Monte Carlo analysis of exempting performance fees from the workplace pensions charge cap

Technical Annex to the cost benefit analysis in CP26/40

November 2026

1 Introduction

Policy context

1. The Mansion House Accord (MHA), signed in May 2025, established commitments from major UK pension providers to allocate 10% of their main DC default funds to private markets by 2030, within which at least 5% of the total is in UK private markets. The MHA is an extension of the Mansion House Compact (MHC), signed in 2023 with the intention of allocating 5% of DC pension funds to unlisted equities.

2. Current regulatory constraints, specifically the 0.75% charge cap inclusive of all fees, create tension with this policy objective due to the higher fee structures typical in private market investments. The charge cap was introduced in 2015 to protect members from excessive charges in workplace pension defaults. It was not designed to limit investment in private assets, which accounted for a much smaller share of default fund portfolios than they do today or are expected to under the MHA.

3. Signatory firms have identified the charge cap as a potential barrier to investing in private markets. These investments often have higher, and more complex, fee structures, including performance fees, partly because they involve resource-intensive sourcing, due diligence, active management and valuation.

4. We propose to exempt specified performance fees from the charge cap, subject to conditions designed to ensure that firms use the exemption in savers' interests. This technical annex supports the cost benefit analysis (CBA) in CP26/40 by providing modelling estimates of portfolio value benefits to savers and associated fees to public and private market asset managers. We compare a baseline in which current private market allocations remain unchanged with an intervention scenario aligned with firms' commitments under the MHA and the MHC.

5. Unless stated otherwise, all monetary values in this technical annex are nominal and not discounted. The CBA usually presents relevant costs and benefits as present values (unless otherwise stated), so the corresponding figures may differ.

6. We use a Monte Carlo simulation to generate a distribution of future portfolio return paths over the 10-year appraisal period. The model captures the transition to the MHA target allocation by 2030 and the subsequent evolution of the portfolio over the remainder of the appraisal period. Within each simulation, we generate returns using a Dynamic Conditional Correlation Exponential Generalised Autoregressive Conditional Heteroskedasticity (DCC-EGARCH) model with Student-t innovations.

7. The model captures key stylised features of financial returns, including time-varying volatility, dynamic cross-asset correlations and fat-tailed return distributions. We use the resulting return paths to compare the distribution of portfolio outcomes under alternative asset allocation strategies.

8. The results should be interpreted with several simplifying assumptions in mind. The analysis is sensitive to the capital market assumptions (CMAs) used, including expected returns, volatility and correlations, and does not capture the full uncertainty around these estimates. It also assumes constant expected returns and full liquidity, while not fully reflecting the valuation lags and smoothing associated with private market assets. These assumptions support a practical analysis but mean

that the results should be viewed as illustrative rather than forecasts of future outcomes.

Background to private and public markets

9. Private and public markets differ in how investments are structured and valued, with these differences affecting the way investors access their capital, the fees they pay, and how performance is measured. This section sets out simplified characteristics of private and public markets, before considering the factors that may drive differences in their performance and the risks investors face.

Structure

10. In both public and private markets, investors typically provide asset managers with funds; however, the funds themselves are structured differently. Private market funds are typically set up as limited partnerships, where a general partner (GP) manages the fund and limited partners (LPs) provide capital but do not participate in investment decisions. Public market funds are usually structured as collective investment schemes with a regulated manager and a broader base of investors.

11. In practice, this means that investors in private market funds make commitments upfront, which are then drawn down over time as investment opportunities become available. This capital is predominantly locked away in a closed-ended fund and cannot be accessed by the LP until distributions are paid by the GP, hence the illiquidity. There are semi-liquid open-ended funds and traded trusts that invest in private assets while offering some liquidity to attract retail investors.

12. In contrast, public market funds are predominantly open-ended and allow investors to invest and withdraw capital on an ongoing basis. Some open-ended fund structures do also invest in private assets, notably long-term asset funds (LTAFs) which were introduced in 2021 to enable investment in long-term, illiquid assets while providing an appropriate liquidity framework for investors.

Asset classes

13. Both private and public market funds invest in different types of assets. Broadly, the main private asset classes are:
    - **Private equity** – investment in unlisted companies. Within this, there are several subcategories:
        - Buyout focuses on taking majority shares in established companies to take them private and restructure.
        - Venture capital provides early-stage equity capital to start-ups.
        - Growth provides later-stage capital to companies looking to scale up their operations.
    - **Private credit –** direct lending to firms by asset managers, typically with a more limited upside but more reliable and continuous returns.
        - Distressed lending to companies in financial or operational distress that cannot access conventional lending.
        - Mezzanine debt is a form of financing that combines elements of debt and equity, commonly used in corporate takeovers.
    - **Real assets –** investment in debt and equity of physical, tangible assets.

- Real estate investment in private and commercial property.
- Infrastructure supplying capital for large-scale projects.

Fees

14. Fee structures differ substantially between private and public markets. In public market funds, investors are typically charged a single ongoing fee (e.g. an annual management charge), expressed as a percentage of assets under management (AUM) and applied consistently over time.

15. In private markets, fees are multi-layered and include both fixed and performance-based elements. Management fees are charged to cover operating costs, while performance fees (carried interest) are contingent on realised investment returns and are typically only paid after certain thresholds are met.

16. While fee structures differ by asset class, strategy and investor type, a commonly used model in parts of the private markets industry is a "2 and 20" arrangement with an 8% hurdle rate. This means that the GP will charge a 2% management fee on invested assets for the costs of running the business and a 20% performance fee on any profits over the 8% hurdle rate. Such fees are substantial when the manager is generating strong returns, although 2% management fees are still much higher than public market funds generally charge.

Performance

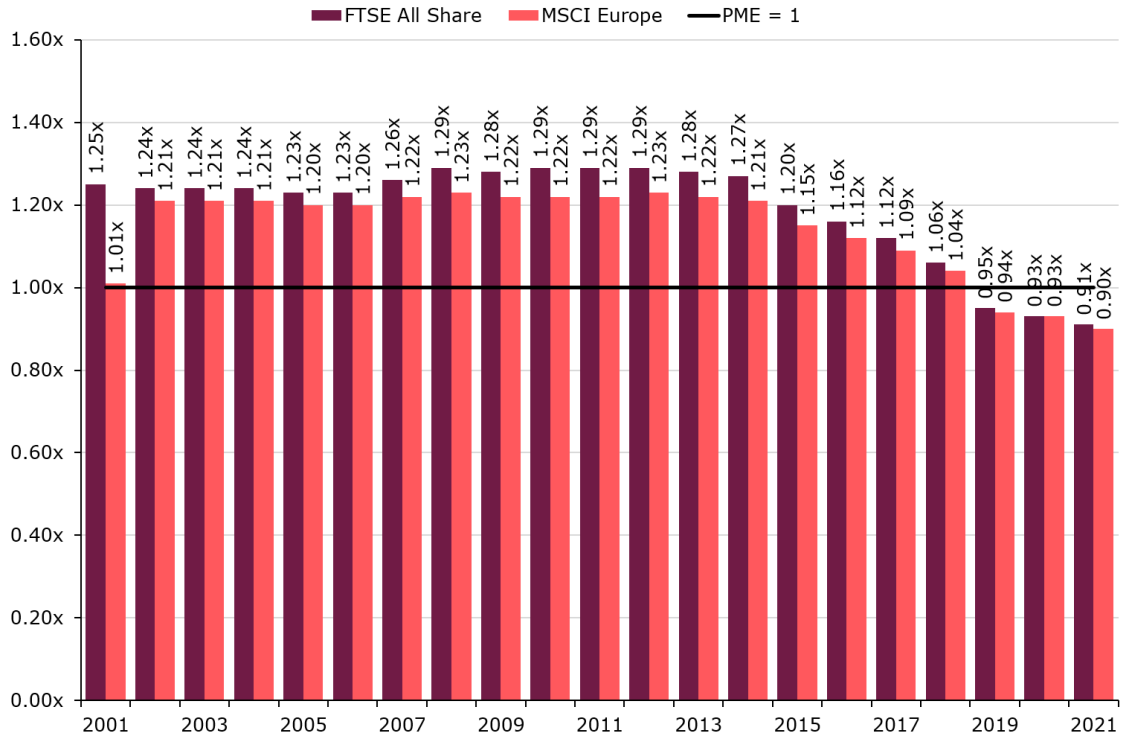
17. In public markets, performance is measured on a continuous and market-based basis, with asset values updated frequently (often daily) using observable market prices. Returns are therefore assessed over short, standardised periods (e.g. daily, monthly, annual), enabling straightforward comparison across funds and benchmarks. Performance is typically expressed as a straightforward percentage change in the value of assets over time.

18. In private markets, performance measurement is less frequent and more judgement-based, as assets are not traded on public exchanges and must be valued using periodic appraisals or models. Returns are typically assessed over the full life of the investment or fund, rather than continuously, reflecting long holding periods. As a result, interim performance metrics are less directly comparable and subject to greater estimation uncertainty. This can lead to revisions in performance figures and requires alternative metrics, such as IRR, that can make comparison to public market performance difficult.

19. To overcome these challenges, private market fund performance is often benchmarked against the performance of a strategy that invests the same amount of capital into a comparable market index using the same drawdown and distribution schedules as the private fund (Ljungqvist, 2024). The market standard is Public Market Equivalents (PMEs) as initially introduced by Kaplan and Schoar (2005).

20. When the PME is greater than one, this implies that private market funds have outperformed public markets. Data published by UK Private Capital found that private markets had a PME greater than one in every vintage from 2001 to 2018, but since then there have been 3 years of underperformance (Figure 1). Private market performance measures are highly sensitive to benchmark selection.

Figure 1: Since inception PME starting from a specific vintage year



Note: Kaplan Schoar Public Market Equivalent (KS-PME)
Source: UK Private Capital, Performance Measurement Survey Report 2024

Factors driving performance

21. Theoretically, private markets should outperform public markets due to the illiquidity premium. Investors in private markets are compensated for holding assets that cannot be readily traded, as well as for bearing greater risk, complexity and information costs.

22. Leverage may also contribute to potentially higher performance by private market funds as the multiples on equity invested can be significantly higher. Greater access to capital enables private market asset managers to grow faster through greater investment and for funds to purchase larger companies.

23. Importantly, while the market has performed well over the last 20 years, there is significant divergence in performance between funds. Data from UK Private Capital illustrates this well: while pooled annualised returns since 2006 were 12.4%, the top 25% of funds returned over 17.8% while the bottom 25% returned 1.2% or less. Over the same period, the S&P 500 generated annualised returns of 11.4%, the FTSE 100 6.7%, and MSCI Europe of 6.2%.

24. Once these factors are taken into consideration, there is debate in the literature as to whether private market funds deliver excess returns. Some papers find no evidence of outperformance when adjusting for risk and fees (e.g. Driessen, Lin, and Phalippou (2012), Boyer et al. (2023), L'Her, Stoyanova, Shaw, Scott, and Lai (2016)), while others do find positive risk-adjusted returns (e.g. Ewens, Jones, and Rhodes-Kropf (2013), Franzoni, Nowak, and Phalippou (2012), Ang et al. (2018)).

25. Therefore, it is not certain that investing in private markets will deliver improved performance once adjusted for the additional risk and fees associated with these

investments. Performance would depend heavily on the choice of individual funds in which the scheme invests.

Rationale for modelling framework

26. Traditional deterministic forecasting produces a single projected outcome based on average expected returns. However, this approach fails to capture the inherent uncertainty and variability of investment returns, particularly the range of possible market conditions and the compounding effects of volatility over time.

27. Furthermore, it does not reflect the non-linear nature of performance-based fee structures, where fees are only charged when returns exceed specified thresholds, meaning outcomes can differ materially depending on the sequence and distribution of returns rather than simply the average level of performance. For example, a pension saver experiencing a sequence of poor returns in early years may experience very different outcomes from a saver who experiences the same average return distributed differently over time.

28. A simple Monte Carlo simulation approach assumes constant volatility and constant correlations between asset classes over the projection horizon. While this simplification is more tractable, it does not capture well-established features in financial markets, including time-varying conditional volatility and dynamic cross-asset correlations. Volatility and correlations can change substantially over time and may increase during periods of market stress.

29. Periods of heightened conditional volatility can increase the uncertainty surrounding portfolio outcomes, while rising correlations during market stress can erode diversification benefits when they are most valuable. Accounting for these features is therefore important when evaluating the distribution of outcomes under alternative asset allocation strategies.

30. To address these limitations, we employ a DCC-EGARCH model. This framework allows asset volatilities to evolve over time using EGARCH (1,1) processes, capturing both volatility clustering (the tendency for high-volatility periods to persist) and the asymmetric impact of market shocks, where negative shocks can have a larger effect on volatility than positive shocks of the same magnitude. Simultaneously, the DCC specification permits correlations between asset classes to vary over time, typically increasing during periods of market stress and declining during calmer market conditions.

