These results were corroborated by the Wilcoxon test, serving as a robustness check against potential distributional concerns.

Finally, in the S&P 500, Sharpe ratios met the normality assumption, whereas pension accumulation displayed mixed distributional properties. Consequently, both paired

t-tests and Wilcoxon tests were employed. Although the results were broadly aligned, the Shapiro-Wilk test indicated non-normality, specifically in the ESGw pension accumulation distribution. Therefore, greater reliance was placed on the Wilcoxon results, which provide non-parametric evidence of a statistically significant difference between ESG-screened strategies and the traditional index-based approach.

Overall, the statistical evidence confirms that ESG-screened portfolios differ significantly from index trackers in both pension accumulation and risk-adjusted returns across all indices. In cases where normality assumptions were not satisfied, non-parametric tests provided consistent support for these differences, strengthening the robustness of the findings.

3.5 Conclusion

This paper set out to address a notable gap in the literature concerning the long-term implications of ESG integration within retirement investing. While most existing research focuses on short-term performance, limited attention has been given to how ESG considerations influence the cumulative outcomes of pension portfolios over extended periods. By aligning ESG integration with the realistic saving and investment dynamics of retirement systems, this paper contributes new empirical insight into whether sustainability-oriented strategies can serve as viable alternatives to traditional index-based approaches without compromising performance.

To capture a broad perspective, the analysis incorporated ESG data sourced from Refinitiv Datastream, covering a 20-year period from 2002 to 2022. Two key financial regions are examined: the United Kingdom, representing a European market with strong regulatory encouragement for ESG adoption, and the United States, a major global investment hub. Pension accumulation outcomes were examined across three major equity indices, FTSE 100, FTSE 250, and S&P 500, allowing for a comparative understanding of ESG integration under different market structures. Pension portfolio trajectories were simulated using glide paths derived from 17 UK master trust funds and 27 US target date funds, ensuring that the allocation patterns reflected realistic lifecycle investment strategies.

Three investment strategies were evaluated: a traditional Index Tracker, an ESG-screened Market-Capitalisation-Weighted strategy (MCw), and an ESG-Weighted strategy (ESGw), with ESG-screening intensity set at the 25th, 50th, and 75th percentiles. ESG integration produced distinct effects across indices. In the FTSE 100, ESGw outperformed both the Index Tracker and MCw at all thresholds, indicating that large-cap markets may reward sustainability overweighting towards best-scoring firms. In the FTSE 250, the dominance of ESGw weakened from the 50th percentile downward, suggesting reduced ESG effects in mid-cap markets. In the S&P 500, ESGw generally exceeded MCw,

while the Index Tracker outperformed both ESG strategies except for ESGw cases at the 75th percentile. Higher ESG thresholds improved pension accumulation, especially under ESGw, indicating that broader ESG inclusion is more effective than strict exclusion in both regions. These performance differences were statistically confirmed in Section 3.4.4.

The component-level analysis of Environmental, Social, and Governance scores added further depth to the results. Under the Environmental pillar, ESGw outperformed in both UK indices, more strongly in the FTSE 100 and with a sustained advantage in the FTSE 250, while in the S&P 500 it closely tracked the index. Social screening produced the most consistent gains, with ESGw outperforming across all indices, though the effect was smaller in the FTSE 250 and still present in the S&P 500. Governance integration delivered strong results in the FTSE 100, though converging toward the index, in the FTSE 250, while producing no notable deviation in the S&P 500. In all cases, MCw strategies consistently underperformed the index tracker under both the top and bottom-performing glide paths.

Overall, the findings suggest that ESG-screened allocation frameworks can support improved pension accumulation, conditional on market context and ESG method specification. This implies that sustainability-oriented strategies may be compatible with long-term pension objectives when applied with appropriate sensitivity to index composition and regional market behaviour.

Appendix for Chapter 3

3.A Additional Results

Master Trust	25 th		50 th		75 th		Index Tracker
	MCw	ESGw	MCw	ESGw	MCw	ESGw	
#MT1	£299,952	£377,023	£326,070	£415,804	£345,394	£433,456	£365,675
#MT2	£300,887	£385,715	£327,380	£425,491	£346,896	£443,857	£367,579
#MT3	£295,834	£391,227	£325,180	£439,202	£348,777	£462,214	£374,235
#MT4	£287,336	£341,343	£304,559	£365,692	£318,044	£377,127	£333,086
#MT5	£297,446	£360,690	£318,531	£390,799	£335,145	£404,891	£352,668
#MT6	£287,499	£347,442	£306,550	£375,252	£320,427	£387,549	£336,410
#MT7	£217,870	£247,823	£227,255	£259,403	£232,815	£264,236	£240,000
#MT8	£306,158	£347,582	£320,169	£366,233	£331,048	£374,732	£342,368
#MT9	£316,131	£382,571	£337,882	£413,220	£353,079	£426,886	£370,363
#MT10	£310,305	£373,121	£331,675	£403,940	£348,478	£418,263	£365,478
#MT11	£314,689	£418,164	£348,762	£472,785	£374,960	£497,954	£401,601
#MT12	£303,666	£360,378	£321,548	£385,224	£335,478	£396,925	£351,159
#MT13	£286,725	£354,552	£306,942	£385,006	£321,584	£398,509	£338,555
#MT14	£297,045	£354,786	£315,516	£380,296	£329,091	£391,993	£344,219
#MT15	£295,863	£371,337	£319,495	£406,160	£337,468	£422,420	£357,315
#MT16	£305,821	£419,570	£339,428	£476,393	£365,807	£503,440	£394,687
#MT17	£305,322	£397,209	£333,218	£442,201	£355,812	£463,759	£381,118

Table 3.14: Master Trust Funds vs. FTSE 100 Tracker across Percentiles and Scenarios

Master Trust	25 th		50 th		75 th		Index Tracker
	MCw	ESGw	MCw	ESGw	MCw	ESGw	
#MT1	£303,274	£401,454	£366,183	£453,441	£425,424	£471,703	£475,546
#MT2	£305,697	£418,345	£372,191	£474,835	£434,158	£494,898	£482,732
#MT3	£301,103	£409,400	£379,949	£474,445	£457,161	£497,073	£522,715
#MT4	£292,768	£357,624	£339,070	£393,025	£382,838	£405,189	£414,487
#MT5	£301,941	£378,685	£355,246	£420,140	£404,926	£434,360	£443,968
#MT6	£292,510	£371,908	£341,571	£411,475	£386,093	£425,417	£418,681
#MT7	£222,700	£274,329	£246,721	£294,224	£268,428	£301,822	£280,522
#MT8	£308,091	£357,442	£341,545	£381,679	£371,243	£389,766	£394,509
#MT9	£322,347	£415,245	£377,879	£460,719	£429,556	£476,970	£465,939
#MT10	£312,419	£383,921	£364,703	£423,949	£412,191	£437,310	£453,422
#MT11	£315,594	£436,656	£397,698	£505,539	£473,840	£529,360	£547,571
#MT12	£308,754	£376,399	£356,656	£412,755	£401,654	£425,294	£433,233
#MT13	£292,244	£380,751	£346,001	£424,625	£394,892	£440,122	£428,847
#MT14	£302,076	£379,121	£349,810	£417,214	£393,997	£430,679	£425,708
#MT15	£303,432	£403,262	£365,827	£454,668	£425,327	£472,936	£468,773
#MT16	£310,258	£441,558	£400,749	£518,600	£489,829	£545,833	£563,466
#MT17	£311,946	£416,795	£389,869	£480,100	£466,948	£502,196	£527,258

Table 3.15: Master Trust Funds vs. FTSE 250 Tracker across Percentiles and Scenarios

Master Trust	25 th		50 th		75 th		Index Tracker
	MCw	ESGw	MCw	ESGw	MCw	ESGw	
~TD1	\$384,762	\$527,146	\$480,228	\$626,626	\$548,274	\$660,589	\$639,109
~TD2	\$377,528	\$485,277	\$449,824	\$557,203	\$499,749	\$581,477	\$564,352
~TD3	\$373,633	\$500,537	\$456,829	\$586,266	\$515,615	\$615,284	\$594,198
~TD4	\$370,521	\$479,099	\$440,364	\$549,631	\$489,318	\$573,188	\$553,955
~TD5	\$359,551	\$446,263	\$411,988	\$496,848	\$448,532	\$513,166	\$496,960
~TD6	\$387,703	\$512,431	\$469,757	\$596,063	\$527,406	\$624,280	\$603,889
~TD7	\$382,807	\$526,970	\$478,394	\$627,871	\$546,632	\$662,390	\$638,763
~TD8	\$387,190	\$533,809	\$485,245	\$636,919	\$555,213	\$672,184	\$649,467
~TD9	\$482,407	\$672,279	\$608,025	\$804,948	\$697,953	\$850,259	\$819,917
~TD10	\$372,209	\$498,077	\$453,237	\$581,189	\$510,930	\$609,112	\$587,988
~TD11	\$376,033	\$499,075	\$456,646	\$583,049	\$513,749	\$611,432	\$589,480
~TD12	\$385,622	\$518,607	\$470,999	\$606,604	\$531,763	\$636,142	\$613,494
~TD13	\$373,273	\$500,496	\$455,211	\$584,818	\$513,455	\$613,131	\$591,640
~TD14	\$369,398	\$459,690	\$423,242	\$511,780	\$461,027	\$528,464	\$511,594
~TD15	\$379,089	\$518,073	\$470,225	\$613,332	\$535,420	\$645,641	\$623,065
~TD16	\$384,590	\$508,687	\$463,421	\$588,388	\$519,219	\$614,813	\$594,151
~TD17	\$379,740	\$516,684	\$471,137	\$611,866	\$536,060	\$644,336	\$622,792
~TD18	\$395,377	\$529,491	\$483,301	\$619,886	\$545,388	\$650,390	\$628,664
~TD19	\$402,579	\$505,297	\$468,096	\$569,151	\$513,395	\$590,128	\$572,971
~TD20	\$384,629	\$511,222	\$465,674	\$593,939	\$522,970	\$621,591	\$599,784
~TD21	\$374,116	\$505,829	\$460,045	\$594,651	\$521,156	\$624,635	\$603,215
~TD22	\$394,783	\$541,354	\$493,064	\$643,323	\$563,107	\$678,055	\$656,651
~TD23	\$391,716	\$553,787	\$498,946	\$668,890	\$576,403	\$708,322	\$682,616
~TD24	\$388,660	\$510,346	\$467,400	\$590,094	\$522,740	\$616,796	\$596,333
~TD25	\$386,437	\$529,092	\$482,865	\$629,862	\$551,405	\$664,420	\$642,770
~TD26	\$342,641	\$458,269	\$419,756	\$537,444	\$474,274	\$564,331	\$546,364
~TD27	\$378,814	\$520,064	\$471,711	\$617,067	\$538,443	\$650,061	\$627,785

Table 3.16: Target Date Funds vs. S&P 500 Tracker across Percentiles and Scenarios

US Market	UK Market
1290 Funds	Aegon Master Trust
American Century Investments	Aon Master Trust
American Funds	Atlas Master Trust
BlackRock	Aviva Master Trust
Dimensional Fund Advisors	Cheviot Trust
Empower Funds	Crystal Trust
Fidelity Investments	Fidelity Master Trust
Franklin Templeton Investments	Legal & General Worksave Master trust
GuideStone Funds	LifeSight
iShares	Mercer Master Trust
John Hancock	National Pension Trust
JPMorgan	National Employment Savings Trust
MassMutual	TPT Retirement Solutions
MFS	The People's Pension
Mutual of America	Scottish Widows Master Trust
Nationwide	SEI Master Trust
Natixis Funds	Smart Pension Master Trust
Nuveen	
PGIM Investments	
PIMCO	
Schwab Funds	
State Street Global Advisors	
T. Rowe Price	
Transamerica	
Vanguard	
Victory Capital	
Voya	

Table 3.17: Master Trust Funds and Target Date Funds by Market

Year-Quarter	FTSE 100	FTSE 250	S&P 500	Year-Quarter	FTSE 100	FTSE 250	S&P 500
2002Q1	54	49	355	2013Q1	98	186	486
2002Q2	55	48	356	2013Q2	98	186	486
2002Q3	56	47	362	2013Q3	99	183	488
2002Q4	58	47	364	2013Q4	100	183	489
2003Q1	59	48	367	2014Q1	98	182	482
2003Q2	60	47	371	2014Q2	98	180	482
2003Q3	61	47	373	2014Q3	98	181	486
2003Q4	62	47	373	2014Q4	98	178	486
2004Q1	74	130	382	2015Q1	98	229	471
2004Q2	76	134	388	2015Q2	99	231	474
2004Q3	76	136	390	2015Q3	99	238	479
2004Q4	76	138	392	2015Q4	99	240	483
2005Q1	94	153	445	2016Q1	97	244	475
2005Q2	94	160	449	2016Q2	97	248	481
2005Q3	94	171	452	2016Q3	98	249	490
2005Q4	94	176	460	2016Q4	100	249	493
2006Q1	94	184	456	2017Q1	99	237	482
2006Q2	95	186	466	2017Q2	99	237	487
2006Q3	96	190	469	2017Q3	99	240	489
2006Q4	95	196	470	2017Q4	99	244	494
2007Q1	89	199	453	2018Q1	97	239	483
2007Q2	92	200	462	2018Q2	98	242	485
2007Q3	93	202	467	2018Q3	98	245	487
2007Q4	93	206	476	2018Q4	98	248	491
2008Q1	94	192	462	2019Q1	99	237	489
2008Q2	97	188	464	2019Q2	98	240	491
2008Q3	98	181	468	2019Q3	98	241	492
2008Q4	99	175	476	2019Q4	98	243	494
2009Q1	97	184	481	2020Q1	98	241	492
2009Q2	96	186	483	2020Q2	100	243	493
2009Q3	96	191	486	2020Q3	100	244	494
2009Q4	98	198	488	2020Q4	100	244	496
2010Q1	99	191	479	2021Q1	98	233	486
2010Q2	100	186	485	2021Q2	98	238	486
2010Q3	100	187	487	2021Q3	99	239	488
2010Q4	100	186	488	2021Q4	98	246	489
2011Q1	97	189	477	2022Q1	93	224	414
2011Q2	98	192	482	2022Q2	94	223	416
2011Q3	98	191	485	2022Q3	94	224	417
2011Q4	99	190	487	2022Q4	96	227	420
2012Q1	98	189	483				
2012Q2	98	188	485				
2012Q3	99	181	488				
2012Q4	99	184	489				

Table 3.18: Total number of stocks with available ESG scores in a specific quarter. Source: Refinitiv Datastream, July 2024.

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Chapter 4

Can retirement portfolios benefit from sustainable investing?¹

Abstract

This paper assesses the potential long-term implications of integrating Environmental, Social, and Governance (ESG) scores into retirement portfolios for an individual US investor. We compare the performance of a traditional equity portfolio with two sustainable ESG-screened portfolios: a market-capitalisation-weighted version and an ESG-weighted version. Our main finding is that the traditional approach to investing outperforms both the sustainable portfolios in terms of retirement security. These results imply that there may be a cost to investing sustainably. If an individual is willing to bear that cost, we find that a sustainable portfolio where the weights are derived from the ESG scores provides better future retirement outcomes than one where the weights are determined by the market capitalisation of the ESG-screened constituent stocks.

4.1 Introduction

This paper contributes to the limited literature on the integration of Environmental, Social, and Governance (ESG) factors into individual retirement investment portfolios. We compare the pension accumulation and decumulation experiences of a representative investor where, on the one hand, the investment portfolio consists of traditional asset classes and, on the other, where the individual invests in sustainable, ESG-screened portfolios.

The choice between a sustainable and traditional investment portfolio is now a very realistic one. Asset managers have made portfolios designed with sustainability in mind

¹This chapter has benefited from discussions with Dr M. Kashif of University of Puebla, Mexico.

available to both institutional and retail investors. In 2024, the size of the U.S. sustainable investment market was estimated at \$6.5 trillion, representing approximately 12% of the overall \$52.5 trillion in professionally managed assets dominated by traditional investing (US SIF, 2024). US SIF defines sustainable investments as those specifically identified or marketed as sustainable or as environmental, social, and governance (ESG)-related in filings with the U.S. Securities and Exchange Commission (SEC). The figure was previously reported at \$8.4 trillion in 2022, though the two estimates are not directly comparable. The 2022 figure was based on voluntary self-reports from asset managers and institutions, whereas the 2024 estimate draws solely on publicly available information, a methodological shift intended to enhance consistency and comparability over time. The 2024 survey covered 265 institutions, including asset managers, asset owners, institutional investors, community development institutions, foundations, endowments, and wealth managers, reflecting the breadth of sustainable investment activity in the United States.

According to J.P. Morgan Asset Management (2021), as of 2021, approximately 80% of global ESG assets under management were domiciled in Europe. More recent evidence confirms this dominance, with Europe accounting for over 80% of global sustainable fund assets (Morningstar, 2024). Complementing this, the Global Sustainable Investment Alliance (GSIA) reported that sustainable investment assets across markets outside the United States - namely Europe, Canada, Japan, Australia, and New Zealand increased by about 20% between 2018 and 2022 (GSIA, 2022).

This shift in investor preference for sustainable investing has led, at least in part, to a significant divestment from industries perceived to be "unsustainable", for example, the fossil fuel industry. As of 2021, a total of 1,667 institutions worldwide had committed to divesting approximately \$40.76 trillion from fossil-fuel-related investments, (Divest-Invest Initiative, 2021). These commitments spanned a wide range of sectors, with faith-based organizations accounting for 35.9% of participating institutions, educational institutions (including universities such as Harvard) representing 16%, pension funds 12%, philanthropic foundations 11.5%, governments 10.5%, and the remainder comprising a variety of other entities. There are currently no published figures available for subsequent years. It has been argued as well that the COVID-19 pandemic was another spur to the growth in sustainable investing: firms with stronger sustainability practices have been shown to have been more resilient to the pandemic's adverse effects (Albuquerque et al., 2020; Adams et al., 2022; Pastor et al., 2021).

Our findings indicate that while an equity portfolio constructed along sustainable lines might align with investor preferences, it underperformed relative to a traditional equity portfolio. This underperformance worsens as we tighten the ESG criteria, that is, by choosing stocks with progressively stronger ESG credentials. These results indicate that there may be a cost to investing sustainably in terms of retirement security. However, if an individual is willing to accept this cost, we find that weighting the components of

a sustainable equity portfolio using the ESG scores as weights rather than the market capitalisation weights of the screened stocks produces a better retirement outcome.

Plan of this chapter. The rest of this paper is organized as follows: we present the related literature in Section 4.2, outline our methodological framework in Section 4.3, while Sections 4.4 and 4.5 discuss our results and conclusions, respectively.

Relationship to previous chapter. In this chapter, our analysis shifts from a fixed accumulation model to a life-cycle approach. It introduces a stochastic simulation framework that combines a VAR(1) model with Monte Carlo simulations, extending the horizon from 20 to 40 years to include both accumulation and decumulation phases. The focus shifts from pension outcomes and risk-adjusted performance at retirement to broader measures, including expected utility, plan failure rates, and income outcomes. The portfolio rebalancing remains on a quarterly basis but considers only the US market through the S&P 500 using the Refinitiv ESG dataset.

Remark on ESG rating scale. In this chapter, we follow the *RepRisk* convention concerning ESG ratings. ESG scores range **from 100 to 0**:

- stocks with the *lowest* sustainability performance are scored 100,
- stocks with the *highest* sustainability performance are scored 0.

4.2 Related Literature

One of the main concerns that investors have in seeking to invest in a sustainable way is the impact that this decision might have on investment returns. Investors may be willing to "pay" a price for investing sustainably, but are uncertain what that price may be. Capital market theory would suggest that lower-risk investments should have an associated lower expected return. Therefore, if sustainable investments are lower-risk since they embody lower environmental, social, and governance-related risks in particular, then these investments should generate lower long-term returns. The relationship between risk and return on the one hand and sustainability (as proxied by ESG ratings) on the other is still in its early stages.

Using data from 2007 to 2016, Sherwood et al. (2017), evaluate the risk-adjusted return that might be derived from integrating ESG strategies into emerging market portfolios. The researchers use a range of portfolio performance metrics - historical return, beta, Sharpe ratio, Sortino ratio, Conditional Value at Risk (CVaR), skewness, and the Omega ratio - and find evidence to suggest that ESG-screened emerging market portfolios offer higher returns and lower downside risk compared to non-ESG portfolios, particularly in regions with greater ESG adoption. These findings are also consistent with those

reported by Renneboog et al. (2008), Lean et al. (2015), and Dyck et al. (2019). Alareeni et al. (2020) examine the impact of ESG disclosure on the financial, operational, and stock performance of firms listed in the S&P 500 index from 2009 to 2018. The study concludes that ESG factors impact firm performance indicators, including Return on Assets (ROA), Return on Equity (ROE), and Tobin's Q. Jin (2017) applies a Fama-French model that accounts for ESG-related factors to analyze returns from 1,425 US open-end equity funds from April 2009 to December 2016. The findings indicate that funds with stronger ESG profiles are less sensitive to overall market movements, though this reduced risk does not necessarily translate into higher returns. Using twenty years of data on 2,354 US equity mutual funds, Jin (2020) found that excluding funds with a low ESG score reduces portfolio risks and that portfolios with higher ESG attributes experience better risk-adjusted returns. The study also highlights that ESG screening influences portfolio performance through systematic factors, market sensitivity, and style factor exposures. Dobrick et al. (2024) showed that ESG metrics could be integrated into multi-factor asset pricing models, because they captured common variation in stock returns. The dataset comprised 4,500 global firms from 2007 to 2020, along with ESG ratings from three prominent providers (ASSET4, Refinitiv, and Moody's Vigeo Eiris), obtained through the application of extended Fama-French and Carhart models.

Arguably, a well-governed company should expect to experience fewer adverse shocks, such as fines from regulators for environmental breaches, earnings restatements due to weak accounting practices, and reputational damage resulting from poor employment practices. They should also be generally more robust and resilient to external shocks. Some authors have tested this hypothesis during the COVID-19 period. Ouchen (2021) employed Markov-switching GARCH and EGARCH models to analyze return volatility from 2005 to 2020 under different market conditions, including crises such as the 2008 financial crisis and the COVID-19 pandemic. The author found that an ESG portfolio (the MSCI USA ESG Select) exhibited [lower volatility] compared to the market benchmark (S&P 500 Index), reduced volatility persistence, and lower probabilities of transitioning into high-risk states. Moalla et al. (2022) analysed the relationship between ESG performance (Thomson Reuters scores) and the volatility of the returns of S&P 500 firms over the Covid-19 period. They found that return volatility was higher for stocks with lower ESG scores. Similarly, Ding et al. (2021) report that firms with stronger CSR/ESG ratings and more robust stakeholder relations experienced smaller stock price declines during COVID-19, suggesting that higher ESG performance is associated with lower volatility and greater resilience to market shocks.

