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IPF RESEARCH

The Drivers of UK Real Estate Funds

FULL REPORT

COMMISSIONED BY THE IPF RESEARCH PROGRAMME

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This Programme supports the IPF's wider goals of enhancing the understanding and efficiency of property as an investment. The initiative provides the UK property investment market with the ability to deliver substantial, objective and high-quality analysis on a structured basis. It encourages the whole industry to engage with other financial markets, the wider business community and government on a range of complementary issues.

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The Drivers of UK Real Estate Funds

Report

IPF Research Programme

August 2026

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About this study

- This report examines the drivers of performance for UK unlisted property funds over the 15-year period from 2011 to 2025. It analyses three fund types-Balanced, Long Income, and Other (Specialist) - using data from the MSCI/AREF Quarterly Property Fund Index and the Property Fund Vision Handbook.
- Over this period, funds operated through markedly different economic regimes: quantitative easing and near-zero interest rates, Brexit-related uncertainty, the pandemic, and a sharp rise in inflation and borrowing costs from 2022.
- This report follows the previous IPF study (IPF, 2012) on Managed, Other Balanced and Specialist fund performance in the period 2001 to 2010.
- This study follows the MSCI/AREF classification, which groups funds into All Balanced Open-Ended Property Funds (Balanced), Long Income Open-Ended Property Funds (Long Income), and Other Property Funds (Other, Specialist). The Other (Specialist) category comprises primarily specialised property funds with concentrated exposures to specific property sectors or investment themes, including retail warehouses, Central London offices, London logistics, industrial property, student accommodation, and leisure assets.

Size of the industry

- The industry appears to be undergoing structural rather than cyclical change. The number of UK unlisted funds has declined, with Balanced funds remaining dominant, Long Income funds grew from zero to eight vehicles, and Other (Specialist) funds shrinking from 32 to just five.
- Despite fewer funds, GAV increased by around 19% to £40.4 billion, while NAV rose by 43% to £38 billion, however, they are both on a downward trend since the peak in early 2022.
- Strong net inflows, which peaked in 2015, reversed sharply from 2016 onwards, particularly for Balanced funds, but stabilised in 2025. Contributing factors include rising fixed income yields, liquidity concerns, the decline of defined benefit (DB) pension schemes, and uncertainty linked to Brexit, the pandemic, and the UK ‘mini-budget’.
- The industry now requires a stronger value proposition and a clearer articulation of its role in portfolios to attract capital. Simply tracking the property cycle may no longer be considered sufficient.

Leverage and cash

- Balanced and Long Income funds make limited use of debt, so leverage has had minimal impact on their returns. Other (Specialist) funds, with leverage typically in the 22-35% range, show a different pattern.
- Across all fund types, leverage added a modest +0.23% per year over the full period, but its effects are cyclical. It supported returns in the low-interest rate environment following the financial crisis but became less favourable from 2022 as borrowing costs increased.
- Balanced funds typically held 4-8% in cash, while Long Income funds held significantly less, consistent with their fully invested approach.
- Cash has generally acted as a drag on returns-reducing performance by around 0.26% per year-but provided a meaningful buffer during 2023-2024 when interest rates rose.

SYNOPSIS

How have the funds performed?

- Balanced and Long Income funds delivered compound annual net returns of 5.2% and 4.8%, respectively, over the full period, comparable to UK REITs (5.2%) and only modestly below the FTSE 250 (5.9%). Other (Specialist) funds lagged at 3.2%, weighed down by weak performance in 2019-2020.
- Importantly, Balanced and Long Income funds achieved these returns with attractive performance on a risk-adjusted basis, compared with listed alternatives.
- The apparent smoothness of returns, driven partly by valuation practices, may overstate stability, but fund returns show only moderate dependence across periods, meaning that returns in one period are only moderately associated with returns in earlier periods. If valuation effects reduce smoothness, the risk adjusted qualities and diversification benefits of unlisted funds may be more fully recognised.
- The probability of negative average returns over medium- to long-term horizons is very low. For a typical seven-year holding period, the likelihood is minimal, reinforcing the capital preservation characteristics of unlisted property funds.

What actually drives returns?

- Economic conditions matter, but unevenly across fund types. GDP growth is a significant positive driver for Long Income funds and particularly for Other (Specialist) funds, which show greater sensitivity.
- Balanced fund performance is significantly correlated with both contemporaneous and lagged REIT returns, suggesting that pricing signals from listed markets spill over into unlisted Balanced funds.
- Past NAV growth is the most consistent driver across all fund types. Funds with stronger NAV growth-partly reflecting momentum and capital flows-tend to deliver higher subsequent returns, over the 10-year period 2016-2025.
- Several fund characteristics influence performance, though their impact varies by fund type:
    - Tenant concentration does not materially affect returns in Balanced and Other (Specialist) funds, but in Long Income funds, concentration in strong-covenant tenants is associated with better performance.
    - Development exposure weighs on short-term returns by deferring income, except in Long Income funds where structures may accelerate income delivery.
    - The negative relationship between returns and reversionary yield in Balanced funds suggests that expected rental growth potential is often not fully realised.
    - Other fund characteristics including weighted average unexpired lease term (WAULT), investment vacancy, number of properties, and the 10 largest investments as a percentage of the portfolio, did not have a significant influence on returns. However, data limitations should be considered when interpreting these results.
- Overall, fund characteristics explain differences in returns well for Balanced funds. In contrast, economic and market factors are the dominant drivers of returns for Other (Specialist) funds. For Long Income funds, economic and market factors, even when combined with fund characteristics, do not adequately explain time dynamics or cross-sectional variation in returns, indicating the presence of additional drivers.

SYNOPSIS

The role of the fund manager

- Even after accounting for observable factors-market conditions, leverage, cash, fund age, tenant concentration, and development exposure-a meaningful portion of performance variation remains unexplained.
- This residual reflects factors not easily captured in data: investment process quality, asset management capability, tenant relationships, governance, and the experience of the investment team.
- A statistically significant positive residual return component is observed for Balanced and Other (Specialist) funds, but not for Long Income funds. This suggests that, after accounting for macroeconomic conditions, NAV growth, and fund characteristics, a portion of returns remains unexplained in Balanced and Other (Specialist) strategies. This is consistent with a greater role for active decision-making, while Long Income strategies appear more fully explained by the factors included in the analysis.
- Sector attribution scores indicate that sector allocation decisions contributed incremental value for about two thirds of the funds, with balanced funds overrepresented in the sample. However, no robust generalisations can be made for long income or other (specialised) funds due to the small sample sizes.
- For investors, the implication is clear: qualitative assessment of the manager should complement quantitative analysis at fund style and fund level. Data alone cannot capture the judgement behind allocation decisions, asset selection, the timing of investments, factors that ultimately differentiate performance between funds with otherwise similar characteristics.

EXECUTIVE SUMMARY

Scope & Objectives

Background

- This study analyses the performance of UK unlisted funds and their drivers over the period from 2011 to 2025. The study extends the previous IPF report (IPF, 2012) on Managed, Other Balanced and Specialist fund performance in the period 2001 to 2010. The IPF (2012) report assessed pooled fund performance over a period of strong growth in the underlying All-Property index (13.6% per annum during 2001-2006) and negative growth during 2007-2010 (average growth of –1.5%), reflecting the impact of the global financial crisis (GFC). The report also highlighted emerging structural challenges within the industry. These included inadequate accounting transparency, pressures from solvency requirements, and increasing competition from joint venture structures.
- During the period of this study, funds operated in a rapidly evolving economic environment that significantly affected real estate markets. UK economic trends were determined by a prolonged period of quantitative easing and low interest rates, uncertainty following the Brexit referendum, and the shock of the pandemic, which was followed by rising inflation and interest rates amid ongoing geopolitical conflicts. Over the 15-year period from 2011 to 2025, the UK economy recorded average annual GDP growth of 1.6%, compared with 2.2% in the preceding 15 years.
- These developments occurred alongside continuous structural changes, including the growth of e-commerce, the adoption of new working practices, and increasing investor interest in power, energy, and operational real estate. The study period also encompasses the rapid pace of broader technological transformation and automation affecting the property market, as well as the implications for property funds arising from the phasing out of DB pension schemes.

Aims

- Within this context, the study aims to:
  i. evaluate performance patterns across the principal types of unlisted property funds-Balanced, Long Income, and Other (Specialist) - over the period 2011 to 2025; and
  ii. identify the systematic factors driving unlisted fund performance over time and across funds.
- IPF (2012) demonstrated the impact of directly held assets, debt, cash, and fees on pooled fund returns. This subject area within the unlisted fund industry has since attracted increasing interest from both industry and the academic community. Subsequent studies have recognised that property fund performance is driven by a complex interplay of fund-specific characteristics, investment strategy, portfolio composition, and broader market conditions.

Outcomes

- The data analysis and findings of this empirical investigation enhance understanding of property fund performance dynamics, improve sector transparency (a need highlighted in IPF, 2012), and identify systematic factors likely to drive future performance, providing valuable insights for both existing and prospective unit holders and fund managers.[1]

1 The data used in this study are drawn from the MSCI/AREF Quarterly Property Fund (QPF) Index and the MSCI/AREF Property Fund Vision (PFV) Handbook. The former provides more aggregated data, covering all funds as well as the three main fund types: Balanced, Long Income, and Other (Specialist) funds. The PFV Handbook offers detailed fund-level information, including key fund characteristics. The study period spans from 2011 Q1 to 2025 Q4. In part of the analysis, the sample begins in 2012 Q1. This start date is dictated by the start of the data for Long Income funds.

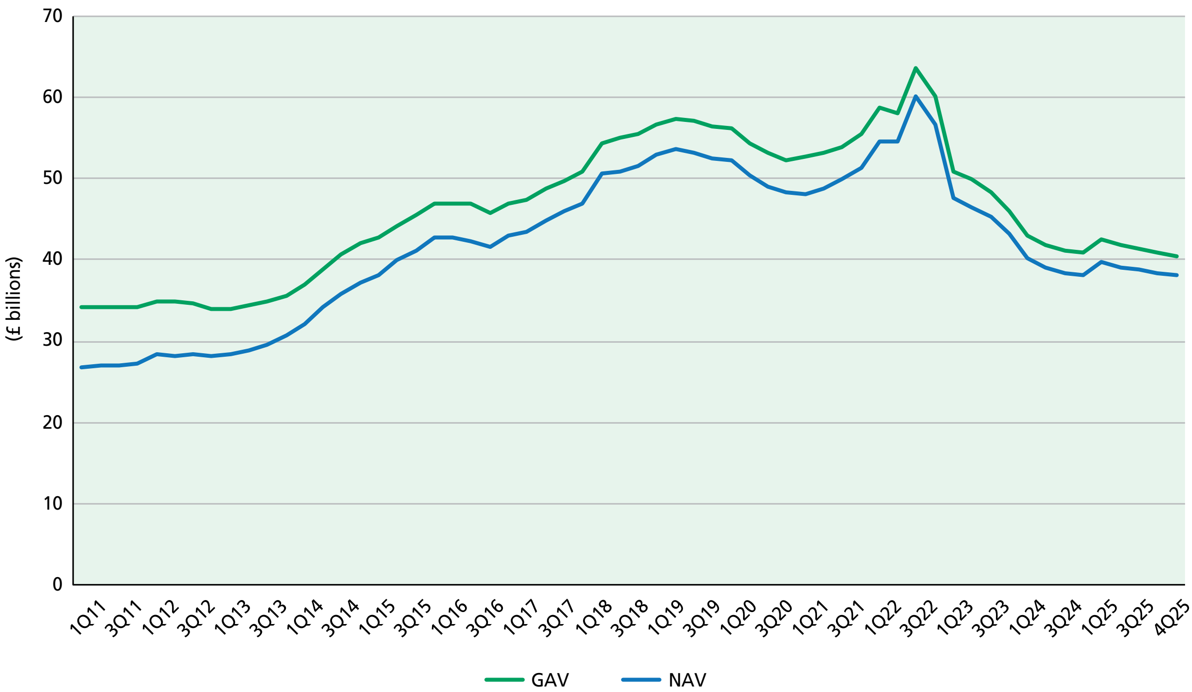
EXECUTIVE SUMMARY

Industry landscape and capital dynamics

Size and structure

- The unlisted property fund universe is predominantly composed of Balanced strategies, with Long Income funds representing a smaller but distinct segment, and a residual Other (Specialist) category capturing more specialised mandates. These categories reflect differing investment objectives and portfolio structures, with Balanced funds maintaining diversified exposures across property sectors while seeking a combination of income and capital growth, Long Income funds focusing on secure, long-duration cashflows, and Other (Specialist) strategies pursuing sector-specific or more opportunistic exposures.
- Over the sample period, the total number of funds has declined from 58 funds in 2011 Q1 to 32 funds in 2025 Q4, mostly reflecting a reduction in Other (Specialist) funds. By contrast, the number of Long Income funds increased over the period from four 2011 Q1 to 11 in 2025 Q4. The decrease in the number of funds reflects the decline of DB schemes, fund closures and mergers (a common stage in a fund's life cycle), as well as broader derisking trends.
- Despite the decline in the number of funds, GAV in 2025 Q4 stood at 18.7% higher than 2011 Q1, representing an increase of £6.4 billion. This suggests a trend towards fewer but larger funds, consistent with broader investment industry patterns of consolidation. Over the period NAV showed a growth of 43%. However, this rise masks two distinct trends in funds GAV and NAV since 2011. A rising trend, despite cycles of small magnitude, gave way to a declining trend since 2022 Q3 when GAV was just under £64 billion declining to £40.5 billion in 2025 Q4 (Figure I).

Figure I: GAV & NAV all funds



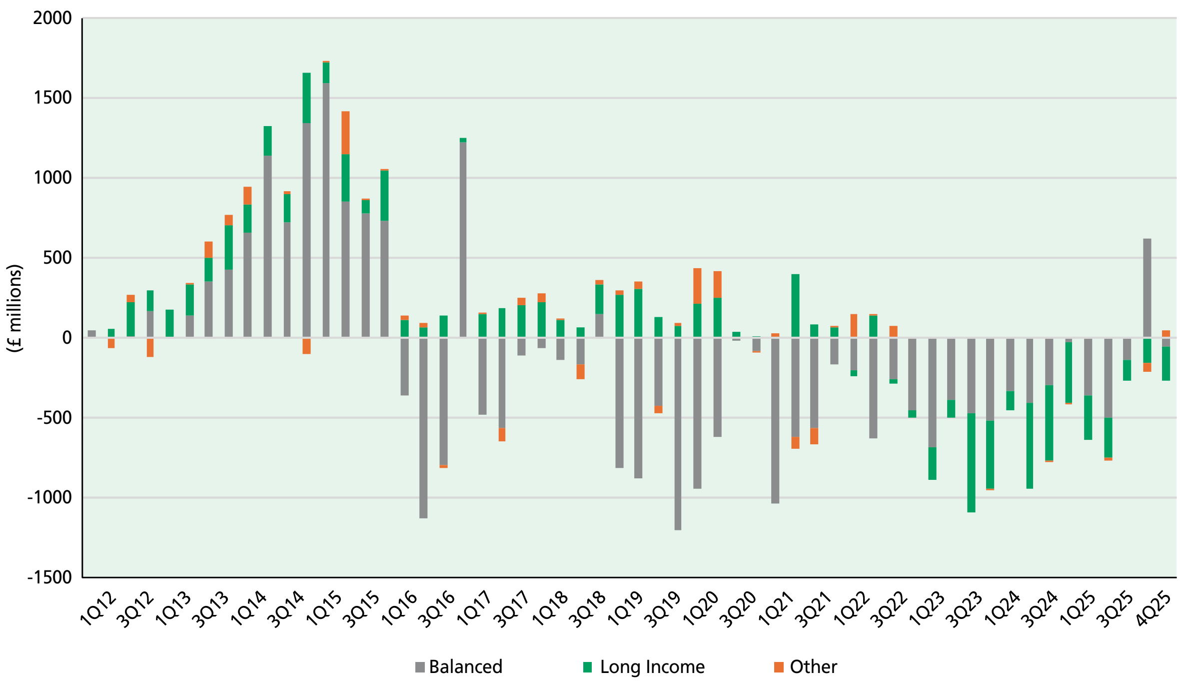
Source: MSCI/AREF QPF Index

EXECUTIVE SUMMARY

- The 18.7% increase in GAV closely mirrors the 17.5% capital growth recorded by the MSCI UK Capital Growth Index over the same period, suggesting that growth in GAV for unlisted property funds broadly tracked underlying capital appreciation in the direct property market, as proxied by the index.
- In contrast, net asset value (NAV) growth significantly exceeds both GAV growth and direct market appreciation, suggesting that while property capital growth is the primary driver of asset-level performance, NAV performance is materially influenced by additional fund-level factors, most notably leverage, cash and fees.

Net Investment flows

Figure II: Net investment flows by fund category



Source: MSCI/AREF PFV Handbook

- The unlisted property fund market has transitioned from a broad-based inflow regime (2013-2015) into a structurally more selective allocation environment. Balanced funds have experienced a persistent reversal of capital flows since 2016, while Long Income funds initially acted as a substitute but have also weakened post-2022. Other (Specialist) funds remain marginal in attracting sustained net inflows.
- This reflects competition from other asset classes, improved fixed income yields, liquidity concerns and redemption pressures, as well as a reduction in DB pension schemes.

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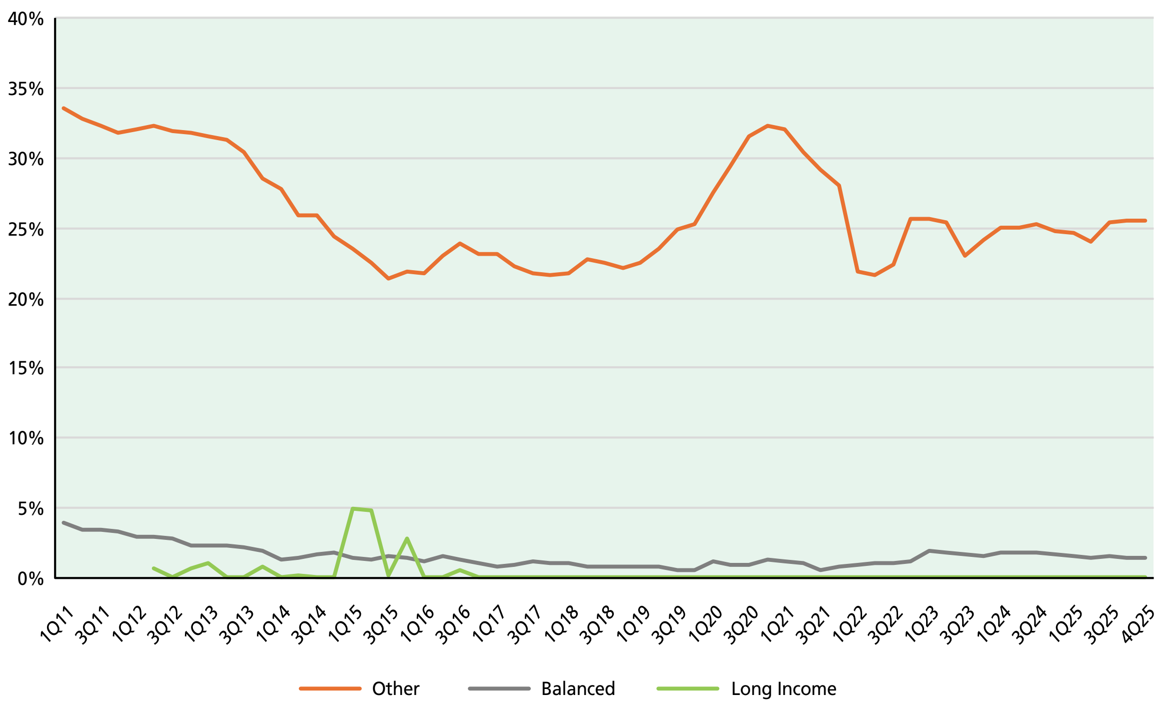
Leverage

- Leverage trends (a key determinant of fund performance in IPF, 2012) differ markedly between Other (Specialist) property funds and the other two categories highlighting distinct risk profiles and strategies over time (Figure III). Balanced funds have consistently operated with very low leverage, declining from around 4% of GAV in the early 2010s to broadly 1-2% in recent years, indicating a conservative approach with limited reliance on debt.
- Long Income funds exhibit even lower leverage, typically close to zero with only occasional positive spikes, reinforcing their positioning as low-risk, income-focused vehicles with minimal balance sheet gearing.
- In contrast, Other (Specialist) property funds have historically maintained significantly higher leverage, starting above 30% of GAV in 2011 and trending down to the low-mid 20% range more recently, albeit with some cyclical variation. This gradual deleveraging, particularly post-2013 and again following the pandemic peak, suggests more cautious financing strategies over time.

Figure III: Leverage structure by fund type



Source: MSCI/AREF QPF Index

- The net impact of leverage across all funds over the study period fluctuates between positive and negative. Overall, the net impact over the period was positive at 0.23% p.a., with no impact for Long Income funds, a negligible 0.03% p.a. for Balanced funds—consistent with their very low exposure to debt—and 0.42% p.a. for Other (Specialist) funds. In IPF (2012), the net impact for the fund universe was a marginal +0.03% p.a.
- However, this effect is largely driven by the low-interest rate environment following the GFC. Splitting the sample roughly in half (2011-2017 and 2018-2025), the annualised impact of leverage for Balanced funds is 0.10% and -0.04% (both practically negligible) in the respective periods, whereas for Other (Specialist) funds the corresponding annualised impacts are 1.53% and -0.54%. The net impact of leverage in the second period primarily reflects the elevated interest rate environment in 2023-2024, which contributed to the negative effect, and to a lesser extent, increases in margins.

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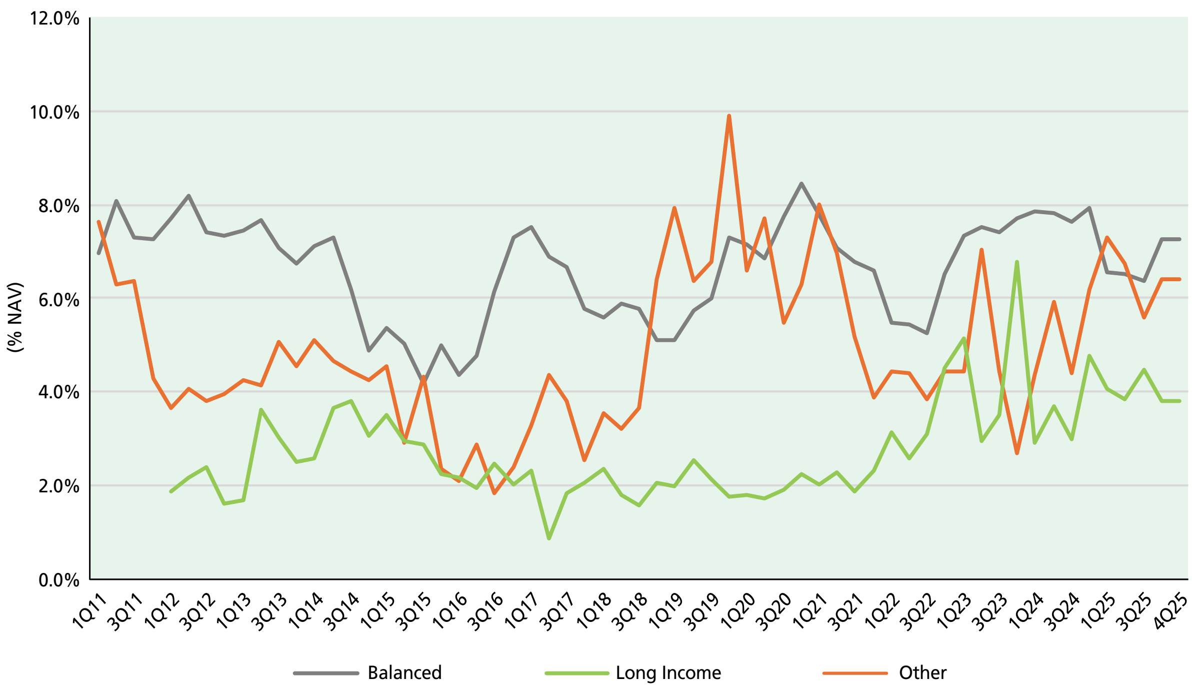
Cash

- In IPF (2012), cash holdings were found to reduce performance. Over a full cycle they lowered overall returns by 0.19% per annum, although this varied significantly by fund type.
- Cash allocations vary across fund types and over time (Figure IV). In Balanced funds, they have typically ranged between 4% and 8%, providing a liquidity buffer. In contrast, Long Income funds tend to hold minimal cash, consistent with their focus on fully invested portfolios of long-duration, income-generating assets.
- The Other (Specialist) fund category exhibits higher and more variable cash holdings in certain periods. These elevated levels may reflect the use of cash as dry powder for acquisitions and development activity, enabling funds to respond quickly to investment opportunities and deploy capital when conditions are favourable.

Figure IV: Cash holdings



Source: MSCI/AREF QPF Index, Authors

- Cash holdings tend to weigh on performance when property returns exceed cash interest rates, but can support returns during periods of higher interest rates, such as in 2023 and 2024. Over the full sample period, cash reduced overall returns by 0.26% per annum: 0.32% for Balanced funds, 0.11% for Long Income funds, and 0.23% for Other (Specialist) funds. Since 2016, this effect has roughly halved across all funds, while for Long Income funds cash has had no material impact on performance.