31. Returns are drawn from a Student-t distribution with 8 degrees of freedom rather than the normal distribution. This produces fat-tailed return distributions in which extreme outcomes occur more frequently than under a normal distribution. The model operates at daily frequency (252 trading days per year) to capture high-frequency volatility and correlation dynamics. We then compound daily returns into annual returns for portfolio valuation, fee assessment and rebalancing. We note that the specific timing of fee assessment may vary depending on scheme arrangements.

32. The model uses forward-looking CMAs to inform expected asset-class returns and volatility. These assumptions are commonly used in long-term institutional pension analysis and may incorporate a range of inputs, including historical data, current market conditions and provider judgement. Our approach provides a forward-looking framework rather than relying solely on the extrapolation of historical average returns, which may not fully capture the factors influencing future returns.

2 Scenario modelling specification and assumptions

33. The analysis aims to understand how exempting performance fees from the current 0.75% charge cap impacts pension portfolio values across time for savers and the allocation of fee revenues between fund managers operating in public and private markets. Our framework is used to simulate the distribution of outcomes under different policy scenarios, enabling the analysis to estimate the marginal impact of the policy relative to a counterfactual baseline scenario where performance fees are not exempt from the cap.

34. By using common random numbers across scenarios (implemented by initialising each simulation with the same random seed), we ensure that the same underlying sequence of market events (i.e. the same pattern of good years and bad years for equities, bonds, and other assets) occurs in each scenario. The scenarios differ only in their private market allocation paths. Differences in fee treatment and portfolio returns arise from the resulting difference in private market exposure.

35. We consider 2 scenarios in our model. The modelling assumptions underpinning each scenario are set out in detail below.

Baseline scenario – current regulatory treatment

36. The baseline represents a counterfactual where current regulatory treatment continues unchanged. Under the current rules, strong private market performance can generate performance fees that create a risk of exceeding the cap. Uncertainty about this risk may constrain schemes' willingness to increase their exposure to private markets, even where they expect the investments to improve net saver outcomes. We therefore assume that the baseline target asset allocation remains at its initial Year 1 (2027) level throughout the 10-year appraisal period to 2036.

37. This is a simplifying assumption rather than a prediction of scheme behaviour. In practice, we acknowledge that pension schemes would be expected to adjust their asset allocations over time in response to changes in market conditions, investment opportunities and regulatory initiatives such as Value for Money or consolidation of pension pots. For the purposes of this analysis, we assume that current allocations remain unchanged because the charge cap would continue to constrain performance-fee structures for contract-based schemes.

Asset allocation

38. As part of our Value for Money Framework consultation published in July 2026, we collected data from 8 firms (7 of which are signatories of the MHA) on how assets are allocated within the accumulation phase of their main workplace pension default arrangements.

39. The information collected supports our understanding of baseline investment strategies and helps inform the modelling assumptions used within the simulation framework, particularly those relating to the composition of current public and private market allocations.

40. The asset allocation survey provides a high degree of granularity across UK and non-UK asset subclasses in both public and private markets. To support a more streamlined modelling framework, these subclasses were consolidated into the main asset classes set out in Table 1.

Table 1: Breakdown of asset sub-classes at the market level

Market	Asset class	Asset sub-class
Public markets	Listed equities	Listed equities (developed market)
		Listed equities (emerging market)
		Listed equities (other market)
	Corporate bonds	Bonds (investment-grade corporate)
		Bonds (non-investment-grade corporate)
		Bonds (securitised)
	Government bonds	Bonds (fixed interest government)
		Bonds (index-linked government)
	Cash	Cash
	Other	Other
Private markets	Private equity	Private equity (venture capital)
		Private equity (growth equity)
	Private credit	Private debt/credit
	Real assets	Infrastructure
		Property/real estate

41. The survey data - as presented in Table 2 below - indicates that baseline asset allocation remains heavily concentrated in public markets, which account for approximately 94.7% of total portfolio assets.

42. There is a heavy skew towards equities, at 74% overall, with 68% being held outside the UK. Only 0.3% of assets are currently invested in private equity and a further 0.3% in private credit. Most private assets are invested in real assets at 4.9%. Based on this allocation, there is potential for increased investment in private markets among these firms.

Table 2: Asset allocations by asset class

	Asset class	Asset allocations	
UK assets	Listed equities	6.8%	**15%**
	Corporate bonds	1.7%	
	Government bonds	4.4%	
	Private equity	0.05%	
	Private credit	0.04%	
	Real assets	1.5%	
	Cash	0.3%	
	Other	0.6%	
Non-UK assets	Listed equities	67.6%	**85%**
	Corporate bonds	9.4%	
	Government bonds	1.6%	
	Private equity	0.2%	
	Private credit	0.3%	
	Real assets	3.4%	
	Cash	1.3%	
	Other	0.8%	

Source: FCA firm survey data

Asset returns and volatility

43. The measurement of private market returns is the subject of a substantial academic literature – some of which is summarised in the background to *private and public markets*. While historical data are informative, future market conditions may differ materially from past experience, particularly in private markets where return histories are shorter and valuation conditions evolve over time. For this reason, our simulation relies on forward-looking CMAs produced by institutional asset managers rather than extrapolating historical averages directly. In doing so, our analysis abstracts from fund-level features of private market investing (such as cash-flow timing) that influence reported returns.

44. Forecasting future capital market performance is inherently uncertain, and CMA providers use different data, judgements and methodologies to estimate future returns and volatility. Different institutional asset managers produce different expectations for future returns, volatilities, and correlations, particularly for private market asset classes where valuation uncertainty is more pronounced because assets are not traded in liquid public markets. To reflect this uncertainty, the analysis adopts a multi-provider approach, incorporating publicly available CMAs from JPMorgan Chase, BlackRock, and AQR. We selected these providers as they are some of the longest-running and most highly regarded providers of CMAs, with extensive institutional investment experience.

45. Rather than averaging assumptions or selecting a single CMA provider, the model incorporates uncertainty in CMAs by randomly selecting the CMAs in each simulation

from 1 of the 3 providers (JPMorgan, BlackRock and AQR) with equal probability. This approach allows differences in provider expectations to be reflected directly in the distribution of model outcomes, alongside stochastic variation in market returns.

46. The model uses volatility assumptions from JPMorgan and BlackRock because equivalent data are not available from AQR. Where the model selects JPMorgan or BlackRock expected returns, it uses volatility assumptions from the same provider. Where it selects AQR expected returns, it uses either JPMorgan or BlackRock volatility assumptions, with each provider assigned an equal probability. Table 3 summarises the parameter sources and selection method.

Table 3: Parameter sources by simulation

Model parameter	Source(s)	Selection method
Expected returns	JPMorgan / BlackRock / AQR	Randomly selected (equal 33% probability)
Volatilities	JPMorgan / BlackRock	Matched to return provider where available: • JPMorgan returns – JPMorgan volatility • BlackRock returns – BlackRock volatility • AQR returns – 50% probability of JPMorgan or BlackRock volatilities

47. To align the survey data with the CMAs used in the simulation, we mapped each survey asset class to the closest corresponding asset category used by each provider. This mapping process aligned the observed portfolio allocations reported by firms with the expected returns, volatilities and correlation assumptions applied in the modelling. Where exact matches were not available (e.g. UK real estate), the closest comparable asset class was selected based on the underlying investment characteristics and risk profile of the asset.

48. We adjusted JPMorgan's and AQR's published net return assumptions to estimated gross returns using the fee assumptions for each asset class. This ensures that the estimates are broadly comparable with BlackRock's gross return assumptions and reduces our reliance on estimates from a single provider. These adjusted figures are analytical estimates produced for this analysis and should not be interpreted as the firms' published gross return estimates.

49. We apply a very small positive volatility floor to BlackRock's zero volatility assets (e.g. cash). This is a safeguard required for the DCC-EGARCH estimation, as the model is undefined when an asset's volatility is zero. The floor is set at a negligible level and has no material impact on the results.

50. A summary of the expected annual returns and volatility estimates by provider at the asset class level is provided in Table 4 and Table 5, respectively.

Table 4: Expected annual gross returns by provider at the asset class level

Asset class	JPMorgan adjusted annual returns (%)	BlackRock annual returns (%)	AQR adjusted annual returns (%)
UK assets			
Listed equities	7.3%	6.5%	7.6%
Corporate bonds	5.9%	4.5%	5.5%
Government bonds	5.0%	5.7%	5.4%
Private equity	18.1%	13.9%	13.5%
Private credit	14.8%	10.3%	10.8%
Real assets	9.3%	5.9%	6.3%
Cash	2.7%	3.4%	3.7%
Other	2.7%	3.4%	3.7%
Non-UK assets			
Listed equities	7.8%	7.3%	6.9%
Corporate bonds	5.2%	4.5%	5.5%
Government bonds	4.0%	4.1%	4.5%
Private equity	18.1%	13.9%	13.5%
Private credit	14.8%	10.3%	10.8%
Real assets	8.9%	5.9%	6.2%
Cash	2.7%	3.4%	3.4%
Other	2.7%	3.4%	3.4%

Note: JPMorgan and AQR return assumptions are adjusted from net to gross using our standard fee assumptions. UK and non-UK private equity and private credit CMA assumptions are assumed to be the same as the CMA data do not split private equity and private credit by geography.

Source: BlackRock, FCA analysis of JPMorgan and AQR Capital Management CMAs

Table 5: Expected volatility by provider at the asset class level

Asset class	JPMorgan annual volatility (%)	BlackRock annual volatility (%)	AQR annual volatility (%)
UK assets			
Listed equities	13.2%	14.4%	N/A
Corporate bonds	7.8%	5.3%	
Government bonds	7.8%	10.6%	
Private equity	17.2%	24.3%	
Private credit	15.6%	10.5%	
Real assets	13.2%	9.7%	
Cash	0.7%	0.0%	
Other	0.7%	0.0%	
Non-UK assets			
Listed equities	14.0%	17.4%	N/A
Corporate bonds	5.6%	5.3%	
Government bonds	3.9%	3.8%	
Private equity	17.2%	24.3%	
Private credit	15.6%	10.5%	
Real assets	11.1%	9.7%	
Cash	0.7%	0.0%	
Other	0.7%	0.0%	

Note: UK and non-UK private equity and private credit CMA assumptions are assumed to be the same as the CMA data do not split private equity and private credit by geography.
Source: BlackRock, FCA analysis of JPMorgan and AQR Capital Management CMAs

Asset fee structures

51. Our simulation uses institutional fee structures that reflect typical institutional investor rates. Our assumed annual management fees of 0.5% for listed equities and 0.3% and 0.07% for corporate and government bonds, respectively, are consistent with the range of fees observed for actively managed institutional mandates reported in the LCP Investment Management Fees Survey. These fees are applied annually at the start of each investment year and are deducted before investment returns are applied.

52. We note that the assumed 0.5% equity management fee is intended as an illustrative fee for active listed equity management rather than a representative blended fee for a large DC default fund. In practice, the overall fee paid by a default fund would depend on its underlying active-passive asset allocation. We assume that cash holdings in pension funds have zero management fees and are simply held as cash.

53. Private equity and private credit are modelled using a "2 and 20" (2/20) structure, comprising a 2% annual management fee charged on committed capital (proxied by the asset value within the model) and a 20% performance fee (carry) applied only to returns above an 8% hurdle rate. While fee arrangements may vary across managers and investment strategies, this structure reflects a typical private markets fee model and provides a consistent basis for the analysis. It also captures the asymmetric nature of private market fee arrangements, where fixed fees are incurred regardless of performance, while performance fees are only triggered when investment returns exceed the specified threshold.

54. We note that this representation is an approximation of typical market fee arrangements and deliberately abstracts from contractual features such as distribution waterfalls and catch-up provisions, which vary across funds and are beyond the scope of this analysis. Furthermore, although the 2/20 structure is commonly used as a reference point for private market fees, private credit fee arrangements are more heterogeneous. The management fee assumptions used in our model may be higher than those observed for some private credit strategies in practice.

55. Real assets are assumed to incur a lower annual management fee of 0.75%, in line with the LCP Investment Management Fees Survey. This reflects the fact that, while these investments are classified within private markets, they typically involve more stable cash flows and lower portfolio turnover relative to private equity and private credit strategies. As a result, we assume they command lower fee structures to reflect variation in fee intensity across private market sub-classes.

56. Table 6 presents our fee structure assumptions by asset class.

Table 6: Fee structure assumptions by asset class

Asset class	Management fee	Performance fee	Hurdle rate
Listed equities	0.5% p.a.	None	N/A
Corporate bonds	0.3% p.a.		
Government bonds	0.07% p.a.		
Private equity	2% p.a.	20% carry	8%
Private credit			
Real assets	0.75% p.a.	None	N/A

Source: LCP Investment Management Fees Survey for listed equities, corporate bonds, government bonds, real assets. For private equity and private credit, we assume the historically standard 2/20 fee structure.