Most of the research that has sought to investigate the risk and return characteristics of portfolios and sustainability relies on scores developed by ESG Ratings agencies. However, the ratings methodologies differ from provider to provider and, unsurprisingly, the rating of one provider does not necessarily correlate well with the rating assessments of

others, Berg et al. (2022). Charlin et al. (2022) investigate four major rating providers, ISS, MSCI, S&P, and Sustainalytics, and reveals significant inconsistencies, with ESG ratings exhibiting very low reliability (18.3%) and agreement (5.4%). Gyönyöróvá et al. (2021) find similar inconsistencies in ESG ratings across providers. They find that these variations in ESG rating are influenced by industry sector, country of domicile, and rating methodology. After controlling for rating agency and industry sector, Gregory (2022) finds a positive relationship between firm size and ESG rating; a result that suggests that ESG scores may be influenced by factors beyond a firm’s actual sustainability performance, such as differences in data availability and perceptions about organizational legitimacy.

4.3 Framework and Methodology

4.3.1 Data and Modeling

In this paper, we evaluate the pension experience of a representative 45-year-old US-based individual expecting to retire in 20 years (the accumulation phase), with an assumed post-retirement lifespan of 20 years (the decumulation phase). The investor’s income is derived from earned wages, a portion of which is allocated to savings and subsequently invested in a diversified portfolio composed of four asset classes: Equity, Fixed Income, Alternatives, and Cash. Our investment model tracks quarterly contributions, representing the savings and pension accumulation over time, following a structured asset allocation strategy. Below, we provide more details of this representative pension member.

1. Salary Component:

- The initial salary is set at USD 45,000, corresponding to the median salary for a 45-year-old individual, based on data from the 2022 Federal Reserve Survey of Consumer Finances (SCF).
- Salary growth is modeled annually in line with the Average Wage Index (AWI) published by the US Bureau of Labor Statistics.

2. Saving Component:

- Initial accumulated savings at age 45 are set at USD 64,428, according to US Bureau of Labor Statistics data.
- Subsequent savings are calculated on a quarterly basis, and represent 15% of the annual salary. The annual contribution is allocated equally across the four quarters of each year.

3. **Asset Allocation:** To model changes in asset class allocations over the investment horizon, we draw on the methodologies of 27 target-date funds operating in the US market. The information about these target-date funds is sourced from Morningstar, and has been cross-checked with relevant prospectuses as of July 2024 (Table 4.1). Among the 27 target-date funds obtained, we adopt BlackRock’s fund as our base case, given its dominant market share. We select three other representative glide paths to reflect varying approaches to equity exposure relative to the overall average across all glide paths. Specifically, we identify:

- (i) the most aggressive glidepath, characterized by the highest equity allocation during the pre-retirement accumulation period;
- (ii) the most conservative glidepath, characterized by the lowest equity allocation during the pre-retirement accumulation period; and
- (iii) a moderate glidepath, defined as the glidepath with equity exposure closest to the average of all 27 target-date funds.

The evolution of equity allocations across the aggressive, moderate, and conservative glidepaths is depicted in Figure 4.1.

4. **Pension Calculation:** We account for portfolio dynamics by modeling the growth in pension wealth at time t .

$$\text{Pension}_t = (\text{Pension}_{t-1} + \text{Savings}_t) \times \left[\sum_i (\text{Weight}_{i,t} \times (1 + \text{Net Return}_{i,t})) \right]$$

where i represents asset classes.

At each quarter, t , the accumulated pension consists of the previous quarter’s balance plus new contributions, compounded by the weighted performance of the portfolio.

5. **Environmental, Social and Governance (ESG) scores:** We source quarterly ESG scores for S&P 500 constituents over the 2002–2022 period from Refinitiv.

- Refinitiv’s ESG database offers standardized assessments of a firm’s environmental, social, and governance performance, expressed as a composite score from 0 to 100, with higher values indicating stronger ESG performance.
- The scores are derived from publicly available sources, including company disclosures, regulatory filings, news outlets, and reports from non-governmental organizations (NGOs).

Target Date Fund Provider

1290 Funds	Nuveen
American Century Investments	PGIM Investments
American Funds	PIMCO
BlackRock	Schwab Funds
Dimensional Fund Advisors	State Street Global Advisors
Empower Funds	T. Rowe Price
Fidelity Investments	Transamerica
Franklin Templeton Investments	Vanguard
GuideStone Funds	Victory Capital
iShares	Voya
John Hancock	
JPMorgan	
MassMutual	
MFS	
Mutual of America	
Nationwide	
Natixis Funds	

Table 4.1: Funds Utilized for Asset Allocation Methodology.

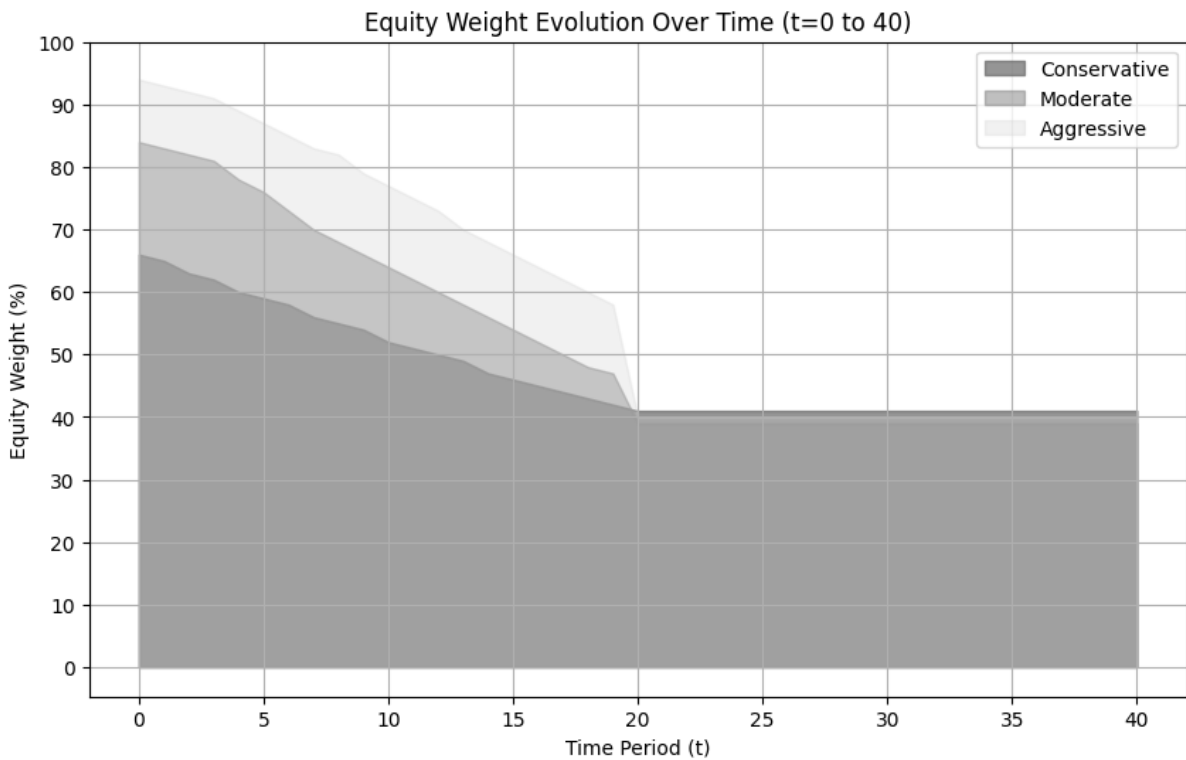


Figure 4.1: Equity allocation patterns across representative glidepaths.

4.3.2 Sustainability Impact

We consider two distinct investment strategies: a "traditional" approach and an ESG-screened approach. The primary distinction between the two lies in the treatment of the equity component of the portfolio, while the non-equity allocations (Fixed Income, Alternatives, and Cash) remain consistent across strategies. The traditional approach is based on an S&P 500 index tracker. The ESG-screened approach incorporates environmental, social, and governance (ESG) scores as an additional portfolio construction criterion, applied at varying intensities.

Building on this enhanced screening process, we define the two distinct ESG-screened investment strategies as follows:

- **Market cap-weighted ESG-screened S&P 500 portfolio (MC weighted):** This investment strategy holds S&P 500 stocks in proportion to their market value, but only includes those with an ESG score above a set threshold (α).
 - *Portfolio Weighting:* Stocks are weighted proportionally to their market capitalization.
 - *Stock Selection:* Only stocks with ESG scores exceeding a predefined threshold (α) are included.
- **ESG Weighted ESG-screened S&P 500 portfolio (ESG Weighted):** Incorporates ESG scores into every stage of portfolio construction.
 - *Portfolio Weighting:* Good ESG scores translate into larger portfolio weights.
 - *Stock Selection:* Similar to the MC weighted, the stock's ESG score must be above a predefined threshold.

Alpha represents the investor's sustainability preference and sets a percentile cut-off for including stocks based on their ESG scores. Only stocks with scores above this cut-off are included in the portfolio; those below are excluded. An alpha of 100 means no exclusion, effectively replicating an index tracking portfolio. We assess portfolio performance at alpha levels corresponding to the 75th (★), 50th (●), and 25th (▲) percentiles.

4.3.3 Conceptual Framework

The investment horizon examined in this study spans 40 years. Due to the limited availability of comprehensive data, we extend the dataset (2002-2022) by estimating a Vector Autoregressive (VAR) model to capture the dynamic interdependencies between the four asset classes, while incorporating the influence of inflation. Several studies have

applied VAR models to ESG investments. For instance, Andersson et al. (2022) show that lagged ESG portfolio returns can predict future returns of other ESG portfolios and reveal significant causal linkages between ESG assets and major financial markets. Umar et al. (2020) use a VAR model to study how shocks move between global ESG markets over time. Arouri et al. (2025) apply a time-varying VAR model to see how the links and hedging benefits between ESG and other assets change as markets evolve. Wang et al. (2024) also use a time-varying VAR model to explore how green and traditional energy markets influence each other under different market conditions.

Returns for the S&P 500 portfolio, along with those of the other asset classes, are derived from historical quarterly returns of selected exchange-traded funds (ETFs), as detailed in Table 4.2. The selected ETFs were primarily sourced from Vanguard due to their data availability and strong market representation. Quarterly inflation data for the same period (2002-2022) is sourced from the U.S. Bureau of Labor Statistics.

Fund Name	Asset Class	OCF
Vanguard 500 Index Fund	Equity	0.14%
Vanguard Total Bond Market Index Fund	Fixed Income	0.15%
Vanguard Real Estate Index Investor	Alternative	0.27%
T Rowe Price Cash Reserves Fund	Cash	0.40%

Source: Morningstar database as of May 2024

Table 4.2: Selected funds and their ongoing charges (OCFs) by asset class

To support our stochastic modeling approach, we first assess the suitability of the dataset for the VAR model using a number of statistical tests: the Augmented Dickey-Fuller (ADF), Kwiatkowski-Phillips-Schmidt-Shin (KPSS), and Phillips-Perron (PP) stationarity tests. The results of these tests are presented in Table 4.3. In practice, these tests are interpreted jointly: if both the ADF and PP tests fail to reject the null hypothesis, and the KPSS test also fails to reject its null hypothesis, the results provide evidence in favor of stationarity. In cases where the tests yield conflicting outcomes, further investigation is typically required.

Strategy	ADF p-value	KPSS p-value	PP p-value	ADF Stat.	KPSS Stat.	PP Stat.	Final Stat.
MC weighted▲	4.82e-14	0.100000	2.13e-14	True	True	True	True
MC weighted●	7.99e-14	0.100000	5.28e-14	True	True	True	True
MC weighted★	5.36e-14	0.100000	2.80e-14	True	True	True	True
ESG Weighted▲	6.69e-14	0.100000	1.38e-14	True	True	True	True
ESG Weighted●	1.46e-14	0.100000	2.21e-15	True	True	True	True
ESG Weighted★	7.54e-15	0.100000	1.03e-15	True	True	True	True
Index	7.46e-14	0.100000	2.93e-14	True	True	True	True
Fixed Income	1.99e-10	0.045135	1.35e-10	True	False	True	True
Alternative	2.49e-10	0.100000	2.47e-13	True	True	True	True
Cash	9.66e-02	0.095170	2.73e-01	False	True	False	False
Inflation	6.58e-01	0.100000	3.05e-14	False	True	True	True

★: 75th Percentile Threshold ●: 50th Percentile Threshold ▲: 25th Percentile Threshold

Table 4.3: Stationarity Test Results for Each Variable

Assessing the stationarity of the cash return series presents certain challenges. Both the ADF and PP tests fail to reject the null hypothesis, while the KPSS test, which assumes stationarity under the null, does not reject stationarity. Such inconsistencies are not uncommon in low-variance series that may exhibit structural breaks. Visual inspection of the series reveals patterns indicative of regime changes, with extended periods of near-zero returns following the 2008 global financial crisis and again after 2020, due to the COVID-19 pandemic. These episodes represent well-documented sources of structural breaks, which are known to affect the power and size properties of standard unit root tests (Perron, 1989; Zivot et al., 2002).

To further test for stationarity in the presence of structural changes in the cash return series, we apply the Zivot-Andrews test in Table 4.4. The test statistic of -4.731 lies just above the 5% critical value (-4.81) but is below the 10% level (-4.57), with a p-value of 0.065. While the evidence is not strong enough to reject the unit root at the traditional 5% level, the result, combined with the KPSS finding and the known structural changes in the cash returns, provides sufficient justification to treat the cash series as weakly stationary.

Statistic	Value
Test Statistic	-4.731
P-value	0.065
Number of Lags	6
Trend	Constant
Critical Values	-5.28 (1%), -4.81 (5%), -4.57 (10%)

Table 4.4: Zivot-Andrews unit root test result Cash return series

Because all of the series in our dataset are now confirmed to be stationary, they are suitable for use in a VAR model. Our best estimate is obtained by allocating 90% of the

data to the training set, with the remaining 10% reserved for testing model performance. Our primary interest lies in the joint dynamic relationships of the variables rather than in testing specific null hypotheses for each parameter. This approach is consistent with the broader VAR literature, where the emphasis is often placed on impulse response functions, forecast error variance decompositions, and overall model dynamics, rather than on the significance of individual coefficients (Stock et al., 2001; Bernanke et al., 2005; Campbell et al., 2005).

As Stock et al. (2001) note, inference based solely on individual coefficient significance can be misleading in multivariate time series settings, and it is more informative to analyze the joint behavior of the system. Similarly, in forecasting and structural VAR applications, model evaluation is typically based on predictive accuracy or the response to identified shocks, rather than on p-value thresholds for individual parameters (Giannone et al., 2015; Blanchard et al., 2002).

The VAR order selection criteria produce mixed conclusions for the three equity strategies and among the information metrics, as shown in Table 4.5. While the Akaike Information Criterion (AIC) and Final Prediction Error (FPE) consistently identify a lag order of 4 or 5 as optimal, both the Bayesian Information Criterion (BIC) and Hannan–Quinn Information Criterion (HQIC) favor a lag order of 1 across all models. These differences reflect the distinct penalty structures applied by each criterion: AIC and FPE tend to favor more complex models with better in-sample fit, whereas BIC and HQIC prioritize parsimony by penalizing additional lags more heavily.

Lag	Index Tracker				ESG Weighted				MC weighted			
	AIC	BIC	FPE	HQIC	AIC	BIC	FPE	HQIC	AIC	BIC	FPE	HQIC
0	-39.07	-38.91	1.077e-17	-39.01	-38.95	-38.79	1.218e-17	-38.88	-39.21	-39.05	9.352e-18	-39.15
1	-40.47	-39.51*	2.662e-18	-40.09*	-40.45	-39.48*	2.723e-18	-40.06*	-40.59	-39.62*	2.365e-18	-40.20*
2	-40.53	-38.76	2.538e-18	-39.83	-40.51	-38.74	2.595e-18	-39.80	-40.64	-38.88	2.263e-18	-39.94
3	-40.62	-38.05	2.381e-18	-39.60	-40.45	-37.88	2.828e-18	-39.43	-40.63	-38.06	2.359e-18	-39.61
4	-40.74*	-37.36	2.235e-18*	-39.40	-40.67	-37.29	2.402e-18*	-39.33	-40.81*	-37.43	2.085e-18*	-39.47
5	-40.68	-36.51	2.589e-18	-39.02	-40.70*	-36.52	2.541e-18	-39.04	-40.79	-36.61	2.330e-18	-39.13

Table 4.5: VAR Order Selection Criteria Across Equity Strategies (* indicates minimum)

To further assess which order is efficient, we employ a naive forecasting model as a benchmark, which assumes that the best predictor of a future value is simply the most recent observation. This approach is widely used in time series analysis to evaluate the incremental predictive value of more sophisticated models, such as a VAR, across multiple asset classes. Its simplicity and minimal assumptions make it particularly useful for evaluating the relative performance of more complex models where series exhibit low autocorrelation or near-random walk behavior. In financial contexts, the naive forecast can be surprisingly difficult to outperform (Diebold et al., 2002; Stock et al., 2001). As such, outperforming a naive model provides evidence that the forecasting method captures meaningful temporal dynamics beyond simple persistence.

The forecasting performance comparison between the VAR(1) and VAR(4) models reveals that the simpler VAR(1) model generally outperforms the more complex VAR(4) across most metrics and asset classes, as illustrated in Table 4.6. Specifically, VAR(1) demonstrates lower RMSE, MAE, and MASE for the majority of assets, indicating superior accuracy in point forecasting. Additionally, VAR(1) exhibits better Theil's U statistics for all series except Fixed Income, suggesting it provides more reliable relative forecasts overall. While VAR(4) marginally improves RMSE for Fixed Income, these gains are minimal and come at the expense of increased forecast errors in other areas, reinforcing the advantage of the more parsimonious VAR(1) model in terms of both efficiency and predictive accuracy.

The VAR models consistently outperform the naive benchmark, with improvements across RMSE, MAE, and MAPE for equity returns, fixed income, and alternative assets. Even for inflation and cash returns, where the models tend to face additional challenges due to lower volatility or near-zero values, VAR(1) still shows lower error metrics than the naive model, indicating that it can still provide valuable insights despite the inherent difficulties in these series. Given the results, we proceed with the VAR(1) model in our modeling because it demonstrates greater efficiency, reliability, and accuracy in forecasting across the majority of asset classes.

Asset	RMSE		MAE		sMAPE (%)		MASE		Theil's U	
	V1	V4	V1	V4	V1	V4	V1	V4	V1	V4
Equity Index	0.0868	0.1142	0.0733	0.0873	132.01	132.02	0.7571	0.9017	0.7052	0.7739
Fixed Income	0.0394	0.0389	0.0299	0.0306	145.67	167.13	0.9375	0.9599	0.9090	0.9084
Alternative	0.0997	0.1450	0.0813	0.1120	119.92	136.60	0.8239	1.1347	0.6908	0.8224
Cash	0.0027	0.0039	0.0018	0.0026	151.55	188.28	1.6182	2.3482	0.5906	0.8922
Inflation	0.0158	0.0166	0.0129	0.0130	129.48	137.23	1.1081	1.1147	0.6675	0.6867

Table 4.6: Forecast Performance Comparison: VAR(1) vs VAR(4)

Let \mathbf{Y}_t represent a five-dimensional vector at time t . The following equation then gives the estimated VAR(1) model:

$$\mathbf{Y}_t = \mathbf{C} + \Phi \cdot \mathbf{Y}_{t-1} + \epsilon_t$$

where: \mathbf{Y}_t is the vector of asset class returns and inflation,

$$\mathbf{Y}_t = \begin{bmatrix} \text{Equity Return } (EQ_t) \\ \text{Fixed Income Return } (FI_t) \\ \text{Alternative Assets Return } (ALT_t) \\ \text{Cash Return } (CASH_t) \\ \text{Inflation Rate } (INFL_t) \end{bmatrix}$$

\mathbf{C} is the intercept vector,

$$\mathbf{C} = \begin{bmatrix} c_{\text{EQ}} \\ c_{\text{FI}} \\ c_{\text{ALT}} \\ c_{\text{CASH}} \\ c_{\text{INFL}} \end{bmatrix}$$

Φ is the coefficient matrix,

$$\Phi = \begin{bmatrix} \phi_{11} & \phi_{12} & \phi_{13} & \phi_{14} & \phi_{15} \\ \phi_{21} & \phi_{22} & \phi_{23} & \phi_{24} & \phi_{25} \\ \phi_{31} & \phi_{32} & \phi_{33} & \phi_{34} & \phi_{35} \\ \phi_{41} & \phi_{42} & \phi_{43} & \phi_{44} & \phi_{45} \\ \phi_{51} & \phi_{52} & \phi_{53} & \phi_{54} & \phi_{55} \end{bmatrix}$$

And $\boldsymbol{\epsilon}_t$ is the residual vector.

$$\boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \Sigma)$$

\mathbf{Y}_t captures current values, while the coefficient matrix Φ is estimated on historical values, and models autoregressive dependencies and cross-variable effects in \mathbf{Y}_{t-1} . The intercept vector \mathbf{C} accounts for constant influences, and the residual vector $\boldsymbol{\epsilon}_t$ captures unexplained variations and stochastic shocks.

Using the estimated VAR(1) model based on 20 years (2002–2022) of quarterly data, we extend the dataset to span a whole 40-year investment horizon through Monte Carlo simulations. Specifically, we generate 10,000 simulated paths, maintaining the estimated dynamic relationships between the asset classes and inflation. The simulation process initializes each path using the historical mean from the available dataset. It evolves forward quarter-by-quarter by applying the estimated VAR coefficients, the constant intercept, and innovations drawn randomly from a multivariate normal distribution, with the residual covariance structure estimated from the data.

Table 4.7 compares the first two moments between the historical and simulated data. The close alignment, with relative errors generally below 10%, indicates that the simulation framework effectively replicates the distributional properties of the original series, providing a robust foundation for the long-term projections used in our retirement investment model. Similar results are drawn for the two sustainable ESG-screened strategies and presented in the appendix.