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Fund fees

- Fund costs, fees, and performance fees are identified in IPF (2012) as the largest negative factor affecting investor returns. Fund outgoings and management and performance fees, reduced returns by 0.26% and 0.99% per annum, respectively.
- In our sample, fees range between 0.2% and 1.3% of NAV. However, in some cases performance fees apply, and fee structures may be tiered or escalating at incremental NAV thresholds (e.g. above £100 million, then £200 million, etc.), or include additional charges based on a percentage of net operating income.
- In this study, total returns are sourced from the MSCI/AREF UK Quarterly Property Fund Index (MSCI/AREF Digest), which reports total returns on a net basis, i.e. after fund-level fees and expenses.

Implied gross return decomposition

- Constructing a waterfall from gross returns to net returns is not straightforward because gross income returns and gross capital returns are not directly observable. The MSCI/AREF Digest database prioritises net, investable, fund-reported performance rather than gross return measures. As a result, gross returns must be estimated indirectly.
- Our estimates suggest an average fund drag of 0.13% per quarter (0.53% per annum) across all funds. Fund drag is defined as the net effect of leverage, cash holdings and an assumed annual management fee of 0.50%. Over the period from Q1 2011 to Q4 2025, average net total returns were 5.1% per annum, implying a synthetic gross return of approximately 5.6% per annum. As some costs may not be explicitly captured in our estimates but are reflected in reported net returns, the true gross return may be somewhat higher.
- Using the same 0.50% annual fee assumption, estimated fund drag is 0.79% per annum for Balanced funds and 0.58% per annum for Long Income funds, largely reflecting the impact of fees, as leverage and cash effects are negligible for these fund types. For Other (Specialist) funds, estimated fund drag is lower at 0.31% per annum, as the positive effect of leverage partially offsets fees and cash drag.
- These estimates should be interpreted with some caution, as fee levels vary across funds and fund types. The use of a common 0.50% annual fee assumption is intended to provide a consistent basis for comparison rather than a precise estimate of the fees incurred by each individual fund. This assumption is also close to the unweighted average of available reported fee data, which is approximately 0.6%.

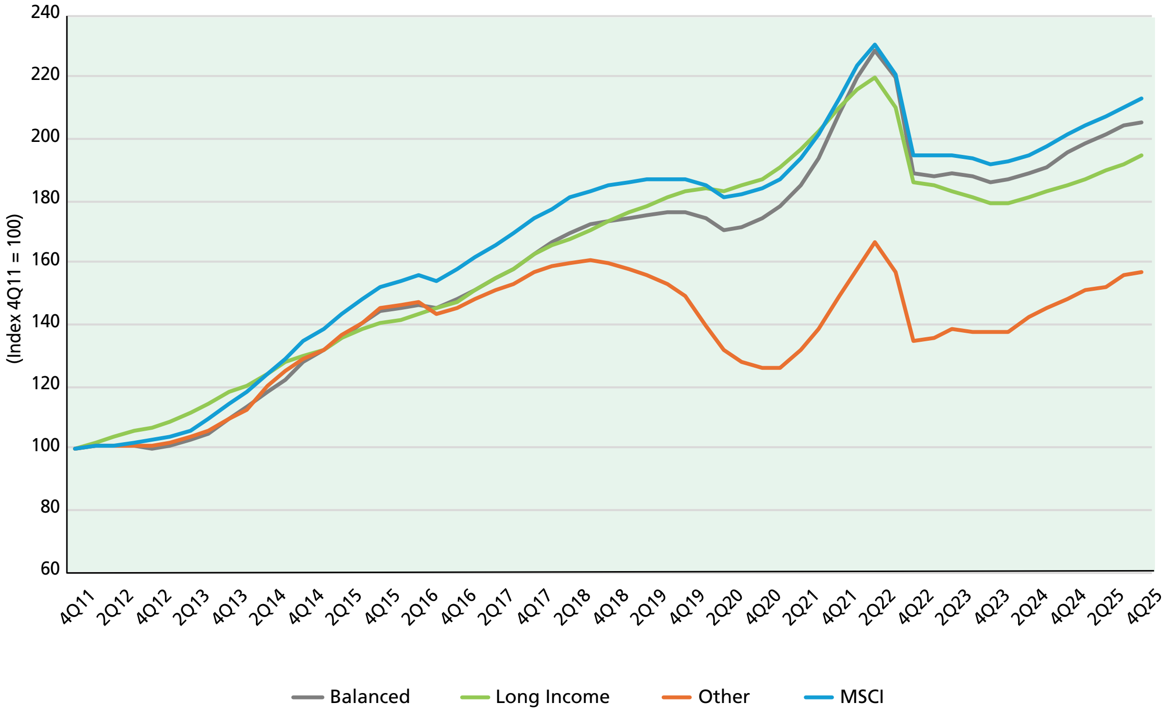
EXECUTIVE SUMMARY

Performance analysis

Comparative return trends

- The UK unlisted fund sector has provided moderate returns with an attractive risk profile.

Figure V: Net total returns



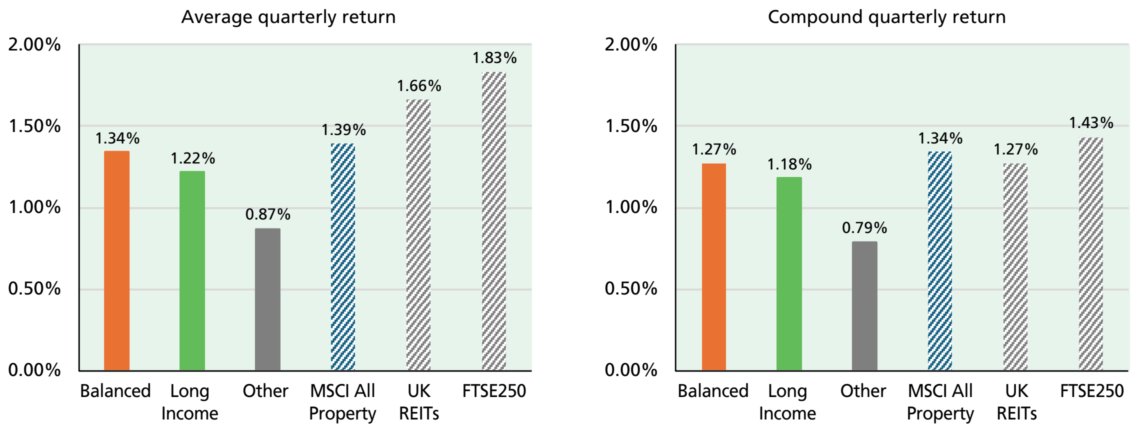
Source: MSCI/AREF QPF Index, MSCI UK Property Index, Authors

- Across the full period, distinct return trends are evident (Figure V). Up to mid-2022, Balanced and Long Income funds show steady growth—accelerating post-2020—and broadly track the MSCI All Property total return benchmark (the line labelled MSCI).
- Other (Specialist) funds diverge from this pattern, with declining returns in 2019 and 2020 before recovering in 2021 and the first half of 2022 in line with the other two fund types.
- Rising interest rates, spikes in gilt yields and the UK mini-budget led to net returns (including the benchmark) falling sharply in 2022 Q4.
- Net returns stabilised in 2023, followed by a gradual recovery and a resumption of upward momentum from 2024.
- Figure V provides a headline return comparison; however, the performance gap should not be automatically attributed to manager skill. The MSCI UK All Property Index is a fully invested market benchmark covering a broad institutional property universe, whereas the MSCI/AREF Property Fund Index is a fund benchmark comprising participating funds that hold cash and have different characteristics.

EXECUTIVE SUMMARY

Absolute and relative returns

Figure VI: Average and compound returns: 2011 Q4-2025 Q4



Source: MSCI/AREF QPF Index, MSCI UK Quarterly Property Index, LSEG Workspace, Authors

- Balanced funds showed the strongest return of fund types, similar to MSCI All Property, but lower than UK REITs and FTSE250.
- On a compound basis, which more appropriately captures the impact of negative periods than simple averages on long-term returns, Balanced and Long Income funds perform more competitively, broadly aligning with REIT returns and only trailing the FTSE 250 by a small margin.
- Over the period 2011 Q4 to 2025 Q4, during which asset classes experienced volatility and negative returns, Balanced and Long Income funds delivered attractive compound annual growth rates (CAGRs) of 5.2% and 4.8% respectively, compared with the MSCI All Property index (5.5%), UK REITs (5.2%), and the FTSE 250 (5.8%).

Risk assessment of returns

- All fund categories exhibit strong performance on a risk-adjusted basis (adjusting for volatility). Balanced and Long Income funds outperform the listed market and remain attractive even when assessed on a downside risk basis.[2] This outperformance may be partly, though not entirely, attributable to the smoothing of underlying data. However, the fund return series exhibit only moderate levels of smoothing despite the quarterly frequency.
- Statistical analysis based on returns over consecutive periods, together with simulations that account for dependence in fund return data, indicates that average returns for Balanced and Long Income funds are highly unlikely to be negative over seven-year holding periods. A seven-year horizon is assumed to reflect a typical investment period in unlisted funds. This probability is slightly higher for Other (Specialist) fund types but still remains below 5%.
- Balanced and Long Income funds are associated with a higher likelihood of achieving modest positive returns, for example, up to around 5% per annum, with relatively fewer negative outcomes compared with Other (Specialist) funds and listed investments. This is an attractive feature for preservation of capital.

2 Downside risk measures focus only on the negative side of return variation, how often and by how much returns fall below zero or the risk-free rate. A fund that performs well on a downside risk basis delivers strong returns while limiting the frequency and severity of negative outcomes.

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- The unlisted property funds appear well positioned to preserve capital. The probability-weighted average of positive returns exceeds the probability-weighted average of negative returns.[3] This holds even when using a benchmark other than 0%, for example, modest target return thresholds (e.g., 4% to 5%) rather than simply distinguishing between positive and negative returns.
- For investors targeting higher return thresholds (for example, above 5% per annum), listed asset classes offer a higher probability-weighted upside (above the investor's required return, assumed to be here 5%) relative to downside outcomes (below the investor's required return) than Balanced and Long Income funds.

Sector allocation Impact – attribution analysis

- The Brinson sector allocation results indicate that sector allocation was not consistently a positive source of performance, with around two thirds of funds generating positive allocation scores. Positive scores indicate the portion of annualised relative performance attributable to sector positioning, typically arising from overweighting outperforming sectors or underweighting underperforming ones. In this context, decisions to overweight or underweight property types (offices, retail, industrial, residential, hotels, and other) relative to the MSCI UK Quarterly Property Index added value for approximately two thirds of the funds analysed.
- Balanced funds were overrepresented among positive outcomes and more frequently added value through allocation, while Long Income funds tend to show slightly negative effects. However, the highest allocation score is observed within a Long Income fund, indicating that strong positive allocation outcomes are still possible within this strategy. Overall, robust conclusions cannot be drawn for Long Income and Other (Specialised) funds due to small sample sizes.

Macroeconomic and market effects on fund performance

Macro and market factors

- Fund performance is significantly associated with GDP growth. Over the study period, based on annual data, the contemporaneous correlations between GDP growth and Balanced, Long Income and Other (Specialist) funds are 0.57, 0.40 and 0.72 respectively, reinforcing the link between real estate returns and the broader economic environment. This confirms that the unlisted sector is cyclical and that long-term performance is not detached from trends in the UK economy.
- A linkage with the REIT market is evident for Balanced funds, but not for Long Income or Other (Specialist) fund types. This suggests varying sensitivity to listed market signals and differing exposure to sentiment generated in the REIT sector. This finding is consistent with conventional wisdom that REITs and direct property correlations are stronger over longer horizons, though this relationship varies across fund types.
- Overall, fund performance is strongly correlated with the underlying property market, suggesting that property market trends and cycles are reflected in fund returns.

Fund size changes & momentum

- Past NAV growth, which incorporates fund size changes reflecting net inflows and short-term momentum effects, is a key performance driver across all fund categories. The effect is strongest for Other (Specialist) funds and weakest for Long Income funds, where the predictability of long-lease cash flows naturally dampens momentum effects.

3 Positive returns and negative returns are weighted by their probabilities of occurrence to calculate the probability-weighted average positive return and the probability-weighted average negative return. These measures are then compared. If the probability-weighted average positive return exceeds the probability-weighted average negative return, the expected gains from positive-return scenarios outweigh the expected losses from negative-return scenarios, indicating a greater likelihood of preserving capital.

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Fund characteristics and performance

- The fund characteristics examined in this study were selected primarily from the existing unlisted property fund literature, where they are widely regarded as key drivers of performance. Analysing these characteristics allows us to assess their contribution to returns across different fund types and whether the observed relationships are consistent with market expectations. The rationale for including these drivers, together with a review of prior evidence on their expected impact, is presented in Section 2, the discussion of the empirical analysis results in Section 7 and Appendix A. The findings suggest that the importance of these drivers varies considerably across fund types, highlighting the heterogeneous nature of unlisted property funds.

Net reversionary yield

- Net reversionary yield has a significant negative relationship with fund returns when examining the full sample and for Balanced funds. This variable was included as a measure of reversionary potential and future rental growth. The negative coefficient suggests, however, that the benefits associated with reversionary potential are not immediately reflected in fund performance and may take time to materialise.

Fund age

- Fund age has a marginal negative impact across the full pool of funds but shows no significant effect when examining individual fund types. Fund age refers to the stage of a fund within its lifecycle at any point in time and differs from vintage year, which reflects the year of fund launch.

Tenant concentration

- Tenant concentration affects returns only in Long Income funds. This variable is directly observed in the dataset and measures the degree of income concentration across tenants. In this fund type, the positive association is consistent with a plausible market view that more concentrated income stream support income stability and returns. However, this relationship is not observed in Other (Specialist) fund categories.

Maximum development exposure

- Maximum development exposure has a negative impact on returns in the full sample, suggesting that development-heavy funds tend to underperform contemporaneously. This likely reflects a combination of factors, including the diversion of resources away from core income-generating activities and the nature of development funding arrangements, which typically involve higher financing costs and delayed income realisation. In Long Income funds, however, the relationship is marginally positive, which may reflect the contribution of pre-let developments and relatively swift income generation from completed projects.

Contribution of fund characteristics as drivers of returns

- Fund characteristics are more successful in explaining the cross-sectional variation in returns among Balanced funds. The effect is smaller in Long Income funds. In Other (Specialist) funds, the impact is even less pronounced. In this category, broader economic conditions (such as GDP growth) and changes in fund size (NAV growth), play a more dominant role in explaining returns.

EXECUTIVE SUMMARY

Fund distinctive factors & manager contribution

Unaccounted influences on fund returns

- The empirical findings suggest that there are additional influences, beyond the factors included in our analysis, that help explain differences in performance across funds.
- This residual component reflects characteristics that are inherently difficult to measure including the quality of the investment process, depth of asset management, tenant relationships, governance, research capacity and skill of the investment team. It also reflects heterogeneity at the underlying asset level. The analysis indicates these have a meaningful and persistent impact on performance alongside the observable drivers.
- For investors, assessing these qualitative attributes should be an important part of the fund selection process, in addition to the quantitative drivers identified in this analysis.

Unexplained return component across fund types

- The intercept term from the panel regression is interpreted as the portion of returns not explained by the variables included in the analysis, rather than representing traditional 'alpha' relative to a market benchmark, it reflects residual performance after controlling for these observable drivers.
- A positive and statistically significant intercept is observed for Balanced funds and Other (Specialist) funds, but not for Long Income funds. This suggests that a persistent component of returns remains unexplained in Balanced and Other (Specialist) funds, whereas returns in Long Income funds are largely accounted for by the model's included factors.
- These differences indicate that the extent of unexplained performance varies across fund types and may reflect unobserved factors such as asset selection, portfolio construction, and manager skill.

Scope of AI in fund performance analysis

Machine learning (ML)

- ML techniques can capture complex, non-linear relationships in the unlisted fund databases that traditional statistical models may not fully identify. However, this flexibility comes at the cost of interpretability and clear economic identification. As such, ML should be viewed as a complement to robust econometric modelling rather than a replacement.
- In the context of this study, the application of ML methods such as random forests[4] have been constrained by data limitations, in particular the incomplete nature of the available dataset.

AI-based sentiment extraction

- Large language models (LLMs) offer the potential to construct proxies for investor sentiment by extracting qualitative information not captured within the structured MSCI/AREF datasets and fund reporting. However, sentiment effects are likely already partially reflected in observable variables used in this analysis, particularly net investment flows and NAV growth, which may act as indirect proxies for investor expectations and behaviour.

4 A random forest is a machine learning method that builds a large number of simple decision-making models and combines their results to produce a final prediction. By drawing on many models rather than one, it reduces the risk of overfitting to the data and is particularly effective at detecting complex patterns among variables. However, unlike conventional regression coefficients, its outputs are not straightforward to interpret in economic terms.

EXECUTIVE SUMMARY

- There are also important measurement considerations. Sentiment indicators derived from LLMs can be highly sensitive to model design and training data, and may introduce issues such as noise, instability, or double counting, which can reduce their practical usefulness. While not undertaken in this study, this remains an active area for future research in property fund performance.

Key Takeaways

Industry headwinds

- The sector faces ongoing structural challenges. Money has been flowing out since 2016, and assets under management have fallen from their 2022 peak. The industry needs to make a clearer case for why unlisted property funds should remain part of investor portfolios.

Strong returns with downside protection

- Balanced and Long Income funds have delivered solid compounded returns of 5.2% and 4.8% per year over the past 15 years, broadly in line with UK REITs and only slightly below the FTSE 250. Importantly, these returns have been relatively stable, with a low chance of losses over typical holding periods such as seven years. This highlights the strength of the sector for capital preservation.

Stable returns-but not artificially so

- Returns for unlisted funds appear smooth, partly due to valuation practices, contributing to a better picture for risks adjusted returns. However, the evidence suggests this smoothing is not excessive. Going forward valuation practices can aim to reduce smoothing effects in underlying valuations and fund return data (i.e. less autocorrelated returns), so that reported performance more closely reflects changes in market conditions in real time. This should help reveal the true diversification and risk benefits of the asset class and increase its appeal to a broader capital base.

Flows and momentum matter

- Past growth in fund value (NAV) is the most reliable indicator of future returns. This reflects both market momentum and investor inflows and outflows. Managing flows is therefore a key part of performance.

The economic backdrop drives returns

- Wider economic conditions and market cycles play a major role in performance. The interest rate cycle matters. Borrowing boosted returns when interest rates were low but reduced them as rates rose sharply from 2022. Cash has also shifted from being a drag on performance to a useful buffer in higher rate environments (2023 and 2024).

Fund characteristics matter-but differ by fund type

- The impact of fund characteristics varies across fund types. They are important in explaining returns for Balanced funds and, to a lesser extent, for Long Income funds. For Other (Specialist) funds, economic and market conditions are the main drivers of performance. In contrast, returns for Long Income funds are not well explained by either set of factors.

EXECUTIVE SUMMARY

Characteristics vary in their relevance

- Factors such as reversionary yield, tenant concentration (tenant income from the top 10 tenants), and development exposure can influence returns, but their impact differs by fund type. Many other characteristics do not show a clear effect. These results should be considered in the light of data limitations present in this study. These data deficiencies should be addressed for a better assessment of fund characteristics on fund returns.

Active management adds value

- There is clear evidence that active decisions make a difference. Sector allocation, that is choosing how much to invest in offices, retail, industrial, and other segments, has consistently added value. In addition, non-quantifiable and non-reported factors (such as investment approach, asset management quality, and team experience) play a role in driving performance.

1. INTRODUCTION

Unlisted property funds are a major channel for allocating capital to commercial real estate offering investors access to both diversified and specialised portfolios. The UK property fund industry has continued to be a major part of the UK real estate capital market.

Given their scale and influence, the performance of unlisted property funds is of significant interest to investors, fund managers, and other participants in the real estate capital markets. This report presents an empirical examination of the key drivers of UK fund performance between 2011 and 2025. While the global financial crisis (GFC) remains a benchmark shock, the post-2011 period has been shaped by diverse macroeconomic trends, political developments, and geopolitical uncertainties.

The empirical analysis builds on existing work examining the determinants of fund performance. A study by the IPF (2012) categorised the drivers of fund performance into four principal groups: the characteristics of the investment portfolio, the use of cash and leverage, fund fees, and the bid–offer pricing mechanism. The study demonstrated that leverage, cash holdings, and fee structures exert a significant influence on fund returns. Importantly, the magnitude and direction of these effects were found to vary across fund types—Managed funds, Other Balanced funds, and Specialist funds.

Since 2011, UK unlisted funds have navigated periods of low and high inflation and interest rates, the uncertainty surrounding Brexit, the global disruptions of the COVID-19 pandemic, the mini-Budget and broader geopolitical shocks. These events have affected rental income, property values, and investor sentiment, requiring fund managers to adopt strategies that sustain performance and manage portfolio risks in an unsettled environment.

More broadly, the performance of unlisted funds has attracted increasing attention from both practitioners and the academic community. Subsequent research has expanded the analytical framework for evaluating fund performance by identifying a wider set of economic and market-related factors, alongside investment styles and fund-specific characteristics, that may influence underlying returns. Building on this literature, the present study extends the analysis of the IPF (2012) by examining these relationships in the period following the global financial crisis. In doing so, it evaluates whether the drivers of fund performance identified in earlier work remain relevant in a period (2011-2025) characterised by markedly different macroeconomic conditions and market shocks. Consequently, the study has important implications for both fund managers, who determine fund structure and investment strategy, and investors seeking to better interpret observed performance.

The study analyses the performance of Balanced, Long Income and Other (Specialist) funds as reported in the MSCI/AREF Quarterly Property Fund (QPF) Index. MSCI reports net total returns for funds in these categories. These returns are calculated after fees and adjusted for cross holdings to avoid double counting when one fund holds units in another. The analysis initially analyses the net returns by fund type with emphasis on downside risks. It then focuses on fund-level data to investigate the impact of specific fund characteristics.

The report is structured as follows. Section 2 reviews the drivers of property fund returns identified in the existing literature. Section 3 presents key stylised facts on the size, structure, leverage, and liquidity of the fund industry, along with net investment flows into unlisted funds. Section 4 analyses fund performance and interprets the findings in light of the statistical properties of fund returns. Section 5 provides a visualisation of fund returns and characteristics, offering context for the results that follow. Section 6 examines the impact of sectoral allocations on performance through attribution analysis. Section 7 presents the main empirical analysis, examining how fund characteristics and market factors influence fund returns. Section 8 considers the scope for artificial intelligence in assessing fund performance, and Section 9 sets out the study's contribution and recommendations.

2. LITERATURE REVIEW SYNOPSIS

2.1 Overview

Section 2 of the report surveys the academic and industry literature on the determinants of UK unlisted property fund performance. The review identifies five principal categories of performance drivers: fund characteristics, investment strategy, portfolio structure, market conditions, and managerial skill (Table 2.1). A recurring finding across studies is that no single factor consistently explains returns; rather, performance reflects a complex, context-dependent interplay of all five domains. Empirical support varies across studies, partly because of differences in data sources, geographies, and sample periods. This section summarises the key findings, with the full literature review provided in Appendix A.

Table 2.1: Summary of key performance driver categories

Category	Key drivers	Overall strength of evidence	Key references
Fund characteristics	Size, age/vintage, leverage, cash, fund style, fees	Mixed-- no single factor consistently significant	Fuerst & Matysiak (2013); Farrelly & Stevenson (2016); Baum et al. (2012); AREF (2021)
Investment strategy	Core vs. non-core style; balanced, Long income, specialist type; asset allocation; development exposure	Moderate to strong-- strategy and sector allocation most consistent	Kiehelä & Falkenbach (2015); Couts (2022); Delfim & Hoesli (2016); Bollinger & Pagliari (2019)
Portfolio structure	Diversification, tenant concentration, number of properties, income metrics (yield, WAULT, vacancy)	Weak to moderate income metrics more supported than diversification measures	Fuerst & Matysiak (2009, 2013); AREF (2019, 2021); Farrelly & Stevenson (2016)
Market conditions	GDP, interest rates, inflation, REIT/equity returns, property market cycle, net capital flows	Strong-- broad consensus that macro/ market variables dominate fund returns	Fuerst & Matysiak (2009, 2013); Delfim & Hoesli (2016); Baum & Farrelly (2009); AREF (2021)
Managerial skill & timing	Manager quality/ experience, performance persistence, market timing ability	Growing-- skill proxies show significance; timing evidence is limited	Lee & Morri (2015); Sleptcova & Falkenbach (2021); Hochberg & Mühlhofer (2017)

2. LITERATURE REVIEW SYNOPSIS

2.2 The impact of fund characteristics

This is the most studied category, yet also the one with the most mixed empirical evidence. The key takeaway is that individual fund-level characteristics are rarely dominant drivers of performance on their own.

Table 2.2: Fund characteristics and fund returns

Driver	Expected effect	Empirical evidence
Fund size (AUM/GAV)	Positive (economies of scale) up to a threshold	Mixed: most studies find limited or no effect; some evidence of diseconomies at very large sizes
Fund age/vintage	Positive (experience); vintage effects reflect entry-point timing	Mixed: often insignificant; J-curve dynamics documented; vintage effects confirmed by Baum et al. (2012)
Leverage	Positive in up markets; amplifies losses in downturns	Weak on average returns; strong on risk-leverage increases volatility and downside losses significantly
Cash holdings	Negative (cash drag) outside stress periods	Generally not significant; AREF (2021) found approximately 0.14%-0.23% p.a. return drag for balanced funds
Fund style (open/closed)	Closed-end: fully invested; open-end: liquidity costs	Not a dominant driver; investment strategy (core vs. non-core) matters more
Fees	Mechanically reduce net returns; incentive effects indirect	Rarely statistically significant in empirical models despite clear mechanical link

2. LITERATURE REVIEW SYNOPSIS

2.3 Investment strategy

Strategy is one of the more consistently supported drivers. The core versus non-core distinction meaningfully separates return and risk profiles across studies and geographies.

