Macro-factors revisited: an evolving approach to portfolio resilience

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Executive summary

This paper revisits and builds upon our 2024 research on macro-factor exposures across public and private markets, with a particular focus on private infrastructure.

Our objectives are to improve the robustness of factor modelling, incorporate new insights and learnings, and provide actionable guidance for portfolio construction under a Total Portfolio Approach.

Key Innovations

- **Enhanced Methodology:** Adoption of an ensemble of penalised linear regression models to reduce overfitting and improve stability; rigorous two-stage unsmoothing of private asset returns to better approximate true volatility; and inclusion of lag structures to capture delayed macro transmission.
- **Validation & Robustness:** Use of target shuffling to estimate statistical significance of factor exposures and mitigate spurious relationships.
- **Expanded Factor Set:** Updated definitions for growth (OECD CLI), real rates (yield curve PCA), credit (HY–IG spread), and a new global liquidity factor.
- **Broader Asset Coverage:** Inclusion of granular listed equity sectors, commodities, and additional private market proxies.

Key Findings

- **Macro Drivers:** Credit, growth, and liquidity dominate risk-asset performance; higher real rates are a broad headwind; inflation matters primarily for commodities and select real assets.
- **Private Markets:** Private equity and venture capital exhibit high macro sensitivity, particularly to credit and growth, while private infrastructure and IFM's UIP remain low-beta, inflation-hedging anchors with non-macro return drivers.
- **Liquidity Dynamics:** Cyclical liquidity amplifies pro-risk assets. We also discuss the structural illiquidity premium that persists in private markets, especially infrastructure.
- **Macro Elasticities:** Public equities and HY credit rank highest; private infrastructure offers defensive characteristics with overall macro sensitivity comparable to fixed income.

Portfolio Implications

- **Macro Risk Budgeting:** Balance macro-sensitive exposures for tactical tilts with macro-insulated allocations for resilience.
- **Illiquidity Budgeting:** Deploy scarce illiquidity where structural premia and diversification benefits are greatest – private infrastructure stands out.
- **Strategic Positioning:** Use factor insights to hedge inflation, manage liquidity risk, and enhance robustness against geopolitical and macro shocks.

1. The motivation

This paper is motivated by two key aims. The first is to improve our initial work on macro-factors (see *Building robust portfolios with private assets: the importance of macro alpha and beta (2024)*) that highlighted the interaction of asset class returns with the economic environment – with a focus on unlisted infrastructure. This is initially from a methodological perspective and a desire to improve our modelling to reflect advances we have made in this space. Our second aim is to incorporate internal and external feedback to address key questions raised. We believe these innovations, which to a large degree support our initial conclusions, allow us to better understand the interaction of private market asset classes, with the economic cycle.

1.2 Factor model redux

We introduce several innovations to extend the framework introduced in our 2024 publication. These innovations fall into two broad categories. The first is a refinement of our methodology by applying insights from our ongoing research of analytical possibilities. The second is building on specific findings from our 2024 paper around how factor choice and construction impact model outcomes. Our overall aim has been to improve upon existing literature with a focus on the estimation of robust results. We outline our innovations below.

1.2.1 An improved model

The modelling methodology is improved in the following ways:

1. **Ensemble approach:** We improve the robustness of our estimation model by adopting an ensemble model composed of five penalised linear regression algorithms (PLRA) which tends to outperform single model approaches. This reduces model selection risk and lessens 'overfitting', improves estimation stability and helps find a better balance between bias and variance – slightly increasing the former to lower the latter resulting in lower error overall.[1] In our previous paper, we opted to use high-frequency proxies as our starting point as we were concerned that a relatively short monthly sample might not provide enough observations for the PLRAs to train effectively. We found that monthly data performed similarly well to higher-frequency data so in this update we more closely examine whether further replacement of daily proxies with monthly proxies will be useful. We make one replacement where the monthly proxy exhibits much stronger links to the underlying economic driver.

2. **Two-stage unsmoothing:** We apply a more rigorous two-stage returns unsmoothing methodology (detailed in our April 2025 paper) to private market asset classes. As private markets valuations are more heavily based on appraisals and manager discretion than transactions, 'smoothness' is introduced and volatility is understated – it is common practice to seek to account for this when comparing public and private asset class characteristics. While the original single-stage unsmoothing approach (Geltner, 1993) partially corrects this, it assumes a simple autocorrelation structure. Our two-stage procedure, drawing on Geltner (1993) and Getmansky, Lo, and Makarov (2004), better captures the multi-period dynamics of reported returns. This yields volatility estimates that more closely approximate mark-to-market behaviour, improving the realism of risk and correlation inputs. While we do not claim to fully recover the true return series, the resulting sensitivities are more credible for portfolio construction and stress testing, reducing the risk of overstated diversification benefits. We find this process is crucial to better understand the interactions between public and private markets in a portfolio and how they are influenced by the macro-environment.