Variable	Historical	Simulated	Abs. Error	Rel. Error (%)
Mean				
Equity Index	0.02274	0.02489	0.00215	9.43
Fixed Income	0.01109	0.01096	0.00012	1.09
Alternative	0.02827	0.03010	0.00183	6.48
Cash	0.00292	0.00260	0.00033	11.15
Inflation	0.00525	0.00509	0.00016	3.07
Standard Deviation				
Equity Index	0.08287	0.08639	0.00352	4.25
Fixed Income	0.01671	0.01739	0.00068	4.07
Alternative	0.11048	0.11525	0.00477	4.32
Cash	0.00365	0.00382	0.00017	4.59
Inflation	0.00950	0.00988	0.00037	3.92

Table 4.7: Comparison of Historical and Simulated Moments (10,000 Simulations)

4.3.4 Investor Utility Evaluation

The expected utility calculation is based on annualized consumption and end-of-year wealth, adjusted for survival and death probabilities, as well as individual preferences for risk, time, and bequests. The key steps are outlined below:

Accumulation Phases

Wealth Tracking During Accumulation

- **Formula:**

$$W_t = (W_{t-1} + s) \cdot (1 + r_t)$$

Where:

- W_{t-1} : Wealth at the previous quarter.
- s : Annual saving rate, fixed at 15% of salary ($\approx 3.57\%$ per quarter).
- r_t : Portfolio return at time t , calculated as:

$$r_t = \sum_{i=1}^4 w_{i,t} \cdot R_{i,t}$$

- * $w_{i,t}$: Weight allocated to asset class i at time t .
- * $R_{i,t}$: Return of asset class i at time t .

Consumption Calculation in the Accumulation Period

- **Formula:**

$$C_t = (1 - s) \cdot \frac{Y_t}{4}$$

Where:

- s : Saving rate (15% annually, $\approx 3.57\%$ per quarter).
- Y_t : Annual salary at time t .

Decumulation Phase

Wealth Tracking During Decumulation

- **Formula:**

$$W_t = W_{t-1} \cdot (1 + r_t) - W_{\text{withdrawal}}$$

Where:

- W_{t-1} : Wealth at the previous quarter.
- r_t : Portfolio return at time t .
- $W_{\text{withdrawal}}$: Quarterly withdrawal, calculated as:

$$W_{\text{withdrawal}} = \frac{0.04 \cdot W_{\text{acc}}}{4} \cdot (1 + \pi_y)$$

- * W_{acc} : Accumulated wealth at retirement.
- * π_y : Quarterly inflation rate for quarter y .

During decumulation, with no residual from salary savings, consumption is fully covered by withdrawals.

$$C_t = W_{\text{withdrawal}}$$

The 4% withdrawal rule is derived from Bengen (1994), who demonstrated that a constant real withdrawal rate of approximately 4% could sustain a balanced portfolio over a long-term retirement horizon. The rule was subsequently validated and popularized by the Trinity Study - Cooley et al. (1998) and has become a standard benchmark in the retirement literature. A large body of work has since evaluated and extended this rule, including Guyton et al. (2006), Spitzer (2007), and Scott et al. (2008), who highlight both its practical usefulness and its limitations under different market conditions.

Expected Lifetime Utility

- **Formula:**

$$E[U(C, W)] = \sum_{t=0}^{T-1} \beta^t \cdot \left[{}_t p_x \cdot \frac{(C_t)^{1-\gamma}}{1-\gamma} + {}_t p_x \cdot q_{x+t} \cdot \kappa \cdot \frac{(W_t)^{1-\gamma}}{1-\gamma} \right]$$

Where:

- ${}_t p_x$: Probability of surviving from age x to $x + t$.
- q_{x+t} : Probability of dying during the next period at age $x + t$.
- β : Discount factor, defined as:

$$\beta = \frac{1}{1 + \rho}$$
- ρ : Rate of time preference.
- κ : Bequest preference parameter.
- γ : Risk aversion parameter.
- C_t : Consumption at time t , contributing to utility if the individual is alive.
- W_t : Wealth at time t , contributing to utility as a bequest if the individual dies.

The model adopts a beginning-of-period timing convention. At time t , the individual is alive with probability ${}_t p_x$, consumes C_t , and subsequently faces a probability of death q_{x+t} during the period. In the event of death, utility is derived from bequeathed wealth W_t .

Event	Inception	Retirement	End of Plan
Time	0	$T = 20$	$\tau = 40$
Age	45	65	85

Table 4.8: Timeline of Events

Input Name	Value	Description
Number of Quarters	160	Total number of quarters (equivalent to 40 years)
Number of Simulations	10,000	Number of Monte Carlo simulation paths
Initial Salary	\$45,000	Annual salary at age 45, based on the 2022 Federal Reserve Survey of Consumer Finances (latest data available)
Initial Saving	\$64,428	Initial retirement savings, sourced from US Bureau of Labor Statistics
Saving Rate p.a.	15%	Annual saving rate; adjusted to quarterly in the model
Equity Ongoing Charge	0.035%	Quarterly fee derived from a 0.14% annual ongoing charge
Fixed Income Ongoing Charge	0.0375%	Quarterly fee derived from a 0.15% annual ongoing charge
Alt. Investments Ongoing Charge	0.0676%	Quarterly fee derived from a 0.27% annual ongoing charge
Cash Ongoing Charge	0.1002%	Quarterly fee derived from a 0.40% annual ongoing charge
Withdrawal Rate p.a.	4%	Annual withdrawal rate during retirement
Bequest Parameter (κ)	5	Strength of the bequest motive
Time Preference (ρ)	3%	Time preference discount factor
Risk Aversion (γ)	5	Degree of risk aversion
Income Floor	\$20,000	Minimum retirement income threshold based on US basic needs estimates.

Table 4.9: Model Input Parameters

Table 4.9 is a summary of our modeling assumptions, which reflect realistic conditions in the US market. The parameters are drawn from recent sources, including the Federal Reserve, the U.S. Bureau of Labor Statistics, and market-based estimates of investment charges. Salary, savings, and income floor values are expressed in U.S. dollars, while saving, withdrawal, and fee rates align with typical patterns observed in U.S. retirement planning. The coefficient of relative risk aversion is consistent with widely used calibrations in lifecycle portfolio choice models (e.g. Cocco et al. (2005); Gomes et al. (2005); Benzoni et al. (2007); Campbell et al. (2002)) and lies within the standard range documented in the literature. The bequest parameter reflects a moderate “warm-glow” motive, consistent with empirical and structural lifecycle models that incorporate bequest preferences to match observed wealth decumulation and intergenerational transfers (e.g. De Nardi (2004); Ameriks et al. (2011)).

4.4 Results and Discussion

We now present our findings by analyzing a range of metrics that allow a comparison between the traditional equity portfolio (proxied by an S&P 500 index tracker) and our two sustainable ESG-screened S&P 500 portfolios: a market capitalization-weighted version and an ESG-Weighted version. The analysis is undertaken from the perspective of a representative US individual investor whose portfolio includes four asset classes: Equity, Fixed Income, Alternatives, and Cash.

4.4.1 Base Case

The analysis focuses on the performance difference between the market-cap-weighted ESG-screened S&P 500 portfolio (MC weighted) and the traditional equity portfolio. The asset allocation for both strategies is guided by BlackRock's glide path over the 40-year investment period. Asset returns and inflation are generated via 10,000 Monte Carlo simulations based on an estimated VAR(1) model. In the MC weighted strategy, the screening threshold (alpha) is set at 75, meaning that the portfolio includes only stocks with ESG scores above the 75th percentile.

In addition to the expected utility covered in Section 4.3.4, we extend our analysis to five other retirement performance metrics.

- **The 5th Percentile Final Wealth**, reflects extreme downside risk by indicating the terminal wealth level that is exceeded in 95% of simulated outcomes.
- **Average Real Income**, refers to the mean inflation-adjusted consumption over the entire investment horizon, reflecting the investor's standard of living.
- **The Income Trend Slope**, estimated by linear regression, indicates whether real income increases or declines over retirement years.
- **Plan Failure Probability**, measures the proportion of simulations in which income falls below a basic needs threshold.
- Finally, **Conditional Expected Shortfall**, captures the average cumulative income shortfall across all simulations where failure occurs, when the income floor is breached.

Metric	Index	MC weighted★
Average Utility	-7.98	-10.35
5 th Percentile Final Wealth	\$432,813	\$359,410
Average Real Income	\$38,961	\$37,241
Std. Dev. Real Income	\$15,207	\$15,997
Income Trend Slope	-\$743	-\$872
Plan Failure Probability	26%	38%
Conditional Expected Shortfall	\$61,884	\$63,226

★: 75th Percentile Threshold

Table 4.10: The S&P 500 Index Tracker vs. MC weighted under Blackrock glide path.

In all examined retirement performance metrics, the traditional equity portfolio outperforms the MC weighted strategy - Table 4.10. The resulting higher average utility (-7.98 versus -10.35) suggests that this approach better captures retiree preferences and delivers superior outcomes in terms of both consumption and bequests. It also leads to reduced tail risk, as captured by a higher 5th percentile final wealth. Furthermore, traditional equity portfolio provides a higher average real income (£38,961 against £37,241) and a less negative income trend (-£743 compared to -£872), suggesting that retiree experience more stable revenue over time.

In terms of downside risk, the MC weighted approach exhibits higher vulnerability. The probability of plan failure rises from 26% with the traditional equity portfolio to 38%, while the Conditional Expected Shortfall is marginally higher at £63,226 compared to £61,884. These findings suggest that while the MC weighted strategy may align with certain sustainable investment principles, *it underperforms the index tracker in delivering financial security and resilience in retirement.*

To assess the robustness of our simulated results, we compared retirement metrics across 10,000 and 100,000 Monte Carlo simulations. The differences observed across utility, income, plan failure rates, and downside risk were minimal and did not affect the interpretation of outcomes. Therefore, we proceed with 10,000 simulations in all subsequent analyses.

Sensitivity to ESG Thresholds

ESG-screening involves setting a threshold to exclude stocks with poor environmental, social, or governance (ESG) characteristics. In this analysis, we implement three screening variations based on percentile cut-offs within the S&P 500. The index case, equivalent to a passive investment in the S&P 500, includes all constituents (100th percentile). By contrast, the ESG-screened portfolios use ESG scores to exclude stocks that fall above three proposed thresholds, denoted in the results by ★, ●, and ▲, corresponding to

sustainability screens applied at the 75th, 50th, and 25th percentiles, respectively. This approach allows us to evaluate the impact of progressively stricter ESG thresholds on retirement investment outcomes. As the screening becomes more restrictive, less stocks are included and portfolio diversification tends to decline, which can increase exposure to concentration risk. We assess how this reduced diversification affects our selected retirement metrics highlighting the extent to which a heavily ESG-screened portfolio may increase the likelihood of plan failure.

Metric	Index	MC weighted★	MC weighted●	MC weighted▲
Average Utility	-7.98	-10.35	-12.81	-20.42
5 th Percentile Final Wealth	\$432,813	\$359,410	\$318,729	\$254,981
Average Real Income	\$38,961	\$37,241	\$35,846	\$33,974
Std. Dev. Real Income	\$15,207	\$15,997	\$16,848	\$18,328
Income Trend Slope	-\$743	-\$872	-\$977	-\$1,118
Plan Failure Probability	26%	38%	53%	92%
Conditional Expected Shortfall	\$61,884	\$63,226	\$62,174	\$74,836

★: 75th Percentile Threshold ●: 50th Percentile Threshold ▲: 25th Percentile Threshold

Table 4.11: The S&P 500 Index Tracker vs. MC weighted Portfolios under BlackRock Glide Path.

Once the ESG screening becomes more restrictive, retirement outcomes worsen across all key measures, Table 4.11. Plan Failure Probability increases steeply, rising from 38% under the mildest screen to 92% under the strictest. Average utility also deteriorates substantially, more than doubling the loss compared to both the S&P 500 index and the MC weighted at 75th percentile threshold. In adverse market conditions, final wealth is significantly lower, and real income becomes both reduced and less stable, with greater variability and a steeper decline over time.

Taken together, the results reveal a notable performance difference between a traditional equity portfolio and a market-cap-weighted ESG-screened S&P 500 portfolio. While the difference is modest with limited screening, it becomes much more pronounced as the ESG screening is tightened. This points to a clear trade-off between pursuing sustainable ESG goals and maintaining retirement security. In particular, more stringent ESG filters, especially those that exclude a significant portion of the S&P 500 constituents, can materially weaken the financial resilience of ESG-screened investment strategies.

4.4.2 Sustainable ESG-screened portfolios

To understand better how portfolio construction influences retirement outcomes, we compare our two sustainable ESG-screened equity portfolios, the market capitalization-

weighted version (MC weighted) and the ESG Weighted version, for a range of thresholds. This comparison provides insight into how design choices affect retirement outcomes under consistent exclusion criteria.

Threshold	Strategy	Mean Utility	5 th Perc. Wealth	Mean Income	St. dev. Income	Failure Prob. (%)
★ (75 th)	MC weighted	-10.35	\$359,410	\$37,241	\$15,997	38%
	ESG weighted	-8.50	\$413,861	\$39,344	\$15,308	27%
● (50 th)	MC weighted	-12.81	\$318,729	\$35,846	\$16,848	53%
	ESG weighted	-8.93	\$397,365	\$38,814	\$15,418	29%
▲ (25 th)	MC weighted	-20.42	\$254,981	\$33,974	\$18,328	92%
	ESG weighted	-11.02	\$340,297	\$37,082	\$16,125	40%

Table 4.12: Performance comparison of MC weighted and ESG Weighted strategies.

There are notable differences between the two sustainable ESG-screened portfolios, Table 4.12, particularly in terms of utility, 5th percentile final wealth, and plan failure probability. These differences become more pronounced as the ESG screening threshold becomes more stringent. Across all thresholds, the ESG-Weighted strategy consistently delivers more favorable retirement outcomes. It tends to achieve higher utility, greater average real income, and lower plan failure probabilities. For instance, at the strictest screening level the failure rate for the MC weighted portfolio reaches 92%, while the ESG Weighted version is only at 40%.

This pattern suggests that ESG-based weighting may enhance the performance of sustainable portfolios by reducing downside risk and contributing to more stable retirement income. The ESG-Weighted portfolio also shows less variability in the assessed retirement metrics, which supports its potential for delivering more consistent outcomes under tight screening conditions. It is also worth noting that conditional expected shortfall remains broadly similar across the two sustainable ESG-screened strategies, suggesting that while the ESG-Weighted approach may reduce the frequency of poor outcomes, it does not necessarily mitigate the severity of the losses.

4.4.3 Impact of Glide Path on Retirement Outcomes

Glide paths play a central role in managing both risk and portfolio growth over the investment period. Most lifetime retirement plans adopt a predefined trajectory for asset allocation, typically reducing equity exposure as retirement approaches. This gradual shift aims to mitigate the impact of potential market volatility on accumulated wealth in the latter stages of accumulation, while allowing for higher growth through equities in the earlier years.

In our analysis, we implement glide path methods based on 27 target-date funds operating in the U.S. market as of July 2024. From this set, three representative glide paths are selected to illustrate the range of asset allocation approaches: an aggressive glide path (characterized by the highest equity allocation during the pre-retirement phase), a moderate glide path (with equity exposure closest to the average of the 27 funds), and a conservative glide path (with the lowest equity allocation during the pre-retirement phase).

These three glide paths are used uniformly across all portfolio strategies under consideration: a traditional equity portfolio and two sustainable ESG-screened S&P 500 portfolios. This approach allows us to examine the extent to which the interaction between glide path and portfolio construction influences retirement outcomes. The moderate glide path serves as the benchmark to assess how shifts in equity exposure either upward (aggressive) or downward (conservative) influence key retirement performance metrics. The results are presented in Tables 4.13, 4.14, and 4.15.

With the traditional equity portfolio, the conservative glide path leads to lower income metrics but slightly higher average utility, with minimal change in the plan failure probability. This suggests that reduced equity exposure can preserve utility, though it may constrain retirement income. By contrast, the aggressive glide path improves income measures and reduces the plan failure probability by roughly 4%. However, these gains come at the cost of lower utility (−8.94 vs. −9.72) and a higher conditional expected shortfall. This trade-off highlights that while prolonged equity exposure can enhance income and downside wealth outcomes, it also exposes the portfolio to greater risk in adverse market conditions, an inherent characteristic of equity investing.

Metric	Index	ESG Weighted*	MC weighted*
Average Utility	−7.98	−8.45	−10.29
5 th Percentile Final Wealth	\$427,872	\$406,730	\$355,276
Average Real Income	\$38,623	\$38,977	\$37,045
Std. Dev. Real Income	\$15,218	\$15,257	\$16,051
Income Trend Slope	−\$769	−\$742	−\$887
Plan Failure Probability	27%	27%	39%
Conditional Expected Shortfall	\$59,352	\$64,265	\$60,967

*: 75th Percentile Threshold

Table 4.13: Conservative Glide Path: Comparison of Index, ESG Weighted*, and MC weighted* Strategies.

The market-cap-weighted ESG-screened S&P 500 portfolio (MC weighted) exhibits the smallest relative changes across glide paths when compared to the other strategies. Like the traditional equity portfolio, it shows consistent directional patterns, with a

notable improvement in plan failure probability with higher equity exposure.

Metric	Index	ESG Weighted*	MC weighted*
Average Utility	-8.94	-9.85	-11.60
5 th Percentile Final Wealth	\$468,330	\$445,072	\$389,018
Average Real Income	\$39,725	\$40,194	\$37,639
Std. Dev. Real Income	\$15,436	\$15,740	\$16,020
Income Trend Slope	-\$686	-\$651	-\$843
Plan Failure Probability	27%	27%	38%
Conditional Expected Shortfall	\$69,791	\$75,187	\$71,300

*: 75th Percentile Threshold

Table 4.14: Moderate Glide Path: Comparison of Index, ESG Weighted*, and MC weighted* Strategies.

The effects of glide path changes are most pronounced in the ESG-weighted strategy, which displays the greatest sensitivity particularly in utility and income measures. A change from the moderate to the aggressive glide path raises average income by 6%, and provides a better plan failure probability. These changes suggest enhanced overall performance and greater income stability over time. However, this shift is accompanied by a sharp deterioration in utility, declining by approximately 16% and a notable increase in downside risk, 14%. By contrast, the conservative glide path follows a similar pattern to the other strategies, with relatively stable utility and some improvement in shortfall severity.

Metric	Index	ESG Weighted*	MC weighted*
Average Utility	-9.72	-11.45	-12.34
5 th Percentile Final Wealth	\$448,531	\$422,339	\$367,592
Average Real Income	\$41,969	\$42,646	\$39,056
Std. Dev. Real Income	\$16,561	\$17,606	\$16,016
Income Trend Slope	-\$518	-\$467	-\$736
Plan Failure Probability	23%	24%	33%
Conditional Expected Shortfall	\$79,287	\$85,406	\$79,601

*: 75th Percentile Threshold

Table 4.15: Aggressive Glide Path: Comparison of Index, ESG Weighted*, and MC weighted* Strategies.

The results indicate that glide path changes have a greater impact on the two sustainable ESG-screened S&P 500 portfolios compared the traditional equity portfolio. The ESG-Weighted strategy responds most strongly to changes in equity exposure, especially

in utility and income metrics, while the MC weighted portfolio remains relatively stable. Despite these differences in sensitivity, both sustainable ESG-screened strategies consistently underperform the index across the three representative glide paths.

4.4.4 Linking Portfolio Contributions to Retirement Security

The saving rate is an essential component in retirement investing because it directly influences the amount invested over time and supports long-term wealth accumulation through compound growth. To evaluate the impact of contribution behaviour on retirement outcomes, we analyse how changes in the saving rate, specifically from 10%, 15%, and 20% affect utility, income and plan failure across different portfolio strategies.

Table 4.16 presents the directional changes in retirement outcomes resulting from adjustments to the saving rate, with the withdrawal rate held constant at 4% and using the BlackRock glide path. Changes are expressed in percentage terms for utility and average real income, and percentage points (pp) for plan failure probability.

Strategy	Avg Utility ($\Delta\%$)		Avg Income ($\Delta\%$)		Plan Failure (Δpp)	
	10→15	15→20	10→15	15→20	10→15	15→20
Index	60.17	46.79	2.72	2.65	-25	-16
MC weighted★	61.01	48.74	2.18	2.13	-29	-23
ESG Weighted★	60.91	47.61	2.84	2.76	-23	-15

★: 75th Percentile Threshold.

Table 4.16: Directional changes between Saving Rates (10% to 20%) with fixed 4% withdrawal.

Across all strategies, average utility displays the greatest improvement when increasing the saving rate, with an average gain of approximately 61% from 10% to 15%, and around 48% from 15% to 20%. This substantial gain in utility highlights the critical role of savings behaviour in enhancing retirement outcomes, particularly by avoiding undersaving during the accumulation phase.

Changes in average real income are modest across the three strategies, with the ESG-weighted strategy displaying slightly greater responsiveness and the MC weighted strategy the least. This suggests that higher savings contribute more to reducing future shortfall risk than to boosting immediate retirement income.

More substantial changes are observed in plan failure probability, with notable reductions across the traditional equity portfolio and both sustainable ESG-screened portfolios. The MC weighted strategy exhibits the largest reduction in plan failure probability, with a 29% drop when the saving rate increases from 10% to 15% (from 67% to 38%), and a further 23% reduction from 15% to 20% (from 38% to 15%).

Overall, higher saving rates substantially improve retirement resilience, particularly by enhancing utility and reducing plan failure risk, irrespective of portfolio strategy. Although the magnitude of these effects varies across portfolios, no strategy demonstrates clear dominance based solely on contribution levels. Because savings are derived from earned income, their impact is most pronounced during the accumulation phase, when the investor is actively employed and salary income is available.

4.4.5 Sustainability of Varying Withdrawal Rates

The accumulation phase enables investors to build sufficient pension wealth for retirement, but the decumulation phase is often more critical. During this stage, the challenge lies in managing the accumulated wealth to provide sustainable income for the remainder of life. With employment income no longer available, an appropriate investment and withdrawal strategy is essential to ensure that wealth lasts throughout the decumulation period.

To assess the sensitivity of retirement outcomes to spending behaviour, we analyse the impact of varying the withdrawal rate from 2% to 8% on key performance metrics. The saving rate is fixed at 15% under the BlackRock glide path, with quarterly withdrawal rates increased in three increments: 2% to 4%, 4% to 6%, and 6% to 8%, Table 4.17.