Table 2.3: Evidence on investment strategy

Strategy Dimension	Findings
Core vs. Non-core (value-add / opportunistic)	Non-core funds deliver higher absolute returns but with greater volatility and vintage sensitivity. Risk-adjusted outperformance is not established — the premium reflects higher risk taken.
Balanced, Long Income, Specialist Types	No single type consistently outperforms over the long run. Long Income funds offer income stability; Specialist funds may outperform in favourable sector conditions but diverge sharply in downturns.
Sector/Asset allocation	Consistent and significant driver. Funds with greater exposure to stronger-performing sectors outperform. Fuerst & Matysiak (2009, 2013) and Farrelly & Stevenson (2016) confirm sector allocation as significant.
Development exposure	Associated with higher return potential but carries construction and market risk. Most common in value-add/opportunistic funds. Couts (2022) and Delfim & Hoesli (2016) confirm its role.

2.4 Portfolio structure

Portfolio-level metrics have mixed empirical support, with income-related indicators (vacancy, yield, WAULT) performing better than pure diversification measures.

Table 2.4: Findings portfolio structure

Driver	Findings
Geographic/Sector diversification (HHI)	Not a robust systematic driver; some upside from specialisation in alternatives (e.g., healthcare, data centres) but greater cyclical sensitivity.
Tenant concentration	Weak empirical link to returns. High concentration increases income risk but can be mitigated by strong covenant quality. No robust direct effect found.
Number of properties	Higher count reduces idiosyncratic risk but not shown to systematically improve returns. AREF (2021) finds negative correlation between top 10 property concentration and Sharpe ratio.
Portfolio yield/Vacancy	Significant in several studies. Lower vacancy = more stable cashflows. Higher initial yield linked to stronger income returns (Lee & Morri, 2015; AREF, 2021).
WAULT	More relevant as a risk indicator than return driver. AREF (2021) finds it significant for both Balanced and Specialist funds, with greater impact for Specialist funds.

2. LITERATURE REVIEW SYNOPSIS

2.5 Market conditions

This is the most robustly supported category. Macro and financial market variables account for a substantial portion of fund return variation across all study types, suggesting that market exposure — not purely fund-level skill — underpins much of observed performance.

Table 2.5: Market conditions

Variable	Role in fund returns
GDP growth	Drives rental income and property values; positive effect well documented
Interest rates/Inflation	Rising rates increase financing costs and dampen capital values; strong effect in post-2022 environment
REIT returns (contemporaneous & lagged)	Strong forward-looking signal for unlisted fund returns from both contemporaneous and lagged REIT returns.
Property market cycle/ MSCI Index	Core driver; large share of fund returns attributable to underlying market movements (Baum & Farrelly, 2009)
Net capital flows	Recognised in practice as important for liquidity and pricing; often captured indirectly via size and liquidity variables.

Key implication: Because macro-financial factors dominate, investors and analysts cannot assess fund performance in isolation from the broader market cycle.

2.6 Managerial skill and market timing

This is an emerging area. Managerial skill is difficult to observe directly and is typically proxied through fund characteristics, performance persistence, or limited partner (LP) reinvestment behaviour.

Table 2.6: Measuring manager contribution

Dimension	Evidence
Manager quality/Active management	Lee & Morri (2015) support the role of active management. Sleptcova & Falkenbach (2021) find skilled managers deliver superior risk-adjusted performance consistently.
Performance persistence	Some persistence found but not universal; LP reinvestment identified as a market signal of managerial quality.
Market timing	Limited empirical tests; Hochberg & Mühlhofer (2017) find most US managers have limited timing ability, though a minority succeed. Asset selection skill more consistently identified than timing skill.
Unobservable fund-specific effects	Studies consistently find residual fund-level effects not captured by observed characteristics- reflecting manager skill, organisational quality, and investment process.

2. LITERATURE REVIEW SYNOPSIS

2.7 Key conclusions from the literature

- Market conditions are the dominant driver of fund returns. Macro-financial factors (GDP, interest rates, REIT returns, property cycles) explain a large share of the variation in performance across time, consistent with the findings of this study.
- Fund-level characteristics matter but are context-dependent. Leverage, cash, size, and age have mixed evidence, and their effects vary by fund type, market phase, and sample period.
- Strategy is the most reliable fund-level differentiator. Core/non-core and sector allocation consistently determine return profiles; absolute outperformance versus risk-adjusted outperformance should be distinguished.
- Portfolio income metrics are more informative than pure diversification measures. Vacancy, yield, and WAULT provide useful signals, while HHI concentration and tenant diversification show weaker and less consistent effects.
- Unobservable fund-specific effects are present and economically meaningful. Even after controlling for all observed factors, residual fund-level variation persists—reflecting managerial quality, processes, and organisational factors that current data cannot fully capture.

3. UK FUND STYLES: SIZE, FLOWS, LEVERAGE & LIQUIDITY

3.1 Size and structure

In the MSCI/AREF database, UK unlisted real estate funds are categorised into three main types which represent investment strategies: Balanced, Long Income, and Other (Specialist), see Appendix B. Balanced funds are sub divided into two types based on their legal structure: Managed property funds and Other Balanced funds, composed of both authorised and unauthorised property unit trusts (PUTs).

Table 3.1 presents a breakdown of the number, GAV and NAV of the main fund categories over the analysis period (2011 Q1 and 2025 Q4).

Table 3.1: UK unlisted funds and size by category (2011–2025)

		Fund category			
		All	**Balanced**	**Long Income**	**Other (Specialist)**
Number of funds	2011 Q1 2025 Q4	58 32	24 19	0 8	32 5
GAV (£ millions)	2011 Q1 2025 Q4 Change	34,063 40,440 18.7%	15,718 24,092 53.3%	- 9,119 -	17,433 7,229 -58.5%
NAV (£ millions)	2011 Q1 2025 Q4 Change	26,664 38,019 42.6%	15,103 23,858 58.0%	- 9,111 -	10,648 5,050 -52.6%

Source: MSCI/AREF

The UK unlisted fund sector saw the total number of funds declining from 58 to 32, reflecting consolidation in the sector between 2011 Q1 and 2025 Q4, alongside a shift in the composition of fund types. This contraction was driven largely by the decline of Other (Specialist) funds, which fell from 32 to just 5. In contrast, the number of Balanced funds declined more modestly (from 24 to 19), while the new Long Income category emerged, growing to eight funds by 2025. This suggests a partial pivot within the sector toward more income-focused investment approaches.

Despite the reduction in fund numbers, the sector experienced substantial asset growth. Gross asset value (GAV) increased from £34.1 billion to £40.4 billion, a rise of 18.7%, while net asset value (NAV) grew more strongly by 42.6% to £38.0 billion. Growth was particularly concentrated in the Balanced and Long Income categories. Balanced funds saw GAV rise by 53.3% and NAV by 58.0%, reinforcing their dominant position in the market. Meanwhile, Long Income funds accumulated £9.1 billion in both GAV and NAV by 2025, highlighting their increasing importance. In contrast, the Other (Specialist) category experienced a steep decline in both GAV (down 58.5%) and NAV (down 52.6%), consistent with the sharp fall in fund numbers.

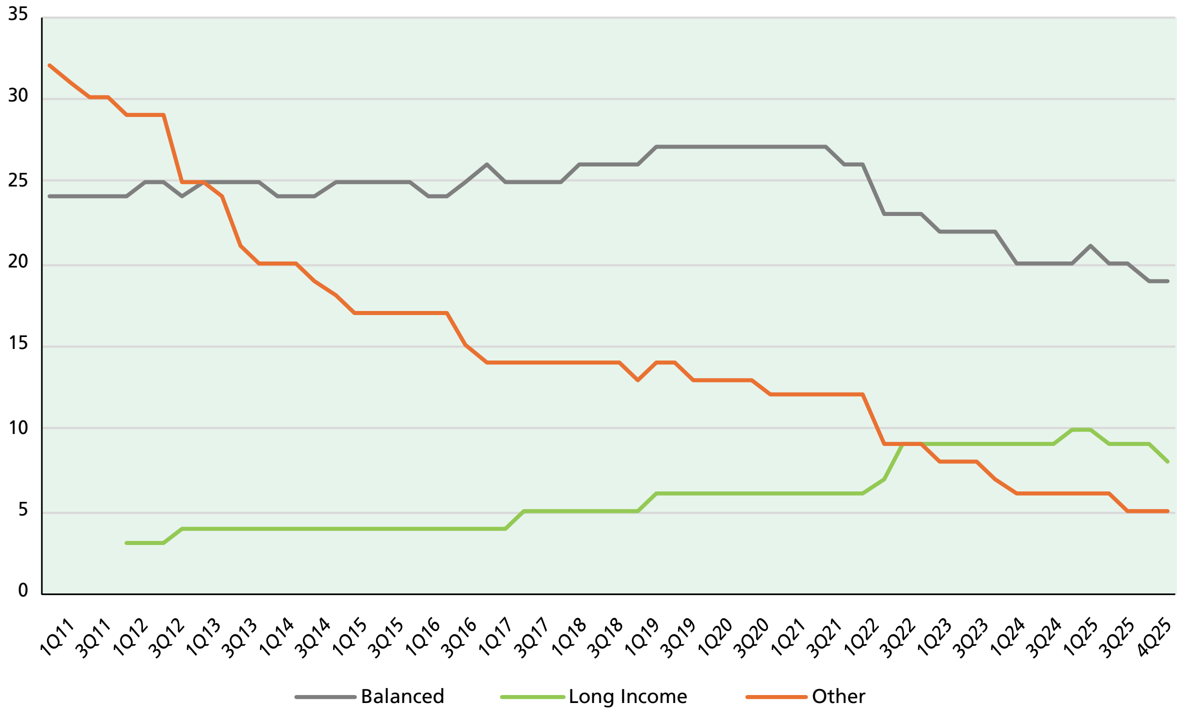
The growth in Balanced and Long Income funds suggests an increasing focus on risk diversification and more stable income generating allocations. The growth in the Long Income category is driven by the adoption of property unit trust (PUT) and property authorised investment fund (PAIF) structures.

The MSCI UK capital growth index recorded capital growth of 17.5% over the period, closely aligned with the 18.7% increase in GAV across UK unlisted funds. The narrow differential suggests that most of GAV growth has been driven by underlying market valuation effects, with net capital inflows and structural changes playing a relatively limited role in explaining overall sector expansion.

3. UK FUND STYLES: SIZE, FLOWS, LEVERAGE & LIQUIDITY

The summary results in Table 3.1 are presented over time to provide a visual representation of trends in fund numbers and size of the industry (GAV) since 2011 (Figures 3.1 and 3.2).

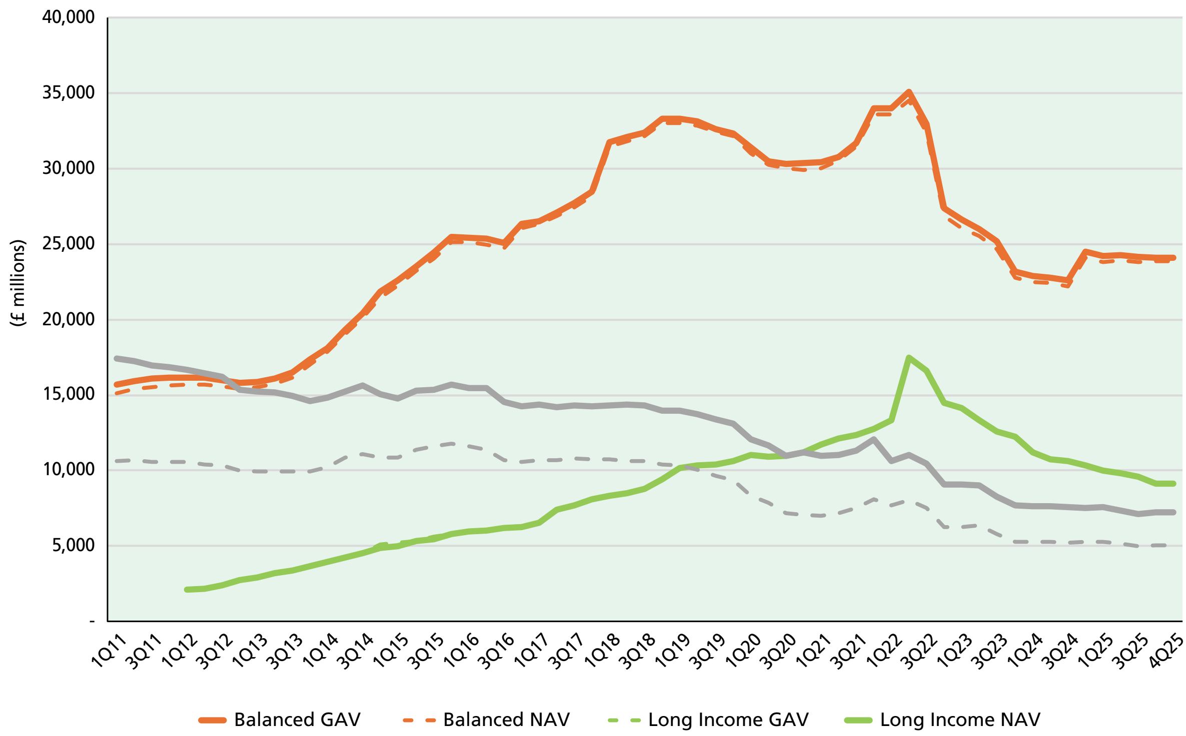
Figure 3.1: Number of funds by category



Source: MSCI/AREF QPF Index

3. UK FUND STYLES: SIZE, FLOWS, LEVERAGE & LIQUIDITY

Figure 3.2: GAV & NAV by fund category



Source: MSCI/AREF QPF Index

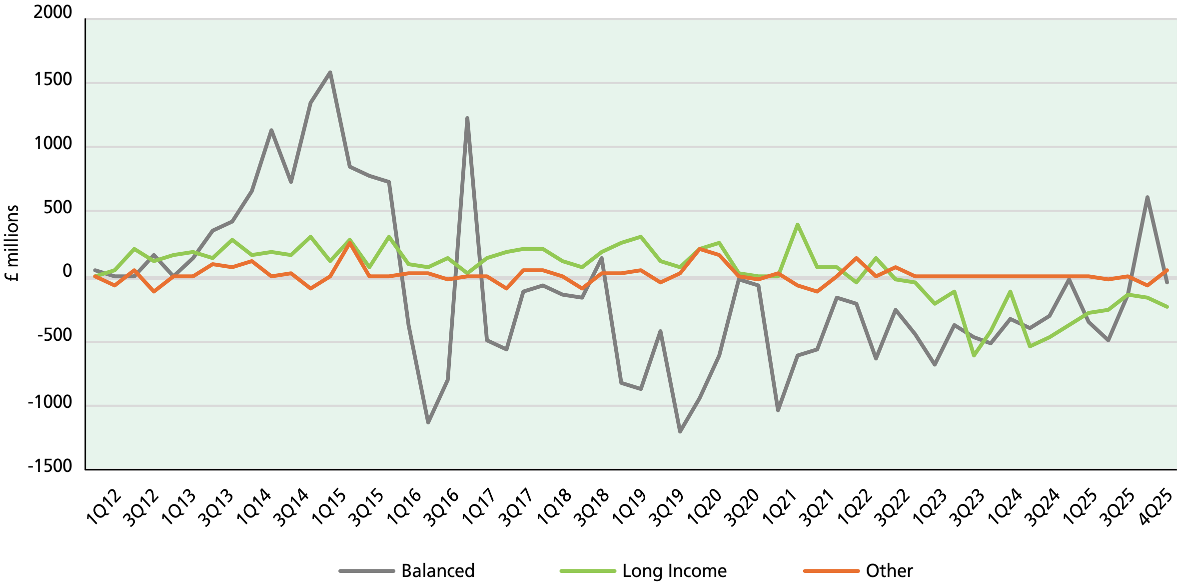
Figure 3.2 reports both GAV and NAV by fund type. There is no material difference between GAV and NAV for Balanced and Long Income funds. This reflects relatively low levels of leverage, with these fund styles exhibiting near-parity between gross and net exposure. By contrast, a clear divergence is observed in specialist funds, where GAV exceeds NAV. This gap is primarily driven by higher levels of leverage.

3.2 Net Investment Flows

Net investment flows into UK unlisted property funds show a clear transition from strong, broad-based inflows in the early part of the sample to sustained and widespread outflows in more recent years, with marked differences across fund types. Between 2012 and 2015, all fund categories attracted positive inflows, led by Balanced funds, reflecting strong demand for real assets in a low-interest rate environment and continued allocations from DB pension schemes.

3. UK FUND STYLES: SIZE, FLOWS, LEVERAGE & LIQUIDITY

Figure 3.3: Net investment flows



MSCI/AREF PFV Handbook

From 2016 onwards, however, Balanced funds experienced a sharp and persistent reversal. This was driven by a combination of Brexit-related uncertainty, the introduction of fund gating to stave off redemptions and a structural decline in DB pension scheme allocations as schemes matured. In contrast, Long Income funds continued to attract inflows during this period, benefiting from their stable, income-focused characteristics.

From 2019 onwards, outflows from Balanced funds intensified and became structural, further exacerbated by the COVID-19 shock. While Long Income funds remained relatively resilient through 2020–2021, they began to weaken from 2022, reflecting rising inflation and interest rates and increased competition from fixed income (10-year gilt yields rose from 0.32% in 2020 Q2 to 4.64% at the end of 2025). The diminishing role of DB pension schemes as a source of new capital, has reinforced this trend. There was also renewed market stress following the 2022 'mini-budget', which again led to episodes of fund gating and heightened investor concerns around liquidity. Other (Specialist) funds remained comparatively small and volatile throughout. Although there are tentative signs of stabilisation in the most recent data, still overall net flows remain subdued, pointing to a more selective and constrained capital environment for UK unlisted property funds.

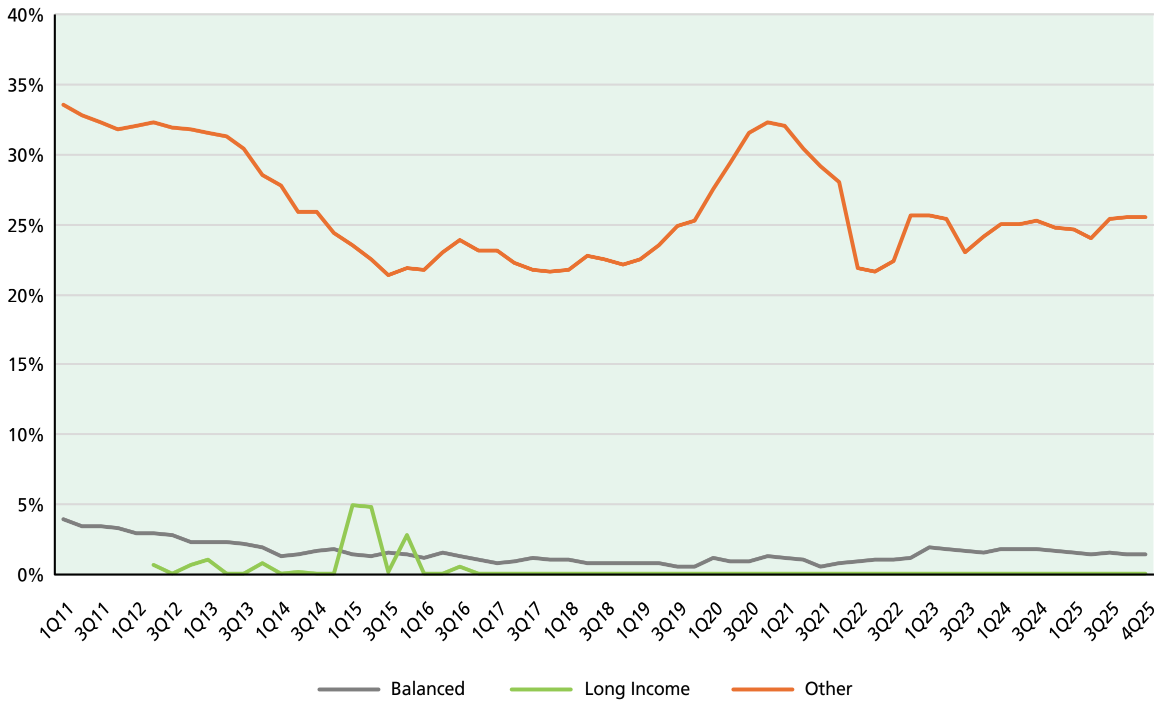
3. UK FUND STYLES: SIZE, FLOWS, LEVERAGE & LIQUIDITY

3.3 Leverage and liquidity

3.3.1 Leverage

Funds operate at distinct leverage levels (Figure 3.4). Leverage is low in Balanced funds, while Long Income funds are effectively unlevered which confirms the near parity between GAV and NAV observed for these fund styles in Figure 3.2. In contrast, the Other (Specialist) fund category exhibits materially higher leverage, ranging between 22% and 35%, with periods of deleveraging followed by phases of increasing leverage. Over the past three years, leverage has remained relatively stable, and at the end of the sample it stands at around the long-term average of 25%.

Figure 3.4: Leverage structure across fund types

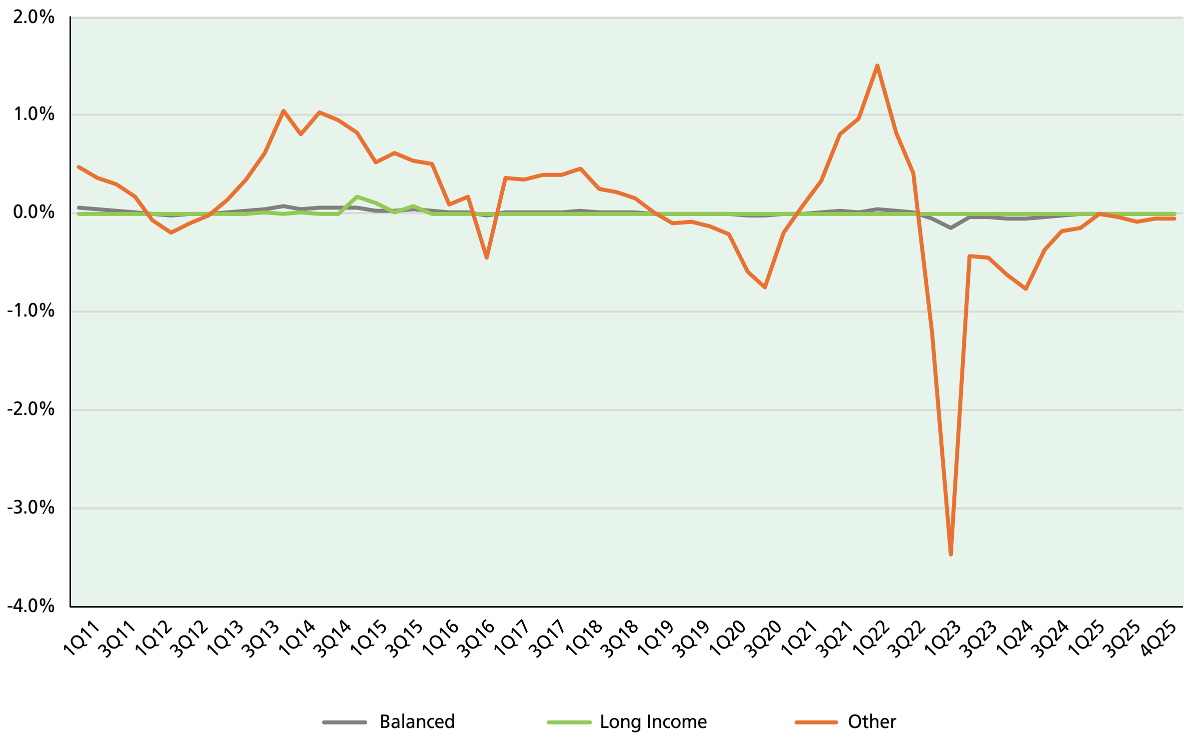


Source: MSCI/AREF QPF Index

The impact of leverage on fund returns is depicted in Figure 3.5. This impact is approximated as the product of the loan-to-value (LTV) ratio (debt as a percentage of gross asset value, GAV) and the spread between property returns and the cost of debt. The cost of debt is estimated using the three-month interbank rate as the benchmark. The lending margin is based on the average margin applied to loans across the main real estate sectors, with data sourced from the Bayes Lending Survey.

3. UK FUND STYLES: SIZE, FLOWS, LEVERAGE & LIQUIDITY

Figure 3.5: Net impact of leverage across fund types



Source: MSCI/AREF QPF Index, Authors

The results indicate a clear cyclical pattern in the impact of leverage on annual fund returns, closely linked to the interest rate environment. In the post-GFC period, persistently low interest rates meant that borrowing costs were generally below property returns, resulting in a positive contribution from leverage to the overall returns of Other (Specialist) funds.