Asset class correlation structure

57. The correlation structure determines how asset classes move in relation to one another. This is represented through a correlation matrix, which specifies pairwise correlations between all asset classes and captures key empirical relationships observed in financial markets.

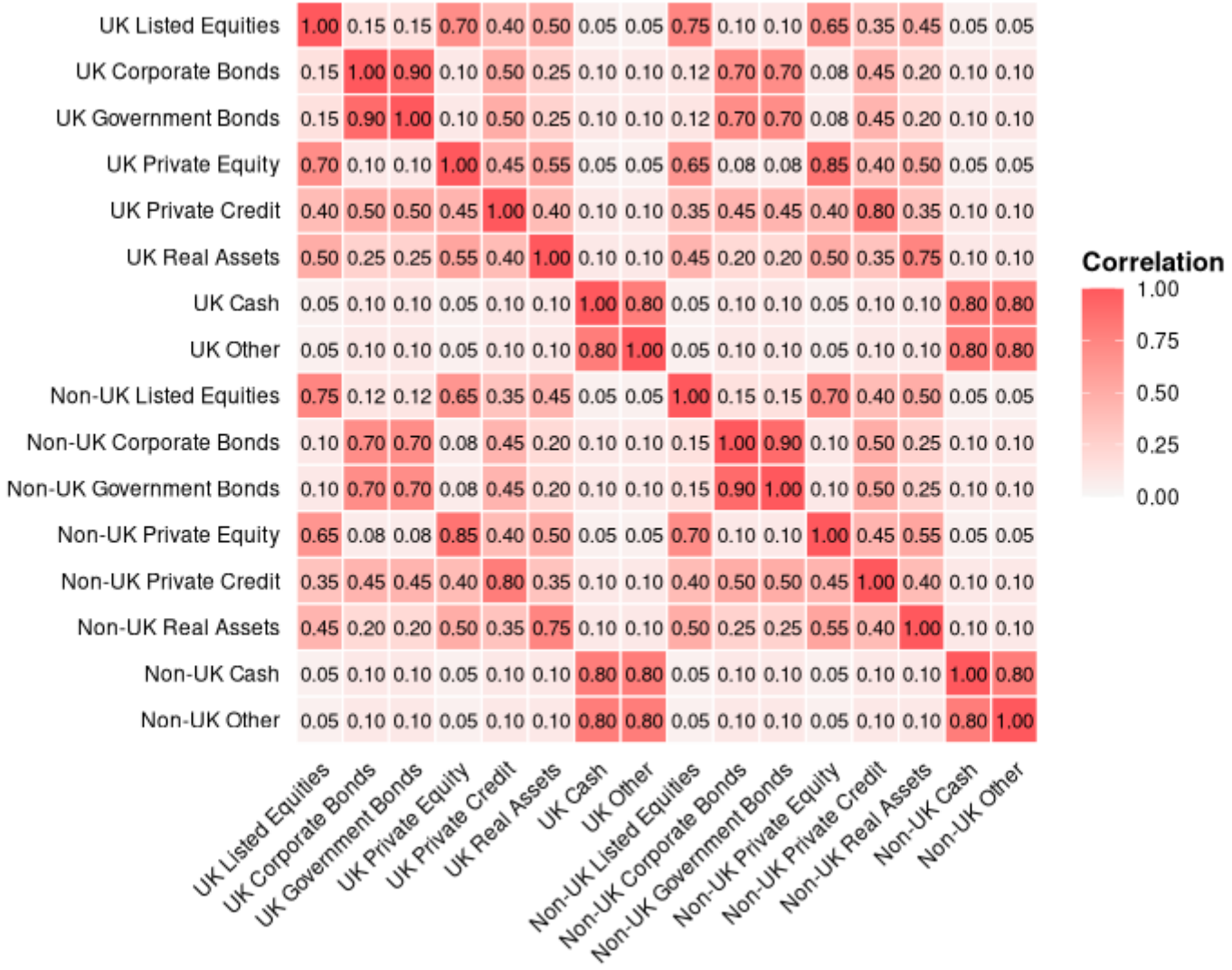
58. Correlation coefficients range from -1 to +1, where higher positive values indicate stronger co-movement, negative values indicate inverse relationships, and zero indicates no linear dependence. Their inclusion ensures that we do not incorrectly assume independence across assets, overstating diversification benefits and understating portfolio risk.

59. Correlations also interact with modelling performance fee dynamics, as they influence the extent to which returns across private market assets are simultaneously above or below hurdle rates. This affects the frequency of performance fee payments across scenarios, which is material to assessing aggregate fee outcomes under different market conditions.

60. The asset correlation assumptions used in the simulation are derived from JPMorgan's CMA dataset and presented in Figure 2 on the next page. A limitation of our approach is that equivalent full correlation matrices are not consistently available across CMA providers used to inform returns and volatility estimates, including BlackRock and AQR. As a result, the simulation relies on a single source for correlation estimates. While this ensures consistency across asset classes within the modelling framework, we acknowledge that it introduces a degree of model dependency on one provider's view of cross-asset relationships.

61. Importantly, these correlations are not held constant throughout the simulation but rather serve as long-run targets around which conditional correlations fluctuate dynamically in response to market conditions. Methodologically, our DCC-EGARCH model allows both conditional volatilities and correlations to vary over time. We provide further detail in the *DCC-EGARCH* methodology section.

Figure 2: Correlation structure across asset classes



Source: JPMorgan

General modelling assumptions

62. Our Value for Money Framework consultation, discussed earlier in the *asset allocation* sub-chapter, found that contract-based pension providers covered approximately £260 billion of assets within the accumulation phase of the main default arrangements of their workplace pension products. After restricting the sample to the MHA signatories, the corresponding asset value is £206 billion. This serves as the aggregated starting portfolio value for both the baseline and intervention scenarios.

63. A short time horizon (e.g. 5 years) would not adequately capture the effects of increased private markets exposure, as much of the portfolio transition would still be underway and we expect that the long-term return characteristics of private market investments would take time to materialise. In particular, private market assets are typically held over longer investment horizons, with returns often realised gradually through asset maturation and exit events rather than immediately upon allocation. Conversely, a longer horizon beyond 10 years would compound uncertainty around CMAs and the durability of the policy environment.

64. On that basis, the model uses 2026 as the baseline (Year 0), with intervention assumptions aligned to the baseline in that year. Outcomes are then projected over the subsequent ten years, with final portfolio values measured in 2036.

65. In addition to the starting portfolio value, the model incorporates ongoing saver contributions over the 10-year period. This reflects the fact that workplace pension default funds receive a continuous inflow of new capital, which forms part of the assets available for investment. Our approach to calculating savers' contributions is set out below.

66. The Department for Work and Pensions (DWP) publishes annual official statistics on workplace pension participation and saving trends. Estimates derived from the Office for National Statistics (ONS) Annual Survey of Hours and Earnings (ASHE) indicate that £60.8 billion was saved into DC pensions in 2023. We assume that this represents the total amount saved across all workplace DC pensions.

67. We apply the proportion of defined contribution (DC) savers who contribute to a Group Personal Pension (GPP) at 28% to estimate annual contributions of £17.2 billion for GPP members. We then apply the estimated proportion of these members who are invested in a default fund in the accumulation phase (49%), based on the share of MHA signatories (£206bn) relative to the total value of FCA-regulated contract-based pension assets (£422bn). This results in estimated annual contributions of £8.4 billion (2023 prices).

68. We uprate this value to 2026 prices using Office for Budget Responsibility (OBR) forecasts for earnings and employment growth. This results in estimated annual contributions of £10.1 billion at the start of the appraisal period. These contributions grow at 2.5% to 3.8% per year in line with OBR forecasts for employment and earnings growth between 2027 and 2036.

69. We assume savers' contributions are made at the start of each year and are immediately invested across all asset classes in proportion to the portfolio's target weights. This ensures that new contributions follow the same strategic asset allocation as existing portfolio assets throughout the simulation period.

70. Portfolio rebalancing is an important feature of the modelling framework as it prevents changes in relative asset-class performance from moving the portfolio away

from its target strategic asset allocation. Without periodic rebalancing, differences in compounded returns cause outperforming asset classes to represent an increasing proportion of the portfolio over time, increasing concentration risk and altering the portfolio's risk-return profile. For example, sustained outperformance in equities relative to bonds would cause the portfolio to become increasingly equity weighted.

71. To address this, the model rebalances the portfolio annually after returns have been realised and fees deducted. At each rebalancing point, the total portfolio value is redistributed across asset classes in line with the target allocation weights.

72. For simplicity, the model assumes frictionless rebalancing with no transaction costs beyond the management and performance fees already captured in the fee structure. In practice, pension schemes may incur additional costs when rebalancing (e.g. broker commissions), though these are typically small for liquid assets such as large-cap equities relative to the management fees modelled.

73. For each asset class i, the post-rebalancing value is:

$$V_{i,t} = V_{total,t} \times w_{i,t}$$

Where:

- $V_{total,t}$ represents the total portfolio value after returns and fees.
- $w_{i,t}$ represents the target weight for asset i in year t.

74. This redistributes capital across all asset classes to restore target asset allocations. In the intervention scenario, these target weights evolve over time as the portfolio transitions toward a higher allocation to private markets, meaning the annual rebalancing process progressively shifts the portfolio toward the new strategic allocation.

Intervention scenario – increased asset allocation in private markets

75. The intervention scenario assumes that specified performance fees are exempt from the charge cap, removing a potential barrier to firms increasing their private market allocations in line with their MHA commitments. Unless stated otherwise, the intervention uses the same modelling assumptions as the baseline.

76. Here, the portfolio undergoes a dynamic time-varying transition in asset allocation. Starting from a baseline of 5.5% asset allocation in private markets in 2027, schemes progressively increase this allocation through a smooth linear transition over three years, reaching the MHA target of 10% allocation in private markets by 2030.

77. This transition follows a linear interpolation formula. For any year t during the transition period (where t =1 corresponds to 2027 and t =4 corresponds to 2030), the private markets allocation weight w_t is calculated as:

$$w_t = w_{baseline} + \left[\frac{(t-1)}{(T-1)}\right] \times \left(w_{target} - w_{baseline}\right), t = 1,2,3,4$$

where:

- $w_{baseline}$ = 5.50% (initial allocation).

- w_{target} = 10% (target allocation).
- T = 4 (number of years in transition period including endpoints).
- $\frac{(t-1)}{(T-1)}$ represents transition progress.

This produces:

- Year 1: 5.50% + (0/3) × 4.50% = 5.5%
- Year 2: 5.50% + (1/3) × 4.50% = 7.0%
- Year 3: 5.50% + (2/3) × 4.50% = 8.5%
- Year 4: 5.50% + (3/3) × 4.50% = 10.0%

The allocation remains at 10% for years 5 through 10.

78. The strategic allocation path is defined by the time-varying weights described above. For implementation purposes, the model assumes annual forward-looking rebalancing, whereby contributions and rebalancing trades are allocated according to the subsequent year's target weights. Consequently, the portfolio is rebalanced to the 2028 allocation during 2027, the 2029 allocation during 2028, and the 2030 target allocation during 2029. This reflects a phased implementation approach designed to ensure schemes remain on track to meet the 2030 Mansion House target.

79. Table 7 sets out asset allocations in the private markets across our appraisal period in this scenario.

Table 7: Asset allocations across the appraisal period in the intervention scenario

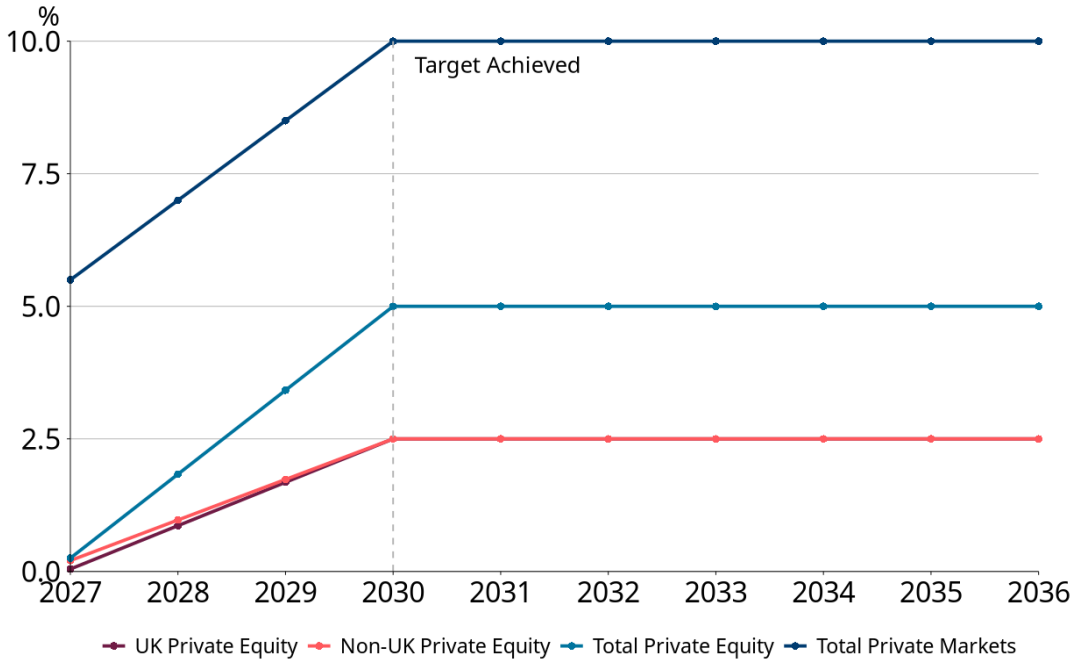
Year	Total private markets (%)	Private equity (%)	Private credit (%)	Real assets (%)
2027	5.50%	0.25%	0.31%	4.94%
2028	7.00%	1.83%	0.86%	4.33%
2029	8.50%	3.42%	1.41%	3.72%
2030+	10.00%	5.00%	2.50%	2.50%

Source: FCA analysis

80. Following the MHA, UK DC pension schemes are expected to continue increasing their allocations to private markets, building on the earlier MHC, announced in 2023. The MHC established an ambition for participating pension providers to allocate around 5% of their DC funds to unlisted equities by 2030.