Strategy	Avg Utility ($\Delta\%$)			Avg Income ($\Delta\%$)			Ruin Probability (%)				Plan Failure (Δpp)		
	2→4	4→6	6→8	2→4	4→6	6→8	2%	4%	6%	8%	2→4	4→6	6→8
Index	93.16	-	94.17	20.66	17.12	14.62	0	0	1.40	29.02	-65.01	-23.83	-2.34
MC weighted*	93.30	-	-	18.49	15.60	13.50	0	0	1.59	38.44	-59.86	-34.24	-3.43
ESG Weighted*	93.20	-	-	21.13	17.44	14.85	0	0	1.81	29.10	-62.10	-23.42	-2.93

*: 75th Percentile Threshold.

Table 4.17: Performance Changes with Withdrawal Rates (2% to 8%) and Fixed 15% Saving Rate.

Withdrawal patterns are closely linked to a portfolio’s ability to sustain an adequate post-retirement lifestyle. During the accumulation phase, when income is derived from salary, the basic needs threshold (\$20,000) is consistently exceeded. In retirement, however, income depends entirely on withdrawals from accumulated wealth, making the sustainability of the withdrawal rate a critical factor. Consequently, plan failure probability, as the proportion of simulations in which income falls below the basic needs threshold, is most relevant in the decumulation phase and is directly influenced by the withdrawal rate. At a 2% withdrawal rate, all three portfolios exhibit elevated plan failure probabilities, with the traditional equity portfolio strategy producing a failure rate of 91.32%, the MC weighted of 97.63%, and the ESG-weighted portfolio of 88.71%. Increasing the withdrawal rate to 4% results in substantial reductions in failure probability by 65.01, 59.86,

and 62.10 percentage points, respectively. Meaning the new plan probability of failure becomes 26.31% (Index tracker), 37.77% (MC Weighted), and 26.61% (ESG Weighted).

Furthermore, a withdrawal rate of 8% results in plan failure probabilities that are close to zero, indicating that nearly all simulated outcomes are able to meet the basic income requirement for all three portfolios. However, higher withdrawal rates introduce a new challenge not observed at lower levels: from 6% and above, the portfolios begin to exhibit a measurable probability of ruin, with MC weighted recording the highest at 38.44%. The increase in ruin probability could also explain deteriorating utility at higher withdrawal rates, “-” denotes a decline in utility (i.e., a movement to a more negative value).

Across withdrawal rate scenarios, the three strategies exhibit broadly similar patterns in utility, income, and plan failure probability, with differences in magnitude rather than direction. The ESG-Weighted portfolio generally delivers the highest real income gains and is largely comparable to the traditional equity portfolio across other metrics. The MC weighted portfolio shows the weakest overall results, with higher risk and lower utility, particularly at withdrawal rates above 6%.

4.5 Conclusion

This paper contributes to the limited literature on the integration of Environmental, Social, and Governance (ESG) factors into individual retirement portfolios. We address this gap by evaluating the performance of a traditional equity investment strategy with two sustainable ESG-screened alternatives: a market-cap-weighted and ESG-weighted approach for a U.S.-based individual pension plan member.

Our analysis reveals several important results. Although ESG integration introduces potential long-term sustainability benefits, it also poses a trade-off for retirement security because both ESG-screened US equity portfolios exhibit weaker performance relative to a traditional US equity portfolio. We assess performance primarily through the average utility derived from 10,000 simulated investment paths per strategy, where the traditional approach outperforms the two ESG-screened approaches. The ESG-screened portfolios also have weaker downside characteristics, including lower 5th-percentile wealth outcomes, higher probabilities of plan failure, and larger conditional expected shortfalls.

However, the degree of underperformance differs across the two ESG-screened portfolios. At the 75th percentile threshold, the ESG-weighted portfolio achieves average utility close to that of the traditional equity portfolio and delivers higher average real income. By contrast, the market-cap-weighted sustainable portfolio consistently underperforms the S&P 500 benchmark. Furthermore, performance is highly sensitive to ESG screening intensity: under stricter ESG constraints such as the market-cap-weighted portfolio at the 25th percentile, plan failure rates rise to critical levels, severely compromising retirement

security.

In conclusion, the findings suggest that sustainable investing and retirement security can be pursued simultaneously, though doing so requires deliberate and well-calibrated portfolio construction. Future research may focus on determining optimal ESG thresholds, experimenting with alternative weighting schemes, and integrating individual-specific sustainability and utility preferences. Because sustainable investing continues to expand, ensuring that sustainability objectives complement, rather than compromise, long-term retirement security will be critical for investors seeking to balance sustainability priorities with financial outcomes.

Appendix for Chapter 4

4.A Additional Results

To complement the main analysis, Table 4.18 presents additional forecast performance results focusing on the two sustainable ESG-screened strategies. Consistent with the broader findings, the VAR(1) specification generally outperforms VAR(4) across key forecast accuracy metrics. Although VAR(4) occasionally yields slightly better relative performance in terms of Theil's U, the overall results reinforce the earlier conclusion that the more parsimonious VAR(1) model provides a more reliable and efficient forecasting approach.

Asset	RMSE		MAE		sMAPE (%)		MASE		Theil's U	
	V1	V4	V1	V4	V1	V4	V1	V4	V1	V4
MC weighted★	0.0765	0.1032	0.0634	0.0773	136.13	138.48	0.7672	0.9348	0.7316	0.7743
MC weighted●	0.0595	0.0813	0.0483	0.0597	133.47	137.37	0.7479	0.9238	0.7185	0.7670
MC weighted▲	0.0391	0.0532	0.0332	0.0392	136.69	124.06	0.7599	0.8964	0.7226	0.7724
ESG Weighted★	0.0939	0.1243	0.0822	0.0982	142.54	148.32	0.8527	1.0181	0.6906	0.6685
ESG Weighted●	0.0835	0.1090	0.0730	0.0882	139.69	147.94	0.8483	1.0250	0.6740	0.6585
ESG Weighted▲	0.0609	0.0804	0.0538	0.0672	134.81	143.54	0.8539	1.0662	0.6460	0.6620

★: 75th Percentile Threshold ●: 50th Percentile Threshold ▲: 25th Percentile Threshold

Table 4.18: Forecast Performance Comparison of VAR(1) vs VAR(4) models for the two sustainable ESG-screened strategies at different thresholds.

Table 4.19 extends the comparison of historical and simulated moments to the sustainable ESG-screened strategies. Across thresholds and strategies, the simulated means and standard deviations closely track the historical values, with relative errors generally below 10%, confirming that the simulation framework reliably preserves the distributional characteristics of the underlying assets.

Variable	Threshold	Historical	Simulated	Abs. Error	Rel. Error (%)
Mean					
<i>Stock portfolios</i>					
Index Tracker	Baseline	0.02175	0.02003	0.00173	7.94
MC weighted	★	0.01717	0.01565	0.00152	8.86
MC weighted	●	0.01375	0.01258	0.00117	8.52
MC weighted	▲	0.00844	0.00762	0.00082	9.70
ESG Weighted	★	0.02335	0.02106	0.00229	9.82
ESG Weighted	●	0.02237	0.02014	0.00223	9.99
ESG Weighted	▲	0.01866	0.01672	0.00193	10.36
<i>Other Assets</i>					
Fixed Income	–	0.00991	0.01017–0.01023	0.00026–0.00033	2.63–3.29
Alternative	–	0.03000	0.02638–0.02672	0.00328–0.00362	10.93–12.06
Cash	–	0.00288	0.00317–0.00323	0.00029–0.00035	10.17–12.32
Inflation	–	0.02079	0.02173–0.02187	0.00094–0.00108	4.54–5.18
Standard Deviation					
<i>Stock portfolios</i>					
Index Tracker	Baseline	0.07584	0.07944	0.00360	4.75
MC weighted	★	0.06564	0.06875	0.00311	4.74
MC weighted	●	0.05367	0.05621	0.00254	4.73
MC weighted	▲	0.03460	0.03626	0.00166	4.81
ESG Weighted	★	0.07904	0.08281	0.00376	4.76
ESG Weighted	●	0.07649	0.08013	0.00364	4.76
ESG Weighted	▲	0.06713	0.07032	0.00320	4.76
<i>Other Assets</i>					
Fixed Income	–	0.01685	0.01763–0.01764	0.00078–0.00079	4.63–4.67
Alternative	–	0.10917	0.11423–0.11429	0.00506–0.00512	4.64–4.69
Cash	–	0.00383	0.00399–0.00401	0.00017–0.00018	4.47–4.70
Inflation	–	0.01331	0.01390–0.01391	0.00059–0.00060	4.45–4.52

★: 75th Percentile Threshold ●: 50th Percentile Threshold ▲: 25th Percentile Threshold

Table 4.19: Comparison of Historical and Simulated Moments Across Strategies (10,000 Simulations)

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Chapter 5

Optimal long-term sustainable portfolios¹

Abstract

We examine the role of sustainable investing within the frameworks of a finite-horizon life-cycle model as well as the classic Merton consumption–investment problem. We construct two sustainable versions of the S&P 500 by screening stocks using their ESG score: a market capitalization-weighted sustainable portfolio and an ESG score-weighted sustainable portfolio. Historical time series of returns are constructed by dynamically screening stocks, and geometric Brownian motions are then fitted to the time series. We find that risk-adjusted returns on sustainable portfolios decline significantly only when sustainability requirements are very stringent. Tail risk reduces the more sustainable a portfolio is. In both the life-cycle model and the Merton setting, we find that optimal consumption declines only very slightly as sustainability preferences strengthen, as long as these preferences remain moderate. Wealth accumulation and annuitization remain stable with moderately sustainable portfolios. The ESG-weighted portfolio performs better than the market capitalization-weighted portfolio in terms of consumption and wealth accumulation over the life cycle.

5.1 Introduction

Over the past decades, Environmental, Social, and Governance (ESG) criteria have gained increasing attention in both academic research and financial practice. This growing interest reflects a broader shift in investor preferences, where financial performance alone is no longer considered sufficient. Instead, there is a rising demand for investment

¹This chapter has benefited from discussions with Dr S.Y. Jeong of Sungkyunkwan University, South Korea, and Dr C. Jang of the University of Nottingham.

decisions to incorporate sustainability and ethical considerations alongside traditional measures of return and risk. The core idea behind ESG investing is to encourage the allocation of capital to companies that demonstrate strong environmental stewardship, social responsibility, and sound governance practices. By rewarding firms that align with these principles and withholding investment from those that do not, investors aim to influence corporate behavior, encouraging lagging companies to improve their practices or face disinvestment.

Many large, long-term investors such as insurance companies, pension funds, and sovereign wealth funds have signed up to the UN Principles for Responsible Investment (UN PRI). Created in 2006 by a global group of investors with support from the UN, these principles offer practical ways to include ESG issues in investment decisions. Since the inception of UN PRI, the number of signatories has grown quickly. By the end of 2024, 5,345 signatories (4,827 investors and 518 service providers) have joined, together managing around US\$128.4 trillion in assets, up from just US\$6.5 trillion in 2006 (UN PRI, 2024). These investors often use their influence as shareholders to push companies to act more responsibly. Individual investors also exhibit a similar trend, with more focus on ensuring that their investments align with ESG values.

This movement has also led to the emergence of a growing industry of ESG rating providers, which play a role similar to credit rating agencies. These providers assess and assign ESG scores to companies based on how well they perform across the three ESG dimensions. These scores help investors evaluate non-financial risks and sustainability performance, guiding portfolio selection and influencing asset pricing in modern financial markets.

Recent research on ESG ratings largely examines how differences across rating providers affect risk, return, and portfolio performance. Gibson Brandon et al. (2021) show that ESG rating disagreements, especially in environmental scores, are positively linked to stock returns. Berg, Kolbel, et al. (2022), building on Chatterji et al. (2016), find that measurement differences are the main source of rating divergence. Dimson et al. (2020) highlight that varying ESG weightings lead to mixed portfolio outcomes, with ESG market indices not consistently outperforming conventional indices. OECD (2020) also stresses that methodological choices and subjective judgments across providers drive large variations in ESG scores.

Even though ESG investing is becoming more popular, research on its impact shows that it has mixed results. Some studies strongly support adding ESG factors to financial decisions (e.g. De Souza Barbosa et al., 2023; Martiny et al., 2024; Friede et al., 2015; Aydoğmuş et al., 2022; Garcia-Bernabeu et al., 2024; Atz et al., 2023), saying that it helps to improve long-term performance and risk management, and also helps to meet investor values. Other research is more skeptical (e.g. Sahut et al., 2015; Calvo et al., 2015; Parfitt, 2024; Shaikh, 2022; Berg, Kolbel, et al., 2022), suggesting that ESG does

not always lead to better returns and that the data used to measure ESG performance can be inconsistent. Because of this, there is still no clear consensus about the necessity and effectiveness of ESG integration in financial planning and investment strategies.

In parallel with the finance literature, the actuarial and insurance literature has also examined sustainability and ESG considerations in various sectors such as insurance, pensions, and investment. Aburto Barrera et al. (2023) review sustainability issues along the insurance and pension value chain and conclude that ESG integration remains fragmented, with significant gaps in metrics and disclosure practices. Korn et al. (2023) show that, when life insurers incorporate sustainable assets in their portfolios, optimal allocations change meaningfully, suggesting that sustainability preferences can be reconciled with solvency constraints. Korn et al. (2025) also introduce a novel concept of sustainable taxation, resulting in adjustments to market drift coefficients that make unconstrained optimal portfolios satisfy sustainability demands. This mechanism aligns investment behavior with ESG objectives without requiring explicit constraints. Conceptually, it resembles state-imposed taxes or subsidies, serving as a theoretical policy tool to steer portfolios toward environmental goals.

Garbarino et al. (2024) demonstrate that subsidized flood insurance distorts housing market prices and can unintentionally increase climate vulnerability, while Berry-Stölzle et al. (2024) find that insurers with higher-quality climate risk management are better able to withstand natural disasters, underlining governance as a key ESG dimension. Gao et al. (2024) develop a dynamic climate–economic model for agricultural insurance products, showing how integrated climate risk modeling can improve pricing and sustainability of coverage.

Portfolio optimization with ESG factors has also been studied by a number of authors. Oikonomou et al. (2018) highlight that the choice of optimization method has a strong effect on ESG portfolio outcomes. A variety of techniques have been explored in this area. Pedersen et al. (2021) derives ESG-efficient frontiers that preserve performance with minimal loss. While Chibane et al. (2024) extends portfolio optimization to a noisy ESG setting, they show empirically that acknowledging ESG uncertainty pushes the frontier inward, eroding the attainable risk-return trade-off, especially for high-responsibility, low-risk portfolios. Wu et al. (2022) shows that multi-objective evolutionary optimization can improve ESG portfolio results while balancing risk and return. Vo et al. (2019) and Garrido-Merchán et al. (2023) use deep reinforcement learning to manage ESG-constrained portfolios, offering strong adaptability to changing market and sustainability conditions. Lauria et al. (2025) propose an approach that blends financial returns and ESG scores using a linearly weighted ESG preference, and find that increasing this ESG weight improves sustainability with only a modest effect on financial returns.

In the context of ESG investing, much of the existing literature has primarily concentrated on two strands of research. The first compares the performance of ESG-focused

funds to that of non-ESG funds, often evaluating whether ESG investments offer better, worse, or similar returns. While this comparison provides valuable insights into relative performance, it overlooks a deeper question: can ESG integration be optimized to enhance outcomes? The second strand of research addresses portfolio optimization, but often in a one-period model or over a short period of 5 years or less. The potential of ESG as a strategic tool, rather than a short-term objective or even merely a label, has received far less attention in the literature. Specifically, research that explores how ESG considerations can be actively incorporated into long-term portfolio optimization to improve risk-adjusted returns with long-term sustainability remains limited. Our paper addresses this gap by examining how a strategy of portfolio optimization under ESG preferences can serve not just as a performance benchmark but as a value-adding component in financial decision-making.

To this end, we construct sustainable portfolios which are weighted either by market capitalization or by ESG score. For the latter, we make extensive use of the softmax function. It is worth considering how this function is used in other disciplines and how it is parameterized. In statistics, a function very similar to the softmax arises in multinomial logistic regression and it is analogous to the logistic function in binary logistic regression (Frees et al., 2014, p. 82). In machine learning, neural networks that are designed for classification consist of several layers of neurons. At the end of the last layer, the raw scores (referred to as ‘logits’) are input to the softmax function to be converted into probabilities. The softmax parameter is known as the temperature (Goodfellow et al., 2017, pp. 185, 603). This terminology originates from statistical mechanics where the softmax is structurally identical to the Boltzmann distribution (Mézard et al., 2009, p. 25). In deep learning, there are several famous applications where the softmax function plays a critical role: image recognition (Krizhevsky et al., 2012; Krizhevsky et al., 2017), knowledge distillation (Hinton et al., 2015), natural language processing (Vaswani et al., 2017), and time series classification (Fawaz et al., 2019). The output of the softmax function is a probability and the softmax parameter, which is inversely related to the entropy in classification problems, is then regarded as a tunable hyperparameter to be empirically determined (Guo et al., 2017).

Plan of this chapter. The structure of this paper is as follows. Section 5.2 outlines the modeling framework, specifically the life-cycle model and the Merton model, as well as the construction of sustainable portfolios. Section 5.3 describes the ESG ratings data that we use as well as the parameterization of our model. Section 5.4 presents the empirical results, highlighting the performance outcomes and key differences between different sustainable portfolios. Finally, section 5.5 offers concluding remarks and reflections on the findings.

Relationship to previous chapter. We extend the life-cycle analysis of the previous chapter by allowing both asset allocation and saving to become decision variables. Instead of Monte Carlo simulations, we introduce a life-cycle optimization framework which compares two sustainable ESG-screened portfolios—market capitalization-weighted and ESG score-weighted—with a traditional S&P 500 index tracker fund. As in the previous chapter, the sustainable portfolios are based on the Refinitiv ESG scores. The previous chapter allowed four asset classes (equity, bond, cash, alternative) but only two asset classes (equity, risk-free asset) are available here, with a constant risk-free rate. Annuity at retirement is possible here but was disregarded in previous chapters. Both the continuous-time Merton model and a finite-horizon life-cycle model are used to numerically compute optimal consumption and portfolio decisions. This structure enables a direct welfare comparison between sustainable and conventional portfolios, moving the analysis from numerical simulation in the previous chapter to closed-form optimization under sustainability preferences in this chapter.

Remark on ESG rating scale. In this chapter, we follow the *Refinitiv* convention concerning ESG ratings. ESG scores range **from 0 to 100**:

- stocks with the *lowest* sustainability performance are scored 0,
- stocks with the *highest* sustainability performance are scored 100.

5.2 Model

We numerically solve for the optimal consumption, investment, and annuitization over an individual’s lifetime when a sustainable stock portfolio is available. We present both a life-cycle model and the classic Merton model below, in order to compare results from both. We also construct sustainable stock portfolios.

5.2.1 Life-cycle Model

The life-cycle framework employed here follows the finite-horizon model, with stochastic labour income correlated with stock returns, as introduced by Cocco et al. (2005), Campbell et al. (2001), and Gomes et al. (2008). In addition to labour income and risky asset returns, the model includes immediate life annuities (Horneff, Maurer, and Stamos, 2008; Horneff, Maurer, and Rogalla, 2010), social security benefits (Inkmann et al., 2011), and a warm-glow bequest motive.

An individual starts working at age x , retires at age x_r after $\tau = x_r - x$ years, and can live to age ω at most. Preferences are represented by additive time-separable power

utility with relative risk aversion coefficient γ and discount factor β :

$$\mathbb{E} \left[\sum_{k=1}^{\omega-x} \beta^{k-1} ({}_k p_x) \frac{C_k^{1-\gamma}}{1-\gamma} + \sum_{k=1}^{\omega-x} \nu ({}_{k-1} p_x) (1 - p_{x+k-1}) \beta^{k-1} \frac{W_k^{1-\gamma}}{1-\gamma} \right] \quad (5.1)$$

where C_k is consumption at the end of year k and ν is the bequest-preference parameter. In the above p_x represents the one-year survival probability at age x and ${}_k p_x$ is the survival probability from age x to at least age $x+k$ (conditional on being alive at age x).

Labour income is received annually until retirement whereupon a pension or social security benefit is received. We follow Cocco et al. (2005), Inkmann et al. (2011), Horneff, Maurer, and Stamos (2008) and Horneff, Maurer, and Rogalla (2010) and denote income in year k by Y_k , comprising both labour and pension income or social security:

$$Y_k = \begin{cases} \exp(w f(x+k) P_k U_k), & k \in [1, \tau], \\ v \exp(w f(x_r) P_\tau), & k \in [\tau+1, \omega], \end{cases} \quad (5.2)$$

where w is the wage rate, $f(\cdot)$ is a deterministic hump-shaped age-income profile, P_k is a persistent productivity shock given by $P_k = P_{k-1} + \epsilon_k$, and U_k is a transitory productivity shock uncorrelated with P_k . At retirement, pension income (which may consist of social security and/or defined-benefit pension) is set as a fraction v of the permanent component of final labour income.

The individual may also purchase an immediate life annuity paying \$1 annually while alive. The price of this annuity is its actuarial fair value adjusted by a loading factor ξ set by an insurer:

$$s = (1 + \xi) \sum_{k=1}^{\omega-x_r} {}_k p_{x_r} (1 + r_f)^{-k}, \quad (5.3)$$

where r_f is the risk-free rate.

Financial wealth W_k is allocated between a risk-free asset, which earns the risk-free rate r_f , and a risky asset, which may be a conventional stock index portfolio or a sustainable stock portfolio. An amount B_k is held in the risk-free asset, and an amount S_k is held in the risky asset, such that $W_k = B_k + S_k$ and the stock share is $\pi_k = S_k/W_k$. The risky asset return is $r_k = r_f + \mu_r + \vartheta_k$, with ϑ_k being normally distributed and correlated with the innovation ϵ_k to the persistent wage shock P_k in equation (5.2). $\tilde{\pi}_\tau$ captures the proportion of wealth converted into annuities at retirement (at time τ). Borrowing and short selling are prohibited. Annuities cannot be surrendered or cashed out, and can only be bought at the time of retirement.

$$W_k \geq 0, \quad 0 \leq \pi_k \leq 1, \quad 0 \leq \tilde{\pi}_\tau \leq 1, \quad \tilde{\pi}_k = 0 \text{ for } k \neq \tau. \quad (5.4)$$

The wealth accumulation equation is:

$$W_{k+1} = (1 + r_f + \pi_k(r_k - r_f))(1 - \tilde{\pi}_k)W_k + Y_{k+1} + Z_{k+1} - C_{k+1}. \quad (5.5)$$

Just like the individual has preferences over risk, time and bequest, specified by coefficients γ , β and ν respectively in equation (5.1), we assume that the individual has a sustainability preference specified by κ which determines which stocks are included in a portfolio. (κ is defined later in section 5.2.3.) With these specified preferences, the individual then faces the inter-temporal problem of maximizing the expected utility in equation (5.1) wrt consumption C_k , investment π_k (for $1 \leq k < \omega - x$) and annuity purchase $\tilde{\pi}_r$, subject to the constraints in equation (5.4).