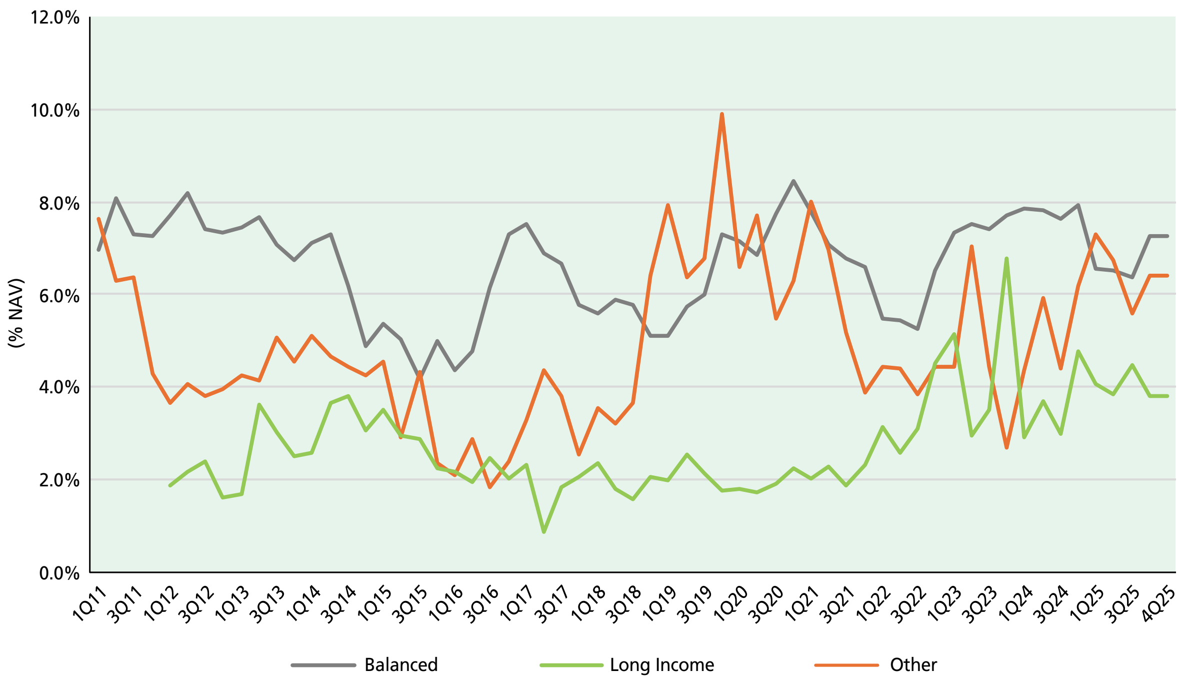
However, this relationship reverses in the later period. As interest rates rose sharply in 2022–2023 and property returns experienced two significant negative movements, leverage had a material adverse impact on annual returns. The positive spike at the end of 2021 and the beginning of 2022 reflects a period of strong quarterly property returns combined with low borrowing costs. More recently, the impact of leverage has been broadly neutral across all fund types.

3. UK FUND STYLES: SIZE, FLOWS, LEVERAGE & LIQUIDITY

3.3.2 Cash holdings

The MSCI/AREF QPF Index contains data on net debt and leverage as a percentage of NAV. From these data, we have derived cash as a percentage of NAV by fund type, as shown in Figure 3.6.

Figure 3.6: Cash holdings by fund type



Source: MSCI/AREF QPF Index, Authors

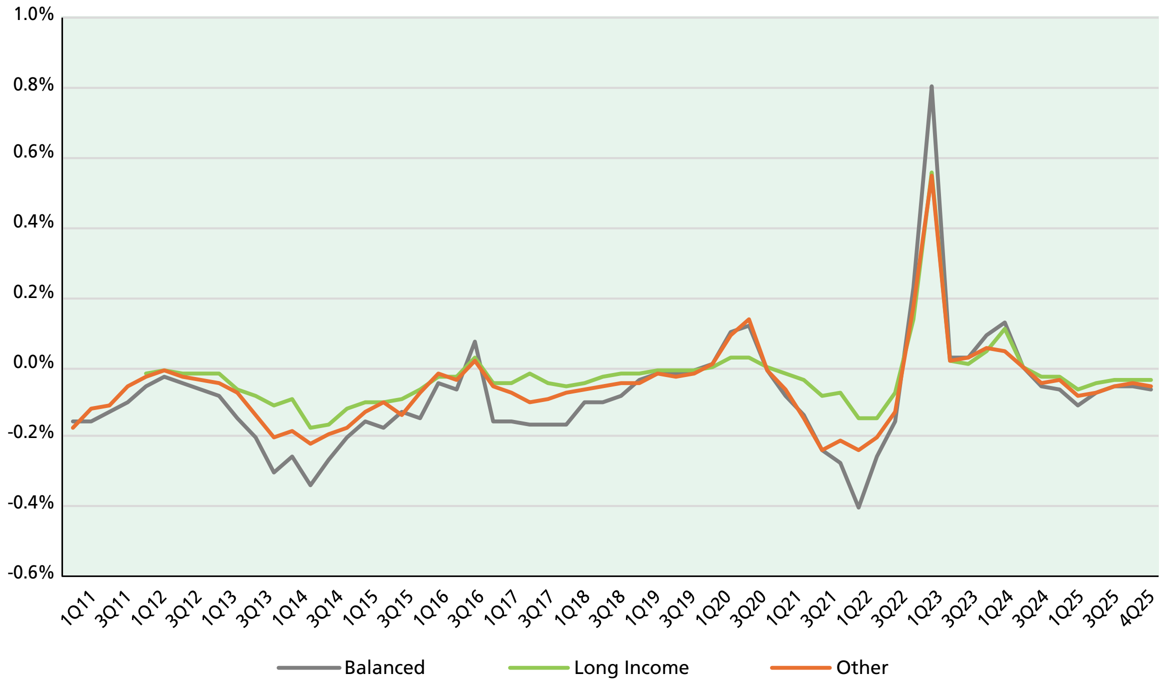
Cash holdings as a percentage of NAV exhibit distinct patterns across fund types over time, pointing to cyclical behaviour. Balanced funds maintained relatively stable cash levels, generally in the 4-8% range, with a dip around 2014-2016, followed by a recovery and sustained elevation through 2020-2024, and a slight moderation in 2025.

Long Income funds consistently held much lower cash allocations, typically between 2-3%, although this has gradually increased in recent years to around 4-5%.

The Other (Specialist) category displayed the greatest volatility, with cash ratios fluctuating widely—from lows near 2% in 2016 to peaks approaching 10% around 2019-before settling into a 4-7% range in the most recent period. This pattern may indicate more variable and tactical cash management over the cycle in this category.

3. UK FUND STYLES: SIZE, FLOWS, LEVERAGE & LIQUIDITY

Figure 3.7: Cash drag estimates



Source: MSCI/AREF QPF Index, Authors

In most periods, cash acts as a performance headwind, although the impact is modest and persistent over time. This negative effect is expected when property returns exceed the return on cash. However, there are periods—such as 2016, early 2020, and particularly late 2022—where cash contributed positively to performance, due to weaker property returns and higher cash returns (driven by rising interest rates), which temporarily reversed the drag effect.

The variation in estimated cash drag is largely common across funds. In these estimates, the return on cash is proxied by the three-month interbank rate. It should be noted that alternative cash return series could alter the precise values shown in the graph, although the overall pattern is unlikely to change materially.

4. ANALYSIS OF FUND RETURNS

This section evaluates the performance of property fund types over the period from 2011 Q4 to 2025 Q4 using total returns from the MSCI/AREF Quarterly Property Fund (QPF) Index. Total returns are net of fees making returns comparable across funds from an investor perspective. Net total returns are unitised and adjusted for crossholdings, capturing overall performance after costs, including both income and capital returns. Unitisation standardises performance to a base value of 100, enabling consistent comparison over time. The study period is determined by data availability, with Long Income fund data commencing in 2011 Q4 when using index levels, or in 2012 Q1 when returns are expressed in percentages.

The analysis examines return trends, long-term performance, volatility, and risk-adjusted performance. This approach is consistent with standard methods in finance and investment analysis. To provide context, property fund performance is compared with UK real estate investment trusts (REITs, FTSE All UK REIT Index) and equities, proxied by the FTSE 250 Index, commonly used as a benchmark for UK domestic economic conditions.

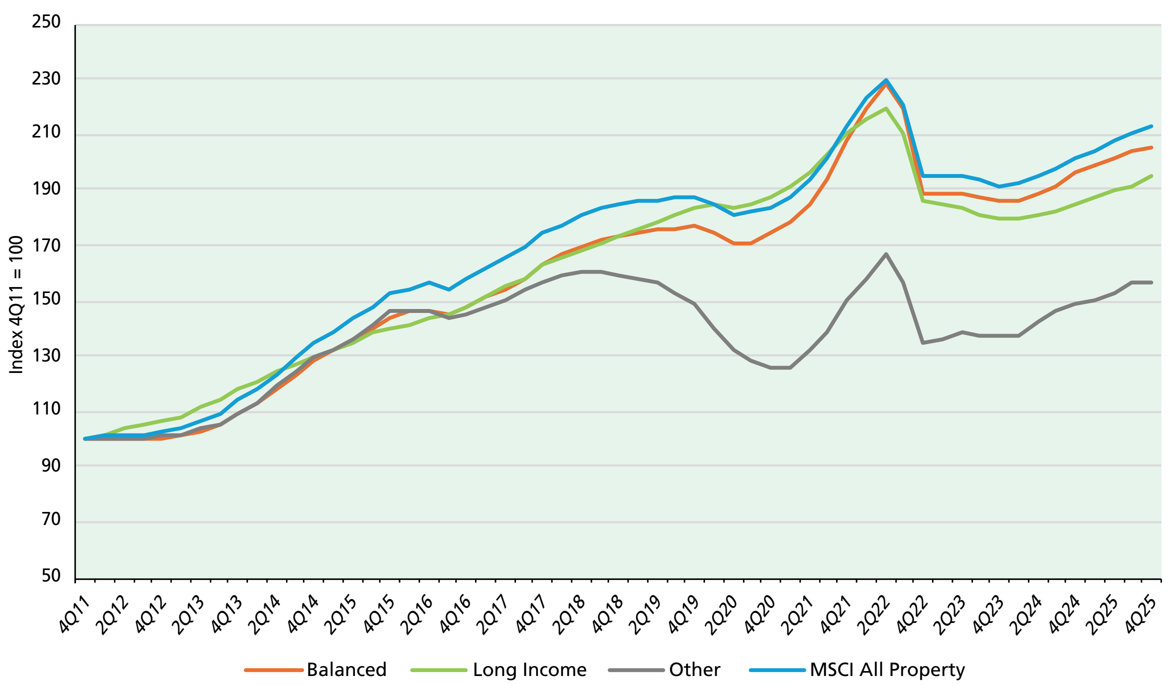
4.1 Comparative return performance

4.1.1 Long-term return analysis

From 2012 Q1 to 2025 Q4, net total returns for the three fund types—Balanced, Long Income, and Other (Specialist)—show that Balanced and Long Income funds followed broadly similar trajectories. In contrast, the Other (Specialist) fund category diverged from early 2019 onward, experiencing nine consecutive quarters of negative returns (Figure 4.1). Figure 4.1 plots the index of net total returns over the sample period, while Figure 4.2 shows the cycle of quarterly total returns.

For comparison, the MSCI All Property Total Return Index (quarterly) is also included. Balanced and Long Income funds broadly mirror the trends in the MSCI index, as would be expected, particularly for Balanced funds.

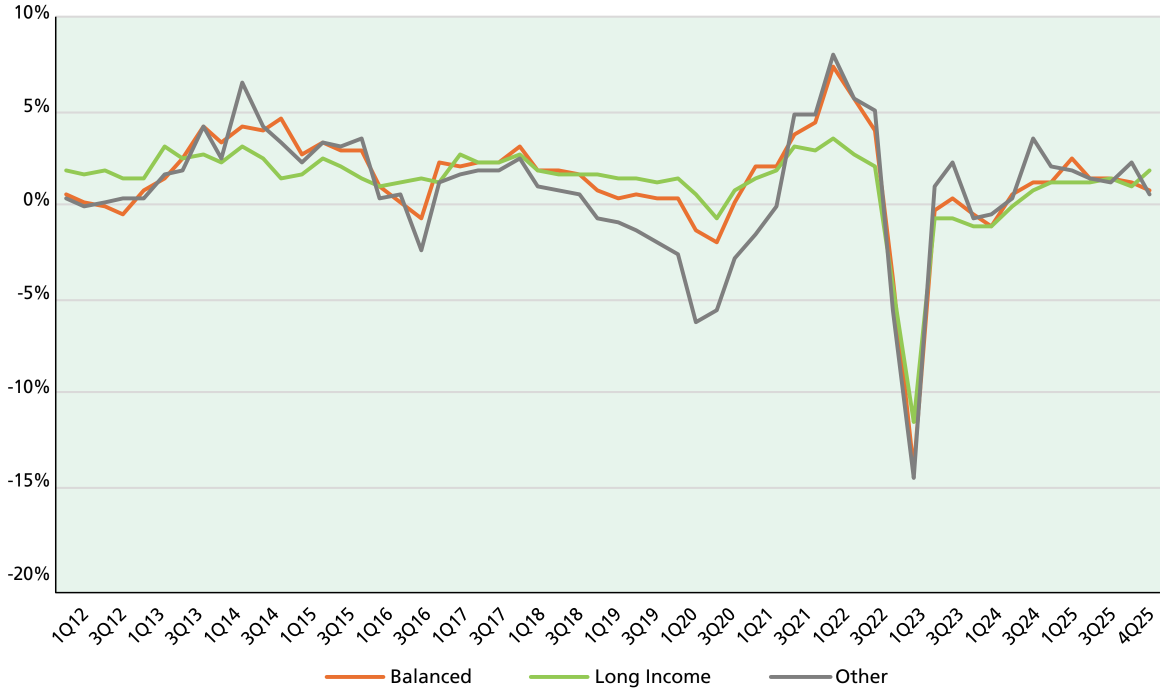
Figure 4.1: Net total return trends by fund category



Source: MSCI/AREF QPF Index, MSCI Quarterly Property Index, LSEG Workspace

4. ANALYSIS OF FUND RETURNS

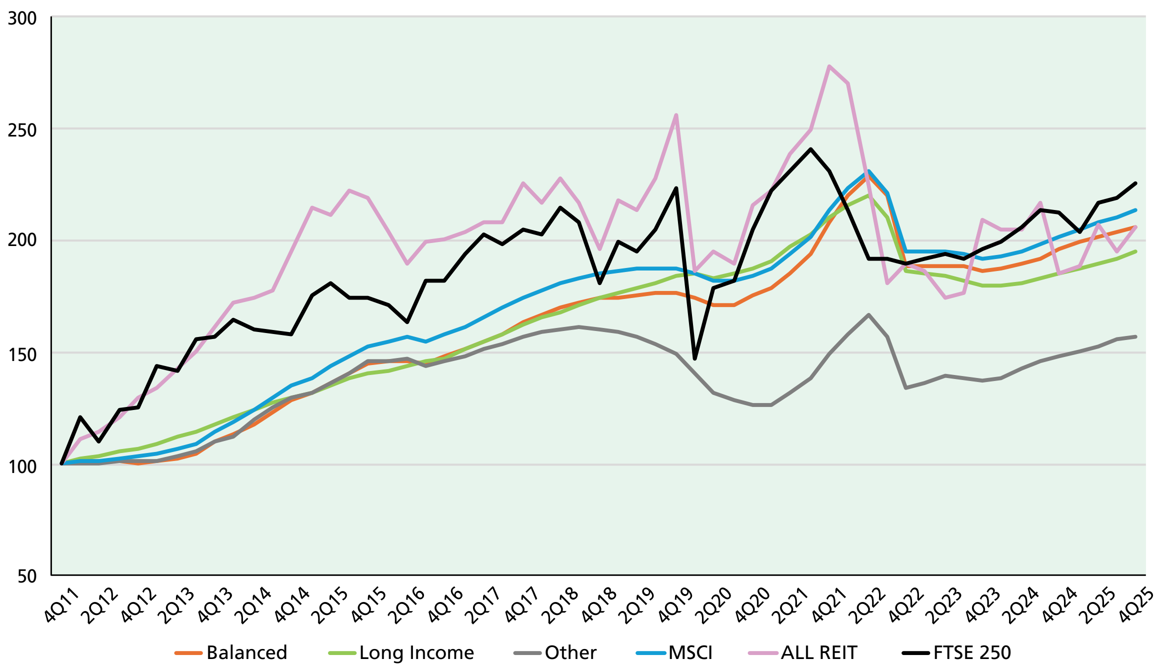
Figure 4.2: Quarterly net total return by fund category



Source: MSCI/AREF QPF Index

Figure 4.3 places fund returns in a broader context by introducing UK All REIT returns and the FTSE 250 total returns. REITs, together with mid-cap property developers and landlords listed in the FTSE 250 Index, account for approximately 7-9% of the index.

Figure 4.3: Property fund returns vs REITs and equities



Source: MSCI/AREF QPF Index, MSCI Quarterly Property Index, LSEG Workspace

4. ANALYSIS OF FUND RETURNS

As expected, the listed indices exhibit more pronounced cycles (the smoothing of fund returns is discussed later). The FTSE 250 total return index ends slightly higher than Balanced funds, while the REIT index finishes at a similar level to Balanced fund returns.

The visual insights into fund performance are complemented by a more formal assessment by fund type, and in comparison, with listed markets, presented in the following tables. These tables quantify trends in returns and provide a more structured view of performance, including actual returns, volatility, and risk-adjusted metrics across fund categories. This enables more meaningful comparisons to be made.

Table 4.1: Headline comparative statistics over sample period

	Fund returns			Market indices		
	Balanced	Long Income	Other (Specialist)	MSCI	All REITs	FTSE250
Min	-14.1%	-11.6%	-14.5%	-11.9%	-27.5%	-34.5%
Max	7.5%	3.7%	8.1%	6.1%	18.9%	21.7%
Mean	1.34%	1.22%	0.87%	1.39%	1.66%	1.83%
Annualised	5.5%	5.0%	3.5%	5.7%	6.8%	7.5%
CQGR	1.27%	1.18%	0.79%	1.34%	1.27%	1.43%
CAGR	5.2%	4.8%	3.2%	5.5%	5.2%	5.9%
St deviation	2.9%	2.2%	3.5%	2.6%	8.4%	8.4%
Smoothness	0.53	0.55	0.55	0.58	-0.04	-0.36

Source: MSCI/AREF QPF Index, MSCI Quarterly Property Index, LSEG Workspace, Authors
Sample period is 2012 Q1–2025 Q4
Note: CQGR is the compound quarterly growth rate and CAGR is the compound annual growth rate.

Insights from average return performance

The pandemic was responsible for the largest negative and minimum returns in the sample period across asset classes. For the three types of funds and the MSCI quarterly index, the minimum returns occurred in 2022 Q4, when REITs returned 4.5% for the quarter, while the FTSE 250 fell by 1.1%. For the listed markets, the lowest returns were recorded in 2020 Q1, during the first UK lockdown at -27.5% for REITs and -34.5% for FTSE 250. Fund returns held up relatively well at that time, except for Other (Specialist) funds, which fell by 6.3%.

In terms of average returns, the FTSE 250 Index and All REITs deliver the highest average quarterly returns at 1.83% (7.5% p.a.) and 1.66% (6.8% p.a.), respectively, indicating stronger headline performance and expected returns. Among the property fund styles, Balanced funds delivered 1.34% per quarter (5.5% p.a.), outperforming Long Income funds (1.22% per quarter, 5.0% p.a.) and Other (Specialist) funds (0.87% per quarter, 3.5% p.a.). The average return in the MSCI quarterly index sits slightly above Balanced funds at 1.39% per quarter (5.7% p.a.), reinforcing that diversified portfolios can closely track the MSCI benchmark as intended.

4. ANALYSIS OF FUND RETURNS

What compound returns reveal about performance and investor returns?

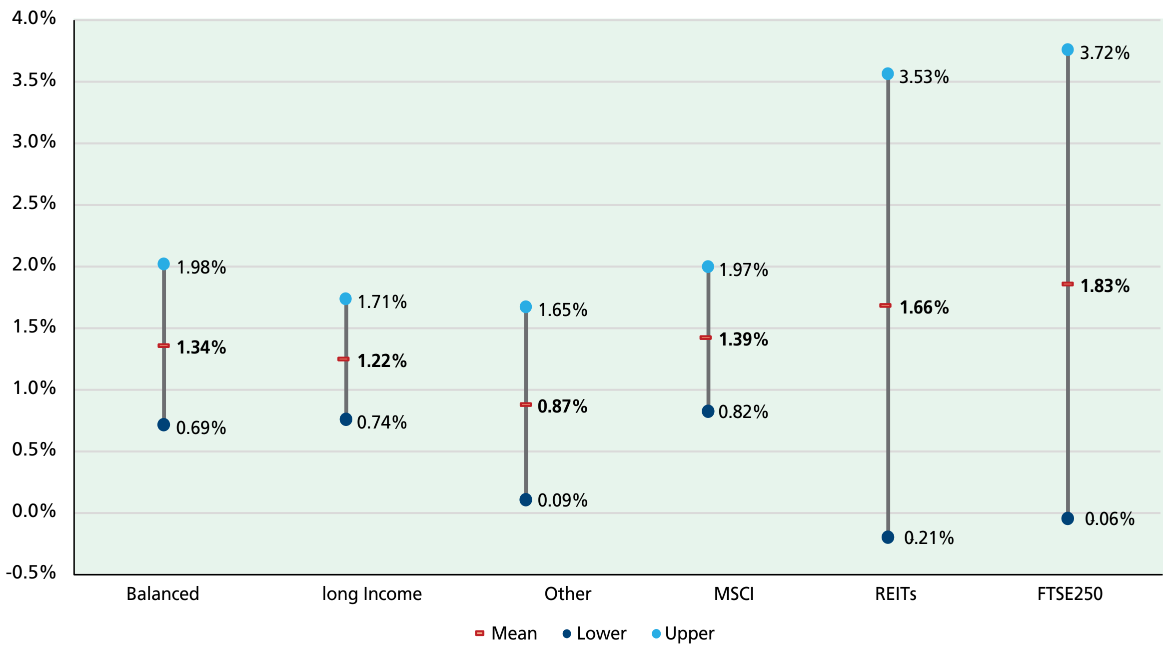
Table 4.1 also reports the compound quarterly growth rate (CQGR) and compound annual growth rate (CAGR), which provide a more meaningful measure of performance as they reflect the effects of compounding over time. Under these measures, returns are systematically lower across all asset classes. Both Balanced and Long Income funds have generated attractive returns relative to Other (Specialist) funds. Balanced and Long Income fund CAGRs (5.2% and 4.8% respectively) are broadly in line with REITs and only marginally below the FTSE 250 CAGR (5.9% p.a.) over the period under consideration.

This divergence between mean-based measures (which average returns) and compound returns arises because the former do not fully capture the sequencing and volatility of returns (e.g. negative return periods), whereas compounded measures incorporate the cumulative effect of gains and losses over time. As a result, CAGR (and CQGR) provides a more appropriate measure of long-run investment performance, particularly when comparing unlisted funds with assets that exhibit different volatility profiles. Compound measures therefore reflect the growth of invested capital over the full sample period and are more relevant for unit holders, as they capture the effect of reinvestment over time.

Expected return ranges

A way to help investors understand the range of potential outcomes, rather than relying on point estimates alone, is to use confidence intervals. These are important for unit holders because they provide a probabilistic measure of the uncertainty around expected returns.

Figure 4.4: 90% confidence intervals for expected quarterly returns



Source: MSCI/AREF QPF Index, MSCI Quarterly Property Index, LSEG Workspace, Authors

Figure 4.4 presents the range of returns by fund type and asset class within which, based on the 2012 Q1 to 2025 Q4 sample, returns are expected to fall with 90% confidence. The range is wider for listed markets, reflecting their higher volatility. This again raises the issue of potential underestimation of volatility in property fund returns due to smoothing effects. Nevertheless, over the long run, investors in property funds can expect, with 90% confidence, that quarterly returns will remain positive.

4. ANALYSIS OF FUND RETURNS

4.1.2 Volatility of returns and smoothness

Standard deviation (stdev), the conventional measure of volatility, indicates that direct property funds—particularly Long Income (2.2%) and Balanced (2.9%)—are significantly less volatile than All REITs and the FTSE 250 (both with a stdev of 8.4%). This brings us to the issue of smoothing in real estate data, which can lead to an underestimation of volatility (lower standard deviations).

The final row in Table 4.1 (Smoothness) reports the first-order autocorrelation of returns as a measure of dependence in fund returns. It shows the extent to which fund returns are correlated with those of the preceding quarter (that is autocorrelation of first order). Values of autocorrelation coefficients ranging from 0.53 and 0.55 suggest a degree of smoothing and persistence, although not at excessively high levels (e.g., above 0.7). Persistence can have several interpretations. In this context, it implies that positive (negative) fund returns tend to be followed by positive (negative) returns, although this dependence is not excessive. It should be noted that UK real estate series tend to show somewhat less valuation smoothing than other jurisdictions. We conclude that fund returns are not heavily smoothed, suggesting some exposure to transaction-based pricing and more active revaluation practices.

In contrast, the equities market exhibits negative autocorrelation (-0.36), which may be considered relatively high, compared with the near-zero autocorrelation expected in equity market returns. REIT returns, on the other hand, show little evidence of autocorrelation. While we acknowledge the smoothing effect in property fund return data, this reflects intrinsic characteristics of the asset class. Property pricing (yields) inherently reflects both illiquidity and a smoothness premium. Attempts to de-smooth returns raise further issues, most notably the extent of adjustment required. The estimated autocorrelations suggest that return volatility is to some degree understated, while diversification benefits may be overstated. However, this effect does not appear excessive.