81. Against this backdrop, this scenario specifically allocates 5% (of the 10% investment in private markets) to private equity to meet the MHC's pledge. As the MHC and the MHA do not require the 5% private equity allocation to be exclusively UK-only, we assume an investment split of 2.5% across UK and non-UK markets.

Figure 3: Asset allocation evolution in private markets



Source: FCA analysis

82. We note that the 5% private equity / 2.5% private credit / 2.5% real assets split is one feasible implementation of the 10% asset allocation in private markets. Alternative compositions (e.g. varying allocations across the private credit and real asset markets) would yield different outcomes. Accordingly, the results presented in this technical note are conditional on the specific asset allocation assumed and should not be generalised to all private market allocations.

3 DCC-EGARCH methodology

83. The DCC-EGARCH framework is designed to capture 2 key empirical characteristics of financial markets that are overlooked by standard models that assume constant volatility and correlations.
    - Rather than remaining constant, asset return volatility tends to alternate between periods of high and low volatility (Bollerslev, 1986; Campbell et al., 1997).
    - At the same time, correlations between assets are time-varying and typically increase during periods of market stress, reducing the benefits of diversification precisely when they are most valuable (Engle, 2002; Forbes & Rigobon, 2002).

84. For pension portfolios with private markets exposure, these features matter. Within the context of our analysis, this is important as the portfolios analysed are heavily exposed to equity markets, with more than 75% allocated to listed and private equities. A model that assumes constant volatility and correlations may underestimate tail risk (i.e. the probability of very low return outcomes) and fail to capture realistic fee dynamics. For example, performance fees in private equity are triggered by returns exceeding hurdle rates; whether these hurdles are breached also depends on the volatility environment. Models that ignore volatility clustering and asymmetry may produce overly optimistic projections.

85. The EGARCH component extends standard volatility modelling by allowing asymmetric responses to positive and negative shocks. In equity markets, bad news (i.e. negative returns) tends to increase subsequent volatility more than good news of the same magnitude - a phenomenon known as the "leverage effect" (Black, 1976; Nelson, 1991). This asymmetry reflects market psychology and financial leverage dynamics, where losses amplify uncertainty and trigger risk-averse behaviour, which elevates volatility more than equivalent-sized gains reduce it.

86. Given these characteristics, we adopt a DCC-EGARCH specification rather than the standard DCC-GARCH model, which assumes symmetric responses of volatility to shocks. This choice is consistent with the empirical features of equity markets outlined above, where volatility is persistent and correlations vary over time.

87. The remainder of this section provides the mathematical details of our technical specification.

Generating returns

88. Asset returns are generated according to the following equation:

$$r_t = \mu + \Sigma_t^{1/2} Z_t$$

Where:

- r_t is the (N × 1) vector of daily asset returns at time t .
- μ is the (N × 1) vector of expected daily returns.
- Σ_t is the (N × N) time-varying covariance matrix.
- $Z_t \sim t_v(0, I)$ are standardised Student-t distributions with 8 degrees of freedom.

89. The core equation can be broken down into the sum of 2 components:
    - First, a deterministic drift term representing long-run expected returns.

- Second, a stochastic term capturing random variation around those expectations.

This decomposition allows the model to separate predictable return patterns that are derived from our CMA modelling inputs, from unpredictable market fluctuations that drive portfolio risk.

90. The stochastic component comprises of a time-varying conditional covariance matrix (Σ_t). This is specified as following a DCC-EGARCH model and determines the scale and dependence structure of the return shocks over time. By allowing both conditional volatilities and correlations to vary dynamically, the model captures changing market conditions across asset classes. More specifically, Σ_t is not constant across time; rather, it evolves according to EGARCH processes (controlling individual asset volatilities) and DCC dynamics (controlling cross-asset correlations). This time-variation is important for risk modelling in pension portfolios where tail events (i.e. severe losses occurring with low probability) are more likely to happen when conditional volatilities and correlations increase.

91. The second element of the stochastic component Z_t is drawn from a multivariate Student-t distribution:

- $Z_t \sim t_v(0, I)$ with v = 8 degrees of freedom rather than a standard normal distribution.

This choice reflects empirical evidence that financial returns exhibit fat tails, with a higher probability of extreme positive and negative outcomes than under a normal distribution. Our modelling approach, with 8 degrees of freedom, provides a realistic balance in which the distribution has sufficiently fat tails to capture tail risk, but not so extreme as to generate unrealistic "black swan" events in every simulation.

92. Together, these components generate daily returns that reflect time-varying volatility, dynamic correlations and fat-tailed return distributions. Daily returns are compounded into annual returns, which are then used for portfolio valuation, fee calculations, and rebalancing. Modelling returns at the daily frequency captures intra-year risk dynamics, including volatility clustering and performance fee triggers, while maintaining computational efficiency over the 10-year simulation horizon.

EGARCH (1,1) conditional volatility

93. Each asset follows a univariate EGARCH (1,1) process:

$$\log\left(\sigma_{t,i}^2\right) = \omega_i + \beta \log\left(\sigma_{t-1,i}^2\right) + \alpha\left|S_{t-1,i}\right| + \gamma S_{t-1,i}$$

Where:

- $\log\left(\sigma_{t,i}^2\right)$ is the conditional variance of asset class i at time t.
- ω_i is the asset-specific constant that anchors conditional variance to its long-run level.
- β is the volatility persistence parameter, which determines how strongly the previous period's conditional variance affects current conditional variance.
- α is the magnitude-effect parameter, which determines how the absolute size of the previous period's shock affects current conditional variance.
- γ is the asymmetry parameter, which allows positive and negative shocks of the same magnitude to have different effects on current conditional variance.

- $S_{t-1,i} = \frac{\varepsilon_{t-1,i}}{\sigma_{t-1,i}}$ represents the standardised residual, where $\epsilon_{t,i} = r_{t,i} - \mu_i$ is the unexpected component of the return for asset i.

94. We note that the more general EGARCH specification (Nelson, 1991) includes an explicit centering term $E(|S_{t-1,i}|)$. Our specification above follows a simplified EGARCH form of Nelson's specification where the centering term is absorbed into the constant ω_i during calibration. For our Student-t innovations, $E(|S|) \approx 0.8$, which is accounted for in the ω_i calibration.

95. EGARCH models the logarithm of variance rather than variance itself such as in the standard GARCH (1,1) process. The log transformation naturally accommodates the empirical observation (Schwert, 1989; Nelson, 1991; Pagan & Schwert, 1990) that volatility changes tend to be proportional rather than additive. To illustrate this, a 10% increase in volatility from a high base (30% to 33%) and a 10% increase from a low base (5% to 5.5%) represent the same proportional change, despite differing in absolute magnitude.

96. The equation describes how today's log-variance depends on three components from the previous period. First, the constant term (ω_i) anchors the process to a long-run average volatility level, calibrated to match CMAs for each asset class.

97. The persistence term $\beta \log(\sigma^2_{t-1,i})$ represents volatility clustering. Our persistence parameter (β = 0.95) is set to match empirical estimates from daily equity return data, which consistently find values between 0.93 and 0.97 across developed markets (Nelson, 1991; Glosten et al., 1993). This parameter assumes that volatility exhibits strong persistence such that a shock that elevates volatility today will continue to influence volatility many days into the future, gradually decaying but remaining elevated over time.

98. The innovation terms $\alpha|S_{t-1,i}|$ and $\gamma S_{t-1,i}$ capture how yesterday's return shock affects today's volatility. The standardised residual $S_{t-1,i}$ measures the size and direction of the previous day's unexpected return relative to that day's volatility. For example,, $S_{t-1,i} = +2$ means the return was two standard deviations above its expected value.

99. The magnitude effect parameter (α = 0.15) determines how the absolute size of shocks, regardless of sign, affects volatility. Larger shocks increase volatility, reflecting heightened uncertainty following unexpected market moves. This effect alone would produce symmetric volatility responses, treating gains and losses identically. It is important to generate volatility that clusters realistically without reacting to every market move.

100. If α is too small, say less than 0.10, volatility barely responds to shocks, producing unrealistically smooth volatility paths. However, if α is too large, say 0.20, every shock creates dramatic volatility spikes. The value of α = 0.15 represents a middle-ground estimate from the empirical EGARCH literature on equity markets, which reports α estimates between 0.10 and 0.18 for daily stock returns across different specifications and time periods (Nelson, 1991; Braun, Nelson, & Sunier, 1995).

101. The asymmetry parameter (γ = -0.05) captures leverage effects whereby negative return shocks increase subsequent volatility more than positive shocks of equal magnitude. Empirical estimates from EGARCH models fitted to equity market data consistently yield negative values between -0.03 and -0.07 (Nelson, 1991; Hentschel, 1995), implying that negative shocks increase volatility by approximately 1.5 to 2 times more than positive shocks.

102. We select γ = -0.05 as a moderate parameterisation that sits squarely within this empirically observed range. It is sufficiently negative to capture documented leverage effects in equity-dominated portfolios (which comprise over 75% of our modelled portfolios), but not so extreme as to produce implausible volatility explosions after every downturn. This parameter remains constant across all asset classes for parsimony, with asset-specific volatility levels introduced through calibration of the ω_i constant terms to match CMA targets.

103. As set out above, the parameters α, β and γ are based on estimates drawn from the broader empirical literature. We do not separately calibrate these parameters by asset class; instead, a common parameterisation is applied across asset classes for parsimony, with asset-specific long-run volatility captured through the calibration of the ω_i terms to the relevant CMA assumptions.

Dynamic conditional correlation

104. Correlations evolve according to the DCC specification of Engle (2002):

$$Q_t = (1 - a - b)\bar{R} + aS_{t-1}S_{t-1}' + bQ_{t-1}$$

$$D_t^Q = diag\left(\sqrt{diag(Q_t)}\right)$$

$$R_t = \left(D_t^Q\right)^{-1} Q_t \left(D_t^Q\right)^{-1}$$

Where:

- $\bar{R}$ is the unconditional correlation matrix (target, from CMAs)
- S_{t-1} is the vector of standardised residuals
- a = 0.05 (response to co-movements)
- b = 0.90 (correlation persistence)
- Q_t is an auxiliary matrix that captures correlation dynamics
- $D_t^Q$is the diagonal scaling matrix constructed from the square roots of the diagonal elements of Q_t
- R_t represents the final conditional correlation matrix

105. While EGARCH processes govern how individual asset volatilities evolve, the DCC specification determines how assets move together over time. During market stress, assets that normally provide diversification benefits tend to move in tandem as investors engage in broad-based risk reduction, whereas during calm periods correlations revert toward lower long-run averages.

106. The DCC framework models this time-variation through two steps. First, an auxiliary matrix Q_t is constructed to capture the dynamics of asset co-movements. Second, Q_t is normalised using its diagonal elements to obtain the conditional correlation matrix R_t, ensuring unit diagonal elements and expressing the off-diagonal elements as correlations.

107. The auxiliary matrix Q_t evolves as a weighted average of three components. The first component is the unconditional correlation matrix $\bar{R}$ derived from CMAs, representing the long-run target toward which correlations gravitate. The second component $S_{t-1}S_{t-1}'$ captures the effect of new information on correlations, with large co-movements in recent standardised shocks leading to adjustments in the conditional correlation matrix. The third component is yesterday's Q matrix Q_{t-1} , providing

persistence - i.e. correlations do not jump instantaneously but adjust gradually based on accumulated evidence of changing co-movement patterns.

108. The weighting parameters a and b determine how quickly correlations respond to new information and how strongly they persist over time. These parameters are selected based on empirical regularities in the DCC literature, where Engle's (2002) original study and subsequent applications report typical estimates of a between 0.01 and 0.08 and b between 0.85 and 0.95 (Cappiello et al., 2006; Engle & Sheppard, 2001).