5.2.2 Merton Model

For the purposes of comparison with our main model, the life-cycle model described in section 5.2.1, we also consider the classic Merton model here (Rogers, 2013; Karatzas et al., 1988). This is an infinite-horizon model where the investor consumes out of wealth allocated between a risk-free asset and a risky asset. There is no labour income and no bequest motive. This framework focuses solely on the dynamic trade-off between consumption and investment under uncertainty.

The risky asset, which could be a conventional stock index or a sustainable stock portfolio, follows a geometric Brownian motion given by:

$$\frac{dS_t}{S_t} = \mu dt + \sigma dZ_t, \quad (5.6)$$

where μ is the expected return, σ is volatility, and Z_t is a standard Brownian motion. The risk-free asset provides a constant, continuously compounded return at a rate r . The market price of risk, or Sharpe ratio, is defined as $\lambda = (\mu - r)/\sigma$.

The investor begins with initial wealth $w > 0$ and chooses, at each time t , the proportion π_t of wealth to invest in the risky asset as well as the consumption rate which is denoted by c_t . Consistent with the life-cycle model of section 5.2.1, preferences are represented by constant relative risk aversion (CRRA) utility, $U(c_t) = c_t^{1-\gamma}/(1-\gamma)$, where γ is the coefficient of relative risk aversion. Future utility is discounted at rate $\delta > 0$, to which is associated the discount factor $\beta = e^{-\delta}$.

The investor's goal is to maximise expected lifetime utility, defined by the value function:

$$V(w) = \max_{\pi, c} \mathbb{E} \left[\int_0^\infty e^{-\delta t} U(c_t) dt \right]. \quad (5.7)$$

The optimal strategy (Rogers, 2013; Karatzas et al., 1988) involves a constant proportion

of wealth allocated to the risky asset:

$$\pi^* = \frac{\mu - r}{\gamma \sigma^2} = \frac{\lambda}{\gamma \sigma}, \quad (5.8)$$

and consumption at a constant rate relative to wealth:

$$\frac{c^*}{W_t} = \eta = \frac{1}{\gamma} \left[\delta - (1 - \gamma) \left(r + \frac{\lambda^2}{2\gamma} \right) \right]. \quad (5.9)$$

Substituting the optimal strategy into the value function yields:

$$V(w) = \eta^{-\gamma} U(w) = \eta^{-\gamma} \frac{w^{1-\gamma}}{1-\gamma}. \quad (5.10)$$

Finally, the certainty-equivalent constant consumption rate that gives the same utility as the optimal strategy is:

$$\tilde{c} = [\delta(1 - \gamma)V(w)]^{1/(1-\gamma)}, \quad (5.11)$$

since $\int_0^\infty e^{-\delta t} U(\tilde{c}) dt = V(w)$.

5.2.3 Sustainable Portfolios

We denote the ESG score of stock i by Z_i . Assume that the ESG score is real-valued and assume that the higher Z_i is, the more sustainable stock i is. Given a sample of $n \in \mathbb{N}$ stocks, index them by ascending order of ESG score so that Z_1, Z_2, \dots, Z_n constitute the order statistics of the sample. (Stocks with identical ESG scores are repeated in the ordered list, by definition.) To construct sustainable portfolios, we follow two steps:

1. ESG screening. Start with all the stocks in a major stock index (such as the S&P 500) but then exclude stocks that do not meet a minimum sustainability standard.
2. Portfolio weighting. Weight the stocks that remain in the portfolio according to a suitable method.

ESG screening. The aim here is to screen out stocks that do not meet a given threshold of sustainability. For this purpose, define $\kappa \in [0, 100]$ as a percentile threshold and let Q_κ be the κ^{th} percentile of the sample $\{Z_i : i \in [1, n]\}$. The eligible set of stocks in a sustainable portfolio, at the percentile threshold κ , is defined as

$$\mathcal{I}(\kappa) = \{i \in \{1, \dots, n\} : Z_i \geq Q_\kappa\}. \quad (5.12)$$

That is, all the stocks whose ESG score lies below the κ^{th} percentile are excluded from the sustainable portfolio.

Sustainability preference. We assume that an investor has a sustainability preference which is captured by the percentile threshold κ . This is analogous to the investor’s risk aversion coefficient γ in equation (5.1). A higher value of κ indicates a stricter sustainability preference, resulting in more selective portfolios. For example, setting $\kappa = 0$ implies no exclusion and yields a traditional market-capitalization weighted S&P 500 tracker, whereas higher values impose increasingly stringent ESG criteria.

Portfolio weighting. The sustainable stock portfolios that we consider can be of two types: they are either weighted by the market capitalization of the constituent stocks or by the ESG scores of the stocks. In the following, we abbreviate “market capitalization-weighted” to “market cap-weighted” or “MC-weighted”, and we abbreviate “ESG score-weighted” to “ESG-weighted”.

MC-weighted sustainable portfolios. Let M_i be the market capitalization of stock i . The weight of stock i in a market cap-weighted sustainable portfolio is

$$w_i^M(\kappa) = \frac{M_i}{\sum_{j \in \mathcal{I}(\kappa)} M_j}. \quad (5.13)$$

Market cap-weighting is the standard way in which major indexes such as the S&P 500 are constructed. Stock holding is directly proportional to company size, as measured by its market capitalization.

ESG-weighted sustainable portfolios. In this type of sustainable portfolio, stock holding is directly related to how sustainable the stock is. We propose to determine the weight of stock i in the portfolio as follows:

$$w_i^E(\kappa) = \frac{\exp(\alpha Z_i)}{\sum_{j \in \mathcal{I}(\kappa)} \exp(\alpha Z_j)}, \quad (5.14)$$

where $\alpha \geq 0$. The rhs of eq. (5.14) represents the softmax function applied to the ESG scores of each stock that is in the sustainable portfolio at percentile threshold κ . The softmax function occurs in a variety of applications and it returns a probability distribution when its inputs are real-valued. That is, the outputs of the softmax function lie between 0 and 1 inclusive and they sum to 1. These are precisely the features that we want for a long-only portfolio, so $w_i^E(\kappa)$ represents the portfolio weight of stock i in the ESG-weighted portfolio.

Softmax parameter In eq. (5.14), the output of the softmax is interpreted as a portfolio weight. When $\alpha = 0$, the portfolio becomes an equally-weighted portfolio: $w_i^E(\kappa) = 1/n(\mathcal{I}(\kappa))$, where $n(A)$ denotes the cardinality of set A . When $\alpha \rightarrow \infty$, the

portfolio is fully invested in the single stock with the highest ESG score, if there is a single such stock. There may be more than one stock with the highest ESG score, in which case the portfolio is equally invested in all the stocks bearing the highest ESG score, when $\alpha \rightarrow \infty$. Since $\{Z_i\}$ is ordered, it follows that $Z_n = \max Z_i$. Letting $\mathcal{M} = \{i \in \{1, \dots, n\} : Z_i = Z_n\}$ be the non-empty set of stocks with the highest ESG score, then

$$\lim_{\alpha \rightarrow \infty} w_i^E(\kappa) = \begin{cases} 1/n(\mathcal{M}) & \text{if } i \in \mathcal{M} \\ 0 & \text{otherwise.} \end{cases} \quad (5.15)$$

This follows by consideration of $1/\sum_j \exp(\alpha(Z_j - Z_i))$ in eq. (5.14) for the two cases when $i \in \mathcal{M}$ and $i \notin \mathcal{M}$. Therefore, as α increases from 0, the portfolio becomes less and less diversified until it is concentrated equally in the few stocks with the highest ESG score.

Portfolio diversification A general rule of thumb in portfolio management is that, in order to achieve diversification, no single stock should have a weight greater than a certain amount, which financial advisers often advertise to be 5 or 10% (e.g. J.P. Morgan, 2025; DeVizio, 2025; Collin, 2024; FCA, 2021). The 5% rule in particular appears to originate from the U.S. Investment Company Act of 1940 which requires diversified funds to allocate no more than 5% of portfolio wealth in any individual stock, for at least 75% of assets under management (Cornell Law School, 2025). There is also an empirical rationale for rules such as the 5% rule. Because mean-variance optimal portfolios are highly sensitive to estimation errors in means and covariances of returns, they are often outperformed by naïve portfolios like equally-weighted portfolios in out-of-sample tests (DeMiguel et al., 2009). This in turn reinforces simple rules like a 5% cap, because an equally-weighted portfolio with a 5% cap means that at least 20 stocks have to be held in the portfolio, thereby resulting in some diversification.

An upper bound on α In our model, the softmax parameter α is chosen based on the requirement for portfolio diversification. Specifically, α is based on the maximum ESG score $Z_n = \max Z_i$ and a portfolio weight cap c , which could be 5%, on portfolio weights for diversification purposes. Interestingly, methods based on the maximum input to the softmax function occur in various disciplines. In deep learning, a method to choose α based on the maximum ‘logit’ is suggested by Matsuyama et al. (2025). In the random energy model of statistical mechanics, when the sample maximum of a sum of Gaussian random variables is estimated using extreme value statistics, one can derive the theoretical temperature of phase transitions (Mézard et al., 2009, pp. 97, 163).

The stocks in \mathcal{M} have the highest ESG score of Z_n and will therefore have the largest weight in the ESG-weighted sustainable portfolio. If no stock in the portfolio has a weight

greater than the cap c (where $0 < c \leq 1$), then we require that

$$\frac{\exp(\alpha Z_n)}{\sum_{j \in \mathcal{I}(\kappa)} \exp(\alpha Z_j)} \leq c. \quad (5.16)$$

Since $\sum_j \exp(\alpha(Z_j - Z_n))$ is positive and strictly decreasing wrt α , the softmax function on the lhs of inequality (5.16) is strictly increasing wrt α . This means that a cap on portfolio weights to seek diversification is equivalent to an upper bound on α .

To estimate this upper bound, we make two assumptions: (1) ESG scores follow a Normal distribution $N(\mu_z, \sigma_z^2)$, (2) the number of stocks $n_\kappa = n(\mathcal{I}(\kappa))$ in an ESG-weighted portfolio, with the percentile threshold κ , is large enough that $cn_\kappa > 1$ and the law of large numbers may be invoked. The denominator on the lhs of inequality (5.16) is then $\sum_j \exp(\alpha Z_j) \approx n_\kappa \exp(\alpha\mu_z + \frac{1}{2}\alpha^2\sigma_z^2)$, so that inequality (5.16) may be rewritten approximately as

$$\frac{1}{2}\sigma_z^2\alpha^2 - (Z_n - \mu_z)\alpha + \ln(cn_\kappa) \geq 0. \quad (5.17)$$

The quadratic function of α on the lhs of inequality (5.17) is convex. If its discriminant $\Delta = (Z_n - \mu_z)^2 - 2\sigma_z^2 \ln(cn_\kappa) \geq 0$, the quadratic will have real, positive zeros because both the sum and product of the zeros are positive. An estimate of the upper bound $\bar{\alpha}$ is then the smaller real zero of the quadratic:

$$\bar{\alpha} = (Z_n - \mu_z - \sqrt{\Delta})/\sigma_z^2. \quad (5.18)$$

In summary, we use the softmax function with $\alpha \geq 0$ to construct the ESG-weighted portfolio as per eq. (5.14). If $\alpha = 0$, this leads to an equally-weighted portfolio and we do not reward higher ESG-scoring stocks with a larger allocation. Conversely, if α is too large, we have an undiversified portfolio with wealth invested in a few highest ESG-scoring stocks. Under some fairly mild conditions, setting $\alpha = \bar{\alpha}$ in eq. (5.18) allows us to create a diversified portfolio where we hold more of a stock, the higher its ESG score.

5.3 Data Analysis and Parameterization

5.3.1 ESG Ratings Data

In our approach, ESG ratings data are obtained from Refinitiv, which provides coverage from 2002 onwards for over 15,500 public and private companies, representing more than 90% of global market capitalisation. The dataset includes more than 630 ESG-related metrics and reports firm-level ESG scores on a quarterly basis. These scores are standardised on a 0–100 scale, with higher values indicating stronger environmental, social, and governance performance. The overall ESG score is calculated as a weighted average of three component scores: environmental, social, and governance, each derived

from a set of subcategories, including emissions, human rights, and corporate social responsibility (CSR). The scoring approach incorporates industry-specific materiality adjustments. Berg, Fabisik, et al. (2020) conduct a detailed examination of the Refinitiv ESG dataset, highlighting the frequent and systematic revisions made to its historical scores. Despite varying acceptance of its methodology, the Refinitiv ESG database has been widely used in empirical research.

The construction of sustainable equity portfolios typically follows a systematic approach that begins with a broad market universe, such as the S&P 500, and applies a combination of exclusionary and sustainability-based screens. The exclusionary criteria generally involve the removal of firms engaged in controversial business activities, including tobacco production, controversial weapons, small arms, certain fossil fuel operations, and violations of international standards such as the UN Global Compact. Beyond these baseline exclusions, methodologies often incorporate sustainability screening, such as ESG scores, whereby companies in the lowest-performing quartile (poor ESG performers) are excluded to ensure that only firms with relatively stronger sustainability profiles remain eligible. These assessments draw on a range of external data sources, including ESG research providers, scoring agencies, and controversy monitoring services, in order to capture both structural exposures and event-driven risks. Portfolios are typically constructed on a float-adjusted, market-capitalization-weighted basis to maintain broad market representation, with some methodologies also incorporating sector neutrality to remain aligned with the parent index. Rebalancing is conducted periodically, quarterly or annually, with provisions for the removal of companies outside regular schedules if significant controversies emerge.

In this paper, we construct sustainable stock portfolios based on the S&P 500 between 2002 and 2023 with a quarterly frequency. Figure 5.1 shows the distribution of the Refinitiv ESG scores of stocks in the S&P 500 near the start, the middle and the end of this period. Figure 5.1 indicates a significant shift in the distribution of ESG scores over time. In 2002, the majority of firms had low ESG scores, resulting in a left-skewed profile. By 2012, the distribution shifted towards mid-range ESG scores. By 2023, the distribution became right-skewed, with most firms scoring above 60. This evolution suggests a general improvement in sustainability performance and reporting across the S&P 500. This also explains why the raw ESG scores cannot be used in our analysis and why we use the ESG percentile κ as defined near equation (5.12).

Table 5.1 shows the average, minimum and maximum number of stocks included in sustainable stock portfolios over the different quarters of the period 2002–2023 at different values of the ESG percentile threshold κ . The higher the percentile threshold κ , the stricter the sustainability requirement, and the smaller the number of stocks in the sustainable portfolio. When $\kappa = 0$, no sustainability filter is applied and all stocks are included. (Because of missing ESG scores particularly in the early years, not all 500

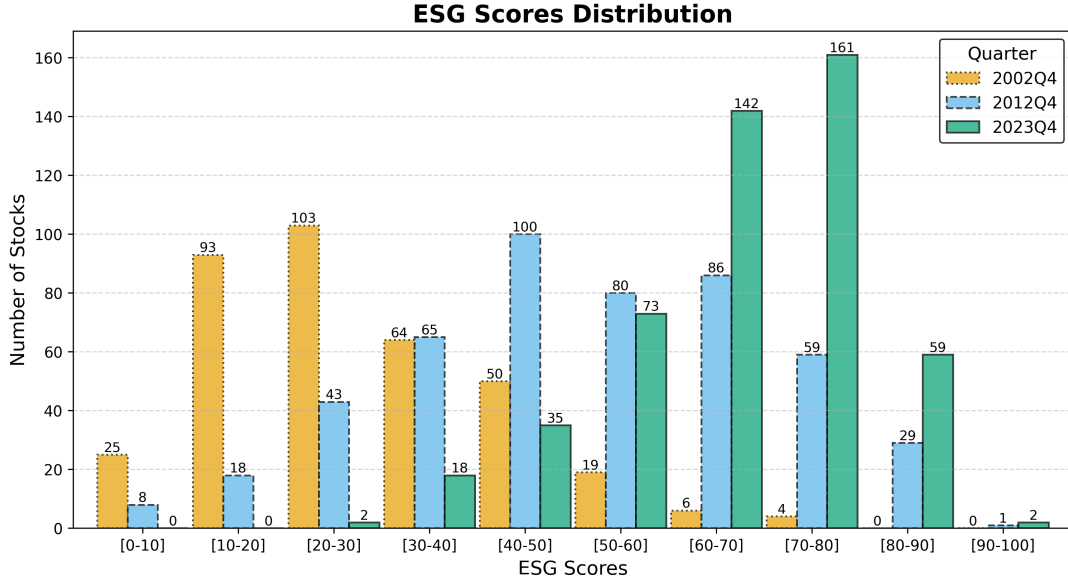


Figure 5.1: Distribution of Refinitiv ESG scores in Q4 of 2002, 2012 and 2023.

κ	0	10	20	25	30	40	50	60	70	75	80	90
Average	465	419	373	349	326	280	233	187	140	117	94	47
Min	358	323	287	269	251	215	180	143	108	90	72	37
Max	493	444	395	370	346	296	247	197	148	124	99	50

Table 5.1: Average, minimum and maximum number of stocks included in sustainable portfolios at a given ESG percentile threshold κ over the period 2002–2023.

stocks in the S&P 500 are included. See Table 5.9 in Appendix 5.A for more details.) Conversely, at very high κ , there are few stocks, which reduces diversification. For this reason, very high κ may not be practical for portfolio construction.

The intensity of ESG screening plays a crucial role in shaping portfolio composition, as it determines the exclusions under different ESG percentile thresholds. Table 5.2 illustrates this by reporting, for each year, the five largest S&P 500 constituents (ranked by market capitalization) that are excluded at the $\kappa = 25, 50, 75$. As shown, several well-known companies that are typically associated with strong market performance do not necessarily achieve the highest ESG scores, leading to their repeated exclusion from the ESG-screened portfolios.

5.3.2 Softmax Parameterization

The ESG-weighted sustainable portfolios introduced in section 5.2.3 rely on the softmax function in equation (5.14). A suitable value for the softmax parameter is given by $\bar{\alpha}$ in equation (5.18). To estimate $\bar{\alpha}$, we assume the following: (1) We consider the Refinitiv ESG scores for stocks in the S&P 500 at the end of the 4th quarter of 2012 (approx.

YEAR	$\kappa = 25$	$\kappa = 50$	$\kappa = 75$
2015	AAPL, AMZN, META, T, GOOGL	AAPL, AMZN, META, BRK.B, ORCL	META, BRK.B, UNH, AGN, KHC
2016	AAPL, AMZN, META, T, PG	META, VZ, BRK.B, ORCL, UNH	META, BRK.B, UNH, CHTR, BKNG
2017	AAPL, META, GOOGL, BRK.B, T	META, BRK.B, ORCL, CMCSA, DD	BRK.B, AVGO, KHC, CHTR, BKNG
2018	AAPL, META, GOOGL, BRK.B, WMT	META, BRK.B, T, ORCL, NFLX	META, BRK.B, NFLX, AVGO, BKNG
2019	AAPL, META, GOOGL, PG, V	META, V, BRK.B, CMCSA, ORCL	META, BRK.B, ORCL, NFLX, AVGO
2020	META, PG, V, MA, HD	META, V, BRK.B, NFLX, CRM	V, BRK.B, NFLX, ORCL, TMUS
2021	META, PG, V, MA, HD	META, V, BRK.B, NFLX, CRM	V, BRK.B, NFLX, ORCL, CHTR
2022	TSLA, XOM, BRK.B, META, LLY	TSLA, BRK.B, META, LLY, PG	BRK.B, PG, TMUS, ORCL, CRM
2023	AAPL, NVDA, TSLA, META, LLY	META, LLY, XOM, BRK.B, V	BRK.B, V, PG, ORCL, NFLX

Legend: AAPL = Apple, AGN = Allergan, AMZN = Amazon, AVGO = Broadcom, BKNG = Booking Holdings, BRK.B = Berkshire Hathaway, CHTR = Charter Communications, CMCSA = Comcast, CRM = Salesforce, DD = Dupont de Nemours, GOOGL = Alphabet, HD = Home Depot, KHC = Kraft Heinz, LLY = Eli Lilly, MA = Mastercard, META = Meta Platforms, NFLX = Netflix, NVDA = NVIDIA, ORCL = Oracle, PG = Procter & Gamble, T = AT&T, TMUS = T-Mobile US, TSLA = Tesla, UNH = UnitedHealth Group, V = Visa, VZ = Verizon, WMT = Walmart, XOM = Exxon Mobil.

Table 5.2: Top 5 stocks that are screened out of the S&P 500 at a given ESG percentile threshold κ .

the midpoint of the 2002–2023 period). (2) We build an ESG-weighted portfolio with a percentile ESG threshold of $\kappa = 0$, so that all stocks are in principle included: $n_0 = 500$. (3) No stock in the portfolio should have a weight greater than $c = 5\%$, as discussed in the neighbourhood of equation (5.15).

From the Refinitiv ESG data, we find that the highest ESG score in 2012Q4 is $Z_n = Z_{500} = 100$, the mean ESG score is $\mu_z = 51.34$, and the standard deviation of the ESG scores is $\sigma_z = 18.68$. From equation (5.18), we estimate $\bar{\alpha} = 0.1079$. Recall from the discussion around equation (5.18) that $\bar{\alpha}$ is an approximate upper bound. In the following, we set $\alpha = 0.1$ throughout in order to achieve a diversified ESG-weighted sustainable portfolio.

5.3.3 Returns on Sustainable Portfolios

We use ESG scores, stock returns, and index constituent data from Refinitiv to construct a range of sustainable portfolios, both MC-weighted and ESG-weighted. These portfolios are rebalanced quarterly from 2002 to 2023, resulting in a time series of 88 quarterly return observations for each portfolio ($22 \times 4 = 88$). The construction is repeated across multiple portfolio types and 12 distinct ESG score thresholds, producing 24 return series in total ($2 \times 12 = 24$).

For each of these time series, we assume that asset prices follow a geometric Brownian motion and we parameterize the stochastic process accordingly. Specifically, we fit a lognormal distribution to the quarterly returns on the sustainable portfolios at different values of ESG percentile threshold κ and hence estimate the mean μ and volatility σ of returns, as per equation (5.6). These return statistics are presented in Table 5.3 and are used in the life-cycle model as well as the Merton model so that we can numerically evaluate optimal risky asset allocation and consumption.