In this section, we adopt a long-term perspective (determined by the study period). Statistics calculated over shorter periods—such as three, five, or seven years—may differ significantly from the results reported in Table 4.1. We address this further in Section 4.3.

4.2 Risk adjusted metrics

We complement the analysis of raw fund returns in Section 4.1 with risk-adjusted metrics to provide a more comprehensive assessment of fund performance. These measures account for the risk taken, highlighting funds that deliver strong returns relative to risk, typically proxied by overall volatility or downside volatility. In the PFV Handbook, the Sharpe ratio is reported as a key measure of risk-adjusted performance. Such metrics can play an important role in portfolio optimisation and fund selection, particularly for multi-asset managers.

4. ANALYSIS OF FUND RETURNS

Table 4.2: Performance of funds on a risk adjusted basis

	Fund returns				
	Balanced	**Long Income**	**Other (Specialist)**	**All REITs**	**FTSE250**
Coefficient of variation[5]	2.2	1.8	4.0	5.0	4.6
Sharpe ratio	0.31	0.35	0.13	0.15	0.17
Adjusted Sharpe ratio	0.25	0.24	0.13	0.14	0.16
Sortino ratio	0.47	0.49	0.40	0.21	0.26
Omega ratio (0%)	4.1	4.4	2.0	1.7	1.9
Omega ratio (0.41%)	2.8	2.9	1.5	1.5	1.7
Omega ratio (1.5%)	0.8	0.6	0.6	1.1	1.1

Source: MSCI/AREF QPF Index, MSCI Quarterly Property Index, LSEG Workspace, Authors
Sample period is 2012 Q1–2025 Q4

Table 4.2 reports the results for the three fund types and the listed markets. The sample period is 2012 Q1 to 2025 Q4.

Coefficient of variation

The coefficient of variation (CV) measures the amount of risk taken per unit of return, calculated as the ratio of the standard deviation to the mean. It is a useful metric for comparing risk-adjusted performance across asset classes because it standardises volatility relative to returns, allowing for meaningful comparisons when average returns differ. Lower CV values indicate lower risk for the level of average return.

Based on the reported figures, Long Income funds and the MSCI Property Index (CV value 1.8 for both) exhibit the most favourable risk–return trade-off, followed by Balanced funds (2.2), which remain relatively efficient. In contrast, Other (Specialist) funds (4.0), the FTSE 250 (4.6), and particularly All REITs (5.0) appear significantly less efficient, reflecting higher levels of volatility relative to their returns. These results suggest that, on a risk-adjusted basis, direct property funds-especially Long Income-offer more stable performance, whereas listed real estate and equities deliver returns with considerably greater variability. For investors, this highlights a clear trade-off: while listed markets may provide higher headline returns, they do so at the cost of substantially higher risk per unit of return.

5 The coefficient of variation measures the dispersion of returns relative to the mean (standard deviation divided by the mean). The Sharpe ratio is defined as excess return (fund type average return minus the yield on the 10-year gilt) divided by the standard deviation of returns. The adjusted Sharpe ratio modifies the standard Sharpe ratio by adjusting for skewness and kurtosis to account for non-normal return distributions. The Sortino ratio is the excess return divided by downside deviation, where downside deviation is measured here as the volatility of negative returns. The Omega ratio compares the probability-weighted gains above a specified threshold (e.g. 0%) with the probability-weighted losses below that threshold. All the above statistics are calculated over the period 2012 Q1 to 2025 Q4.

4. ANALYSIS OF FUND RETURNS

Sharpe ratio

The Sharpe ratios calculated for the excess returns of the five indices highlight differences in risk-adjusted performance, with larger values indicating better risk-adjusted returns. In this metric, risk is measured as the overall volatility of returns. For the Sharpe ratio calculation, we used the five-year government bond yield as the risk-free rate; using alternative risk-free rates would not change the relative performance of the funds and listed indices. Among the indices, the Long Income fund exhibits the highest Sharpe ratio at 0.35, followed closely by the Balanced fund index at 0.31, suggesting that these two funds delivered the strongest returns relative to the risk taken. In contrast, Other (Specialist) and All REITs show lower Sharpe ratios of 0.13 and 0.15, respectively, indicating more modest risk-adjusted performance. The FTSE 250 has a Sharpe ratio of 0.17, slightly higher than the REIT indices but still below the Balanced and Long Income funds, highlighting that equity market returns, while positive, carried more risk relative to their rewards over this period.

The Sharpe ratio is influenced by both the volatility and smoothness of returns. Since returns in our sample are not normally distributed, the standard deviation may not fully capture risk, and the conventional Sharpe ratio may overstate performance. To address this, we also calculate the adjusted Sharpe ratio. For the Balanced and Long Income funds, the adjusted Sharpe ratios are lower, reflecting the large negative returns experienced during the pandemic. For Other (Specialist) funds and the listed markets, the adjusted Sharpe ratios remain broadly similar to the unadjusted values.

Sortino ratio – the downside risk to returns

The Sortino ratio focuses on downside risk, defined in this analysis as the volatility of negative returns, under the assumption that investors are primarily concerned with losses. Higher values indicate better performance relative to downside volatility. Long Income funds have the highest Sortino ratio at 0.49, closely followed by Balanced funds at 0.47 and Other (Specialist) funds recording a Sortino ratio of 0.40. These values indicate moderate downside-adjusted performance, while All REITs and the FTSE 250 have lower values of 0.21 and 0.26, respectively, highlighting greater exposure to downside fluctuations. It should be noted that the relatively better Sharpe and Sortino ratio results may partly reflect return smoothing and persistence effects.

Omega ratio – partially addressing smoothness

We calculate the Omega ratio to mitigate the effect of smoothing in fund returns. Although this ratio is less sensitive to smoothing than Sharpe or Sortino, it is not totally immune. The Omega ratio quantifies the balance between returns above and below a chosen benchmark or threshold, for example 0%. If returns above a specified threshold are strong and occur with high probability, while returns below the threshold are weak (including negative) but occur infrequently, this will be reflected in an Omega ratio significantly greater than 1. An Omega greater than 1 indicates that gains above the benchmark outweigh losses below it, while a value below 1 suggests the opposite. The ratio also incorporates the probabilities of returns occurring above or below the specified benchmark.

4. ANALYSIS OF FUND RETURNS

We initially set the threshold at 0%. At this threshold, Omega ratios between 2.0 and 4.4, indicating that probability-weighted positive returns substantially exceed probability-weighted negative outcomes. In other words, there is roughly two to four times as much upside as downside relative to a zero-return threshold. In contrast, equities have an Omega ratio of 1.9. While the FTSE 250 generated negative quarterly returns in approximately 40% of the sample period, this result is driven primarily by the sharp market decline in the first quarter of 2020 rather than by consistently poor performance. The scale of this drawdown offsets gains in other periods, resulting in probability-weighted losses exceeding probability-weighted gains over the sample. This highlights the sensitivity of the Omega ratio to severe downside events. These results suggests that property funds offer more consistent capital preservation and a higher likelihood of achieving non-negative returns, whereas equities exhibit greater downside risk around this threshold.

When the benchmark is raised to 0.4% per quarter—to reflect the average annual risk-free rate (10-year gilt yield) of 1.7% over the sample period—fund returns remain relatively attractive. However, at a higher threshold of 1.5% per quarter (approximately 6% annualised), the picture reverses. Property funds then exhibit Omega ratios of 0.8 and 0.6, indicating difficulty in consistently exceeding this higher return target, with downside outcomes (less than 1.5% quarterly) dominating. Equities, with an Omega of 1.1, now demonstrate a stronger ability to generate probability-weighted returns above this threshold than below it. In general, property funds maintain positive Omega ratios for annual return thresholds of up to 5% per annum. For Other (Specialist) funds, positive Omega ratios are observed only up to a threshold of approximately 4% per annum.

The key takeaway is that relative performance is highly dependent on the target return (benchmark). Property funds are better suited for lower-return, income-focused objectives emphasising stability and downside protection. Equities, on the other hand, are more effective at achieving higher return targets but entail greater volatility and a higher likelihood of short-term losses.

Are returns and volatility similar across asset classes in the long run?

Analysis, based on statistical tests of equality of average (mean) returns and return volatility, suggests that over long investment horizons, the average performance of Balanced, Long Income, and Other (Specialist) property funds is not materially different from each other or from the MSCI quarterly property index. This suggests that, in practice, these fund types tend to deliver comparable outcomes to the benchmark over time. A similar pattern is observed when comparing them with REITs and the FTSE 250, where differences in average returns are not meaningful over longer periods. However, this alignment becomes less consistent over shorter timeframes. Over say three- or five-year periods, performance gaps can appear, often reflecting market cycles, divergent trends in listed and real estate, and timing effects.

What stands out more clearly is the difference in risk. Balanced and Other (Specialist) funds, along with the MSCI Property index, exhibit similar levels of volatility, indicating broadly comparable risk profiles. Long Income funds, by contrast, display a different volatility pattern, while REITs and FTSE 250 equities are significantly more volatile. Taken together, this suggests that although average returns may converge over time, risk profiles remain materially different across fund types. For investors and fund managers with a long-term perspective, this implies that managing volatility - and the associated risk of drawdowns - is likely to be more important than targeting small differences in expected returns.

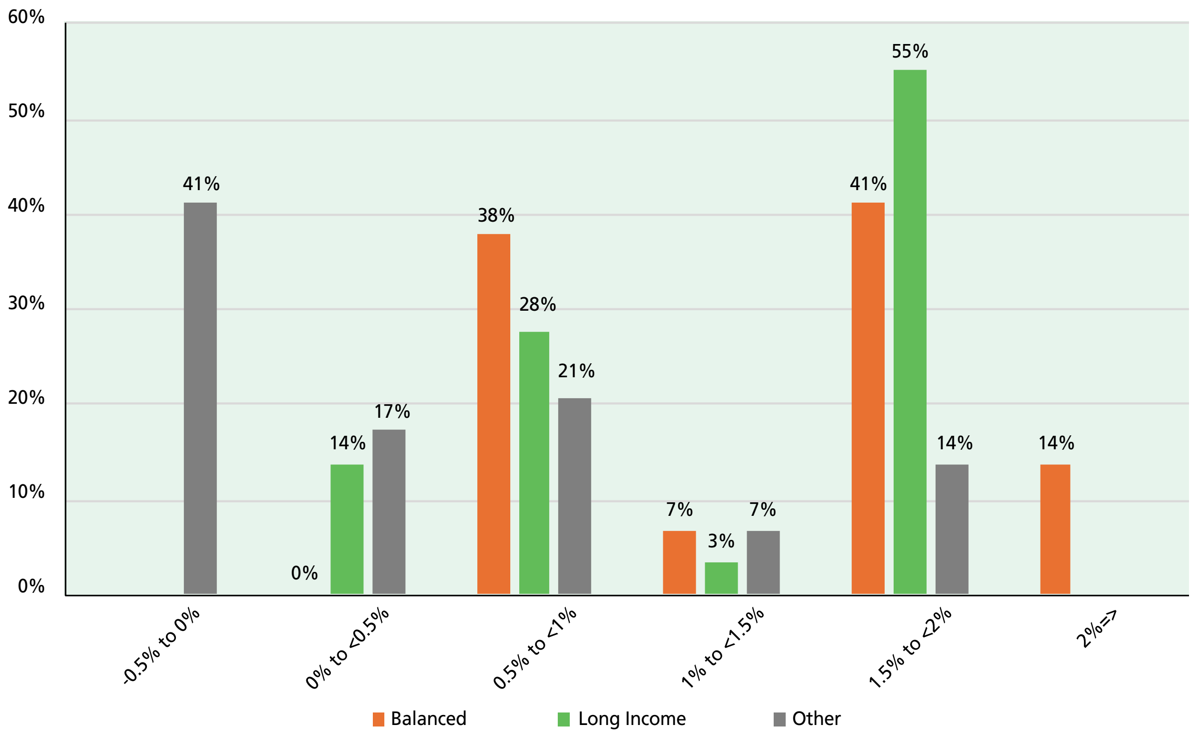
4. ANALYSIS OF FUND RETURNS

4.3 Fund return behaviour over a seven-year investment horizon

4.3.1 Rolling seven-year fund returns: average performance over seven-year holding periods

Examining returns over typical holding periods, such as five, seven, or ten years, provides useful insight into investors' long-term outcomes and downside risk. To illustrate this, we assume a seven-year holding period and analyse average quarterly returns on a rolling basis, allowing assessment of likely performance and downside exposure.

Figure 4.5: Distribution of average quarterly returns over rolling seven-year holding periods



Note: The figure shows the percentage of rolling seven-year holding periods that achieved average annual returns within each return range.

Source: MSCI/AREF QPF Index, Authors

Figure 4.5 shows that 41% of the time, the 28-quarter (seven-year) average return for Other (Specialist) funds lies between -0.5% and 0%. Over the sample period, Other (Specialist) funds did not exhibit negative seven-year growth. For Long Income funds, the seven-year average quarterly return lies between 1.5% and 2% in 55% of cases. Balanced funds record seven-year average quarterly returns between 0.5% and 1% in 38% of cases and between 1.5% and 2% in 41% of cases. Balanced funds are also the only category to achieve returns of 2% or higher in 14 out of 100 instances.

4.3.2 Simulated seven-year returns: scenario-based analysis

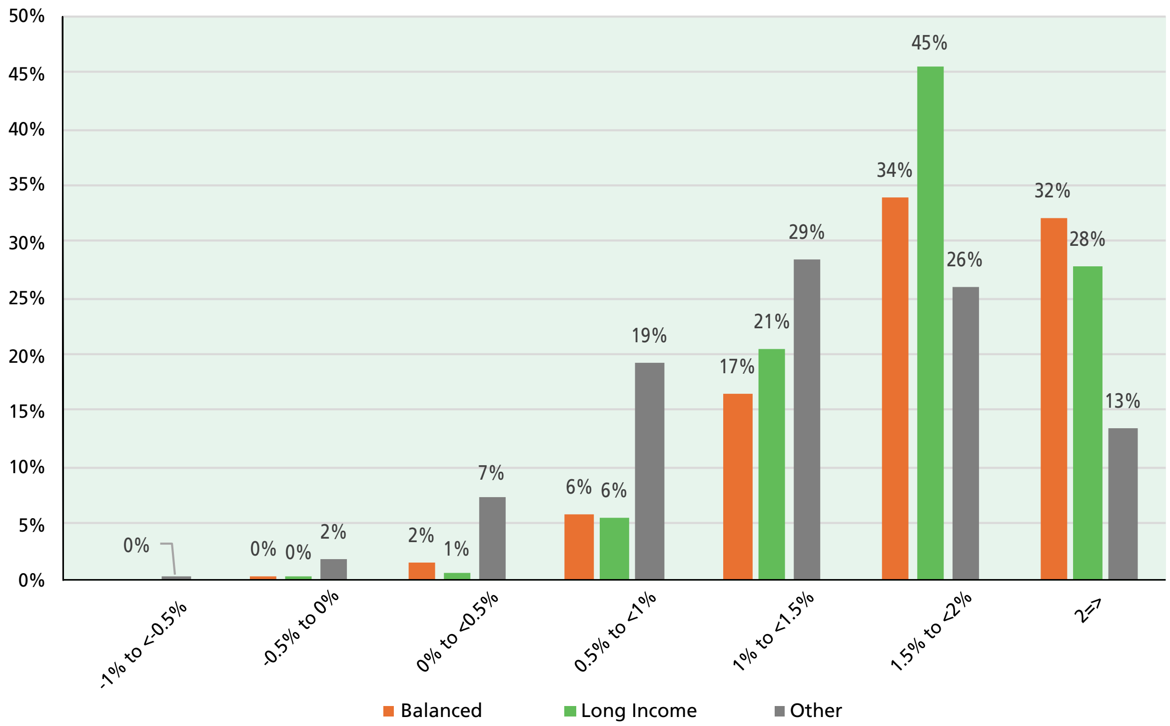
The seven-year average returns are calculated on a rolling basis, with the first period spanning 2012 Q1 to 2018 Q4, the second 2012 Q2 to 2019 Q1, and so on until the sample is exhausted. While this approach provides useful information on realised performance, simulations incorporating a wider range of return paths provide additional insight into potential downside risk.

4. ANALYSIS OF FUND RETURNS

More specifically, a given simulated path may include quarterly returns drawn from periods such as 2021 Q1 and 2022 Q3 (pandemic-related volatility), 2016 Q3 and 2017 Q1 (post-Brexit referendum conditions, when some funds experienced gating), as well as quarters from the low-interest rate environment of 2012-2015. Each of the 1,000 simulated paths randomly combines quarterly returns from across the full sample period, generating a wide range of possible seven-year outcomes. As a result, simulated average returns reflect a broad set of market environments rather than a single historical sequence.

The simulation exercise does not preserve the time structure of returns (e.g., clustering, momentum, or crisis persistence), which may appear unrealistic. However, when considered alongside the rolling analysis, the two approaches highlight the importance of dependence in fund returns. In particular, return clustering during adverse periods can materially affect outcomes relative to an assumption of independence. Investors may interpret the simulated results as reflecting expected performance under conditions in which returns are independent, and in this sense as a useful benchmark for risk.

Figure 4.6: Simulated average returns over seven-year holding periods



Source: MSCI/AREF QPF Index, Authors

The probabilities across return ranges are interpreted in the same way as in the previous figure. A notable difference emerges between the two approaches, particularly for Other (Specialist) funds. Focusing on negative outcomes, the rolling 28-quarter analysis indicates that the probability of negative average quarterly returns for Other (Specialist) funds is 41%, whereas the simulation approach reduces this probability to around 2%. This substantial difference suggests that return dependence and the clustering of adverse performance periods are important drivers of downside risk, implying that approaches assuming independent returns may materially understate the likelihood of negative long-horizon outcomes. In other words, ignoring dependence (autocorrelation) in returns can materially understate downside risk.

4. ANALYSIS OF FUND RETURNS

4.3.3 Rolling vs simulated returns: implications for downside risk

The higher incidence of negative outcomes in the rolling analysis for Other (Specialist) funds reflects the impact of specific periods of negative performance in the historical data. Because rolling windows preserve the actual sequence of returns, sustained downturns persist across overlapping periods, increasing the proportion of negative seven-year outcomes.

By contrast, the simulation approach produces a much lower probability of negative seven-year returns because it breaks the persistence observed in the actual data by combining returns across different periods, including those outside adverse regimes. This disperses negative returns more evenly across simulated outcomes.

For Balanced and Long Income funds, results in the negative return region are broadly consistent across both approaches, suggesting relatively subdued downside risk despite return dependence. Differences between the approaches are more evident in positive return ranges; however, the key concern remains the likelihood of negative or weak (0% to 0.5%) average returns.

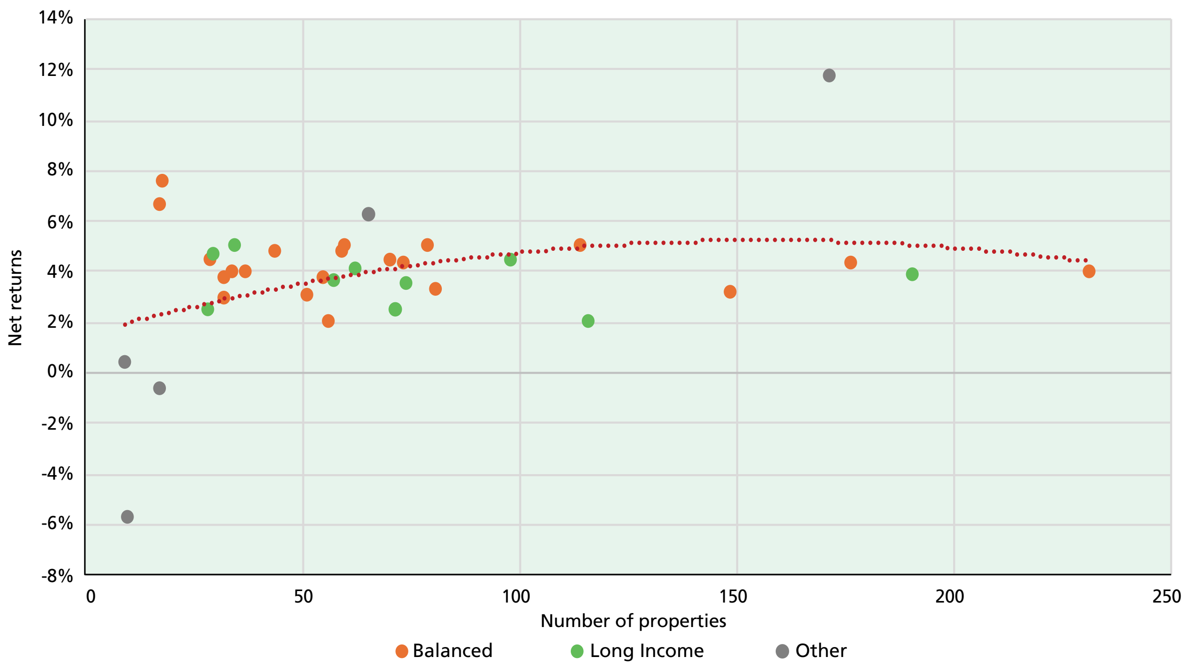
5. DESCRIPTIVE RELATIONSHIPS BETWEEN UNLISTED FUND RETURNS AND FUND CHARACTERISTICS

To illustrate the relationship between unlisted fund returns and underlying fund characteristics, the analysis focuses on long-term averages to smooth short-term volatility and highlight structural patterns. Specifically, the average quarterly net return is calculated over the 10-year period ending in 2025 Q4, alongside the average values of key fund characteristics observed over the same horizon. These characteristics include portfolio scale (number of properties); concentration metrics (the contribution of the ten largest tenants to rental income and the ten largest investments as a percentage of the portfolio); risk and liquidity indicators (maximum development exposure, cash as a percentage of the portfolio, and leverage as a percentage of gross asset value); as well as income and lease structure measures (weighted average unexpired lease term and reversionary yield).

The aim of this section is to present a simplified, visual representation of relationships that are analysed more formally in the subsequent section, helping to build intuition and provide context for those findings. Scatter plots with trend lines are used to visualise the relationships between average returns and each characteristic. This approach offers an intuitive and transparent way to assess whether positive or negative associations exist-for example, whether higher leverage or greater tenant concentration tends to coincide with stronger or weaker returns. As a visual tool, this approach is commonly adopted as an initial step in exploratory analysis, allowing patterns, outliers, and potential non-linear relationships to be identified. The number of funds included in each scatter plot varies, reflecting differences in data availability.

Number of properties

Figure 5.1: Net returns and number of properties



Source: MSCI/AREF PFV Handbook, MSCI/AREF QPF Index, Authors

The chart suggests a positive but weak relationship between the average number of properties and average net returns over the ten-year period to 2025 Q4. Returns tend to be higher for funds with a greater average number of properties, but at a decreasing rate, flattening out for portfolios with more than 100 properties. However, the apparent positive relationship beyond roughly 70 properties is influenced by an outlier fund, which skews the trend slightly upward. This finding is consistent with that of the Association of Real Estate Funds (AREF) (2019). Similarly, at the lower end of the sample, an outlier fund pulls the trend line downward. Excluding these outliers, the relationship appears broadly flat. There is also considerable variation, with funds holding a similar average number of properties exhibiting a wide range of returns.

5. DESCRIPTIVE RELATIONSHIPS BETWEEN UNLISTED FUND RETURNS AND FUND CHARACTERISTICS

Tenant contribution to income

Figure 5.2: Net returns and 10 largest tenant contribution to rental income

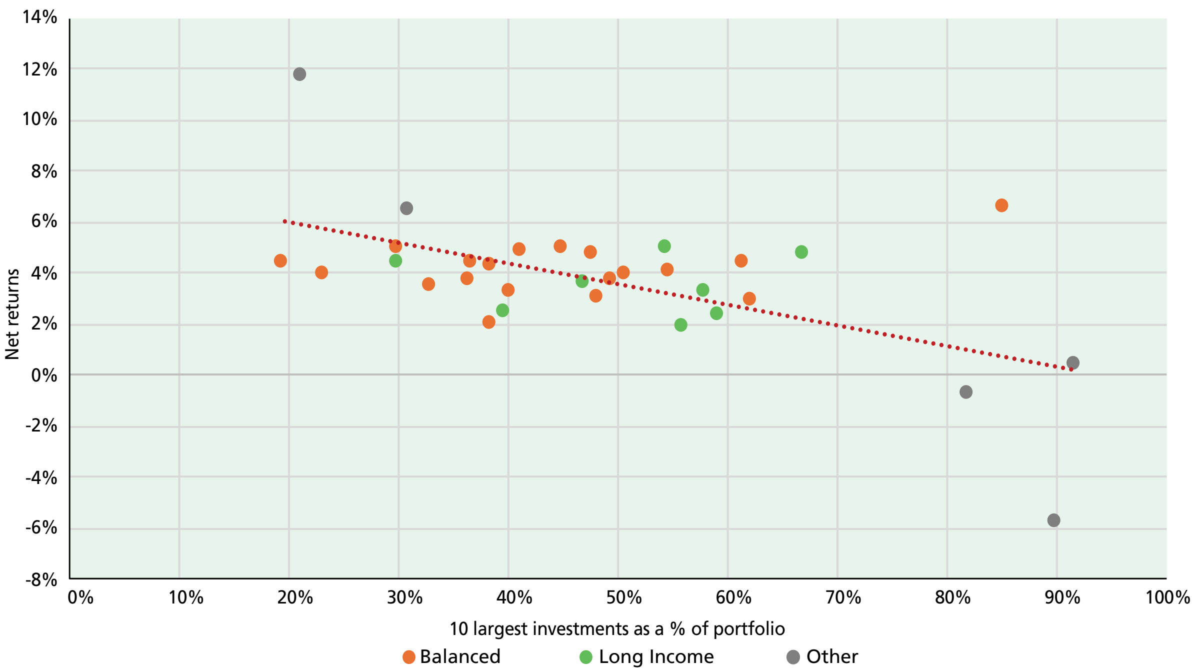
Source: MSCI/AREF PFV Handbook, MSCI/AREF QPF Index, Authors

Figure 5.2 suggests no clear relationship between share of income from the 10 largest tenants (average share over the ten-year period to 2025 Q4) and long-term net returns. Initially with rising average contributions to rental income are associated with lower average returns but then the relationship turns positive. Over 60% average contributions the range of average annual returns is wide. We observe across most of the sample that similar average returns can be associated with very different levels of income concentration from the largest tenants. Overall, the pattern in Figure 5.2 suggests that higher concentration does not consistently lead to either better or worse performance. This finding is consistent with the results of the studies reviewed in Section 2.