109. We adopt a = 0.05 and b = 0.90 as representative values within this empirically observed range. This parameterisation implies that correlations adjust gradually: a 5% weight is placed on new co-movement information, 90% on the existing correlation structure, and the remaining 5% on mean reversion toward the long-run CMA target (1 - a - b = 0.05). This high persistence (a + b = 0.95) generates sustained periods of elevated correlations following market stress, with a persistence half-life of approximately 14 trading days.

Covariance decomposition

110. The time-varying covariance is decomposed as:

$$\Sigma_t = D_t R_t D_t$$

111. The diagonal matrix D_t contains the conditional standard deviations (volatilities) of each asset at time t. These volatilities are time-varying: they increase following large return shocks and respond asymmetrically to positive versus negative returns (i.e. the leverage effect outlined above). The diagonal structure of D_t means that it captures only individual asset volatilities. Each asset's volatility evolves according to its own EGARCH process without directly depending on other assets' returns. In practice, this means that listed equity volatility can surge during market turbulence while bond volatility remains stable.

112. The correlation matrix R_t captures how assets move together at time t. Unlike D_t, which is diagonal (only describing individual assets), R_t is a full matrix with off-diagonal elements measuring pairwise correlations between all asset classes in the portfolio. These correlations evolve dynamically according to the DCC specification, typically increasing during market stress when risk-off behaviour causes investors to sell multiple asset classes simultaneously. During calm periods, correlations revert toward their long-run averages, allowing diversification to function as intended.

113. The covariance matrix is obtained by pre- and post-multiplying the dynamic correlation matrix R_t by the diagonal volatility matrix D_t. This transforms the unit-free correlations into covariances by scaling each pairwise correlation by the product of the corresponding assets' conditional standard deviations.

114. Intuitively, the same correlation can imply very different contributions to portfolio risk depending on the prevailing level of volatility. For example, two assets with a correlation of 0.5 contribute substantially more to portfolio risk when their volatilities are 20% than when they are 5%, because higher volatility increases the magnitude of the covariance implied by a given level of correlation.

115. By separating these effects, the model allows volatility spikes to interact with correlation changes. To provide an example of how this works in practice, during the

2008 financial crisis, both equity volatilities and equity-bond correlations increased simultaneously, compounding portfolio losses. Standard models that assume constant volatilities and correlations would miss this compounding effect entirely.

116. This decomposed structure has direct implications for performance fee dynamics. Performance fees are triggered when private equity returns exceed hurdle rates, which depends not only on private equity volatility (captured in D_t) but also on how private equity co-moves with public equities that dominate the rebalancing flows (captured in R_t).

Model calibration approach

117. A key advantage of our approach is that the DCC-EGARCH model does not require historical data estimation. Instead, it is calibrated directly to match the unconditional moments (means, variances, correlations) implied by the forward-looking CMAs. The calibration procedure is set out below.

118. Annual expected returns from CMAs are converted to daily expected returns:

$$\mu_{daily,i} = \frac{\mu_{annual,i}}{252}$$

where 252 is the number of trading days in a standard year. This assumes continuous compounding and is accurate for small daily returns.

119. For each asset, the unconditional variance from CMAs is:

$$\sigma^2_{annual,i}$$

This is converted to daily unconditional variance:

$$\sigma^2_{daily,i} = \frac{\sigma^2_{annual,i}}{252}$$

using 252 days for annualisation.

120. The EGARCH volatility process is calibrated to the daily volatility implied by the CMA assumptions. For each asset i**,** the target unconditional variance is given by the square of the CMA-implied daily volatility, $\sigma^2_{\text{daily},i}$. Since the EGARCH model is specified in terms of log variance, the intercept ω_i is calibrated as:

$$\omega_i = (1-\beta)\log\left(\sigma^2_{\text{daily},i}\right) - \alpha E[\,|\,S_i\,|\,]$$

where α and β are the EGARCH magnitude and persistence parameters, respectively, and $E[\,|\,S_i\,|\,]$ is the expected absolute value of the standardised innovation. For the standardised Student-t innovations used in the simulation, $E[\,|\,S_i\,|\,]$ is approximated by 0.7655. This value accounts for the rescaling of the Student-t innovations to unit variance, as implemented in the simulation. Thus:

$$\omega_i = (1-\beta)\log\left(\sigma^2_{\text{daily},i}\right) - 0.7655\alpha.$$

This calibration ensures that the unconditional expected log-variance of the EGARCH process is consistent with the variance implied by the CMA daily volatility.

121. The DCC process targets the unconditional correlation matrix:

$$\bar{R} = Correlation\ matrix\ from\ CMAs$$

122. The CMA correlation matrix serves directly as the long-run target ($\bar{R}$) toward which time-varying correlations gravitate. No adjustment is required because the DCC parameters a and b control only the speed of adjustment and persistence around this target. Over sufficiently long periods, the average correlation between any two assets converges to the CMA value in $\bar{R}$, even though daily correlations fluctuate above and below this level in response to market shocks.

123. For each simulation, the initial log conditional variance is set to the log of the target unconditional variance:

$$\log(\sigma_{o,i}^2) = \log(\sigma_{daily,i}^2)$$

The initial DCC auxiliary matrix and conditional correlation matrix are set to the unconditional correlation matrix:

$$Q_o = R_0 = \bar{R}$$

124. By initialising at long-run averages rather than arbitrary values, volatility and correlation paths immediately reflect realistic market behaviour without requiring an adjustment period to reach equilibrium.

125. The CMA-implied daily volatility estimates are used to scale the standardised Student-t innovations and generate the stochastic component of daily returns. Specifically, the simulated innovation for each asset is obtained by multiplying the standardised shock by its conditional volatility, after which the expected daily return is added to obtain the simulated return. The resulting innovation is then standardised by the conditional volatility and fed back into the EGARCH and DCC processes, where it determines the subsequent evolution of volatility and correlations.

4 Results

Does the cap exemption deliver net benefits to pension savers through increased investment in private markets?

126. The final net portfolio values in 2036 represent the modelled value of pension assets at the end of the 10-year appraisal period, after deducting all management and performance fees applied within the model. We use these values to compare saver outcomes under the baseline and intervention scenarios. Table 8 shows the distribution of final net portfolio values across the interquartile range (IQR).

Table 8: Final net portfolio values across baseline & intervention scenarios, £bn

Scenario	25th percentile	Median	75th percentile
Baseline	£414.3	£520.1	£652.4
Intervention	£422.9	£530.9	£664.7
% change in value by scenario	+2.1%	+2.1%	+1.9%

Source: FCA analysis

127. The baseline scenario produces a median final portfolio value of £520bn. This represents the expected business-as-usual outcome under existing regulatory constraints. The distribution of outcomes around this central estimate is substantial. The IQR spans from £414bn (25th percentile) to £652bn (75th percentile), a spread of £238bn that reflects the inherent uncertainty in long-horizon pension investing even under relatively conservative allocation strategies.

128. The intervention scenario generates a median final portfolio value of £531bn. This exceeds the baseline median by approximately £10.8bn, representing a 2.1% improvement in the final portfolio value. While relatively modest in percentage terms, this equates to a material increase in benefits to savers at the aggregate level. For savers, the result suggests that allowing greater exposure to private markets through the proposed policy could improve long-term retirement outcomes after accounting for both management and performance fees.

Table 9: Final gross portfolio values across baseline & intervention scenarios, £bn

Scenario	25th percentile	Median	75th percentile
Baseline	£428.4	£536.6	£671.0
Intervention	£443.3	£555.2	£692.7
% change in value by scenario	+3.5%	+3.5%	+3.2%

Source: FCA analysis

129. In gross terms, the final portfolio values in 2036 are presented in Table 9. The baseline scenario produces a median final gross portfolio value of £537bn compared with £555bn under the intervention scenario. Before fees are deducted, this represents a 3.5% increase in final portfolio value.

130. Comparing the gross and net results shows that while the intervention delivers higher investment returns, part of these gains is offset by higher management and performance fees associated with the increased allocation to private markets. We discuss the impact of the intervention on manager fees in the following sub-chapter.

131. The intervention increases portfolio variance as schemes trade higher private market allocation for higher expected returns. The IQR increases from £238bn in the baseline to £242bn under the intervention, representing a 1.7% increase in outcome dispersion. This reflects the higher volatility of most private market asset classes relative to public market assets, particularly the uncertainty around performance fee triggers when returns exceed the 8% hurdle rate. Despite this modest increase in risk, the estimated standard deviation remains stable at approximately 32% of median portfolio value under both scenarios.

132. While the intervention introduces a small increase in the dispersion of outcomes, the change in the overall risk profile remains limited relative to the potential benefits of enhanced return generation. This suggests that the projected gains are not solely driven by a small number of favourable outcomes but instead reflect a broader upward shift in the distribution of simulated portfolio values.

133. We note that risk is captured primarily through the stochastic modelling framework rather than through a mechanical adjustment to estimated returns. The DCC-EGARCH model generates a distribution of potential outcomes that reflects uncertainty in asset returns, correlations and market conditions over the appraisal period. This simulation framework explicitly models the distribution of risky outcomes, but the resulting estimates do not themselves adjust for savers' risk aversion or the utility associated with those outcomes.

134. As a sensitivity check, we also estimate certainty-equivalent outcomes using a constant relative risk aversion (CRRA) utility function to assess whether the intervention's estimated benefits remain after accounting for saver risk aversion. This approach is discussed in further detail in the *sensitivity analysis* chapter.

Downside and upside scenario analysis

135. In addition to the central scenario discussed above, we also report the 5th and 95th percentile outcomes from the intervention model to represent our downside and upside scenarios, respectively. By reporting the full distribution of outcomes, we evaluate greater dispersion in potential outcomes, including both the upside potential and downside risks inherent in higher private market exposure.

136. The downside scenario captures outcomes worse than 95% of simulations, reflecting weaker private market returns, prolonged high-volatility regimes, and increased market correlations that reduce diversification benefits during stress periods. Conversely, the upside scenario captures outcomes better than 95% of simulations, driven by stronger returns, sustained low volatility, and correlations remaining near long-term assumptions.

137. Table 10 presents the difference in portfolio value across our downside and upside scenarios for the baseline and intervention.

Table 10: Final net portfolio values (year 10) for 5th and 95th percentile outcomes, nominal £bn

Scenario	5th percentile	95th percentile
Baseline	£299.9	£905.0
Intervention	£306.0	£918.4
% change in value by scenario	2.0%	1.5%

Source: FCA analysis

138. At the downside, the baseline scenario delivers a gain of £6.1bn or 2.0%. At the upside the baseline delivers a gain of £13.4bn or 1.5%. The relative similarity in absolute gains at both tails suggests the intervention delivers a consistent benefit, relative to the baseline, irrespective of whether outcomes are favourable or adverse.

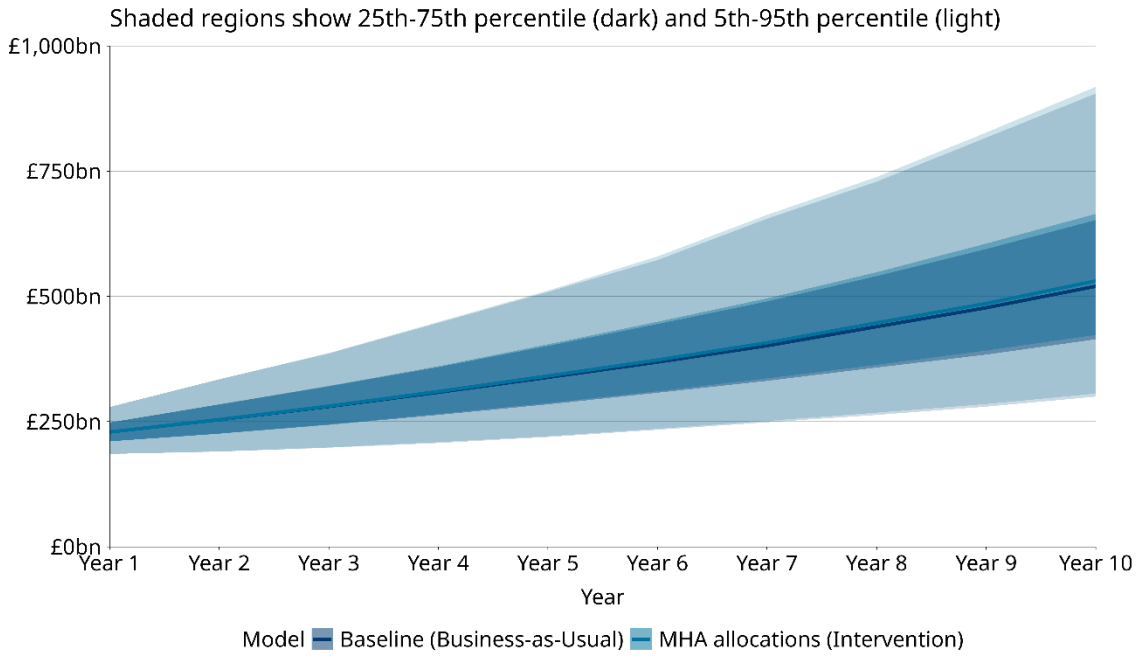
139. The improvement across both tails reflects the interaction between higher private market exposure and the asymmetric nature of performance fees. By replacing lower-returning public market assets with private markets (particularly private equity and private credit), the intervention increases expected returns; however, in weaker market environments, private equity and private credit performance fees are less likely to be triggered. As a result, schemes retain more of the benefit from increased private market exposure in adverse scenarios, while in stronger scenarios a greater share of incremental returns is transferred through performance fees. This creates an improvement across the outcome distribution, with the relative benefit more pronounced in downside scenarios.