κ	Sustainable portfolios			
	MC-weighted		ESG-weighted	
	μ	σ	μ	σ
0	0.0770	0.1684	0.0851	0.1836
10	0.0735	0.1610	0.0850	0.1831
20	0.0701	0.1524	0.0845	0.1818
25	0.0689	0.1479	0.0842	0.1807
30	0.0677	0.1426	0.0837	0.1794
40	0.0614	0.1318	0.0822	0.1756
50	0.0574	0.1195	0.0801	0.1699
60	0.0505	0.1063	0.0766	0.1614
70	0.0424	0.0880	0.0711	0.1488
75	0.0369	0.0772	0.0663	0.1408
80	0.0291	0.0651	0.0596	0.1310
90	0.0178	0.0403	0.0435	0.0996

Table 5.3: Mean (μ) and volatility (σ) of returns for two types of sustainable portfolios (market capitalization (MC)-weighted and ESG-weighted) at different ESG percentile threshold κ . In bold, two portfolios with similar risk-return characteristics but higher sustainability performance for the ESG-weighted portfolio than for the MC-weighted portfolio.

5.3.4 Labour Income Process Parameterization

In the life-cycle model described in section 5.2.1, the labour income process is captured in equation (5.2). We follow the procedure of Cocco et al. (2005) to parameterize this process. We use labour income data from the U.S. Panel Study of Income Dynamics (PSID) from 2001 to 2023, complementing the Refinitiv ESG scores data. Details are given in Appendix 5.B.

It is crucial to estimate the correlation between stock portfolio returns and the persistent wage shock in equation (5.2) as this will influence an individual’s equity investment during his lifetime. We group individuals in the PSID according to educational attainment, similar to Cocco et al. (2005). Tables 5.4 and 5.5 present the estimated correlations between labour income innovations and sustainable portfolio returns for MC-weighted sustainable portfolios and ESG-weighted portfolios respectively. The correlations are broken down by education group. We find that the correlations range from about -0.02 to -0.01 . These modest negative correlations indicate that labour income provides a small natural hedge against equity market downturns. The near-zero correlation suggests that labor income risk and equity market risk are largely independent, supporting the diversification benefits of stockholding for households with stable employment.

κ	College (N = 22,095)	High school (N = 29,044)	No high school (N = 4,602)
0	-0.0105 (0.1170)	-0.0147 (0.0124)	-0.0059 (0.6899)
10	-0.0109 (0.1042)	-0.0149 (0.0111)	-0.0057 (0.6978)
20	-0.0112 (0.0959)	-0.0150 (0.0106)	-0.0064 (0.6652)
25	-0.0113 (0.0917)	-0.0152 (0.0095)	-0.0067 (0.6507)
30	-0.0117 (0.0829)	-0.0153 (0.0089)	-0.0069 (0.6377)
40	-0.0128 (0.0565)	-0.0159 (0.0066)	-0.0077 (0.6021)
50	-0.0129 (0.0551)	-0.0157 (0.0074)	-0.0069 (0.6412)
60	-0.0139 (0.0388)	-0.0173 (0.0032)	-0.0079 (0.5916)
70	-0.0147 (0.0292)	-0.0189 (0.0013)	-0.0121 (0.4112)
75	-0.0148 (0.0278)	-0.0190 (0.0012)	-0.0137 (0.3515)
80	-0.0148 (0.0282)	-0.0180 (0.0022)	-0.0153 (0.3002)
90	-0.0138 (0.0406)	-0.0161 (0.0061)	-0.0163 (0.2675)

Table 5.4: Correlations between labour income innovations and MC-weighted sustainable portfolio returns at a given ESG percentile threshold κ (with p -value in parentheses), broken down by education group (N is the number of observations in the PSID dataset).

κ	College (N = 22,095)	High school (N = 29,044)	No high school (N = 4,602)
0	-0.0104 (0.1218)	-0.0164 (0.0052)	-0.0046 (0.7564)
10	-0.0104 (0.1224)	-0.0163 (0.0053)	-0.0046 (0.7562)
20	-0.0103 (0.1242)	-0.0163 (0.0055)	-0.0047 (0.7517)
25	-0.0103 (0.1249)	-0.0163 (0.0056)	-0.0048 (0.7467)
30	-0.0103 (0.1246)	-0.0162 (0.0056)	-0.0049 (0.7387)
40	-0.0103 (0.1256)	-0.0163 (0.0056)	-0.0051 (0.7286)
50	-0.0104 (0.1216)	-0.0165 (0.0049)	-0.0058 (0.6931)
60	-0.0105 (0.1183)	-0.0164 (0.0053)	-0.0069 (0.6418)
70	-0.0107 (0.1103)	-0.0164 (0.0052)	-0.0078 (0.5958)
75	-0.0112 (0.0964)	-0.0170 (0.0038)	-0.0091 (0.5359)
80	-0.0112 (0.0959)	-0.0170 (0.0037)	-0.0087 (0.5531)
90	-0.0129 (0.0561)	-0.0191 (0.0011)	-0.0137 (0.3517)

Table 5.5: Correlations between labour income innovations and ESG-weighted sustainable portfolio returns at a given ESG percentile threshold κ (with p -value in parentheses), broken down by education group (N is the number of observations in the PSID dataset).

Parameter	Value	Parameter	Value
		<i>Labour income</i>	
<i>Individual</i>		Wage–stock return correlation ρ	Tables 5.4 and 5.5
Risk aversion coefficient γ	6	Persistent wage shock volatility σ_ϵ	0.0192
Discount factor β	0.96	Transitory wage shock volatility σ_u	0.0881
Retirement age	65	Education level	College graduate
Minimum age	20	Wage rate w	19,646
Maximum age	100	<i>Other</i>	
Sex	male	Life table	SSA 2019 male
<i>Financial</i>		Pension replacement ratio ν	0.50
Risk-free rate r_f	1.55%	Annuity loading factor ξ	0
		Bequest preference parameter ν	0

Table 5.6: Baseline parameter values for the life-cycle model.

5.3.5 Calibration of Life-cycle Model and Merton Model

The parameter values for the life-cycle model, described in section 5.2.1, are primarily drawn from Jeong et al. (2025) and Love (2013) and are summarised in Table 5.6. Where applicable, these parameter values are also used in the Merton model of section 5.2.2. The labour income process is calibrated using the 2001–2023 waves of the U.S. Panel Study of Income Dynamics (PSID) as detailed in section 5.3.4 and Appendix 5.B, with correlation coefficients in Tables 5.4 and 5.5. In addition, the model uses estimates of the mean and volatility of returns for both the MC-weighted and ESG-weighted sustainable portfolios at different values of the ESG percentile threshold κ , as reported in Table 5.3. The risk-free asset is assumed to be a 3-month U.S. Treasury bill, and the constant risk-free rate is estimated as the average of continuously compounded 3-month T-bill continuously compounded rates from 2002 to 2023.

5.4 Results

In this section, we investigate numerically the composition and risk-return performance of the sustainable portfolios, as well as optimal consumption and investment when these sustainable portfolios are available.

5.4.1 Composition of Sustainable Portfolios

Market cap (MC)-weighted sustainable portfolios and ESG-weighted sustainable portfolios are defined in equations (5.13) and (5.14) respectively. Table 5.7 shows the weights of different sectors in the S&P 500 as well as in the different sustainable portfolios for varying ESG percentile threshold κ . This is shown for the 4th quarter of 2023 only. We observe that the tech sector (information technology) is overweight in the S&P 500 as

Sector	S&P 500	Sustainable MC-weighted			Sustainable ESG-weighted		
		$\kappa = 25$	$\kappa = 50$	$\kappa = 75$	$\kappa = 25$	$\kappa = 50$	$\kappa = 75$
Comms. Serv.	8.95%	6.79%	4.49%	6.59%	2.90%	2.61%	2.82%
Cons. Discr.	11.17%	11.62%	12.01%	12.42%	8.64%	8.91%	9.07%
Cons. Staples	7.13%	6.18%	7.12%	10.11%	11.71%	12.28%	16.04%
Energy	4.66%	4.97%	1.82%	1.67%	4.34%	4.11%	4.44%
Financials	12.30%	9.52%	9.02%	11.35%	12.18%	11.95%	11.69%
Health Care	13.21%	14.87%	15.40%	19.30%	15.39%	15.84%	16.61%
Industrials	8.37%	8.53%	7.29%	6.60%	12.36%	11.58%	10.57%
Info Tech	27.18%	30.03%	35.73%	26.20%	12.26%	12.16%	11.02%
Materials	2.40%	2.61%	2.75%	3.22%	7.91%	8.20%	7.49%
Real Estate	2.31%	2.72%	2.46%	1.47%	7.97%	8.22%	7.41%
Utilities	2.32%	2.17%	1.90%	1.07%	4.34%	4.15%	2.84%

Table 5.7: Sector weights in 2023Q4 for the S&P 500 and for different sustainable portfolios.

well as in the sustainable MC-weighted portfolios, reaching 35.73% in the MC-weighted portfolio with $\kappa = 50$. By contrast, ESG-weighted portfolios diversify away from tech and exhibit a more evenly balanced sector allocation. Defensive sectors such as consumer staples and utilities have a higher weight in the ESG-weighted portfolios than in the MC-weighted and S&P 500 portfolios. In general, a stricter sustainability preference (higher κ) leads to lower allocation to the tech, industrials, utilities and energy sectors, but a higher allocation to health care and consumer staples.

5.4.2 Performance of Sustainable Portfolios

Recall that a geometric Brownian motion is fitted to asset prices representing the sustainable portfolios. The estimated mean μ and volatility σ of returns, as per equation (5.6) and for different values of ESG percentile threshold κ , are shown in Table 5.3 in section 5.3.3. We observe in Table 5.3 that, at the same sustainability preference (same κ), the ESG-weighted sustainable portfolio achieves a higher average return, at the cost of greater risk, than the MC-weighted portfolio. More interestingly, a roughly similar risk-return performance can be achieved by the two types of sustainable portfolios, but with a stricter sustainability profile on the ESG-weighted portfolio: in Table 5.3, the ESG-weighted portfolio at $\kappa = 60$ has approximately the same μ and σ as the MC-weighted portfolio at $\kappa = 0$ (this is highlighted in bold). This means that the same risk-return performance can be achieved with the ESG-weighted portfolio compared to an MC-weighted portfolio, but with an improved sustainability.

To investigate this further, we consider the risk-adjusted return on both types of sustainable portfolios by evaluating the Sharpe ratio at different values of ESG percentile

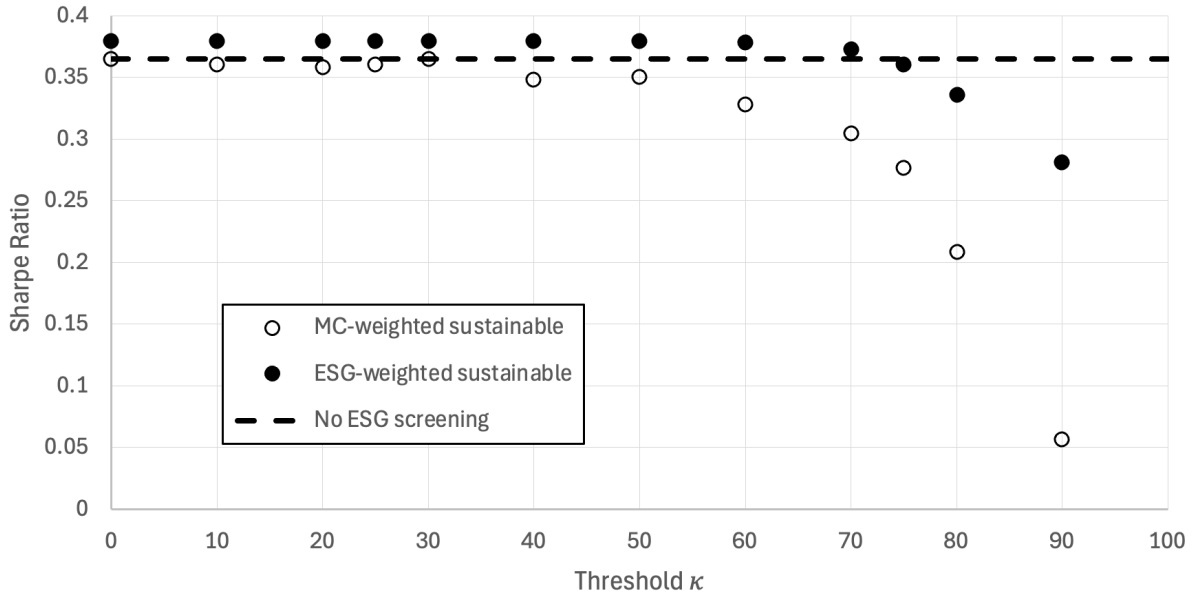


Figure 5.2: Sharpe ratio of sustainable portfolios for different values of ESG percentile threshold κ .

threshold κ . This is plotted in Figure 5.2. The risk-adjusted return on the ESG-weighted portfolio is higher than on the MC-weighted portfolio. Risk-adjusted returns decline, the higher the investor’s sustainability requirement, i.e. the higher κ is. However, this drop-off occurs only for $\kappa \geq 60$ for the MC-weighted sustainable portfolio. The corresponding range is $\kappa \geq 80$ for the ESG-weighted sustainable portfolio. This shows that an investor needs not forgo financial performance even with fairly stringent sustainability preferences.

Volatility is not a perfect measure of risk, so we also evaluate tail risk in the sustainable portfolios using the 5th percentile of return. This is presented in Figure 5.3. The higher the 5th percentile of return, the lower the tail risk in the portfolio. We find that tail risk decreases as sustainability preference becomes more stringent. For $0 \leq \kappa < 20$, the ESG-weighted portfolio performs better than the MC-weighted portfolio but the situation reverses for $20 \leq \kappa < 100$. Tail risk is lower under both types of sustainable portfolios than without ESG screening, indicating milder downside outcomes when sustainability considerations prevail.

These results are consistent with results in the extant literature. For example, Ouchen (2021) finds that a U.S. ESG portfolio based on MSCI ratings is less risky than the S&P 500 during both the 2008 financial crisis and the Covid pandemic. Ding et al. (2021) conclude that firms with better CSR/ESG ratings suffer smaller stock price drawdowns during the Covid pandemic. These results appear to hold in markets other than the U.S. Nakai et al. (2016) obtain a similar finding on socially responsible funds, compared to conventional stock funds, during the 2008 financial crisis in the Japanese stock market. Broadstock et al. (2021) confirm that, during the Covid crisis, stocks in the China CSI

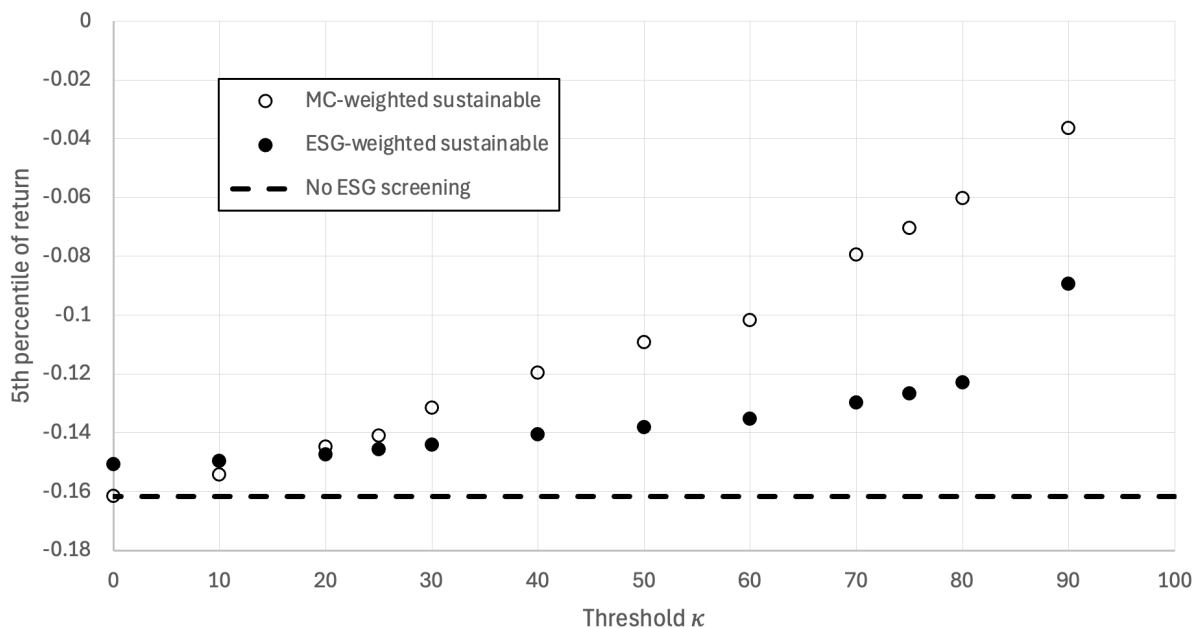


Figure 5.3: Tail risk (5th percentile of return) on sustainable portfolios for different values of ESG percentile threshold κ .

300 perform better, the higher their ESG rating.

5.4.3 Results for the Merton Model

Next, we consider the results under the Merton model described in section 5.2.2. We assume that the risky asset is a sustainable stock portfolio, as defined in section 5.2.3. Using the relevant model parameter values in Table 5.6 and the estimated mean and volatility of returns in Table 5.3, it is straightforward to substitute in equations (5.8)–(5.11) and evaluate optimal consumption, optimal risky asset allocation and the certainty-equivalent consumption.

Figure 5.4 shows that, for the MC-weighted sustainable portfolio, the optimal consumption (as a proportion of wealth) remains relatively stable for ESG percentile thresholds between 0 and 50, but then declines as κ increases above 50. The same holds for ESG-weighted sustainable portfolios except that the critical threshold where optimal consumption declines is about 75. This means that an investor’s consumption is not curtailed by sustainability preferences, except when these become very strict.

In Figure 5.5, we see that the optimal weight allocated to the sustainable stock portfolio generally increases as the ESG percentile threshold κ increases, i.e. as preference for sustainability increases. This means that more stock market participation becomes possible under higher sustainability preferences. However, risky asset allocation decreases at very high values of κ (for $\kappa > 75$) in the MC-weighted sustainable portfolio. This is because the mean return on a very strict sustainable MC-weighted stock portfolio ap-

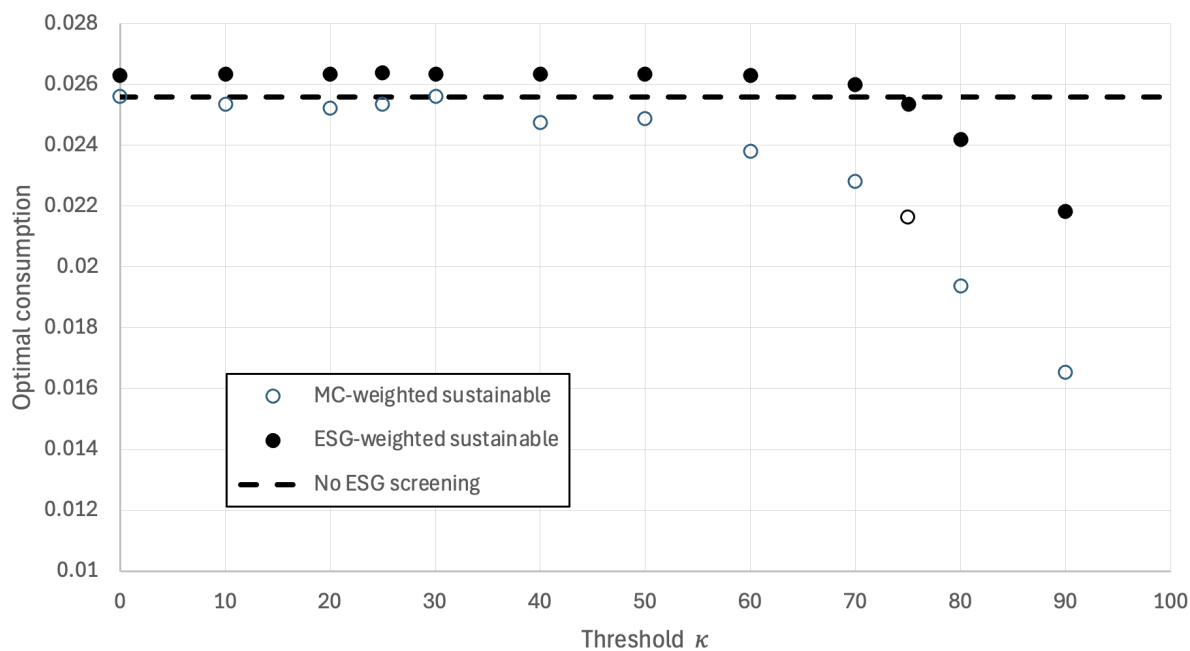


Figure 5.4: Optimal consumption as a proportion of wealth in the Merton model for the two types of sustainable portfolios at different values of ESG percentile threshold κ .

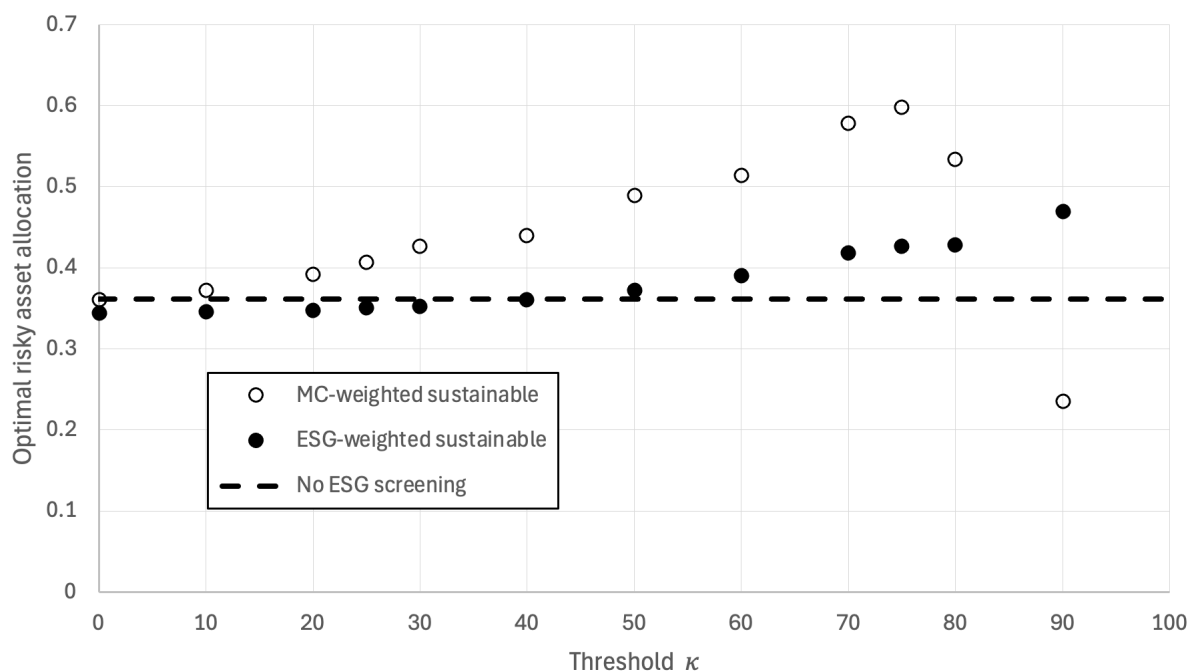


Figure 5.5: Optimal risky asset allocation in the Merton model for the two types of sustainable portfolios at different values of ESG percentile threshold κ .