5. DESCRIPTIVE RELATIONSHIPS BETWEEN UNLISTED FUND RETURNS AND FUND CHARACTERISTICS

Proportion of largest investments

Figure 5.3: Net returns and 10 largest investments



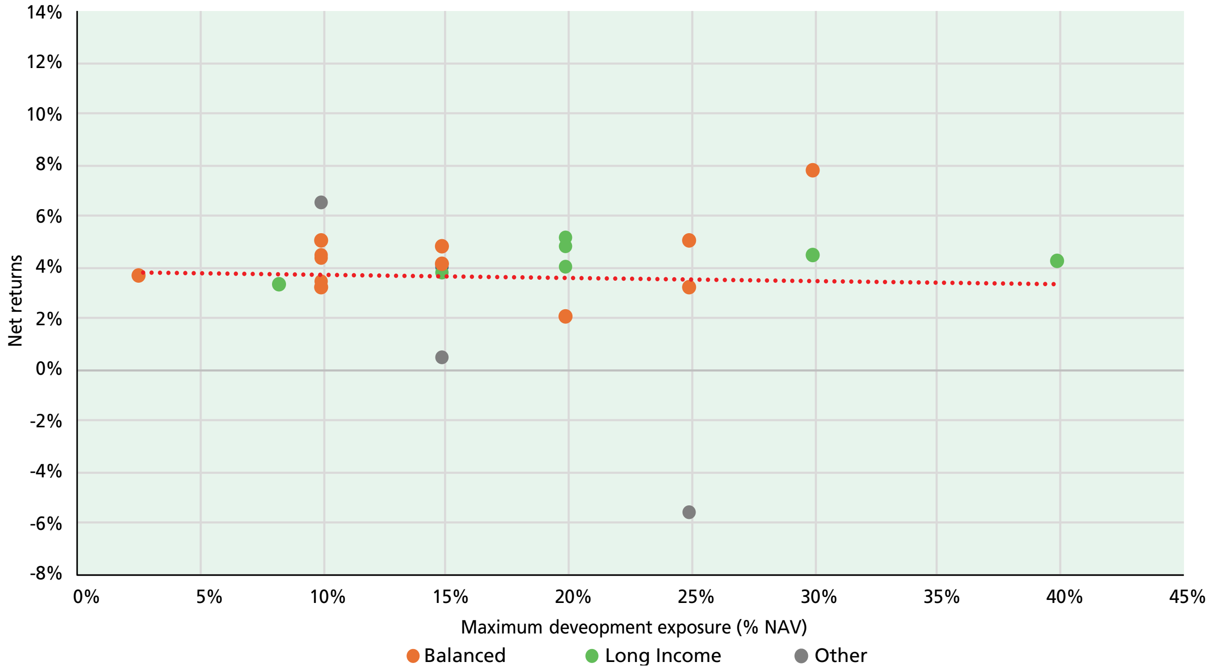
Source: MSCI/AREF PFV Handbook, MSCI/AREF QPF Index, Authors

The trend line in Figure 5.3 indicates a negative relationship between investment concentration and returns. Three funds with concentration ratios above 80% recorded particularly low average returns, pulling the trend line downward. For portfolios where the 10 largest investments account for between 20% and 70%, the relationship appears flat. Overall, the evidence suggests no clear performance penalty associated with high portfolio concentration once outlier funds are excluded. However, for some funds, the results indicate that greater diversification across assets may help sustain returns over the long run.

5. DESCRIPTIVE RELATIONSHIPS BETWEEN UNLISTED FUND RETURNS AND FUND CHARACTERISTICS

Maximum development exposure

Figure 5.4: Net returns and maximum development exposure



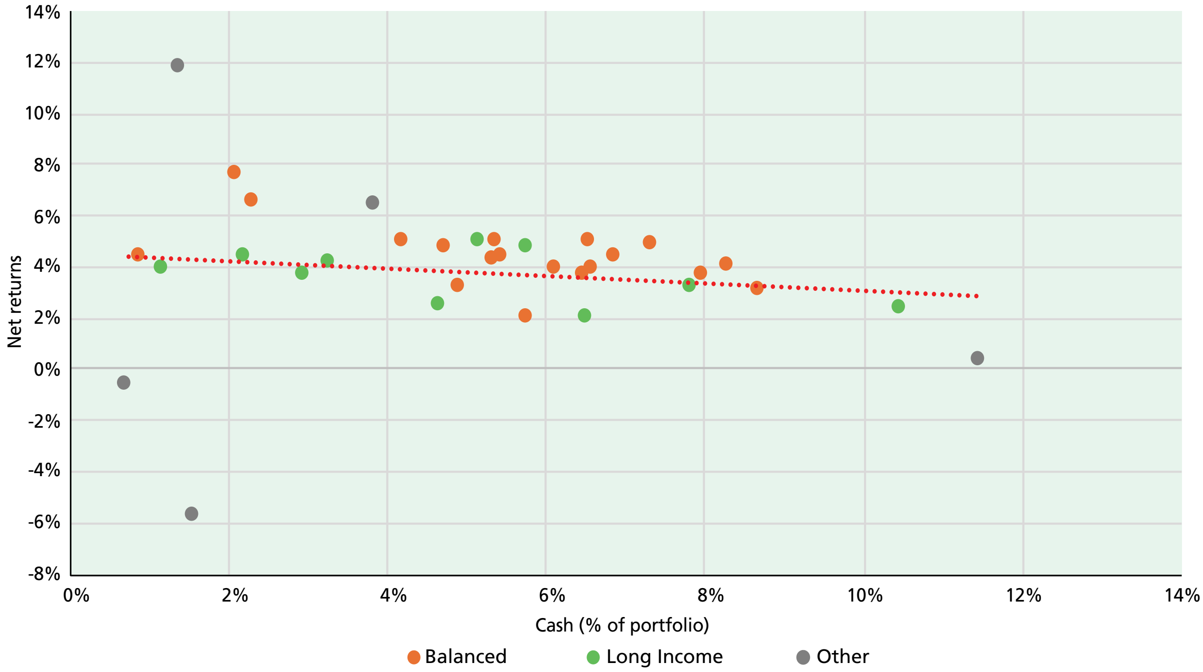
Source: MSCI/AREF PFV Handbook, MSCI/AREF QPF Index, Authors

The data suggests little to no relationship between maximum development exposure and long-term returns for UK unlisted real estate funds. We observe a wide dispersion of outcomes, with funds at similar levels of development exposure achieving markedly different average returns over the period. Unlike some studies that view development as a source of higher returns, our sample shows no consistent pattern linking development exposure to fund performance.

5. DESCRIPTIVE RELATIONSHIPS BETWEEN UNLISTED FUND RETURNS AND FUND CHARACTERISTICS

Cash holdings

Figure 5.5: Net returns and cash



Source: MSCI/AREF PFV Handbook, MSCI/AREF QPF Digest, Authors

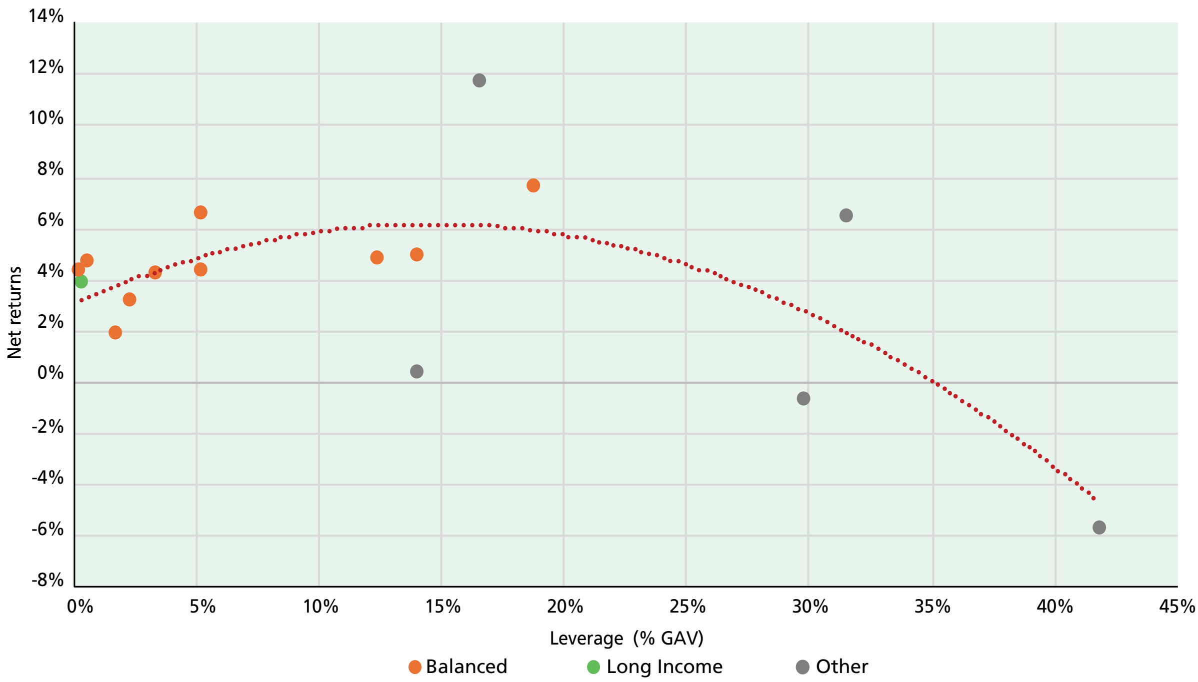
The trend line is slightly downward sloping, suggesting a weak negative association, with higher average cash holdings linked to marginally lower average returns. Most funds cluster within low cash levels (1-8%) and net returns of around 3-5%. The wide dispersion of points indicates that this relationship is not strong. For example, average returns of about 4% have been achieved by funds with a broad range of cash holdings over the period, from around 1% to over 8%. The slight negative relationship is consistent with findings from the IPF (2012) and AREF (2021) studies, among others. We find that each 1% increase in average cash holdings is associated with a 0.14% reduction in average returns over the period. However, this effect can be more pronounced at higher cash levels; for example, when average cash holdings rise from 6% to 7%, the impact on returns can be around 0.30%.

5. DESCRIPTIVE RELATIONSHIPS BETWEEN UNLISTED FUND RETURNS AND FUND CHARACTERISTICS

Leverage

The relationship between leverage—measured as the average loan-to-GAV ratio over the 10 years to 2025 Q4—and average annual net returns for UK unlisted real estate funds exhibits two distinct trends as Figure 5.6 illustrates.

Figure 5.6: Net returns and leverage



Source: MSCI/AREF PFV Handbook, MSCI/AREF QPF Index, Authors

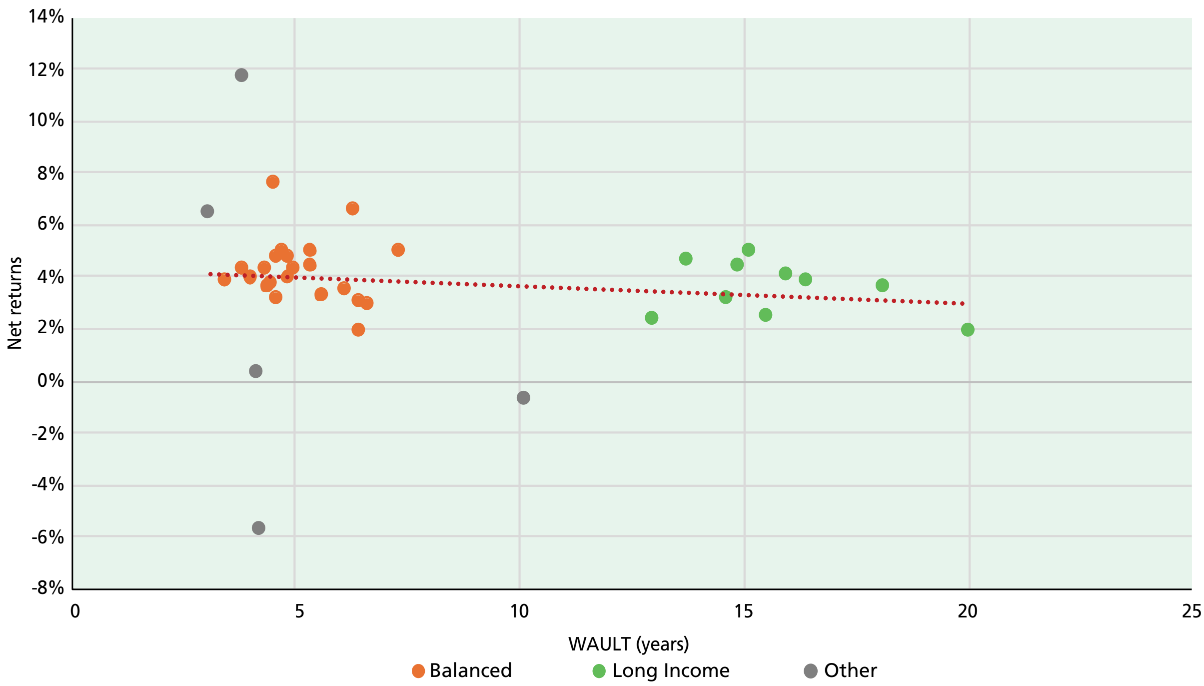
Leverage appears to have a positive effect on returns up to a certain threshold, beyond which it adversely affects performance. Based on the trend line in our sample, average returns peak at an average leverage ratio of approximately 15-18% of GAV, suggesting that moderate use of debt can improve returns. Beyond this level, the relationship turns negative, although this is largely driven by three funds. Notably, at around 30% leverage, two funds exhibit materially different average returns, highlighting the dispersion of outcomes. Overall, while moderate leverage can add to returns, higher levels of debt expose funds to significant downside risk, particularly over a 10-year period that includes phases of market stress and elevated interest rates.

5. DESCRIPTIVE RELATIONSHIPS BETWEEN UNLISTED FUND RETURNS AND FUND CHARACTERISTICS

WAULT

The data indicates a weak negative relationship between WAULT and long-term returns for UK unlisted real estate funds, as reflected by the gently downward-sloping trend line (Figure 5.7).

Figure 5.7: Net returns and WAULT



Source: MSCI/AREF PFV Handbook, MSCI/AREF QPF Index, Authors

Most funds cluster at WAULT levels of around three to seven- years, where average net returns are generally in the 3-5% range, representing a typical operating zone. Within this range, however, there is considerable variation, including both strong and weak performance, indicating that lease length alone does not determine outcomes.

At higher WAULT levels (10+ years), returns tend to be slightly lower on average, although dispersion remains. This may reflect the trade-off whereby longer unexpired leases provide income stability but limit opportunities for rental reversion. While the AREF (2021) study finds evidence that WAULT can drive fund performance, it does not emerge as a strong driver in this sample. On average, each additional five years of unexpired lease term is associated with a reduction in returns of less than 0.35%.

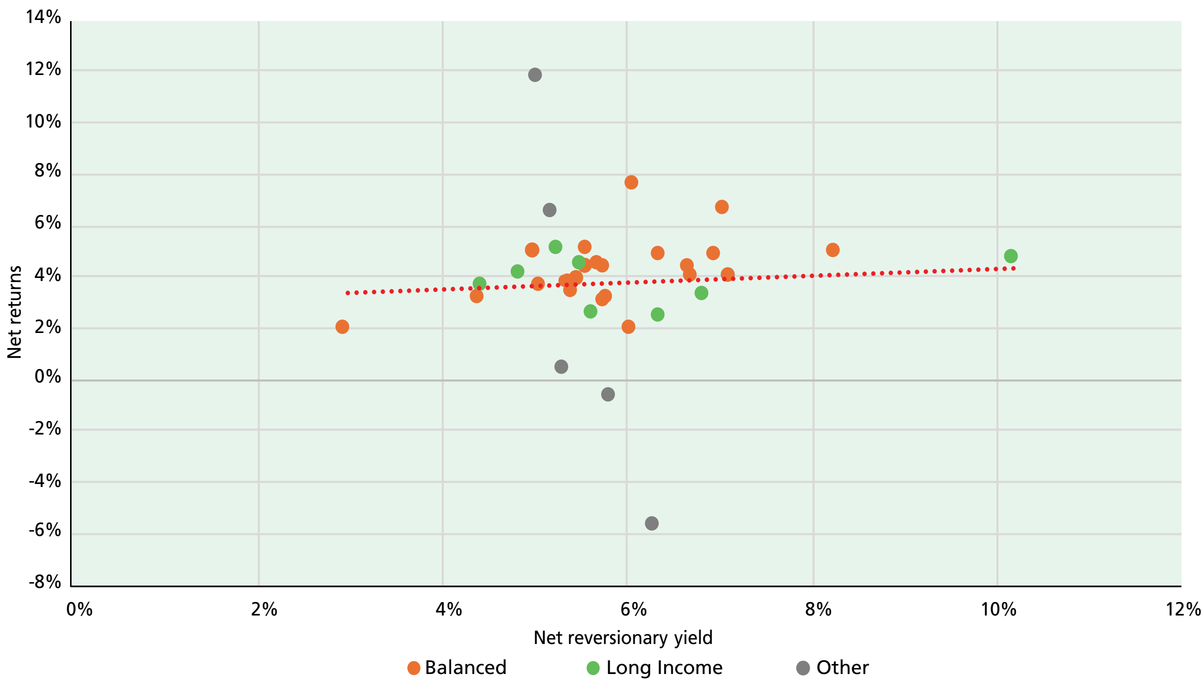
Reversionary yield

The PFV Handbook reports two metrics that indicate the potential for future income growth: investment vacancy as a percentage of rent passing and rent voids as a percentage of ERV (estimated rental value). Investment vacancy measures the drag on current income, while the rent voids/ERV ratio provides a forward-looking indicator of income relative to full market potential. Taken together - and particularly through the gap between them - these measures signal reversionary potential.

The PFV Handbook also reports the net reversionary yield, which incorporates these dynamics, but it further reflects the current pricing of the asset, indicating how much upside exists relative to its value. Figure 5.8 illustrates the relationship with net returns which is broadly flat. Funds with the same reversionary yield show diverse average net returns.

5. DESCRIPTIVE RELATIONSHIPS BETWEEN UNLISTED FUND RETURNS AND FUND CHARACTERISTICS

Figure 5.8: Net returns and reversionary yield



Source: MSCI/AREF PFV Handbook, MSCI/AREF QPF Index, Authors

While the approach presented in this section to study the connection between returns and fund characteristics provides an initial sense of the relationships between fund returns and fund characteristics, it is important to recognise its limitations. Scatter plots do not control for interactions between variables, nor do they establish causality. The relationships observed may be influenced by other factors or by co-movements among the characteristics described above. The associations presented in this section are therefore explored more rigorously, and within a broader analytical framework, in Section 7 that includes the study of lagged relationships.

6. IMPACT FROM SECTORAL ALLOCATIONS

Sectoral attribution analysis in unlisted real estate funds helps identify which property sectors (e.g., office, retail, industrial) are driving performance and where value is being added or lost. It allows practitioners to assess top-down allocation decisions by linking sector exposures to relative returns.

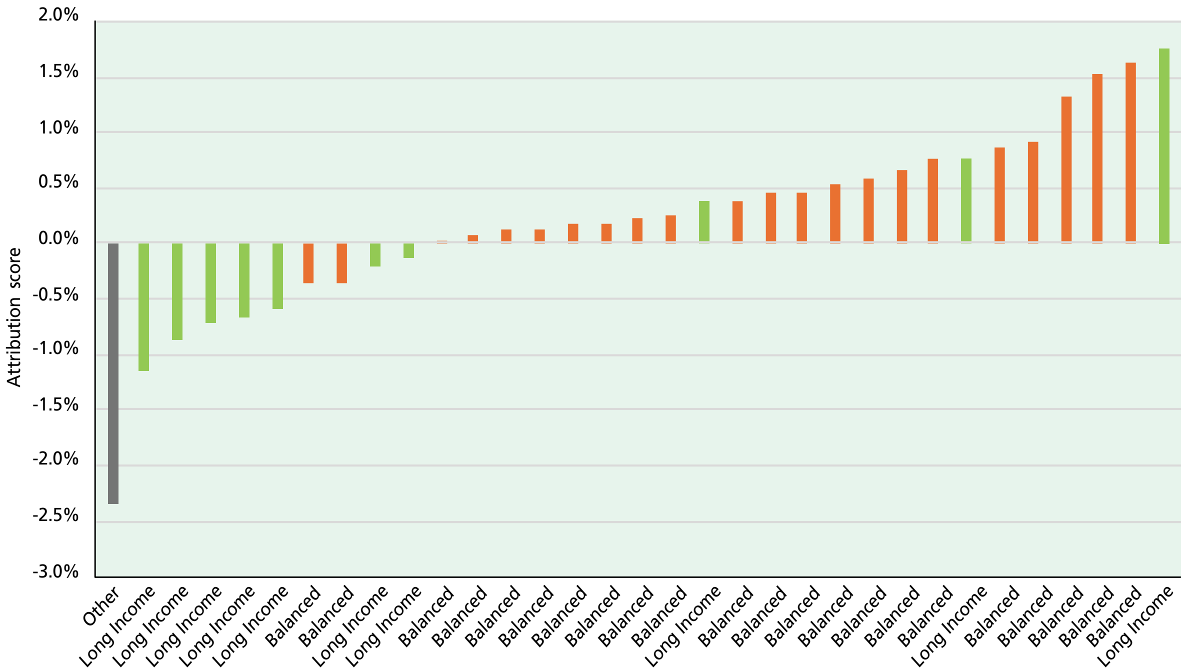
For performance attribution, we apply the Brinson attribution model, focusing explicitly on sector allocation effects rather than selection effects. The analysis captures the impact of overweight and underweight positions relative to the benchmark and does not reflect asset-level or within-sector performance differences.

Sector allocations are evaluated across seven segments—offices, retail, industrial, hotels, residential, and other—using the structure of the MSCI UK Quarterly Property Index. This index provides both benchmark sector weights and the corresponding quarterly sector returns used in the attribution framework.

The allocation effect measures the contribution to performance arising from deviations between fund and benchmark sector weights, applied to benchmark sector returns. Positive or negative attribution therefore reflects the effectiveness of top-down sector positioning, independent of security selection.

Where total fund allocations sum to less than 100%, the residual is assumed to be held in cash earning the UK three-month interbank rate. Where allocations exceed 100%, the excess is assumed to be financed through leverage, with a financing cost equal to the same base rate plus a margin reflecting typical UK property lending spreads (taken from the Bayes Property Lending Survey).

Figure 6.1: Sector attribution scores (2016 Q1–2025 Q4)



Source: MSCI/AREF QPF Index & PFV Handbook, MSCI UK Quarterly Property Index, Authors

Figure 6.1 shows the annualised Brinson sector allocation results for the sample of funds with available data over the period 2016 Q1 to 2025 Q4.

6. IMPACT FROM SECTORAL ALLOCATIONS

The Brinson sector allocation results reported in Figure 6.1 indicate that sector allocation was not a consistently positive source of performance across the sample. Around two thirds of funds generated positive allocation scores, suggesting that for the majority of managers, sector positioning either added value or had a limited impact on relative performance versus the benchmark.

For example, the positive allocation score of 0.93% for one of the balanced funds means that 0.93% of the fund's annualised performance relative to the benchmark is attributable to sector allocation decisions, typically reflecting overweight exposure to sectors that outperformed or underweight exposure to sectors that underperformed.

Differences emerge across fund types. Balanced funds more frequently exhibit positive allocation effects, consistent with their greater flexibility to shift exposure across sectors and respond to relative value opportunities. In contrast, long Income funds tend to show slightly negative allocation scores, which may reflect income-focused strategies, where sector positioning is often driven by income return rather than tactical allocation decisions.

The most negative observation is recorded for a specialist Central London office fund, where the allocation score reflects a substantial negative contribution relative to the diversified benchmark. This indicates that the fund's concentrated exposure to Central London offices reduced annual relative performance versus the benchmark by approximately 2.5%. The fund still generated minor positive absolute returns, but these were lower than they would have been had benchmark sector weights been maintained. The largest attribution score is also reported by a Long Income fund with high exposure to industrials.

It should be noted that results are partly influenced by the assumption that any allocation shortfall is held in cash, which generated relatively high returns in the post-2022 interest rate environment. This in some cases may bias attribution scores upward.

Finally, it should be noted that interpreting sectoral attribution in isolation can be misinforming in an environment where return drivers interact. Other sources of performance may partially capture or overlap with the effects attributed to sector allocation, as discussed in the next section.