140. Furthermore, the DCC model allows correlations between private and public markets to increase during periods of market stress, reflecting the tendency for asset classes to become more closely linked during volatile periods. However, correlations remain below one, indicating that private equity does not move exactly in line with public markets and therefore continues to provide some diversification benefits, even when public markets experience significant pressure.

141. This finding may also reflect a model limitation. The calibration to unconditional CMAs means expected returns are not state-dependent, so private market premiums do not explicitly shrink during severe downturns as might occur if liquidity dries up or exit markets freeze. The true intervention benefit is likely therefore more variable across market states than these results suggest.

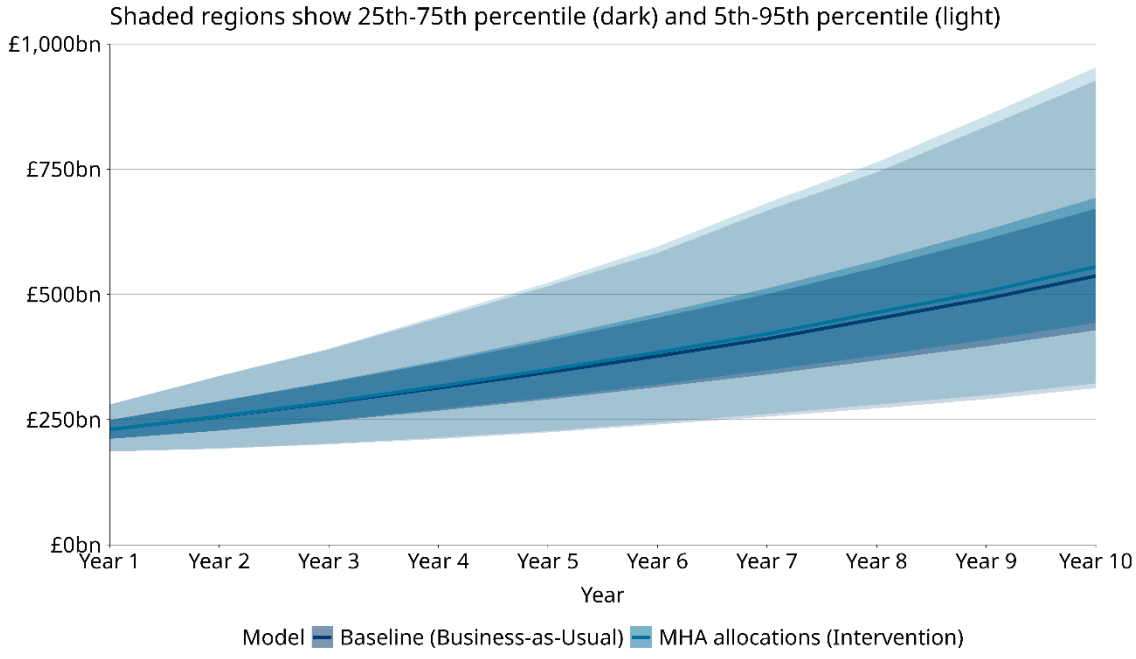
142. Figure 4 (net of fees) and Figure 5 (gross) below show the trajectory in portfolio value under the intervention and baseline scenarios at different percentiles over our appraisal period. The distribution fans out substantially over time, reflecting compounding return uncertainty. The 5th and 95th percentile range spans significant value differences of approximately £600bn (as discussed in Table 10 above), demonstrating the fundamental long-horizon projection uncertainty.

Figure 4: Portfolio value (net of fees) trajectory by percentile over the appraisal period



Source: FCA analysis

Figure 5: Portfolio value (gross of fees) trajectory by percentile over the appraisal period



Source: FCA analysis

143. For completeness, in Table 11 we present the median portfolio values for the baseline and intervention scenarios across the ten-year appraisal horizon.

Table 11: Breakdown of median portfolio value (net) across scenarios by year

Year	Baseline (£bn)	Intervention (£bn)	Difference in value (£bn)	% change
1	£229.2	£229.2	-	-
2	£253.8	£254.0	+£0.2	+0.08%
3	£280.1	£280.9	+£0.8	+0.29%
4	£308.4	£310.1	+£1.7	+0.55%
5	£338.2	£341.2	+£3.0	+0.89%
6	£368.8	£373.1	+£4.3	+1.17%
7	£401.5	£407.5	+£6.0	+1.49%
8	£439.5	£447.2	+£7.7	+1.75%
9	£477.3	£485.9	+£8.6	+1.80%
10	£520.1	£530.9	+£10.8	+2.08%

Source: FCA analysis

To what extent does the exemption shift revenues from public market asset managers toward private market managers?

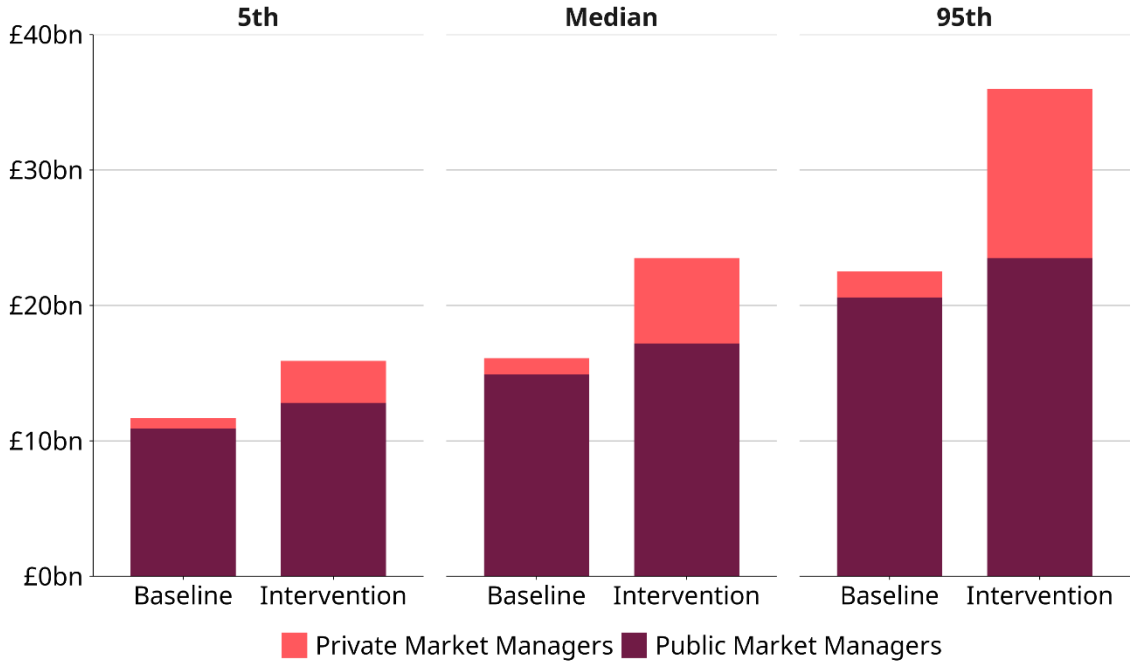
144. Table 12 and Figure 6 below disaggregate total fee revenue between public market managers and private market managers across the median and upside/downside scenarios for baseline and intervention.

Table 12: Total cumulative fee revenue by manager type, £bn

Manager type	Baseline (5%)	Intervention (5%)	Baseline (median)	Intervention (median)	Baseline (95%)	Intervention (95%)
Public market	£10.3	£12.6	£14.9	£17.8	£21.4	£22.9
Private market	£0.7	£1.6	£1.2	£5.0	£2.3	£18.4
Total	£11.0	£14.2	£16.1	£22.8	£23.7	£41.3
% change across scenarios	29.1%		41.6%		74.3%	

Source: FCA analysis

Figure 6: Breakdown of private and public manager fee revenue by simulation percentile



Source: FCA analysis

145. The intervention increases total median fee revenue across the 10-year horizon from £16.1bn (baseline) to £22.8bn in the intervention scenario, an increase of £6.7bn or 42%. This additional fee burden is distributed asymmetrically between public and private market managers.

146. Public market manager median fees increase from £14.9bn to £17.8bn, despite their allocation share declining from 94.5% to approximately 90% in the intervention scenario. Given the reduced share of public market assets, this result appears

counterintuitive. However, there are a few potential mechanisms that drive this result.

147. First, private market assets are assumed to generate higher returns than public market assets. As these assets outperform, their share of the portfolio rises above the target allocation. Annual rebalancing restores the target weights by transferring part of these gains from private markets into public market assets. Over the 10-year horizon, this process occurs repeatedly, meaning that public market managers receive a series of inflows funded by private market outperformance. Although public markets represent a smaller proportion of the portfolio under the intervention, they are, in effect, managing a larger asset base over time than a static 90% public market allocation would suggest, resulting in higher total management fees.

148. Second, as established earlier, the intervention generates a larger portfolio value relative to the baseline. Although public market managers oversee a smaller share of assets, fees are charged as a percentage of AUM. The larger portfolio value therefore offsets the lower allocation share, resulting in higher public market AUM and higher total management fees.

149. Private market manager median fees increase significantly from £1.2bn to £5.0bn. This is driven by two factors: (i) the increase in the private markets allocation from 5.50% to 10%, and (ii) the introduction of substantial performance fees linked to private equity returns above the 8% hurdle rate. Under the baseline, limited private equity exposure (0.3% of a 5.50% private market allocation) results in negligible performance fee income. By contrast, under the intervention, a 5% private equity allocation combined with a 20% carry above the 8% hurdle generates substantial performance fee income, which becomes the dominant component of private market manager revenue. On average, performance fees in the intervention scenario represent around 73% of private market manager revenue.

150. Overall, at the median level, public market managers remain the dominant fee recipients, capturing 78% of total fee revenue even under the intervention scenario. This reflects the continued scale of public market allocations within pension portfolios, even as private market exposure increases under the intervention scenario.

Charge cap breaches

To assess the potential implications of including performance fees within the charge cap calculation, we consider a counterfactual scenario in which charge caps continue to apply where providers increase their private market allocation to 10% to meet their MHA commitments.

Table 13: Breach rates in the intervention scenario (assuming charge cap exemptions do not apply)

Metric	Value
Median charge rate (across all simulations)	0.62%
Maximum charge rate	1.80%
Total observations assessed	100,000 simulation-years
Number of breaches (>0.75%)	22,326 breaches
Breach percentage	22.3%

Source: FCA analysis

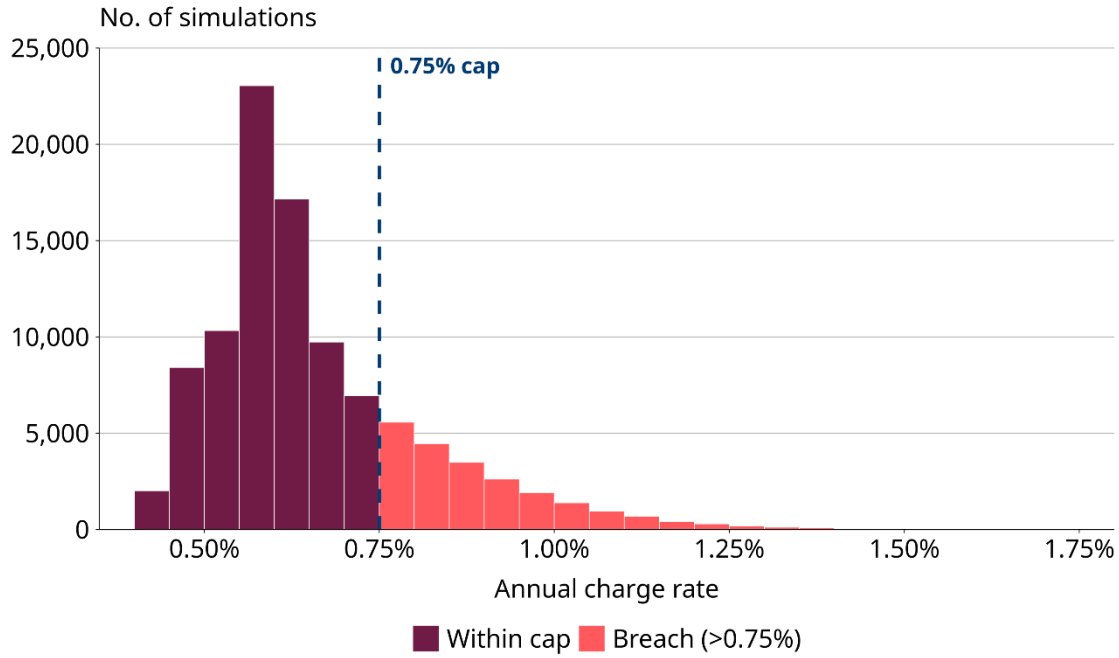
151. We find that, even if performance fees were included in the charge cap calculations, breaches would occur in approximately 22% of simulation-years. This is an increase from a 0% breach rate at baseline (assuming full compliance with the charge cap), despite a significant increase in private equity allocation from 0.3% at baseline to 5% in our intervention scenario.