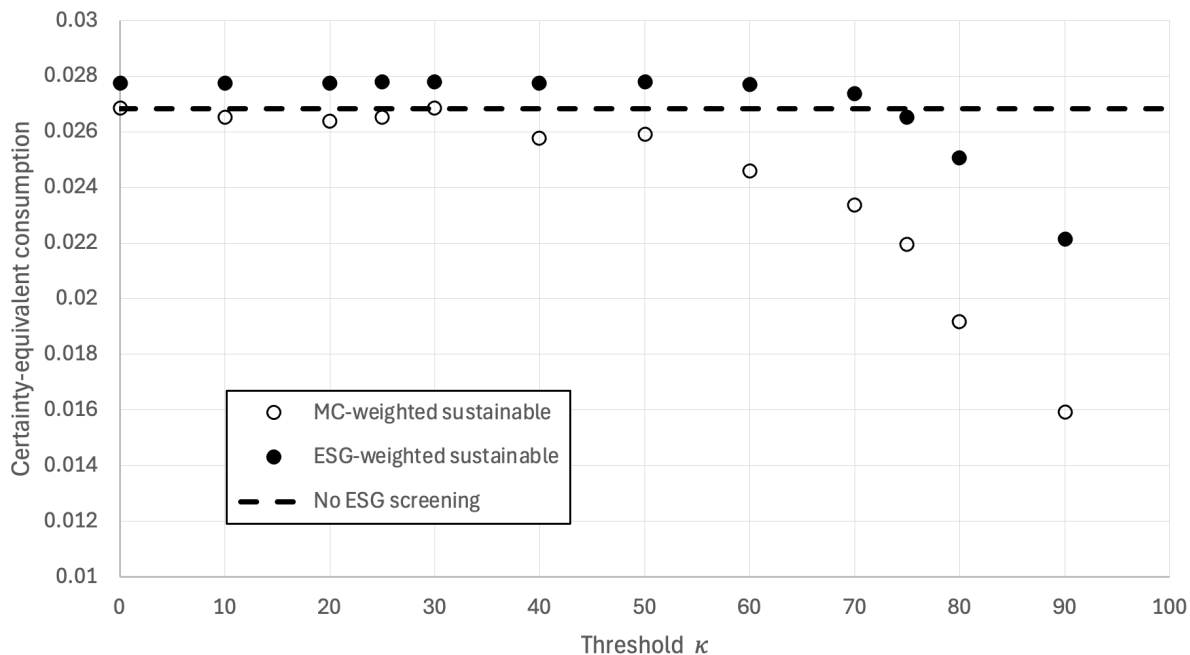


Figure 5.6: Optimal certainty-equivalent consumption in the Merton model for the two types of sustainable portfolios at different values of ESG percentile threshold κ .

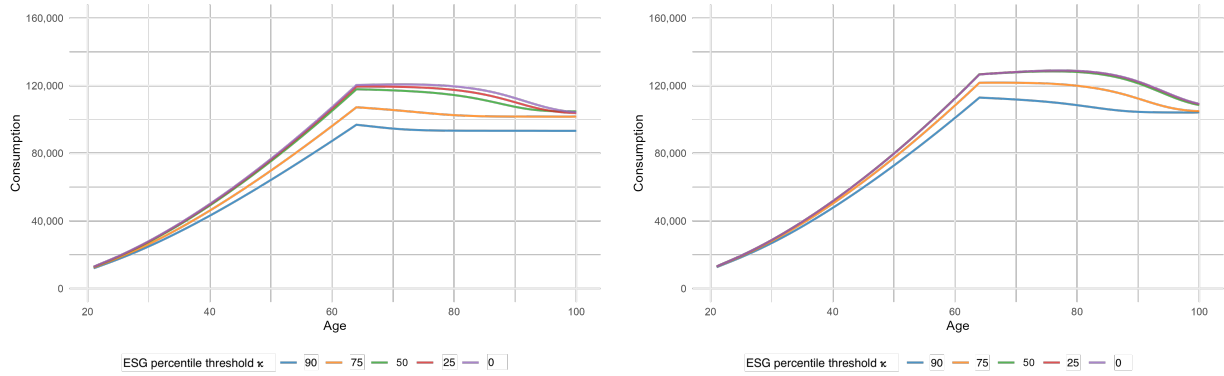
proaches the risk-free rate, as can be observed from Tables 5.3 and 5.6, so that greater risk-free investment becomes optimal.

Finally, Figure 5.6 shows the certainty-equivalent consumption and is therefore a measure of welfare. This tracks closely the pattern of the optimal consumption of Figure 5.4. Little welfare loss occurs when sustainability requirements are moderate ($\kappa \leq 50$ for MC-weighted portfolios and $\kappa \leq 75$ for ESG-weighted portfolios). Welfare declines when sustainability is very stringent. One can do well while doing good, but not if too much good is being done. It is notable that the ESG-weighted portfolio allows an investor to do much more good before incurring a financial loss than does the MC-weighted portfolio.

5.4.4 Results for the Life-cycle Model

We now turn to the full life-cycle model, described in section 5.2.1. Like with the Merton model, we assume that the risky asset is a sustainable stock portfolio, as defined in section 5.2.3 and we employ the estimated mean and volatility of returns in Table 5.3. Baseline parameter values for the life-cycle model are given in Table 5.6. The life-cycle model is solved numerically by backward induction using dynamic programming (Cocco et al., 2005; Horneff, Maurer, and Stamos, 2008; Fagereng et al., 2017; Jeong et al., 2025) and the Fortran routines of Fehr et al. (2018). The Bellman equation is computed using grid search, spline interpolation, and Gaussian quadrature.

We report optimal life-cycle profiles for consumption, labour income, annuity income, wealth accumulation and risky asset share under the two sustainable S&P 500 portfolio



(a) MC-weighted sustainable portfolio

(b) ESG-weighted sustainable portfolio

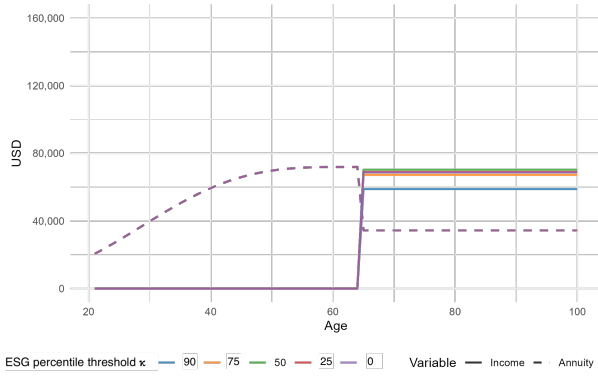
Figure 5.7: Consumption over the life cycle at various values of the ESG percentile threshold κ .

specifications: the market cap (MC)-weighted portfolio and the ESG-weighted portfolio.

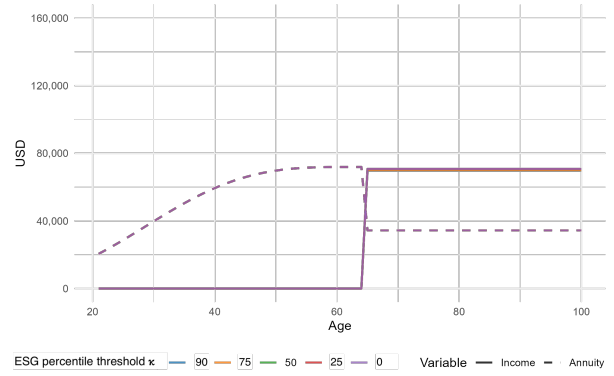
Figure 5.7 depicts optimal consumption over the life-cycle for the MC-weighted sustainable portfolio (left panel) and the ESG-weighted sustainable portfolio (right panel), and for various ESG percentile thresholds. We note that consumption declines when stricter sustainability is preferred. However, this decline is barely noticeable for ESG percentile threshold κ up to 50 in the MC-weighted case and up to 75 in the ESG-weighted case. This means that sustainable investment leads to very little loss in consumption even at fairly high sustainability preferences. Comparing left and right panels, we also observe higher consumption with the ESG-weighted sustainable portfolio than with the MC-weighted one, for the same sustainability preference (same ESG percentile threshold). In retirement, consumption is about 8% higher with the ESG-weighted portfolio than with the MC-weighted one (\$130k as opposed to \$120k for $\kappa \leq 50$).

Pre-retirement, income is just labour income, but this is replaced by a pension or social security during retirement: see equation (5.2). Annuity payments depend on the amount of annuity optimally purchased at retirement: see equation (5.3) and the text in its vicinity. Lifetime income and annuity payments over the life cycle are shown in Figure 5.8. At retirement, labour income is replaced by social security (flat dotted line) plus a purchased annuity. We observe from Figure 5.8 that annuity income is almost unchanged even up to $\kappa = 90$ in the ESG-weighted portfolio and $\kappa = 75$ for the MC-weighted portfolio. This suggests that sustainable investment does not have a sizeable effect on annuity purchase.

Figure 5.9 shows wealth over the life-cycle at different levels of sustainability (different values of the ESG percentile κ). Again, the MC-weighted sustainable portfolio is shown on the left panel and the ESG-weighted portfolio is on the right panel to facilitate comparison. Higher sustainability preferences reduce wealth accumulation but the decline is almost negligible for $\kappa \leq 50$. This means that sustainable investment leads to very little

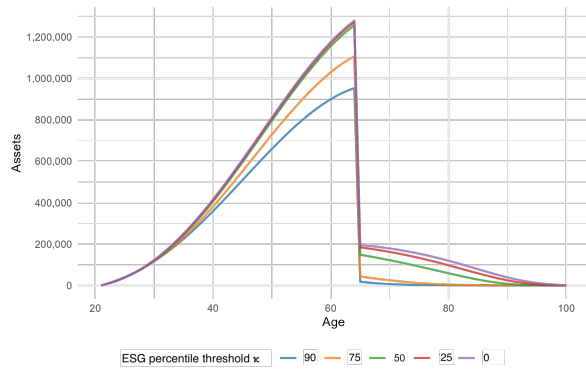


(a) MC-weighted sustainable portfolio

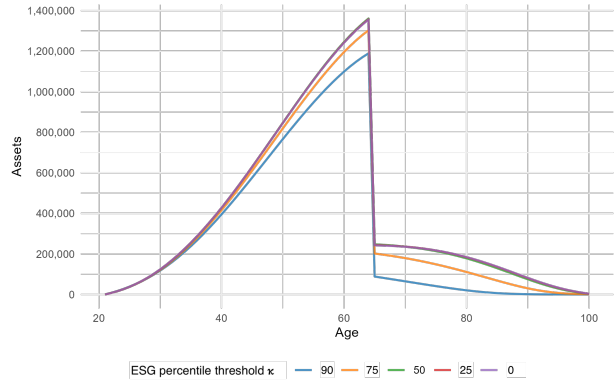


(b) ESG-weighted sustainable portfolio

Figure 5.8: Income and annuity payments over the life cycle at various values of the ESG percentile threshold κ .



(a) MC-weighted sustainable portfolio



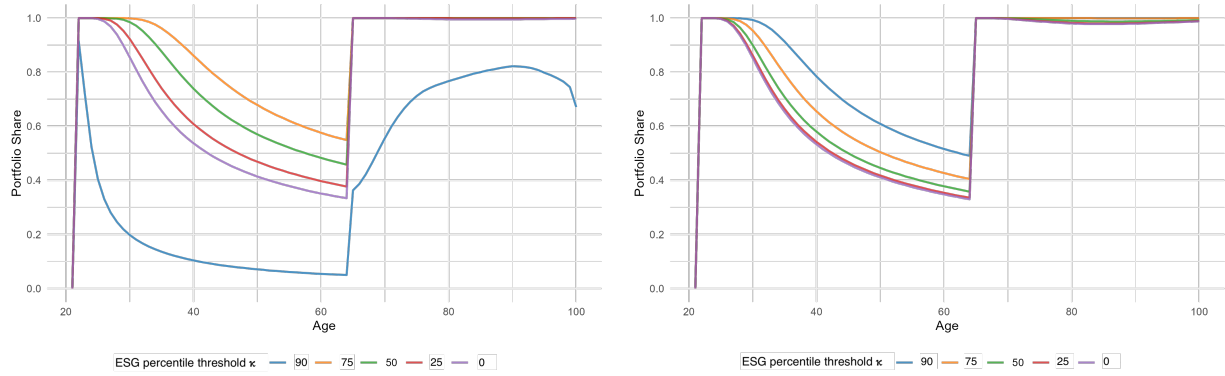
(b) ESG-weighted sustainable portfolio

Figure 5.9: Wealth over the life cycle at various values of the ESG percentile threshold κ .

loss in wealth accumulation even at fairly high sustainability preferences. A comparison of the left and right panels demonstrates that wealth is higher under the ESG-weighted portfolio than the MC-weighted portfolio, for the same value of κ .

Recall that wealth is invested either in a risk-free asset or in a risky asset, the latter being a sustainable stock portfolio. The proportion of wealth invested in the risky asset is shown in Figure 5.10. In the life-cycle model, human capital reduces as the individual gets older, since the present value of labour income declines. The labour income stream is bond-like since it is weakly correlated to stock return, as shown in section 5.3.4. Stock market investment therefore declines with age prior to retirement. At retirement, financial wealth is used to purchase an annuity and a pension (or social security) benefit also becomes available, both of which provide secure retirement income, so stock market investment jumps back to nearly 100%.

We observe in Figure 5.10 that stock market investment is in general higher when the investor prefers more sustainability (i.e. when κ is higher). This is to compensate for the lower returns that are available on average as κ increases, as shown in Table 5.3.



(a) MC-weighted sustainable portfolio

(b) ESG-weighted sustainable portfolio

Figure 5.10: Risky asset allocation over the life cycle at various values of the ESG percentile threshold κ .

With the MC-weighted sustainable portfolio at $\kappa = 90$, stock market investment is very low and it declines precipitously (left panel of Figure 5.10). This is because the average return on this portfolio is close to the risk-free rate (see Tables 5.3 and 5.6), meaning that it is optimal to hold more of the risk-free asset. A similar effect was noted in the Merton model in Figure 5.5 when $\kappa = 90$.

Finally, Table 5.8 reports key statistics from the life-cycle model for the MC- and ESG-weighted sustainable portfolios for different levels of sustainability κ . Average consumption, annuity payment and wealth are almost unchanged as sustainability preferences increase from $\kappa = 0$ to 50 (as was also seen in Figures 5.7–5.9). Thereafter, they decline more noticeably as κ increases. At comparable sustainability levels (same values of κ), the ESG-weighted portfolio performs better than its MC-weighted counterpart. For example, at $\kappa = 75$, average consumption is 12% higher and average wealth is 26% higher with the ESG-weighted sustainable portfolio than the MC-weighted one. Annuity income also stays relatively stable for $0 \leq \kappa \leq 75$, meaning that insurers should be confident about maintaining annuity sales even when policyholders invest sustainably over their lifetime.

5.5 Conclusion

Very few studies have examined the effects of optimal long-term sustainable investment. In this paper, we construct sustainable S&P 500 portfolios by screening stocks using their ESG score as determined by Refinitiv. Stocks in the S&P 500 are screened dynamically every quarter between 2002 and 2023 and are retained only if their ESG score lies above a given percentile threshold. This percentile threshold is specified by the investor according to their sustainability preference. Two types of sustainable S&P 500 portfolios are synthesized according to the portfolio weighting method. The first is weighted by market capitalization (like the S&P 500 itself and like most market indices).

κ	Consumption (Average)	Annuity	Wealth (Average)	Wealth (Max)	Risky Asset (Avg Proportion)
<i>MC-weighted sustainable portfolio</i>					
0	84,988	30,907	352,729	1,279,171	0.7604
25	83,977	31,022	343,955	1,271,843	0.7900
50	82,667	31,623	327,693	1,256,735	0.8373
75	76,407	30,244	280,389	1,107,229	0.8796
90	69,879	26,478	250,596	953,263	0.4051
<i>ESG-weighted sustainable portfolio</i>					
0	90,032	31,844	387,382	1,356,163	0.7536
25	89,998	31,835	387,353	1,357,539	0.7582
50	89,740	31,844	386,010	1,361,134	0.7754
75	85,396	31,446	353,371	1,303,158	0.8074
90	79,730	31,358	302,456	1,189,349	0.8530

Table 5.8: Average consumption, annuity income, average wealth, maximum wealth, and average risky asset allocation for both MC-weighted and ESG-weighted sustainable portfolios at different levels of ESG percentile threshold κ .

The second is weighted according to the ESG score of the stock using a softmax transformation which ensures portfolio diversification by imposing an upper bound on portfolio weights.

Historical time series of returns on these portfolios for various sustainability preferences are generated from S& P 500 total returns data and using Refinitiv ESG ratings. Geometric Brownian motions are fitted to these time series. We find that the correlation of these stock portfolio returns with wages is very low, after fitting a labour income model involving a deterministic, age-related component, as well as persistent and transitory stochastic shocks to income data between 2001 and 2023 from the U.S. Panel Studies on Income Dynamics (PSID).

A key finding is that risk-adjusted returns on sustainable stock portfolios remain relatively stable, except at very high sustainability levels when they decline. This shows that individuals do not forgo investment performance over the long term if they invest sustainably. Another finding, which is consistent with the extant literature, is that tail risk in sustainable stock portfolios is lower, the more sustainable the portfolios are.

Turning to optimal consumption and investment, we find that consumption is not significantly reduced when investment is sustainable over the long term, at least for moderate sustainability preferences. Greater stock market investment may be required when sustainability requirements are high, in order to compensate for somewhat lower risk-adjusted returns. Wealth accumulation and annuitization do not decline significantly for moderate sustainability preferences. The sustainable portfolio where stocks are weighted according to their sustainability (ESG) rating performs better than the sustainable port-

folio which is weighted according to market capitalization. These results are consistent across both a finite-horizon life-cycle model with stochastic labour income and the classic infinite-horizon Merton model. Overall, these results suggest that sustainable investment produces lifetime outcomes which are commensurate with conventional investment.

There are various limitations to our modeling and further work will be performed to address these. First, we relied on sustainability (ESG) ratings from a single provider, Refinitiv. We intend to repeat our analysis with other ESG ratings data, for example from RepRisk, Bloomberg and MSCI, to check the robustness of our conclusions. Second, ESG ratings are available for other stock markets, so extending our work to an international context is desirable. Third, the ESG-weighted sustainable portfolio is promising, but there are other ways of weighting such a portfolio, and optimizing this is an obvious next step. Finally, our baseline case in the life-cycle model is a college-educated male with specific risk and bequest preferences, and variations of this should be investigated.

Appendix for Chapter 5

5.A Additional Results

Year	ESG percentile threshold κ											
	0	10	20	25	30	40	50	60	70	75	80	90
2002	358	323	287	269	251	215	180	143	108	90	72	37
2003	370	333	296	278	260	223	185	148	111	93	75	38
2004	387	349	310	291	271	233	194	155	117	97	78	39
2005	438	395	351	329	307	263	220	176	132	110	88	44
2006	464	418	372	348	325	279	232	186	140	117	93	47
2007	464	418	371	348	325	278	232	186	140	116	93	47
2008	467	420	374	351	327	280	234	187	140	117	94	47
2009	484	436	387	363	339	291	242	194	146	121	97	49
2010	484	436	388	363	339	291	242	194	146	121	97	49
2011	482	434	386	362	338	290	241	193	145	121	97	49
2012	485	437	389	364	340	292	243	195	146	122	98	49
2013	486	438	389	364	341	292	244	195	147	122	98	49
2014	483	435	387	362	339	290	242	194	146	122	97	49
2015	476	429	381	357	333	286	238	191	143	120	96	48
2016	484	436	388	363	339	291	242	194	146	121	97	49
2017	487	439	390	366	342	293	244	196	147	122	98	49
2018	486	437	389	365	340	292	243	195	146	122	98	49
2019	491	442	393	368	344	295	246	197	148	123	99	50
2020	493	444	395	370	346	296	247	197	148	124	99	50
2021	491	442	393	369	344	295	246	197	148	123	98	49
2022	490	442	392	368	344	295	245	197	148	123	99	49
2023	488	440	391	367	342	293	245	196	147	123	98	49

Table 5.9: Number of stocks above a given ESG percentile threshold, averaged over 4 quarters in each year from 2002 to 2023. The higher κ is, the stricter the sustainability preference, and the fewer stocks are included in the sustainable portfolio.

Table 5.9 shows the average number of stocks that are included in sustainable portfolios in each year between 2002 and 2023. The stocks are those in the S&P 500 and are of course identical for MC-weighted and ESG-weighted sustainable portfolios, as only the portfolio weighting differs between them. In our model, quarterly rebalancing takes place, so we average the number of stocks over the four quarters in each year. The stronger an

investor’s sustainability preference, the higher the ESG percentile threshold κ is, and the fewer stocks there are in the sustainable portfolio. Fewer stocks are included in the very early years (especially 2002–2005) than in the later years because Refinitiv ESG ratings were available for fewer stocks historically.

5.B Labour Income Process Parameterization

This section reproduces the analysis of Cocco et al. (2005) and updates the results using the U.S. Panel Study of Income Dynamics (PSID) data from 2001 to 2023, complemented with ESG screening data from 2002 to 2023 and MC screening data from 2002 to 2023. Firstly, we estimate income to education using a fixed effects regression where log real income is regressed on education dummies and a third-order polynomial in age, including year fixed effects to control for macroeconomic conditions. Table 5.10 reports fixed-effects regressions of log income by education group and age. The sample is restricted to working-age individuals (ages 25–65). This specification identifies the education premium from cross-sectional variation in educational attainment, conditional on age profiles and time-varying aggregate shocks.