7. EMPIRICAL ANALYSIS

7.1 Statistical methodology

This section outlines the empirical approach used to examine the drivers of property fund returns. Building on the literature review presented in Section 2, the empirical analysis identifies which factors have a systematic and measurable impact on fund performance. In practical terms, the objective is to determine which drivers consistently matter for returns and to quantify the direction and relative magnitude of their effects.

Main methodology

The analysis employs a panel data model with random effects. This approach is well-suited to the research objective because it captures two distinct dimensions simultaneously: how the key drivers of fund performance affect an individual fund over time, and how those same drivers explain differences in performance across funds at any given point. By combining these dimensions, the methodology provides a richer and more complete picture of performance than a purely cross-sectional or time-series approach would allow.

Selection of drivers

The selection of explanatory variables to include in the model is guided by the evidence reviewed in Section 2. The explanatory variables fall into two broad categories. The first covers fund-specific characteristics, including size, leverage, and structure, which reflect the internal features of each fund. The second encompasses macroeconomic and financial market factors, which capture the influence of the broader market environment on fund performance. Together, these two sets of variables are combined within a single empirical framework, providing practitioners with a clear and robust basis for understanding what drives property fund returns and how these drivers behave across different fund types and market conditions.

Beyond Observable Fund Characteristics: Unobserved Effects

The random effects specification allows the model to separately identify the contribution of observable fund characteristics, such as age, leverage, yield profile and tenant concentration, from a residual fund-level component that captures persistent but unobservable differences across funds. This residual component reflects features that are inherently difficult to quantify, including the quality of the investment process, the depth and consistency of asset management, the strength of manager relationships with tenants and vendors, organisational structure and governance, and the accumulated experience and skill of the investment team. These attributes are not captured by any of the variables available in the dataset, yet the random effects framework makes it possible to test whether they exert an influence on fund performance over and above the observable drivers.

A range of model specifications is explored to ensure robustness, with the analysis conducted across all funds as well as within the three fund categories: Balanced, Long Income, and Other (Specialist). An iterative approach is used to test the sensitivity of results to alternative specifications. Full details of the statistical methodology are provided in Appendix C.

7. EMPIRICAL ANALYSIS

7.2 Variables and data

Table 7.1 presents the variables tested as potential influences on fund performance in the panel regressions.

Table 7.1: Variables entering the empirical investigation of fund returns

Determinant variable	Description
Fund characteristics:	
Number of properties	Total count of individual properties held by the fund.
Net reversionary yield	Expected yield once current leases expire and rents adjusted to estimated market levels.
Fund Age	Age of the properties in the fund (calculated in years since fund inception).
WAULT (weighted average unexpired lease term)	Average remaining lease term of tenants, weighted by rental income.
Investment vacancy	Proportion of rentable space that is unoccupied and generating no income, expressed as a percentage.
Top 10 concentration	Percentage of the fund's rental income coming from the 10 largest tenants.
Tenant concentration	Share of income from the largest single tenant
Maximum development exposure	Highest proportion of the fund's portfolio invested in properties under development.
Cash holdings	Proportion of fund assets held in cash or cash equivalents.
Leverage/GAV	Borrowings as a percentage of Gross asset value.
NAV growth (lagged)	This variable captures the combined effect of market performance and capital movements in the prior period and can be interpreted as an indicator of short-term momentum in fund performance.
Attribution score	Measures the contribution to relative performance arising from differences between fund and benchmark sector weights.
Macroeconomic and financial variables:	
GDP growth	Quarter on quarter GDP growth (%)
Inflation rate	Quarterly change in CPI index (%)
FTSE250 total returns	Quarterly returns on FTSE250
REIT returns	NAREIT/EPRA UK All REIT quarterly returns

7. EMPIRICAL ANALYSIS

The source of the fund characteristics data is the MSCI/AREF Property Fund Vision Handbook (PFV Handbook). For each quarter over the period from 2016 Q1 to 2025 Q4, fund-level variables are populated using the corresponding quarterly edition of the PFV Handbook. Macroeconomic and financial market data are sourced from LSEG Workspace. Table 7.2 presents the summary statistics for each variable.

Table 7.2: Summary statistics

Variable	Obs.	Mean	Median	Standard deviation
Total fund return	1,512	0.98%	1.30%	3.97%
Number of properties	1,159	75.92	64.00	58.81
Net reversionary yield	1,095	5.77%	5.65%	15.16
Fund age	1,595	22.66	17.75	0.14
WAULT	1,159	7.51	5.30	4.97
Investment vacancy rate	664	11.01%	9.68%	10.62%
Top-10 tenant concentration	745	48.66%	43.90%	20.26%
Tenant concentration	1,029	39.26%	34.66%	18.64%
Maximum development exposure	713	16.95%	15.00%	8.59%
Cash holdings	1,121	5.91%	4.60%	5.93%
Leverage/GAV	438	16.38%	12.85%	13.32%
NAV growth	1,316	0.00	0.00	0.08
Attribution score	988	0.26%	0.13%	0.41%
GDP growth	1,600	0.41%	0.38%	4.33%
CPI inflation	1,600	0.84%	0.57%	0.90%
FTSE 250 return	1,600	1.04%	1.52%	8.46%
FTSE NAREIT return	1,600	0.29%	1.51%	9.19%

Fund-level data are drawn from the MSCI AREF Quarterly Property Funds Digest and the MSCI AREF Quarterly Property Fund Vision Handbooks, covering 2016 Q1 to 2025 Q4. MSCI Handbook data for 2011 Q1 to 2015 Q4, 2016 Q3, and 2017 Q2 are absent from the final dataset. Total fund return and leverage/GAV are sourced from the Property Funds Digest Historic Data. Number of properties, net reversionary yield, fund age, WAULT, investment vacancy rate, top-10 tenant concentration, tenant concentration, maximum development exposure, cash holdings, and NAV growth are extracted from the MSCI Quarterly Property Fund Vision Handbooks. Fund age is calculated as the time elapsed since each fund's inception to each quarter-end, expressed in years. WAULT is constructed by converting the percentage of rent passing in each lease maturity band into decimal weights, assigning representative lease terms to each band (e.g., 20, 15, 10, 5, and 2.5 years), and computing a weighted average for each fund-quarter observation.

7. EMPIRICAL ANALYSIS

For Attribution score the source is MSCI/AREF QPF Index & PFV Handbook, MSCI UK Quarterly Property Index, Authors. GDP growth, CPI inflation, FTSE 250 return, and FTSE NAREIT return are macroeconomic and market variables drawn from LSEG Workspace.[6]

7.3 Results

Table 7.3 presents the panel regression estimates examining the key drivers of returns across property funds. While a broad set of candidate fund-characteristic variables was identified in Section 7.2, not all could be included simultaneously, as the pattern of missing values across variables would have rendered estimation unfeasible. The final set of explanatory variables was selected from those with sufficient data coverage, guided by economic intuition, that is, whether each variable has a theoretically grounded relationship with property fund returns. Of the macro and market variables, only GDP growth and FTSE NAREIT returns were retained in the final model, with the remaining variables failing to achieve statistical significance at conventional levels.

The estimation results are reported for the full sample and separately for three fund strategy sub-groups: Balanced, Long Income and Other (Specialist).

Table 7.3: Regression results – Drivers of property fund returns

Drivers	Full Sample	Balanced	Long Income	Other (Specialist)
NAV growth (lagged value)	0.244	0.26	0.149	0.496
FTSE NAREIT return	n.s.	0.079	n.s.	n.s.
GDP growth	n.s.	n.s.	0.119	0.401
Net reversionary yield	-1.315	-1.009	n.s.	n.s.
Fund age	-0.0002	n.s.	n.s.	n.s.
Tenant concentration	-0.078	n.s.	0.126	n.s.
Maximum development exposure	-0.296	n.s.	0.063	n.s.
Constant	0.181	0.204	-0.079	0.104
R-squared within	0.27	0.28	0.16	0.33
R-squared between	0.98	0.98	0.35	1.000

All coefficients in this table are statistically significant. n.s.: not statistically significant.
The full table results are in Appendix D.Fund characteristics that were excluded due to insufficient number of observations: Leverage, cash, number of properties, WAULT, proportion of largest investments in the portfolio, investment vacancy.

6 The variation in observation counts across variables reflects incomplete reporting by individual funds, with investment vacancy rate (664 observations), leverage/GAV (438), and top-10 tenant concentration (745) exhibiting the highest rates of missingness. The standard deviation of 3.97% indicates that fund returns are volatile relative to the mean, reflecting significant variation in performance across funds and time. Number of properties: the high standard deviation of 58.81 relative to the mean of 75.92 suggests that while some funds hold a small number of properties, others are highly diversified. WAULT: the standard deviation (4.97) is large relative to the mean (7.51), indicating considerable variation in lease length across funds. Tenant concentration exhibits moderate dispersion, suggesting that many funds depend on a relatively small number of tenants, increasing concentration risk. Development exposure is moderate on average (16.95%), indicating some growth-oriented strategies without excessive risk-taking. Cash holdings: the small gap between the mean (5.91%) and median (4.60%) indicates slight right-skew in the variable. Leverage/GAV: the mean of 16.38% indicates that most funds use moderate leverage. NAV growth is centred around zero, as expected given that aggregate inflows and outflows broadly offset one another across the sample. Notably, the standard deviation of GDP growth (4.33%) is elevated relative to its mean, largely reflecting the sharp contraction and rebound associated with the COVID-19 pandemic.

7. EMPIRICAL ANALYSIS

Past NAV growth – momentum and capital flows

Lagged NAV growth is the most robust and consistently significant predictor of total fund returns across all fund categories. In the full sample, a coefficient of 0.244 implies that a one percentage point increase in NAV growth in the prior period is associated with a 0.244 percentage point (24.4 bps) increase in subsequent total returns. This relationship persists across all sub-samples, although the magnitude varies. Returns for Other (Specialist) funds are the most responsive: a one percentage point increase in NAV growth translates into nearly a 0.50 percentage point (50 bps) increase in subsequent returns for these funds.

Overall, these results suggest that momentum effects, as well as the influence of net flows -which are key components of NAV growth- play a significant role in driving fund returns.

Macroeconomic and market effects

GDP growth is found to be a significant determinant of fund returns for both Long Income and Other (Specialist) funds. For Long Income funds, a one percentage point increase in quarterly GDP growth is associated with a 0.12 percentage point (12 bps) increase in total fund returns. For Other (Specialist) funds, the same macroeconomic impulse translates into a substantially larger effect, with returns increasing by 0.40 percentage points (40 bps).

The results for FTSE NAREIT Index returns contrast with those for GDP growth. A statistically significant effect is identified only for Balanced funds, and its magnitude is relatively small. Specifically, a one percentage point increase in REIT returns is associated with a 0.079 percentage point increase (7.9 bps) in Balanced fund returns. This suggests that while listed real estate market performance may provide a sentiment signal, its direct influence on Balanced fund pricing is modest.

The absence of a significant REIT return effect for Long Income funds likely reflects the fact that their pricing is more closely anchored to lease cash flows. For Other (Specialist) funds, the stronger sensitivity to macroeconomic conditions may limit the transmission of REIT market effects.

Fund characteristics

In interpreting the results in Table 7.3, two considerations are important. First, there is no clear consensus in the literature on persistent drivers of fund performance; different studies identify different significant characteristics depending on sample periods, data, and market context. Second, the descriptive (stylised) analysis in Section 5 did not reveal strong or consistent relationships between fund returns and fund characteristics. However, that analysis was indicative only. The results presented here are based on quarterly observations and control for multiple drivers simultaneously.

After controlling for momentum and capital flows (via NAV growth), as well as macroeconomic and broader market effects, there is no consistent pattern of influence from fund characteristics across fund types. However, sub-group analysis reveals that certain characteristics do exert influence within specific fund types, suggesting that the relevance of fund-level drivers is conditional on fund type.

An important feature highlighted in Table 7.3 is that results at the aggregate (all-funds) level may differ from those at the individual fund-type level. For example, relationships that appear negative in the pooled sample can become positive within specific fund categories. This suggests more complex interactions in the aggregated data. While fund-level results should be prioritised when assessing the impact of specific characteristics, such differences may reflect non-linear relationships or, in this case, underlying data limitations.

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Net reversionary yield exerts a significant negative effect on total fund returns in the pooled sample and within the Balanced fund category. At first glance, this appears counterintuitive, as a higher gap between passing and reversionary rents would typically signal upside potential. However, the negative sign suggests that this potential is not being realised in practice. In Section 5, where average values were considered rather than quarterly observations, the relationship appeared largely flat. For Balanced funds, the coefficient of –1.009 implies a large effect: a one percentage point increase in reversionary yield is associated with a roughly one percentage point (100 bps) reduction in returns. However, this should be interpreted with caution. Reversionary yield is an annual measure, while returns are observed quarterly, so the effective quarterly impact is smaller (though not a simple linear division). Another point is the expectation of lagged effects of this driver on fund returns. Given the high correlation of reversionary yield across quarters, the contemporaneous variable partly captures these lagged dynamics.

Fund age carries a negative coefficient (–0.0002) in the full sample, but it is not statistically significant in any sub-sample. In magnitude, this implies that each additional year of fund age is associated with a very small reduction in quarterly returns. However, the lack of statistical significance suggests that fund age does not have a meaningful impact on performance.

Regarding tenant concentration, whether the 10 largest tenants contribute most to overall income does not matter for Balanced and Other (Specialist) funds. However, it does matter for Long Income funds, where it has a positive effect on returns. A narrow tenant base in this fund style supports rental income and overall performance. The coefficient of 0.126 implies that a 10-percentage point increase in concentration is associated with a 1.26 percentage point (126 bps) increase in quarterly total returns. The negative relationship observed at the aggregate (all-funds) level can be explained by the offsetting positive and negative trends shown in Figure 5.2. This suggests that the relationship is better identified at the fund level.

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Maximum development exposure is significant only for Long Income funds. The positive coefficient suggests that a one percentage point increase in development exposure is associated with a 0.063 percentage point increase in returns (6.3 bps). This may reflect the role of pre-let developments, where projects are structured to minimise speculative risk and generate income upon completion. At the aggregate level, however, the relationship appears negative, while the descriptive analysis in Section 5 suggested a largely flat relationship.

Across specifications, a positive and statistically significant alpha (Constant term) is observed for the full sample, Balanced funds, and Other (Specialist) funds, but not for Long Income funds. This suggests that active management, portfolio construction, or asset selection may contribute to performance in Balanced and Other (Specialist) funds, whereas such effects are less relevant for Long Income strategies.

Other (Specialist) fund characteristics (listed at the bottom of Table 7.3), including leverage and cash holdings, are not found to be significant drivers of performance when considered alongside other variables in the empirical model, and hence have been excluded from the final model.

Finally, two further statistics are reported at the bottom of the table for each fund type. The within R-squared reflects the model's ability to explain variation in returns over time for a given fund, while the between R-squared captures how well the model explains differences in average performance across funds. The between R-squared varies considerably across fund types: it is exceptionally high for Balanced and Other (Specialist) funds, but less so for Long Income funds, suggesting that cross-sectional differences in performance within this sub-group are less well explained by the variables included in the model.

The within R-squared is more modest across all specifications, ranging from 0.16 for Long Income funds to 0.33 for Other (Specialist) funds. This indicates that the model is less able to explain when and why a given fund has a strong or weak quarter, therefore implying that a substantial share of performance dynamics likely reflects idiosyncratic factors that are difficult to capture in a systematic model.

8. AI AND ASSESSMENT OF FUND PERFORMANCE

AI in investment vs performance evaluation

Artificial intelligence (AI) encompasses a wide range of applications in real estate and fund analysis, including asset selection, portfolio construction, risk management, and predictive analytics, as extensively documented in equities and fixed income investments. While these applications are potentially highly valuable, they primarily relate to decision-making frameworks. The present study, by contrast, is deliberately focused on the evaluation of past fund performance. As such, it abstracts from the use of AI as an investment tool and instead concentrates on understanding realised outcomes and their underlying drivers.

Machine learning: Potential and trade offs

Machine learning (ML) techniques offer the capacity to model complex, non-linear relationships, high-dimensional interactions, and latent structures that may be difficult to capture using conventional econometric models. This flexibility is particularly appealing in environments characterised by heterogeneous assets and limited transparency, such as unlisted real estate funds. However, this strength comes with trade-offs in terms of interpretability, model stability, and economic identification. Importantly, the adoption of ML methods should not be viewed as a substitute for established statistical approaches, but rather as a complementary research direction. Any claimed incremental value of AI/ML in explaining fund performance must be rigorously benchmarked against well-specified econometric models, with careful attention to out-of-sample performance, robustness, and economic interpretability.

Data limitations

In this study, the applicability of AI/ML methods for feature selection is severely constrained by the pattern of missingness in the dataset. The proportion of missing values across several key variables is too high so that standard algorithms cannot operate on complete cases alone, as doing so would reduce the effective sample to a trivially small number of observations. To address this, missing values could be imputed using each variable's series mean prior to estimation. While mean imputation is a pragmatic solution that preserves sample size, it attenuates variation within the affected variables and should be interpreted with appropriate caution.

AI-derived sentiment: Opportunities and strategies

A further potential application of AI within this context concerns the use of large language models (LLMs) and related natural language processing tools to construct proxies for market sentiment toward the unlisted fund sector. In principle, such sentiment measures could capture forward-looking expectations, narrative dynamics, and qualitative information not directly observable in structured datasets. Nevertheless, it is important to recognise that sentiment is likely to be, at least partially, embedded in observable market variables, most notably capital flows and valuation adjustments, which already serve as indirect proxies for investor beliefs.

It must be noted that evidence from related applications indicates that sentiment indicators derived from AI-based models can be highly sensitive to model architecture, training data, prompt design, and data preprocessing choices. This sensitivity may lead to substantial volatility in the resulting indicators and raises concerns regarding their stability, reproducibility, and economic interpretability. In addition, issues such as data selection bias, overfitting, and the lack of a clear structural mapping between textual inputs and economic outcomes further complicate their use in empirical analysis. A rigorous assessment of the role of sentiment in driving fund performance would therefore require a dedicated empirical framework. This would involve (i) constructing alternative sentiment measures using different methodologies (e.g., dictionary-based approaches, supervised ML models, LLM-based embeddings); (ii) systematically comparing their statistical properties and economic content; and (iii) evaluating their predictive and explanatory power for fund returns within a well-defined econometric setting. Such an analysis would need to incorporate robustness checks, out-of-sample validation, and careful benchmarking against traditional proxies, thereby constituting a substantial and distinct extension beyond the scope of the present study.

9. CONTRIBUTION AND RECOMMENDATIONS

The context for the present study is informed by the earlier IPF report, A Decade of Fund Returns (IPF, 2012), as well as a substantial body of subsequent research on unlisted fund performance, reflecting sustained interest in the sector. Covering the period from 2011 to 2025, this analysis examines unlisted property fund returns during a period characterised by moderate economic growth, both low and high interest rate and inflation environments, and episodic shocks that required funds to actively manage liquidity. This phase also includes a peak in net investment flows, followed by a prolonged decline and early signs of stabilisation in 2025. These conditions differ, to some extent, from those examined in earlier studies, particularly the 2012 IPF report.

The IPF (2012) study demonstrated that the performance of pooled unlisted property funds is primarily driven by the underlying direct real estate portfolio, but is also materially influenced by cash holdings, leverage, fees, and structural features of fund design. Fees, especially performance fees, were identified as the most significant drag on returns, reducing performance by close to one percentage point, with additional erosion from other fund costs. Cash holdings were found to dampen returns during rising markets while offering only limited downside protection.

Leverage was shown to be highly cyclical and volatile, rather than a consistent source of return enhancement. Although its overall contribution across the decade was broadly neutral, it significantly increased return volatility, amplifying losses during downturns. Differences across fund types were also evident: Specialist funds achieved higher gross property returns, but this advantage was partly offset by higher fees and greater leverage-related volatility, whereas Balanced funds delivered lower but more stable performance.

The present analysis focuses on net returns, reflecting the actual outcomes experienced by investors after all fees. It extends the earlier IPF study in several ways and aligns with subsequent research in this area. First, it provides a more detailed examination of return behaviour across fund styles (Balanced, Long Income, and Other (Specialist)), allowing unlisted funds to be more clearly positioned within the broader investment landscape. Second, it analyses return drivers within a dynamic framework, assessing the relative contribution of each factor across funds and over time. The set of drivers considered is also broader, incorporating both fund-specific and wider economic influences, consistent with approaches adopted in existing research.

The results indicate that unlisted funds deliver competitive performance, with favourable average returns, risk-adjusted metrics, and very low probabilities of negative returns over medium- to long-term investment horizons (for example, periods longer than five years). While it may be argued that these outcomes partly reflect valuation smoothing in fund returns, which can obscure underlying volatility, the evidence suggests that such smoothing is not excessive, implying meaningful exposure to transaction-based pricing.

Past NAV growth, included as a proxy for momentum and net investment flows, emerges as a dominant factor across all fund types. This finding suggests that fund performance is strongly influenced by capital flows and momentum effects, raising important considerations for fund managers. In particular, it highlights the need to manage inflows and outflows effectively, as these can reinforce return dynamics but may also introduce procyclicality in returns.

A key implication of this empirical investigation for both fund managers and investors is the central role of broader market conditions in driving returns in unlisted property funds. Economic activity and real estate market cycles emerge as important determinants of performance and should therefore play a central role in allocation decisions. In addition, sentiment in the listed REIT market appears to provide useful signals for Balanced funds, with pricing in that segment reflecting sentiment in the listed market.

9. CONTRIBUTION AND RECOMMENDATIONS

At the same time, the results are consistent with industry practice. They confirm that unobserved and non-quantifiable fund-specific characteristics remain important, even after controlling for market conditions and observable variables reported in the MSCI/AREF PFV Handbook. Investors should assess these characteristics when allocating capital and selecting managers.

This is further supported by evidence of persistent remaining performance after known effects in Balanced and Other (Specialist) funds, where more active management strategies may be employed compared with Long Income funds. This residual return component represents net-of-fees returns that are not explained by macroeconomic conditions, market factors, fund characteristics, or NAV persistence.

The analysis leads to several recommendations:

- For fund managers, investors, and the wider industry, improving the quality of data reported in the PFV Handbook should be a priority. The analysis encountered persistent gaps in fund-level characteristics, limiting both empirical investigation and outputs. These issues have also been highlighted in prior work, including AREF (2021) observations on PFV Handbook data reporting. While it is not expected that databases will capture every dimension suggested in the literature, existing fields could be more consistently and comprehensively populated. For example, data gaps constrained the ability to conduct a fuller attribution analysis or assess the importance of a particular fund characteristic.
- The risk-adjusted performance of unlisted funds would be more reliable to the broader investment community if based on less smoothed data. Efforts to improve underlying valuation practices, thereby reducing the smoothing of fund returns, would help achieve this objective.
- Future research should place greater emphasis on net investment flows, particularly given sustained outflows since 2016. While this study focuses on net returns, liquidity remains a critical issue and warrants further analysis, building on prior work such as AREF (2021).
- Understanding investor sentiment will be central to explaining these flows, as well as their impact on pricing dynamics, including bid–ask spreads. In this context, AI-based sentiment indicators may offer a promising avenue for capturing behavioural factors not reflected in traditional datasets.
- Finally, greater use could be made of the PFV Handbook through regular (e.g., quarterly) analysis of changes in fund characteristics and market conditions. The dataset contains a wealth of information that can be leveraged to address specific research questions and to provide a timelier view of developments in the unlisted property fund industry, subject to appropriate data quality improvements.

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APPENDIX A

Existing literature

This appendix expands on the literature review summarised in Section 2. While the main text focuses on the key findings that motivate the empirical analysis, the appendix provides a more comprehensive discussion of the academic and practitioner literature on property fund performance drivers. Owing to the length and scope of the literature review, it is presented in an appendix to preserve the conciseness of the main paper while providing readers with a comprehensive account of the existing evidence.

The determinants of property fund performance have attracted research interest from both academics and industry professionals, and several studies have examined the topic. Overall, the literature suggests that performance is shaped by a complex interaction of fund-specific characteristics, investment strategy, portfolio structure, and broader market factors. In empirical research, these factors are represented by measurable variables, and their effects on performance are primarily evaluated using statistical methods. The measurement of these determinants is often conditional on the data sources employed and the geographical scope of the studies. A general observation from the existing literature is that the set of identified drivers varies across studies, and the level of empirical support as well as the sensitivity of returns to these drivers differs accordingly. Nevertheless, a degree of consensus appears to exist regarding several key determinants, which are outlined below.

A1 Fund characteristics

Fund size and scale

The literature generally expects a positive relationship between fund size and performance, reflecting economies of scale (that is cost efficiencies achieved as fund size increases), in property management and transactions. Larger funds may also benefit from improved access to debt markets and a broader opportunity set, enabling greater diversification. However, beyond a certain threshold, diseconomies of scale (i.e., inefficiencies arising from excessive size, may emerge, potentially dampening returns.

Fund size is typically measured by total assets under management (AUM) or gross asset value (GAV) of the fund's portfolio. While fund size is measured by GAV (or the log of GAV), net asset value (NAV) may serve as a reasonable alternative in settings with low leverage.

Empirical evidence on fund size as a performance determinant is mixed. Several studies, including Fuerst and Matysiak (2013), Farrelly and Stevenson (2016), and Kiehelä and Falkenbach (2015), find that fund size is not a consistent driver of returns. Couts (2022) and Morawski and van den Heuvel (2014) find only a limited role for fund size. In contrast, Tomperi (2010) and Baum et al. (2012) provide some evidence of negative scale effects, suggesting that very large funds may experience diseconomies of scale that adversely affect performance.