152. Performance fees are triggered when private equity and private credit returns exceed the 8% hurdle rate in our modelling. This creates a high threshold before carry is payable, meaning fees are incurred in scenarios where private equity and private credit have delivered strong investment performance and generated material portfolio gains. The 20% performance fee applies only to returns above the hurdle, meaning it is paid from investment gains rather than the original capital invested. In more typical return scenarios (for example, where private equity and private credit returns are around 8–10%), carry payments are limited or zero.

153. This indicates that charge cap breaches are likely concentrated in scenarios where private market assets deliver exceptional performance and performance fees are triggered. While including performance fees within the charge cap calculation increases the likelihood of breaches, these occur alongside strong underlying investment performance and significant portfolio value creation for savers.

154. Overall, the analysis suggests that including performance fees within the charge cap calculation would introduce some additional compliance risk (without a charge cap exemption). However, breaches are concentrated in scenarios where private markets deliver strong performance and contribute positively to saver outcomes. This highlights the importance of considering the trade-off between charge cap rules and investment structures designed to access higher returning (albeit riskier) asset classes.

Figure 7: Distribution of annual charge rates in an intervention scenario without performance fee exemption



Source: FCA analysis

Sensitivity analysis

155. We recognise that estimating the costs and benefits of increased investment in private markets following the removal of pension charge caps is subject to considerable uncertainty. In particular, projections of future investment returns, asset allocation decisions, and wider market responses are inherently uncertain. If our assumptions do not materialise, the estimated costs and benefits presented in the CBA may be overstated or understated.

156. To assess the robustness of our findings, we set out some sensitivity checks that test how the estimated costs and benefits change under alternative assumptions, while keeping all other model inputs unchanged.

Certainty-equivalent analysis

157. As mentioned in the *results* section, we estimate certainty-equivalent (CE) outcomes using a CRRA utility function. The CRRA framework captures the idea that savers are generally risk averse and therefore place less value on uncertain outcomes than on guaranteed outcomes with the same expected value.

158. For each scenario, the 10,000 simulated terminal portfolio values generated by the DCC-EGARCH model are converted into wealth ratios relative to the initial portfolio value:

$$w_i = \frac{W_i}{W_0}$$

Where:

- W_i is the terminal portfolio value in simulation i
- W_0 is the initial portfolio value

159. Utility is then calculated for each simulated outcome using a CRRA utility function:

$$U(w_i) = \frac{w_i^{1-\lambda}}{1-\lambda}$$

Where λ represents the coefficient of relative risk aversion.

160. The analysis assumes a λ of 2. This assumption is informed by the DC pensions literature (Schlechter, 2007; Canessa and Dorich, 2008), which adopts values in the range of 1.81 to 2.42 when modelling long-term retirement saving behaviour. In particular, Vigna (2009) characterises a coefficient of 2 as representing a medium level of risk aversion and notes evidence suggesting relative risk-aversion coefficients for pension scheme members are centred broadly around this level. In line with Vigna's approach, alternative values of λ equal to 1 and 5 are also tested to assess the sensitivity of the results to lower and higher levels of saver risk aversion, respectively.

161. We note that λ represents a preference parameter, not a characteristic of the investment strategy. The same value of λ is therefore applied to both the baseline and intervention scenarios so that the comparison isolates differences in the distributions of outcomes rather than differences in saver preferences.

162. Expected utility is calculated as the average utility across all simulated outcomes:

$$E[U(w)] = \frac{1}{B}\sum_{i=1}^{B} U(w_i)$$

Where B = 10,000 simulations.

163. The CE wealth ratio is then obtained by inverting the utility function:

$$CE = [(1-\lambda)E[U(w)]]^{\frac{1}{1-\lambda}}$$

This represents the guaranteed multiple of initial wealth that would provide the same utility as the full distribution of simulated outcomes.

164. Finally, the CE wealth ratio is converted into an equivalent annual return over the ten-year appraisal period:

$$r_{CE} = CE^{\frac{1}{10}} - 1$$

Where r_{CE} represents the certainty-equivalent annual return.

165. Under this approach, the certainty-equivalent wealth ratio increases from 2.25 under the baseline scenario to 2.30 under the intervention scenario. This implies a risk-adjusted welfare gain of approximately 2.1% over the ten-year appraisal period, equivalent to an increase in certainty-equivalent annual returns from 8.45% to 8.68% per annum.

166. The similarity between the certainty-equivalent and the headline unadjusted results reflects the point that the intervention improves outcomes across much of the simulated distribution, rather than simply increasing exposure to higher-risk, higher-return outcomes. While the intervention modestly increases outcome dispersion, portfolio values are higher at all reported percentiles of the simulated distribution. As a result, the additional expected returns are not materially offset by increased downside risk when viewed through the lens of a utility-based framework.

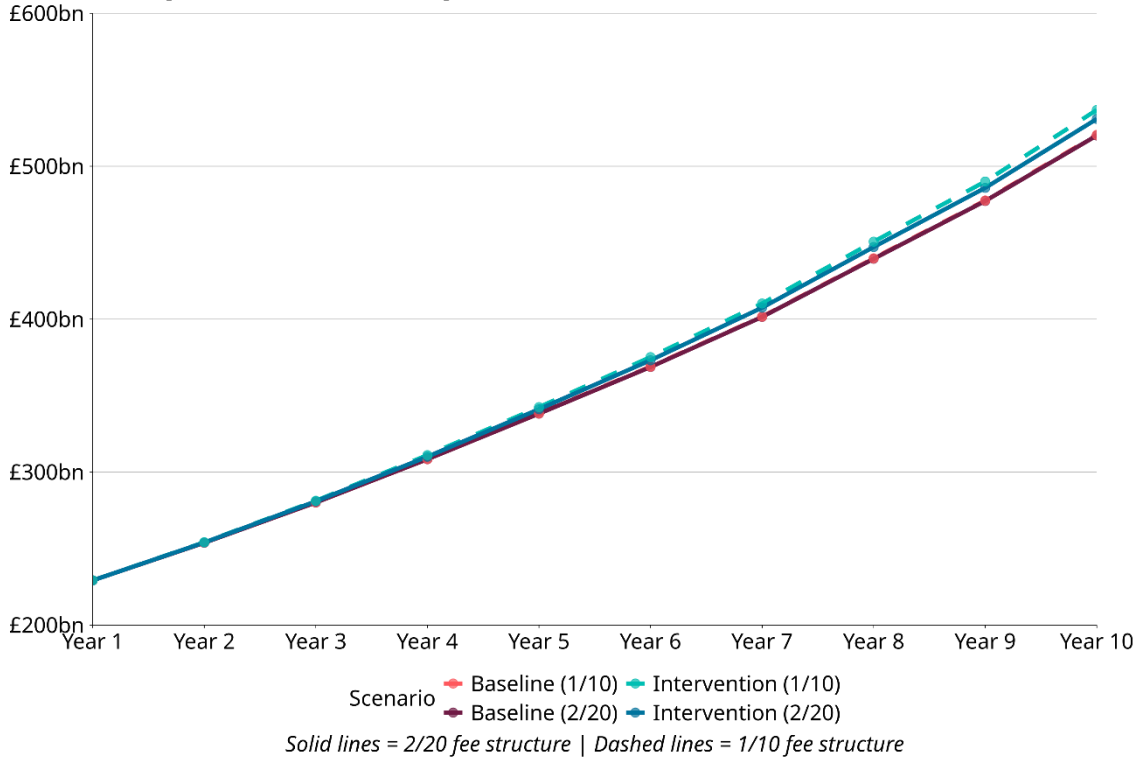
167. Furthermore, while changes in the levels of risk aversion reduce the certainty-equivalent value of both the baseline and intervention scenarios, they do so by a similar proportion (2.0% to 2.1%).

Private markets fee structure

168. We consider alternative private market fee structures to reflect uncertainty around the level of fees that may apply under the intervention. As set out in our assumptions, a traditional "2 and 20" fee structure is commonly associated with private market investments. In practice, however, fee arrangements can vary across private market strategies and managers. Large institutional investors, including pension funds, typically have negotiating power and often agree fee arrangements below the traditional "2 and 20" structure. Fee levels may also evolve over time as the market develops.

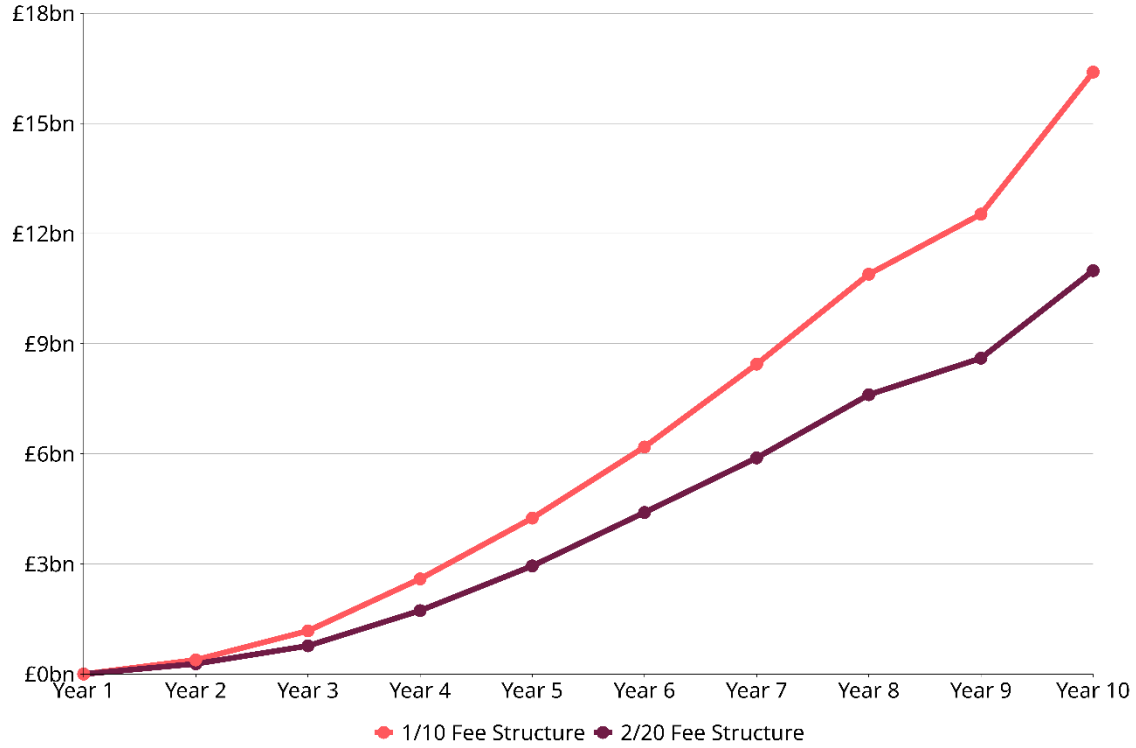
169. We therefore test a lower "1 and 10" (1/10) fee structure (1% management fee and 10% performance fee) to assess the extent to which the results are sensitive to lower fee assumptions.

Figure 8: Trajectories in portfolio value (net) for scenarios with different fee structures (2/20 versus 1/10)



Source: FCA analysis

Figure 9: Increases in portfolio value (net), relative to the baseline, for 1/10 and 2/20 fee structures



Source: FCA analysis

170. The figures above show that net portfolio values differ marginally between the two fee structures, with the 1/10 structure consistently outperforming the 2/20 structure. These differences are particularly modest in the early years as pension schemes transition to increased private market allocations. They become more pronounced from 2031 onwards, driven by the compounding effect of lower fees combined with higher private market exposures. By 2036, the intervention scenario under the 1/10 fee structure shows a portfolio value of £16.4bn higher than the baseline, relative to a value difference of £10.8bn in the standard 2/20 scenario.

171. The higher saver benefit under the 1/10 fee structure suggests that the 2/20 assumption in our main model is conservative. However, the alternative fee structure changes the scale of the estimated benefit rather than our qualitative conclusion.

Rebalancing asset allocations

172. Our central analysis assumes that portfolios are rebalanced annually to maintain their target asset allocations. This reflects the approach typically used by pension schemes to manage investment exposures over time and ensures that the simulated portfolios remain aligned with the intended strategic asset allocation.