College education is associated with about 106% higher real income than no high school, and high school is associated with about 31% higher income; the implied college–high school gap is roughly 57%. These percentages are obtained by transforming log coefficients to levels ($e^\beta - 1$) and are statistically significant at conventional levels. The age terms indicate a hump-shaped profile: log income increases through mid-career and then declines, conditional on year fixed effects. Interpret these as between-person associations rather than causal effects.

Secondly, to estimate deterministic income profiles over the working life-cycle, we follow Cocco et al. (2005) and fit separate polynomial regressions for each education group without year fixed effects. Year fixed effects are excluded because the estimated profiles will be used to calibrate a lifecycle model spanning 80 years, where capturing the unconditional age-income relationship is more appropriate than isolating within-year variation. Figure 5.11 presents income profiles estimated using both 3rd and 5th degree polynomials in age, restricting the sample to individuals aged 25–65. While Cocco et al. (2005) employ a 5th degree polynomial, we find that the 3rd degree specification (Table 5.11) provides superior model fit, with higher adjusted R-squared values and statistically significant coefficients across all age terms. In contrast, the 5th degree polynomial (Table 5.12) exhibits coefficient instability and loses statistical significance for higher-order terms. Consequently, we adopt the 3rd degree polynomial for extracting residuals used in subsequent correlation analysis.

We estimate the correlation between labor income innovations and ESG portfolio returns as Cocco et al. (2005). A key challenge in this analysis is aligning the temporal

Dependent Variable: ln(real income)	
<i>Variables</i>	
<i>college</i>	0.7214*** (0.0130)
<i>highschool</i>	0.2719*** (0.0117)
<i>age</i>	0.1403*** (0.0123)
<i>age</i> ²	-0.0024*** (0.0003)
<i>age</i> ³	1.29×10^{-5} *** (2.24×10^{-6})
<i>Fixed-effects</i>	
<i>year</i>	Yes
<i>Fit statistics</i>	
Observations	87,848
R ²	0.17713
Within R ²	0.17593
<i>Standard-errors in parentheses</i>	
<i>Note: ***: 0.01, **: 0.05, *: 0.1</i>	

Table 5.10: Log real income regressed on education dummies and age polynomials with year fixed effects; coefficients are relative to No high school

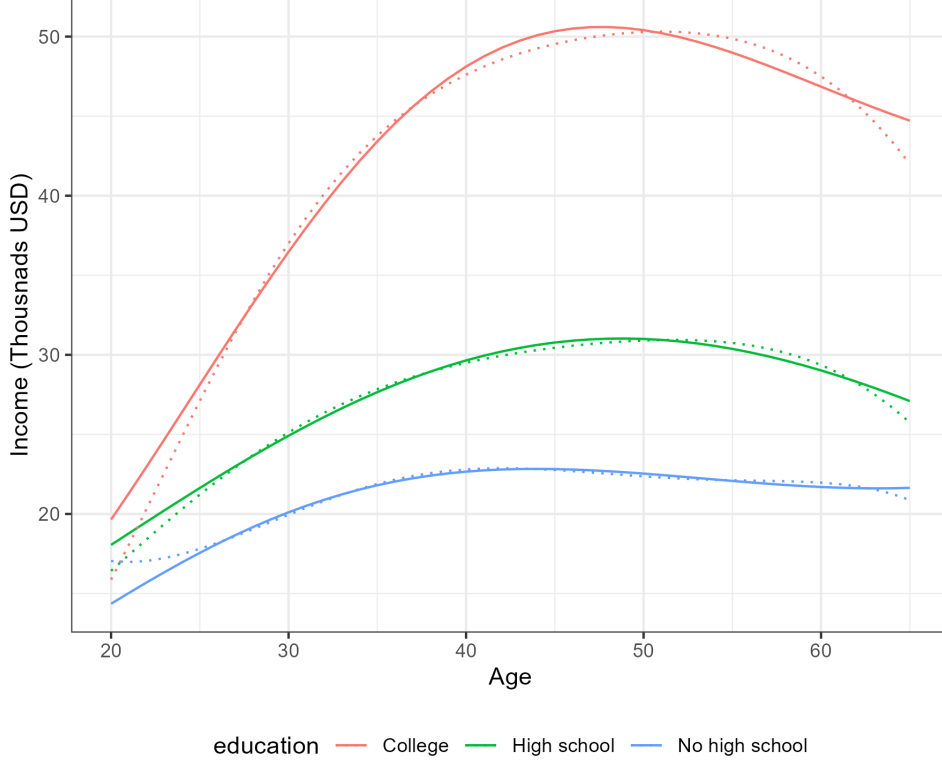


Figure 5.11: Labor income processes estimated from the PSID for the three different education groups: households without high school education, high school graduates, and college graduates. 3rd polynomial in solid and 5th polynomial in dotted line

structure of PSID income data with financial returns. The PSID is conducted biennially, with income measured at two-year intervals (2001, 2003, 2005, etc.), while financial returns are available at higher frequencies. To ensure consistency, we construct two-year cumulative returns for each ESG portfolio by compounding annual returns over the corresponding two-year windows:

$$R_{t,t+2} = (1 + R_{t+1})(1 + R_{t+2}) - 1 \quad (5.19)$$

where $R_{t,t+2}$ denotes the cumulative return from year t to year $t + 2$.

We impose sample restrictions to maintain temporal alignment. Specifically, we exclude observations where the gap between consecutive PSID interviews exceeds two years. While some respondents skip survey waves and return in later periods, including such observations would introduce measurement error, as the innovation would span variable time horizons. After applying this restriction, our analysis sample retains approximately 60-70% of the original panel observations.

To isolate idiosyncratic income variation, we estimate individual fixed effects regressions separately for each education group:

Dependent Variable: education	$\ln(\text{real income})$		
	College	High school	No high school
<i>Variables</i>			
<i>constant</i>	0.2720 (0.2400)	1.730*** (0.1705)	0.9698** (0.3883)
<i>age</i>	0.1953*** (0.0175)	0.0774*** (0.0124)	0.1280*** (0.0283)
<i>age</i> ²	-0.0034*** (0.0004)	-0.0010*** (0.0003)	-0.0025*** (0.0007)
<i>age</i> ³	1.85×10^{-5} *** (3.1×10^{-6})	3.14×10^{-6} (2.21×10^{-6})	1.54×10^{-5} *** (5×10^{-6})
<i>Fit statistics</i>			
Observations	33,404	46,370	8,074
R ²	0.05616	0.03311	0.01598
Adjusted R ²	0.05607	0.03305	0.01561
<i>standard-errors in parentheses</i>			
<i>Note: ***: 0.01, **: 0.05, *: 0.1</i>			

Table 5.11: Log real income regressed on age polynomials of degree 3 with no fixed effects

$$\log(y_{it}) = \beta_1 \text{age}_{it} + \beta_2 \text{age}_{it}^2 + \beta_3 \text{age}_{it}^3 + \alpha_i + \varepsilon_{it} \quad (5.20)$$

where y_{it} denotes real labor income, α_i captures time-invariant individual characteristics, and ε_{it} represents the income residual after removing the predictable age profile and permanent individual differences. The individual fixed effects are critical for this analysis, as they ensure that the residuals capture income shocks rather than permanent cross-sectional variation in income levels. Income innovations are then defined as:

$$\Delta \varepsilon_{it} = \varepsilon_{it} - \varepsilon_{it-2} \quad (5.21)$$

representing the unexpected change in log income over the two years.

Tables 5.5 and 5.4 present the estimated correlations between income innovations and ESG portfolio returns by education group. The correlations range from -0.01 to -0.02 for college and high school graduates, and are statistically significant at the 5% level. These modest negative correlations indicate that labor income provides a small natural hedge against equity market downturns. The near-zero correlation suggests that labor income risk and equity market risk are largely independent, supporting the diversification benefits of stockholding for households with stable employment.

We decompose labor income variance into permanent and transitory components using the Carroll-Samwick method (Carroll et al., 1997), which has become standard in the lifecycle consumption literature (Cocco et al., 2005). The method relies on the theoretical

Dependent Variable: education	<i>ln</i> (real income)		
	College	High school	No high school
<i>Variables</i>			
<i>constant</i>	-4.014 (4.074)	0.8042 (2.896)	8.475 (6.582)
<i>age</i>	0.6275 (0.5005)	0.1261 (0.3562)	-0.8099 (0.8073)
<i>age</i> ²	-0.0194 (0.0240)	-0.0001 (0.0171)	0.0432 (0.0387)
<i>age</i> ³	0.0003 (0.0006)	-9.55×10^{-5} (0.0004)	-0.0011 (0.0009)
<i>age</i> ⁴	-1.71×10^{-6} (6.48×10^{-6})	2.01×10^{-6} (4.62×10^{-6})	1.26×10^{-5} (1.04×10^{-5})
<i>age</i> ⁵	2.04×10^{-9} (2.92×10^{-8})	-1.28×10^{-8} (2.08×10^{-8})	-5.7×10^{-8} (4.68×10^{-8})
<i>Fit statistics</i>			
Observations	33,404	46,370	8,074
R ²	0.05665	0.03344	0.01616
Adjusted R ²	0.05651	0.03334	0.01555
<i>standard-errors in parentheses</i>			
<i>Note: ***: 0.01, **: 0.05, *: 0.1</i>			

Table 5.12: Log real income regressed on age polynomials of degree 5 with no fixed effects

restriction that under certain conditions, the variance of k -period income changes has a linear relationship with the horizon k .

Let $r_{i,t,k} = \varepsilon_{i,t} - \varepsilon_{i,t-k}$ denote the k -period change in the income residual for individual i . If income follows the process:

$$\varepsilon_{it} = \sum_{s=1}^t \eta_{is} + \nu_{it} \quad (5.22)$$

where η_{it} represents permanent shocks (random walk component) and ν_{it} represents transitory shocks (i.i.d. component), then the variance of k -period changes satisfies:

$$\text{Var}(r_k) = 2\sigma_\nu^2 + k \cdot 2\sigma_\eta^2 \quad (5.23)$$

where $\sigma_\nu^2 = \text{Var}(\nu_{it})$ and $\sigma_\eta^2 = \text{Var}(\eta_{it})$.

We estimate equation (5.23) by OLS regression of sample variances on k :

$$\widehat{\text{Var}}(r_k) = \alpha + \beta \cdot k + u_k \quad (5.24)$$

The intercept α identifies the transitory variance ($\hat{\sigma}_\varepsilon^2 = \alpha/2$), while the slope β identifies

Table 5.13: Carroll-Samwick Variance Decomposition

	<i>Dependent variable:</i>		
		Var(r_k)	
	College	High School	No High School
k	0.0384*** (0.0026)	0.0229*** (0.0027)	0.0143*** (0.0024)
Constant	0.1761*** (0.0085)	0.1643*** (0.0091)	0.1661*** (0.0079)
σ_ϵ^2 (Transitory)	0.0881	0.0821	0.0830
σ_η^2 (Permanent)	0.0192	0.0115	0.0072
Observations	5	5	5
R^2	0.9868	0.9590	0.9229
Adjusted R^2	0.9824	0.9453	0.8972

Note:

*p<0.1; **p<0.05; ***p<0.01
Standard errors in parentheses.

the permanent variance ($\hat{\sigma}_\eta^2 = \beta/2$). This approach requires choosing the maximum lag K . We set $K = 5$, corresponding to 10-year income changes, which provides 11 variance estimates (one for each $k \in \{1, 2, \dots, 5\}$ and potentially intermediate values if data permit) over our 22-year sample period (2001-2023). This choice balances precision (more data points at shorter horizons) with the need to identify long-run variance dynamics.

Table 5.13 reports the estimated variance components by education group. The regression fits the data well, with R^2 values exceeding 0.95 in all cases, indicating strong support for the linear variance profile predicted by theory.

For college graduates, transitory shocks account for 82% of total income variance ($\sigma_\epsilon^2 = 0.0881$), with permanent shocks contributing the remaining 18% ($\sigma_\eta^2 = 0.0192$). The permanent shock variance is statistically significant and economically meaningful, implying that a one-standard-deviation permanent shock changes lifetime income by approximately 14%. High school graduates exhibit a similar pattern but with somewhat lower permanent variance ($\hat{\sigma}_\eta^2 = 0.0115$, or 12% of total variance), while individuals without a high school degree show the lowest permanent variance ($\hat{\sigma}_\eta^2 = 0.0072$, or 8% of total variance), suggesting their income shocks are predominantly transitory. The high R^2 values (ranging from 0.92 to 0.99) indicate that the linear variance profile fits the data well, providing strong empirical support for the permanent-transitory decomposition.

These estimates are remarkably consistent with those of Cocco et al. (2005), who report transitory variances ranging from 0.05 to 0.07 and permanent variances from 0.01 to 0.015 across education groups using 1969–1992 PSID data. Our slightly higher transi-

tory variance estimates (0.08 compared to their 0.05–0.07) may reflect increased income volatility in recent decades, but the overall pattern, declining permanent variance with lower education, matches theirs closely. The ratio of permanent to total variance decreases monotonically with education level (18% for college, 12% for high school, 8% for no high school), consistent with the hypothesis that higher education provides insurance against permanent income shocks through greater occupational flexibility and skill transferability. This external validation strengthens confidence in our estimated income process parameters, which we use to calibrate the life-cycle portfolio choice model.

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Chapter 6

Conclusion

6.1 Summary

This thesis investigates the long-term effects of incorporating Environmental, Social, and Governance (ESG) factors into retirement investment strategies. While most existing literature often focuses on short-term analysis, this research extends the scope to assess how sustainability considerations influence long-term pension outcomes. Through four interrelated chapters, each structured as a stand-alone paper, the analysis focuses on an individual investor's perspective and employs realistic portfolio frameworks, retirement glide paths, and extensive empirical data.

Collectively, these chapters show that ESG integration can support long-term retirement security when implemented with careful calibration. By combining empirical analysis, cross-market evaluation, simulations, and optimization modeling, this thesis enhances understanding of how sustainable investment strategies can align ethical priorities with financial efficiency in retirement planning.

We begin our analysis in **chapter 2** by focusing on a UK-based retail investor whose investment performance is evaluated under five distinct strategies over a 20-year horizon. The investment universe comprises four asset classes: Equity, Fixed Income, Alternatives, and Cash, each represented by well-established exchange-traded funds (ETFs) available throughout the investment period (2002-2022). Among the five strategies, the benchmark follows a traditional index-tracking approach based on the FTSE 100, while the remaining four incorporate ESG scores in portfolios constructed from the same FTSE 100 constituents. Consequently, the key difference across strategies lies in the treatment of the equity component.

The ESG-screened strategies differ in their portfolio construction methods. The first applies a market-cap-weighted (MCw) framework similar to an index tracker, while the second uses an ESG-weighted (ESGw) approach: the better the ESG score, the higher the portfolio weight. Both ESG-screened strategies select stocks from the FTSE 100 based on their ESG scores, but assign portfolio weights differently. Each of these two strategies

is further extended to include short positions in stocks with weak ESG performance, resulting in two additional strategies: MCw-Short and ESGw-Short. Our ESG data is obtained from two leading providers: Refinitiv and RepRisk. The model accounts for annual rebalancing and applies a constant ongoing charge figure (OCF) to reflect typical administrative expenses. Other costs, such as transaction fees, rebalancing charges, and taxes, are excluded to focus solely on the strategies' underlying performance.

Our findings indicate that over a 20-year accumulation period, all ESG-screened strategies outperform the traditional index-tracking approach, achieving better pension outcomes and higher risk-adjusted returns. This result holds consistently across different ESG data providers, overall ESG scoring, and the stand-alone E, S, G component considerations, and remains robust under varying sustainability preferences defined by ESG-score percentile thresholds. These thresholds are set at the 75th, 50th, and 25th percentiles and represent different levels of investor preference for sustainability. A lower percentile implies stricter screening, as more stocks with bad ESG scores are excluded from the portfolio. The observed differences in performance and risk-adjusted returns are further validated through statistical testing, confirming the positive impact of ESG integration on long-term investment results.

In **chapter 3**, the analysis is extended by including additional indices: the FTSE 100 and FTSE 250 for the United Kingdom, and the S&P 500 for the United States. The investment period remains under the pre-retirement scenario from 2002 to 2022, using only ESG data from Refinitiv. These two financial regions represent distinct contexts: the UK, a European market with strong regulatory standards for ESG adoption, and the US, a central global investment hub, enabling a comparative assessment of ESG integration across different market structures.

The investment strategies are limited to three approaches: a traditional Index Tracker, an ESG-screened Market-Capitalisation-Weighted (MCw) strategy, and an ESG-Weighted (ESGw) strategy. Each strategy is examined under varying sustainability preferences, represented by ESG percentile thresholds, considering both the overall ESG score and the individual Environmental, Social, and Governance components. The only methodological difference across these portfolios is the application of quarterly rebalancing.

Under these extended conditions, ESG-screened portfolios do not consistently outperform the index tracker as in our previous model, indicating that their performance depends strongly on the methodological choices made during their construction, such as screening intensity and weighting scheme. In the UK market, large-cap portfolios show strong ESG-weighted (ESGw) outperformance across all sustainability levels, while mid-cap portfolios deliver higher pension outcomes but weaker relative returns, especially below the 50th percentile. The market-cap-weighted (MCw) strategy underperforms in both indices at all ESG percentile thresholds. In the US context, ESGw generally exceeds MCw, although the Index Tracker remains superior, except for the ESGw cases

at the 75th percentile, across the twenty-seven target-date fund asset allocation methods examined. All performance differences are statistically tested and significant.

The ESG component-level analysis provides additional insight into the performance of ESG-screened strategies. The Environmental pillar shows that ESGw strategies outperform in both UK indices, most notably in the FTSE 100 and with significant improvement in the FTSE 250, while in the S&P 500, they perform similarly to the benchmark. The Social pillar delivers the most consistent positive effect across all indices, though smaller in magnitude for the S&P 500. Governance integration yields strong results in the FTSE 100 but converges toward index-level performance in the FTSE 250 and shows minimal impact in the S&P 500. The Market-Capitalisation-Weighted (MCw) strategies underperform the index tracker under both the best and worst asset allocation scenarios.

A stochastic modeling framework is introduced in **chapter 4** to capture the full retirement life cycle rather than focusing solely on the accumulation phase. The investment horizon is expanded from 20 to 40 years by combining a VAR(1) model with Monte Carlo simulations, covering both the accumulation period (ages 45–65) and the decumulation period (ages 65–85). We again compare two ESG-screened strategies, MCw and ESGw, with a traditional index-tracking benchmark.

The results reveal several key insights. While ESG integration provides potential sustainability benefits, it also introduces trade-offs for long-term retirement security. Across 10,000 simulated investment paths, the traditional index tracker achieves higher average utility and stronger downside protection than both ESG-screened portfolios. The ESG strategies show lower 5th percentile wealth outcomes, higher probabilities of plan failure, and greater conditional expected shortfalls. However, performance varies between the two ESG approaches: at the 75th percentile threshold, the ESGw delivers utility levels comparable to the traditional benchmark and slightly higher average real income, whereas the MCw consistently underperforms the S&P 500. Overall, the findings indicate that sustainable investing and retirement security can coexist, provided ESG-screened portfolios are carefully calibrated to balance financial performance with sustainability objectives.

Chapter 5 switches to optimization modeling. We consider sustainable investment in the context of a finite-horizon life-cycle model, which is solved numerically, as well as in the context of the classic Merton model for which closed-form solutions are available. We construct two sustainable versions of the S&P 500 by screening stocks using their ESG score: a market capitalization-weighted sustainable portfolio and an ESG score-weighted sustainable portfolio. Historical time series of returns on these portfolios for various sustainability preferences are generated from S&P 500 total returns data and using Refinitiv ESG ratings. Geometric Brownian motions are fitted to these time series. We find that the correlation of these stock portfolio returns with wages is very low, after fitting a labour income model involving a deterministic, age-related component, as well as persistent and transitory stochastic shocks to income data between 2001 and 2023 from

the U.S. Panel Studies on Income Dynamics (PSID).

We find that risk-adjusted returns on sustainable portfolios decline significantly only when sustainability requirements are very stringent. Tail risk reduces the more sustainable a portfolio is. In both the life-cycle model and the Merton setting, we find that optimal consumption declines only very slightly as sustainability preferences strengthen, as long as these preferences remain moderate. Wealth accumulation and annuitization remain stable with moderately sustainable portfolios. The sustainable portfolio where stocks are weighted according to their sustainability (ESG) rating performs better than the sustainable portfolio which is weighted according to market capitalization. These results are consistent across both a finite-horizon life-cycle model with stochastic labour income and the classic infinite-horizon Merton model. Overall, these results suggest that sustainable investment produces lifetime outcomes which are commensurate with conventional investment.

6.2 Further work

This thesis offers a clear foundation for understanding the impact of incorporating Environmental, Social, and Governance (ESG) factors into retirement investments. Nevertheless, several aspects represent limitations and opportunities for future research, as outlined below.

The main constraint arises from limited ESG data availability prior to the mid-2000s. This restricts the effective sample period and necessitates backward assumptions when extending the model to earlier years. Such assumptions may introduce survivorship bias, as only firms with continuous ESG and financial records are included, potentially overstating performance by excluding delisted or failed firms. A future extension could explore methods to mitigate this bias and evaluate the sensitivity of results to data selection.

The model could be enhanced by incorporating investor heterogeneity, such as differences in risk tolerance, sustainability preferences, and behavioral characteristics. Currently, ESG-screening thresholds remain constant across the investment horizon, although investors may adjust screening intensity dynamically in response to new information or changing market conditions. Future studies could explore optimal ESG thresholds, alternative weighting schemes, and the integration of individual-specific sustainability preferences into the utility framework. Additionally, while the analysis includes an ongoing charge figure (OCF), it excludes transaction costs, taxes, and rebalancing charges, potentially overstating net returns.

The simulations rely on stationary historical relationships and do not account for structural regime shifts, such as financial crises, pandemics, or climate transition shocks. Incorporating regime-switching or shock-responsive models could enhance realism and robustness. Future research might also extend the analysis across different indices, asset

classes, and geographical regions to assess the global consistency and resilience of ESG-screened investment strategies.

The optimization modeling that we perform can also be extended. Our analysis should be repeated using the ESG ratings from other data providers and not just Refinitiv, so that the robustness of our conclusions can be verified. We should also consider other stock markets beyond the US stock market. The ESG-weighted sustainable portfolio utilizes the softmax function, but there are other ways of weighting such a portfolio, and optimizing this is a key next step. Finally, our baseline case in the life-cycle model is a college-educated male with specific risk and bequest preferences, and variations of this should be investigated.