Fund age and vintage effects

Fund age is commonly measured as the number of years since fund inception and reflects both organisational maturity and accumulated management experience. Older funds may benefit from more experienced management teams, established investment processes, and more stable portfolios, which can positively influence performance. Conversely, younger funds may achieve higher returns due to stronger incentives, greater investment flexibility, or fewer portfolio constraints. In addition to fund age, vintage year captures the market conditions prevailing at the time of fund formation, reflecting the point in the real estate cycle at which capital is committed. Funds launched in favourable market conditions may benefit from advantageous entry pricing, while those raised at cycle peaks may face more challenging return environments over their life cycle.

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The literature provides mixed evidence on the relationship between fund age and performance, with the effect often found to be statistically insignificant. In some studies, the relationship is weakly positive, but the significance is limited. Performance is often found to vary across the life of the fund, reflecting the J-curve, where early-stage funds may initially show modest or negative returns that improve as the fund matures (Couts, 2022; Kiehela and Falkenbach, 2015; Tomperi, 2010). Fuerst and Matysiak (2013) find supporting evidence through time effects, whereas Morawski and van den Heuvel (2014) argue that older funds may stabilise but do not necessarily outperform. Baum et al (2012), find evidence that vintage effects are an important determinant of performance, with funds raised in different market conditions exhibiting different return outcomes over time.

Leverage

Leverage can enhance returns when the returns on underlying assets exceed the cost of debt, known as positive leverage. However, it can also amplify losses during market downturns, particularly at high levels of debt. Excessive leverage can therefore exacerbate negative performance during periods of market stress.

The expected relationship between leverage and performance is generally positive at moderate levels, as debt financing can amplify returns through financial gearing. The observed relationship, however, depends on the timing of the study period; results may differ if the sample primarily reflects normal market conditions versus periods that include substantial market downturns.

Therefore, empirical evidence on leverage and property fund performance is mixed. As a standalone determinant of average returns, leverage is often statistically weak or insignificant. When included alongside other determinants such as vintage, market trends, age and fund strategy, its significance typically diminishes. Limited effects on returns have been reported by Baum and Farrelly (2009), AREF (2021), and Delfim and Hoesli (2016). Studies that examine sensitivities (in addition to significance) suggest that a 10% increase in leverage can increase returns by around 1% per annum in up markets but can reduce returns by up to 5% in down markets (Fuerst et al., 2014). Studies overwhelmingly indicate that leverage has a stronger effect on risk than on returns, increasing the volatility of fund performance (Baum & Farrelly, 2009).

Cash holdings & liquidity

Liquidity is essential to meet investor withdrawals and reduce the risk of forced property sales during periods of high redemption demand, thereby supporting more stable fund performance. However, high cash holdings may negatively affect returns, as cash typically generates lower yields than real estate assets. Liquidity is commonly measured through cash holdings as a proportion of total assets, redemption conditions, or lock-up periods in open-ended funds.

Empirical evidence on the impact of cash holdings is limited, partly due to data availability. Existing studies generally find that cash is not a significant determinant of unlisted real estate fund performance (Fuerst and Matysiak, 2009, 2013; Lee and Morri, 2015). In the AREF (2021) study, cash holdings were found to reduce overall fund returns. Over the period 2004 to 2019, cash positions lowered annual returns by approximately 0.14% for all funds, and by around 0.23% for Balanced funds. While cash provides important liquidity benefits, such as meeting redemptions during market downturns, it is generally a drag on performance outside periods of severe stress.

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Fund style

The distinction between open-ended and closed-end fund structures has been highlighted in several studies as a potential determinant of fund returns. Open-ended funds must accommodate investor subscriptions and redemptions, requiring cash reserves that can reduce the proportion of capital invested in target assets.

In contrast, closed-end funds operate with a fixed number of units, allowing managers to remain fully invested and pursue longer-term strategies, often with greater use of leverage. By comparison, open-ended and evergreen funds allow investor withdrawals, but periodic liquidity windows can create challenges due to the mismatch between withdrawal demand and the illiquidity of the underlying assets.

Empirical evidence is mixed. Baum et al. (2012) find that open-ended funds tend to have more stable, income-oriented returns but may underperform in total return relative to closed-end funds due to liquidity constraints and cash drag. ANREV (2013) claim that open-ended and closed-end fund structures affect fund performance differently across countries. Other studies suggest that the open/closed classification is not a dominant factor in fund performance (Delfim & Hoesli, 2016; Baum & Farrelly, 2009), with fund strategy — core versus higher-risk non-core — appearing to have a greater influence on returns.

Fees

Fees affect net returns by definition, as higher fees reduce gross-to-net performance. However, this is a mechanical effect rather than a structural determinant of performance. The same is broadly true of cash holdings and, to a considerable extent, leverage, both of which do not directly reflect differences in manager skill but instead enable different investment strategies.

Fees can influence managerial incentives. Management fees, typically charged as a percentage of assets under management, may encourage managers to increase fund size and focus on asset growth, as fee income rises with larger portfolios regardless of performance. Performance fees, by contrast, are designed to align the interests of managers and investors by rewarding returns above a benchmark or hurdle rate. However, such structures may also incentivise managers to pursue higher-return strategies that involve greater risk, for example through higher leverage or more concentrated investments that can have an impact on fund returns (indirect impact of fees on fund performance). Industry reports (AREF, 2019; INREV, 2018; ANREV, 2013) consistently highlight that fee levels vary across fund types and strategies and can erode net performance.

Empirical evidence on the impact of fees on unlisted real estate fund performance is mixed and generally limited. Some studies including Fuerst and Matysiak (2009, 2013), Farrelly and Stevenson (2016), Tomperi (2010), and Kiehelä and Falkenbach (2015) typically include management and performance fees as control variables, but these variables rarely emerge as statistically significant determinants of fund returns.

A2 Investment Strategy

Core, core plus, value-add, opportunistic strategies

Core, value-add, and opportunistic strategies each exhibit distinct risk–return profiles. Core funds are characterised by lower risk and stable income but typically deliver more moderate total returns. Opportunistic funds pursue higher-risk strategies, targeting greater capital appreciation but with increased volatility. Core-plus funds sit between core and value-add strategies, typically maintaining a relatively low-risk profile while seeking modest increases in income and returns through small scale property improvements or active management.

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Empirical studies such as Kiehelä and Falkenbach (2015), Tomperi (2010), Farrelly and Stevenson (2016), and Couts (2022) find that non-core strategies are linked to higher dispersion of outcomes and greater sensitivity to market cycles, with performance varying significantly across vintages. Bollinger and Pagliari (2019) further show that strategy explains a substantial portion of return differences across funds, while Delfim and Hoesli (2016) highlight that higher-risk strategies are more exposed to systematic risk factors. Strategy style (core vs non-core) strongly affects return profiles (Couts, 2022). Overall, the evidence suggests that strategy is a consistent driver of fund performance, with the return premium of value-add and opportunistic funds reflecting compensation for higher risk rather than sustained outperformance once returns are adjusted for volatility (for example higher returns for the same volatility of returns). The literature shows that non-core (value-add and opportunistic) strategies tend to outperform core funds in absolute terms, but this reflects higher risk rather than superior risk-adjusted returns (higher risk undertaken and hence returns are higher)

Balanced, Long Income and Specialist funds

The question of whether certain fund types consistently outperform others has been widely examined, though the evidence remains mixed. Balanced funds tend to be less exposed to sector-specific downturns due to diversification, while specialist funds may outperform during periods of strong growth in their target sectors. Long Income funds typically deliver more stable returns as a result of long lease structures but offer limited potential for capital appreciation and their lower yields increase sensitivity to interest rate swings. Empirical studies, including Fisher and Hartzell (2016), suggest that no single fund type consistently outperforms.

Asset allocation and property type exposure

Property type exposure is typically measured as the proportion of a fund's portfolio allocated to specific sectors such as office, retail, industrial, residential or other. The impact on performance is expected to vary with sectoral market conditions and broader economic cycles. Funds with greater exposure to sectors experiencing strong demand, rental growth, or favourable supply dynamics are likely to outperform, while exposure to weaker sectors may dampen returns.

Empirical evidence supports the importance of sector allocation as a determinant of fund performance. Studies such as Fuerst and Matysiak (2009, 2013) and Farrelly and Stevenson (2016) find that underlying property market conditions and sector exposure are significant drivers of returns in non-listed real estate funds. Similarly, Delfim and Hoesli (2016) show that sector-specific and macroeconomic factors play a key role in explaining return variation, while Kiehelä and Falkenbach (2015) highlight that funds with higher exposure to non-core sectors exhibit greater return dispersion and sensitivity to market cycles.

Development exposure

Exposure to development projects can significantly enhance fund returns when projects are successful, as they provide opportunities for capital appreciation beyond income from stabilised assets. In practice, development exposure is often embedded within broader and higher risks fund strategies (development, major refurbishment or asset repositioning), particularly in value-add or opportunistic funds.

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However, development investments carry substantial construction, planning, and market risks, making them inherently high risk. While development exposure is most commonly associated with value-add and opportunistic strategies, it varies significantly within these style categories and should be considered as a continuous source of risk and return rather than a defining feature of any fund type. Empirical evidence indicates that development exposure is an important driver of unlisted real estate fund performance within these broader strategy categories. Couts (2022) documents that funds with higher development activity tend to exhibit greater return potential, while Delfim and Hoesli (2016) identify development exposure as a strategic factor that helps explain variations in fund returns across European non-listed property funds

A3 Portfolio structure

Portfolio diversification

Concentration measures-by region within a country or by property sector-are often used to assess the impact of geographical and sector diversification on fund performance. Greater diversification can reduce exposure to localised market shocks and help stabilise returns, while excessive diversification may dilute management focus and limit the benefits of specialisation (and specialist investment expertise). This mirrors the analysis between Balanced versus Specialist funds, and even within Balanced, Long Income, or Specialist fund strategies, the distribution of assets across regions and sectors can vary. Balanced or diversified funds may deliver more stable returns, mitigating downside risk, as noted by Baum et al. (2012) and Delfim and Hoesli (2016). INREV (2018) also emphasises that while specialisation can offer upside, it increases sensitivity to cyclical shocks.

Diversification is typically measured using the distribution of assets across property sectors, often via concentration indicators such as the Herfindahl-Hirschman Index (HHI), where lower concentration reflects higher diversification.

Several studies (Fuerst and Matysiak, 2009, 2013; Tomperi, 2010; Kiehelä and Falkenbach, 2015) include sector exposure as a control variable in empirical investigations but results often show it is not a statistically robust determinant of returns across all markets or vintages. Couts (2022) similarly finds that non-core allocations, which often overlap with sector specialisation do not consistently explain average fund performance. Fuerst et al (2021) claim that sector specialisation might offer more benefits in alternative sectors (e.g., healthcare, data centres, self-storage) compared to main sectors.

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Tenant concentration

Tenant concentration refers to the extent to which a real estate fund's rental income depends on a small number of tenants. It is typically measured as the share of total rental income generated by the largest tenant(s) in the portfolio (e.g., top one, five, or 10 tenants). High tenant concentration can increase income risk and volatility, as the departure or default of a major tenant may lead to significant cash flow disruptions. Conversely, a diversified tenant base tends to stabilise income streams and support more consistent, risk-adjusted performance, particularly in broadly diversified core funds. However, the relationship is more complex in specialist strategies, where exposure to a limited number of tenants or sectors can be intentional and may improve returns when supported by strong covenant quality and long-term lease structures. In such cases, concentration in financially strong tenants with long-term leases can also provide stable income and mitigate the risks associated with tenant turnover and frequent reletting.

The limited empirical literature that explicitly examines the relationship between tenant concentration and performance provides little robust quantitative evidence of a strong direct effect. Fuerst and Matysiak (2009, 2013) and Farrelly and Stevenson (2016) do not identify a clear or statistically robust link between concentration and average returns, while Farrelly and Matysiak (2012) report a positive but weak association. Overall, within the subset of studies that directly investigate this relationship, the evidence suggests a weak impact on performance.

Number of properties

The number of properties held by a fund can influence diversification, risk, and stability of returns. Funds with a larger number of properties are generally better diversified across locations and assets, which can reduce exposure to idiosyncratic shocks from a single property and help stabilise income streams. Portfolios with fewer properties may deliver higher returns in strong market conditions if individual assets perform well, but they carry greater downside risk.

According to AREF (2021), there is no evidence that funds with a higher proportion of their portfolio concentrated in a small number of properties achieve additional returns. In fact, the study finds a negative correlation between the concentration of fund value in the top 10 properties and the risk-adjusted Sharpe ratio, suggesting that more concentrated portfolios may deliver lower risk-adjusted performance. Callender et al (2007) examine diversification and tracking error reduction using a large dataset of over 10,000 UK properties. They provide estimates of diversification benefits based on returns, risks, and cross-correlations across individual assets. The results show that substantial risk (tracking error) reduction can be achieved with portfolios of around 30–50 properties, but full diversification of idiosyncratic risk requires very large portfolios.

While a higher number of properties can reduce risk and stabilise income, empirical studies show it is not a systematic determinant of unlisted fund performance

Portfolio income metrics

Portfolio income metrics capture the current operational performance of a real estate fund and are commonly used to assess both income stability and potential total returns. Key indicators include the vacancy rate, reversionary potential, WAULT (weighted average unexpired lease term) and the initial yield of the portfolio. Low vacancy rates indicate more stable cash flows, while reversionary potential reflects the opportunity to increase rents as leases expire and are renewed at market levels. Initial yield and changes in initial yields capture capital value impacts.

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Empirical evidence on these income characteristics is indicative. AREF (2021) find that portfolio vacancy rates affect performance for both Balanced and Specialist funds although the effect could be period specific. Fuerst and Matysiak (2009, 2013) include portfolio yield in their analyses and identify it as a significant factor, while Lee and Morri (2015) note that funds with higher initial yields tend to perform better in income terms, although this does not always translate into higher total returns.

The WAULT measures the average remaining lease length across a fund's properties, weighted by rental income or property value. It is widely used as an indicator of income security and lease risk in real estate portfolios. WAULT influences both the stability of rental income and the potential for rental growth, thereby affecting total fund returns. Longer WAULTs generally provide greater income security and lower income volatility, while shorter WAULTs increase exposure to reletting risk but may offer higher potential for rental growth. Consequently, WAULT is commonly considered a key portfolio characteristic in empirical studies of real estate fund performance.

In empirical studies WAULT appears more relevant as an indicator of income security and risk management than a systematic driver of fund performance (Fuerst and Matysiak, 2009, 2013; Farrelly and Stevenson, 2016. On the other hand, AREF (2021) finds support for WAULT as a driver both of Balanced and Specialist funds, although the impact on fund returns is greater for Specialist funds.

A4 Market conditions

Macroeconomic, financial indicators and property market indicators.

Studies of real estate fund performance typically incorporate broader market influences, as returns are shaped not only by fund characteristics and investment strategies but also by the macroeconomic environment and conditions in financial and property markets. Variables such as gross domestic product (GDP), interest rates, inflation, stock market performance, and property market returns are commonly included in empirical models to capture wider economic and property market conditions affecting underlying trends. Empirical studies provide strong support for these aggregate variables, suggesting that fund returns are closely linked to economic developments and property market conditions.

The evidence from both academic studies and industry reports consistently shows that real estate fund performance is closely linked to broader economic and market conditions. Factors such as GDP growth, interest rates, and overall property market returns play a significant role in shaping outcomes, with many studies finding these variables to be statistically significant drivers of fund returns. In practice, this means that a substantial portion of performance reflects exposure to underlying market movements-particularly property market cycles-rather than purely fund-level decisions. As a result, understanding the economic backdrop and property market trends is essential when evaluating fund performance.

Several studies explicitly confirm that fund returns are significantly linked to economic and market conditions (Fuerst and Matysiak, 2009, 2013; Delfim and Hoesli, 2016; ANREV, 2013). Farrelly and Stevenson (2016) and Morawski and van den Heuvel (2014) identify property market performance and cycles as key explanatory variables, while Baum and Farrelly (2009) show that a large share of returns is attributable to broader market movements. Similarly, Baum et al. (2012) highlight that differences in fund performance are heavily influenced by exposure to specific market segments and cycles, and AREF (2021) provides further support for the importance of market return variables.

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However, some studies (e.g., Lee and Morri, 2015; Tomperi, 2010) place greater emphasis on fund-specific or managerial factors, suggesting that market variables do not fully explain performance-though this does not contradict earlier findings, but rather highlights the complementary role of fund-level drivers.

Net investment flows

Net investment flows measure the net capital entering or leaving property funds. These flows (inflows – outflows) reflect investor sentiment. Investor sentiment is driven by the perception of property performance and risks (both of the underlying property but also of funds) relative to other asset classes. Similarly, investor capital allocations across funds may reflect investor preference for a style or strategy.

Net investment flows capture changes in investor demand for real estate as an asset class, which can influence asset prices and liquidity in property markets. Flows of funds can affect returns through fund trading (funds buying or selling assets due to flows).

The industry recognises flows as important in practice, particularly for liquidity and pricing, although this factor has rarely been examined directly in empirical models. INREV (2018) and ANREV (2013) acknowledge that investor demand and capital-raising cycles influence market pricing and fund outcomes. AREF (2021) similarly notes that capital inflows and outflows affect fund liquidity, pricing, and performance, particularly in open-ended structures. In empirical work, net cash flows are more often captured indirectly through variables such as fund size, liquidity, and leverage.

Overall, by incorporating both macroeconomic and real estate–specific variables, researchers are better able to distinguish between performance driven by market-wide factors and performance attributable to fund-specific characteristics or managerial decisions.

A5 Managerial skill and market timing

Management skill and experience

Managerial quality is difficult to measure directly, so studies often rely on observable proxies such as the experience of the management company, fee structures, and measures of performance persistence. While these characteristics are sometimes related to attribution-based estimates of skill, they are conceptually distinct: attribution analysis seeks to isolate performance after accounting for systematic risk exposures, whereas managerial quality proxies are used to explain cross-sectional differences in performance that may not be fully captured by attribution alone. The expected relationship is generally positive, as more experienced or better-resourced managers may be better able to identify attractive investment opportunities, manage assets efficiently, and time acquisitions and disposals across the property cycle to enhance fund performance.

Several studies examine managerial skill indirectly through fund characteristics, such as the fund's investment style (ANREV, 2013; Delfim and Hoesli, 2016). Lee and Morri (2015) provide evidence supporting the role of active management in unlisted funds. Sleptcova and Falkenbach (2021) find that skilled managers consistently deliver superior risk-adjusted performance, using measures such as performance correlation and the probability of repeating strong results. Their study also shows that limited partner reinvestment can serve as a signal of managerial skill.

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Market timing

Market timing can be considered part of managerial skill, as it reflects a manager's ability to anticipate property cycles and is therefore embedded within overall managerial quality or active management. However, market timing can also be examined separately from other aspects of skill, such as asset repositioning, to assess whether timing decisions independently contribute to performance. Empirical tests in unlisted real estate funds are rare. Hochberg and Mühlhofer (2017) find that many US commercial real estate fund managers exhibit limited market timing ability, although a notable minority can successfully time entry and exit across submarkets. They also provide evidence that some managers demonstrate skill in selecting higher-performing sectors and assets, leading to relative outperformance. However, the timing ability may be influenced by the timing of fund flows, as capital inflows can increase during market peaks and be absent at the bottom of the market when outflows can also occur.

APPENDIX B

Types of UK unlisted real estate funds

Balanced funds

A Balanced real estate fund is diversified across the various property sectors and regions, i.e. it holds a well-diversified (Balanced) portfolio, with the intention to match the performance of a general real estate index benchmark like the MSCI Quarterly Property Index. However, the weightings in the property sectors of the Balanced funds could be very different from those of the benchmark, which will lead to tracking error issues.

Balanced funds, may be either authorised, i.e. regulated by the Financial Conduct Authority (FCA), and designed for investment primarily by private investors, or unauthorised funds only open to institutional investors who are completely exempt from capital gains tax or corporation tax (e.g., pension funds and charities).

In the MSCI/AREF database Balanced funds are sub divided into two types based on their legal structure: Managed property funds and other Balanced funds, composed of both authorised or unauthorised property unit trusts (PUTs).

Specialist property funds (now called Other funds)

A specialist real estate fund focuses on particular types of property or on properties in particular geographic regions and are now called Other funds in the MSCI/AREF database. MSCI/AREF define the real estate funds as Other if 70% or more of their capital is invested in one specific market sector (e.g. Retail, Office, Industrial or Residential). In other words, Specialist funds typically provide investors with an exposure to property types that are difficult for investors to access due the size of the properties or the level of specialist management skills required. In other words, the holdings of Specialist/Other funds are concentrated in a particular market sector and then diversifies within the sector, i.e. hold market sector weights radically different to the benchmark index. These funds often have significant debt in their portfolios. This suggests that such funds will behave differently from the general benchmark, i.e. will display large tracking errors compared with Balanced funds.

Long Income funds

The most significant change in the UK unlisted real estate fund industry has been the development of Long Income (or long-lease) funds since the post-global financial crisis period (circa 2009–2010), driven by investors' search for higher yielding alternatives to persistently low UK gilt returns. MSCI/AREF define Long Income real estate funds as "Funds with a non-property specific performance objective to out-perform long-term bonds or gilts." Such funds therefore typically hold properties with an average unexpired lease length of over 15 or 20 years, have no debt, or negligible vacancy, i.e. provide a secure long run return equal to or greater than that in UK government bonds. This suggests that such funds will behave differently from the general benchmark, i.e. will display large tracking errors.

APPENDIX C

Econometric methodology

The empirical analysis presented in Section 7 estimates a panel regression model of fund-level total returns on a set of independent variables using quarterly data spanning 2016 Q1 to 2025 Q4. The baseline equation takes the form:

$$r_{it}=\alpha_i+\beta' x_{it}+\gamma' z_{it}+\varepsilon_{it} ,$$

where r_{it} denotes the total return of fund i in quarter t; α_i is a fund-specific intercept capturing time-invariant unobserved heterogeneity; $x_{(i,t)}$ is a vector of fund-level characteristics; $z_{(i,t)}$ is a vector of macroeconomic and market controls; and ε_{it} is an idiosyncratic error term.

The vector of fund-level characteristics includes the following variables: number of properties, net reversionary yield, fund age, weighted average unexpired lease term (WAULT), investment vacancy rate, top-10 tenant concentration, tenant concentration, maximum development exposure, cash holdings, leverage/GAV, NAV growth, and Attribution score. The vector of macroeconomic and market controls includes the following variables: GDP growth, CPI inflation, FTSE 250 return, and FTSE NAREIT return. No time dummies are added to the specification, as the macroeconomic and market control variables included in z_{it} already absorb common time variation across funds. For details regarding variable sources and descriptive statistics, refer to Section 7.

Given the presence of missing values across several variables, estimating a full specification including all candidate independent variables is not feasible across all subsamples. Variable selection is therefore guided by economic intuition and prior empirical evidence on the determinants of property fund returns, retaining those variables considered most likely to exert a meaningful influence on performance. The selected specification is reported and discussed in Section 7.

The selected specification is estimated first for the full sample of funds and then separately for each fund type, namely Balanced, Long Income, and Other, to allow for heterogeneity in the determinants of returns across investment strategies. For each sample, both fixed effects and random effects panel estimators are applied. The preferred estimator is selected on the basis of the Hausman test: where the null hypothesis of no systematic difference between the two estimators is rejected, the fixed effects model is adopted on consistency grounds; where the null cannot be rejected, the random effects estimator is preferred on statistical efficiency grounds. Standard errors are computed using a cluster-robust variance estimator to account for heteroscedasticity and within-fund serial correlation.

APPENDIX D

Statistical analysis: Full set of results

The table below reports the full set of estimation results for the econometric model explaining the drivers of property fund returns.

Table D.1: Full regression results - drivers of property fund returns

Drivers	Full sample	Balanced	Long Income	Other (Specialist)
NAV growth (lagged value)	0.2438*** (0.0809)	0.2596** (0.1077)	0.1494** (0.0645)	0.4956*** (0.0401)
Net reversionary yield	-1.3149** (0.6225)	-1.0090** (0.4444)	-0.3038 (0.0013)	-0.4127 (0.0056)
Fund age	-0.0002*** (0.0001)	0.0001 (0.0004)	0.0003 (0.0013)	0.0009 (0.0056)
Tenant concentration	-0.0778*** (0.0260)	-0.1749 (0.1409)	0.1255*** (0.0271)	-0.0722 (0.0839)
Maximum development exposure	-0.2960*** (0.0983)	-0.4362 (0.2719)	0.0628* (0.0351)	-0.3383 (0.5121)
Leverage/GAV	-0.0214 (0.0215)	-0.0573 (0.0373)		0.0372 (0.0802)
Cash holdings	0.0552 (0.0626)	0.1063 (0.1772)	-0.0286 (0.0576)	0.0597 (0.1372)
Attribution score (lagged value)	-1.1423 (0.9502)	-0.3870 (0.5135)	-0.2795 (1.5429)	
FTSE NAREIT return	0.0496 (0.0331)	0.0790*** (0.0287)	0.0252 (0.0171)	0.1176 (0.1540)
GDP growth	0.1177 (0.0838)	0.1238 (0.1085)	0.1185*** (0.0371)	0.4007*** (0.0394)
Constant	0.1807*** (0.0688)	0.2042* (0.1094)	-0.0785** (0.0348)	0.1041** (0.0418)
R-squared within	0.273	0.280	0.159	0.328
R-squared between	0.976	0.957	0.348	1.000

Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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