173. In practice, however, private market investments are generally less liquid than publicly traded assets, and capital is typically deployed and returned over multi-year investment cycles. As a result, pension schemes may not always be able to rebalance private market exposures as assumed in the central model.

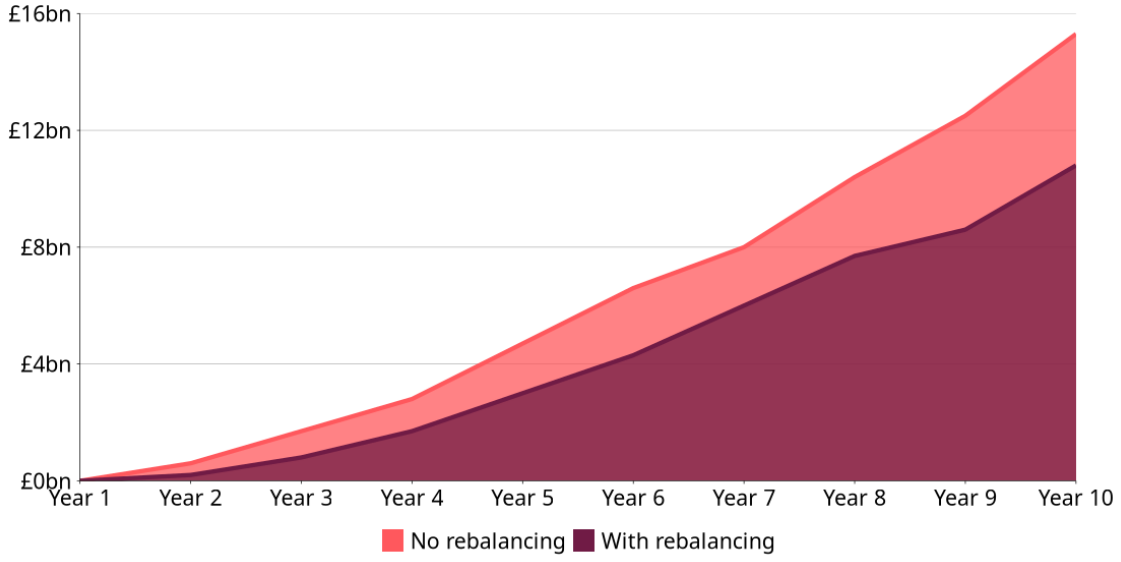
174. As a sensitivity test, we remove the assumption of annual rebalancing after target allocations have been reached in 2030, allowing asset weights to evolve according to relative investment performance.

Table 14: Median net portfolio values in no annual rebalancing scenario, £bn

Year	Baseline (£bn)	Intervention (£bn)	Difference in value (£bn)	% change
1	£229.4	£229.4	-	-
2	£253.8	£254.3	+£0.6	+0.22%
3	£279.7	£281.4	+£1.7	+0.61%
4	£308.1	£310.9	+£2.8	+0.90%
5	£337.5	£342.1	+£4.7	+1.39%
6	£367.8	£374.4	+£6.6	+1.79%
7	£400.5	£408.6	+£8.0	+2.00%
8	£438.3	£448.7	+£10.4	+2.38%
9	£475.0	£487.5	+£12.5	+2.63%
10	£518.4	£533.8	+£15.3	+2.95%

Source: FCA analysis

Figure 10: Cumulative difference in portfolio value (net) across baseline and intervention for rebalancing scenarios



Source: FCA analysis

175. The sensitivity analysis indicates that removing annual rebalancing does not materially alter the overall conclusions of the analysis. We observe that the final median net values of the baseline (£518.4bn) and intervention scenarios (£533.8bn) drop slightly in the no rebalancing scenario, relative to our main model estimates of £520.1bn and £530.9bn for baseline and intervention scenarios, respectively.

Robustness to simulation size

176. Our central analysis is based on 10,000 Monte Carlo simulations, which was selected to provide a robust estimate of the distribution of possible outcomes while balancing computational efficiency. However, we note that simulation-based results may still be subject to a degree of sampling variability, particularly in the tails of the distribution.

177. To assess whether the estimated benefits are sensitive to the number of simulations performed, we repeat the analysis using 20,000 simulations. Increasing the number of simulations improves the precision of the estimated distributions by reducing random sampling error but should not materially affect the underlying expected outcomes if our main model is stable.

178. Our findings indicate that the estimates are robust to the number of simulations performed. We estimate a final median net portfolio value of £524.4bn in the baseline, relative to £535.8bn in the intervention. This difference of £11.4bn (2.2%) is almost identical to the £10.8bn (2.1%) difference estimated in the main model, indicating that increasing the number of simulations does not materially affect the estimated benefits.

5 Limitations and model dependencies

179. The DCC-EGARCH framework makes deliberate simplifications to balance realism against transparency and practicality with respect to data availability. This section discusses some of the modelling limitations in our analysis.

CMA uncertainty

180. Our findings depend on the CMA assumptions used for expected returns and volatilities across all asset classes, as well as the correlation matrix used in the model. Our multi-provider approach captures some variation in expected returns and volatilities, but it does not capture the full range of uncertainty within each provider's assumptions. For example, some providers do not provide separate assumptions for both UK and non-UK asset classes. Where a UK- or non-UK-specific assumption is not available, we use the closest available asset class as a proxy. While this provides a practical way to align the assumptions, the proxy is not necessarily a perfect match and therefore introduces an additional source of uncertainty into our results.

181. As noted earlier, we also rely on a single provider's correlation matrix, so our findings depend partly on assumptions about cross-asset relationships.

182. The reported percentile ranges (5th-95th) capture variation around CMA expectations due to volatility shocks and provider selection, providing some indication of downside and upside risk, but they do not address scenarios where the CMA point estimates themselves prove systematically optimistic. If all 3 CMA providers systematically overestimate or underestimate private market returns, for example, because structural changes in market conditions are not reflected in their forecasts, the full distribution of modelled outcomes would shift. The 5th and 95th percentile estimates could therefore overstate or understate the range of future portfolio values.

EGARCH asymmetry specification

183. As discussed earlier, the EGARCH model incorporates asymmetric volatility responses ($\gamma = -0.05$) to capture the leverage effect documented in equity markets. However, this asymmetry is imposed rather than estimated from our pension portfolio data, with the same asymmetry applied across all market states. This means the model may understate volatility spikes during tail events where fire sales and margin calls amplify asymmetric responses beyond typical levels. Additionally, while $\gamma = -0.05$ is appropriate for listed equities, its appropriateness for private markets - where leverage operates through portfolio company capital structures and illiquidity amplifies downside volatility - is less clear, and applying the same asymmetry to cash and government bonds likely overstates their leverage effects.

Constant expected returns

184. The model assumes expected returns (μ) remain constant over the 10-year simulation horizon. In reality, expected returns may vary with valuation levels or shifts in risk premia. By fixing expected returns at CMA estimates throughout, the model assumes current institutional forecasts remain valid across all future states,

ignoring the possibility that return expectations should be adjusted based on performance.

185. Regime-switching extensions where expected returns vary across identified market states would address this limitation but add substantial complexity, requiring specification of regime transition probabilities and state-dependent return forecasts where empirical evidence is limited. For 10-year pension projections, constant expected returns are defensible if CMAs represent long-run averages rather than point-in-time forecasts, but results should be interpreted as conditional on current return expectations persisting rather than adjusting dynamically as market conditions evolve.

Valuation lags

186. Private market assets are modelled using contemporaneous underlying returns, whereas reported valuations are typically appraisal-based, may lag changes in underlying asset values by around one quarter on average (Stafford, 2022), and smooth reported volatility through the appraisal process, resulting in artificially low measured risk. CMA volatility assumptions may capture economic variation that is not fully reflected in appraisal-based valuations. The model may therefore show higher short-term volatility than pension schemes observe in reported private market returns.

Perfect liquidity assumption

187. The model assumes annual rebalancing with no transaction costs or liquidity constraints, meaning all assets can be traded freely. This is unrealistic for private equity, where investments are made gradually through capital calls, are subject to long lock-up periods, and typically follow a J-curve. In practice, private equity exposure cannot be adjusted quickly and may drift above target during public market declines due to denominator effects. Transaction costs may also be material for illiquid assets, as positions cannot necessarily be adjusted at their modelled values without incurring liquidity discounts, bid–ask spreads or other costs. As a result, the model overstates the flexibility to increase or reduce private market allocations, making it more representative of public markets than private markets.

6 Academic review

188. We are grateful to Dr Gustavo Fruet Dias from the University of East Anglia for his helpful feedback on our approach and review of the technical note. His academic expertise in financial econometrics, Monte Carlo simulation and volatility modelling, including EGARCH models used to capture asymmetric effects in financial time series volatility, made him well suited to advise on the specification of the model.

189. An overview of Dr Fruet Dias's key feedback points is provided in Table 15 below.

Table 15: Summary of academic recommendations

Feedback area	Academic recommendation	Implementation
Constant correlation matrix	Adopt DCC multivariate GARCH to capture time-varying correlations that increase during high volatility periods.	Our use of a DCC-EGARCH framework now allows correlations to vary dynamically. DCC parameters are calibrated to literature-typical values, enabling correlations to increase during periods of market stress before gradually reverting towards their long-run levels.
Constant volatility assumption	Use DCC-type models calibrated to market data to capture time-varying volatilities alongside correlations.	We initially considered a standard DCC-GARCH(1,1) specification as a baseline approach for modelling time-varying volatility and correlations, before adopting a DCC-EGARCH framework to capture additional empirical features of asset returns. Our DCC-EGARCH specification models conditional volatilities that evolve daily. GARCH(1,1) uses $\alpha=0.05$, $\beta=0.90$; EGARCH(1,1) uses $\alpha=0.15$, $\gamma=-0.05$, $\beta=0.95$. Volatilities cluster realistically (high volatility follows high volatility) and are calibrated to match CMA unconditional variances.
Fat tails	Instead of using the standard normal Gaussian distribution, adopt a rescaled multivariate Student-t distribution approach with ~8 degrees of freedom to capture tail risks.	Returns are generated using a multivariate Student-t with degrees of freedom of 8 across all simulations. The distribution is rescaled to unit variance (for degrees of freedom>2) while preserving fat tails. This provides a representation of extreme events without requiring asymmetric distributions.
Regime switching extension	As an alternative to DCC-type models, time variation in volatility and correlation could be introduced through a regime-switching (exogenous) framework, where different regimes capture distinct market conditions (e.g. low vs high volatility), jointly affecting both volatility and correlation structures.	We adopted the DCC-EGARCH approach as recommended above rather than regime-switching, as it provides smooth time-variation without requiring specification of discrete regimes or transition probabilities where empirical evidence is limited.
Number of simulations	The original approach used the Central Limit Theorem (CLT) to justify the use of 1,000 replications. While this is generally adequate for many applications, it may be insufficient for nonlinear functions and tail-based measures. The recommendation was to increase from 1,000 to 10,000 simulations in the base model for stable tail-	Our base approach is based on 10,000 simulations. We supplement this with 20,000 simulations as part of the sensitivity analysis to test the robustness of outputs.

Feedback area	Academic recommendation	Implementation
	based measures. This could be complemented by a robustness exercise using an even larger number of replications to confirm the convergence of outputs.	
Comparability of portfolios	When comparing expected returns, it is important that comparisons are made on a like-for-like basis in terms of risk (e.g. by controlling for variance). When rebalancing the portfolio to include private markets, the variance of the portfolio may change (and potentially increase). Maintaining fixed allocation weights across scenarios implies that the overall risk profile of the portfolio is not held constant. It would be preferable to state that allocation weights are kept as close as possible to their targets, while ensuring that the overall portfolio variance is constant across alternative scenarios.	We maintain target allocation weights rather than normalising to constant portfolio variance. The policy intervention under evaluation explicitly involves schemes accepting higher risk in exchange for higher expected returns. Holding variance constant would require endogenising portfolio weights to offset the higher volatility of private markets, which would obscure the fundamental allocation-return trade-off that is central to the policy question. As a sensitivity check, we estimate certainty-equivalent outcomes using a constant relative risk aversion (CRRA) utility function to assess whether the intervention's estimated benefits remain after accounting for saver risk aversion.
Change the data-generating process	Generate data at a daily frequency such that t = 1, …, 2,520. This would allow the model to better capture the high persistence typically observed in conditional volatility and correlation processes, while still evaluating portfolio values at an annual frequency.	We implement a daily frequency simulation with 252 trading days/year × 10 years = 2,520 daily steps. Daily returns are generated via $R_t = \mu + \Sigma_t^{1/2} Z_t$ and then compounded to annual returns for portfolio evaluation.
Sensitivity analysis	Include a more systematic sensitivity analysis on key modelling assumptions to assess the robustness of the results.	We provide an overview of our checks in the *Sensitivity analysis* chapter.

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