3. **Lag structure:** Private asset returns tend to incorporate macroeconomic information with delays due to appraisal-based valuations and illiquidity. Accordingly, residual lagging persists even after unsmoothing. To capture this partial-adjustment dynamic, our model specification now includes a one-quarter lag for each macro factor and defines an asset's exposure as the cumulative response – the sum of the contemporaneous and lagged coefficients. This treatment aligns with empirical evidence of staggered private-market responses (e.g., Ilmanen, Chandra, & McQuinn, 2020), mitigates residual smoothing effects, and produces more realistic sensitivities for risk attribution and scenario analysis by allowing shocks to propagate over time rather than arriving entirely on impact.

4. **Target shuffling:** We use target shuffling to test whether the estimated macro-factor relationships reflect genuine economic structure rather than spurious correlations. This procedure repeatedly randomises the dependent variable, re-fits the model, and builds a null distribution of fit statistics and coefficients – what we'd expect if no true linkage existed. We then compare our observed factor loadings to this distribution; results that fall in the tails are deemed significant. This is useful because it sidesteps fragile parametric assumptions, works well with short, noisy, 'appraisal-smoothed' series and correlated predictors, and reduces false discoveries from 'data-mining', useful as we add an increased number of asset classes to the analysis. It provides a simple, auditable validation that factor exposures reflect economic signal rather than noise.

[1] Please refer to the Technical Appendix for a fuller discussion of models and testing.

5. **More granular asset class universe:** We expand the input universe to strengthen signal quality and improve cross-sectional coverage. The enhanced dataset adds: (i) more granular listed equity series by sector; (ii) a detailed commodity breakdown to capture diverse macro sensitivities; and (iii) additional private market proxies to better represent illiquid exposures.

6. **Reduced factor universe:** To maintain interpretability and avoid factor proliferation, we exclude variables such as the VIX, the US Dollar Index (DXY), and broad commodity indices from the model (these were applied but not heavily analysed in our 2024 paper). While these indicators have explanatory power, they are overly correlated with other factors, potentially exacerbating multicollinearity, and can obscure the impact of fundamental macroeconomic drivers. This is particularly important in the private market specification, where lagged terms already double the number of estimated exposures. By limiting redundant variables, we reduce multicollinearity, improve model stability, and ensure that factor loadings reflect distinct economic channels – critical for clear attribution and conclusions.

1.2.2 Improving the factors

We based our framework in our previous paper on growth, inflation, interest rates, credit, and commodities. These are well-recognised macro factors from the literature. Since then our thinking has evolved, facilitated by our improved methodology, and has led to the following updates:

Economic growth: Our original factor in this space was cyclical equities less defensives, a widely used, high-frequency proxy for economic growth. This variable has become increasingly problematic as a proxy for GDP growth, however. Reasons for this are unorthodox monetary distorting valuations, the increase in share buybacks impacting momentum, the rise of passive investing and ETFs reducing signal and the market thematics driving index gains that do not reflect economic activity (notably tech/AI). We replace this metric with the OECD Composite Leading Index (CLI) which is far more aligned (conceptually and statistically) with actual trends in economic activity.

Interest rates: We have improved on a relatively simple approach that was to take the first differences of US 10-year yields. We found that this factor definition, while well recognised, was too narrow for global markets and portfolios. To convey more information from the entire term structure of the yield curve we construct a principal component from real yield curves of major advanced economies (constructed using nominal yields and break-even inflation swaps). The approach synthesises the information into a clearer signal, better linking real rate dynamics with asset returns.

Credit: We also seek to get a clearer signal out of the credit curve. Our original factor was the return on a portfolio long investment grade (IG) corporate credit and short government bonds. This is altered to be the portfolio return of long high yield (HY) corporate credit and short IG corporate bonds. This better captures credit conditions and risk perception/appetite and reduces the interaction with base rates and liquidity effects.

Inflation: This factor remains actual advanced economy CPI inflation and is a driver distinct from real rates and growth. Its inclusion supports a cleaner decomposition across growth, inflation, interest rate (real), credit and liquidity channels.

Liquidity: This is a new factor aimed at capturing the illiquidity premium that we would expect in private market assets and that in part characterises their risk-return profile. It is seeking to quantify underlying market conditions in markets that affect pricing power and exit risk.

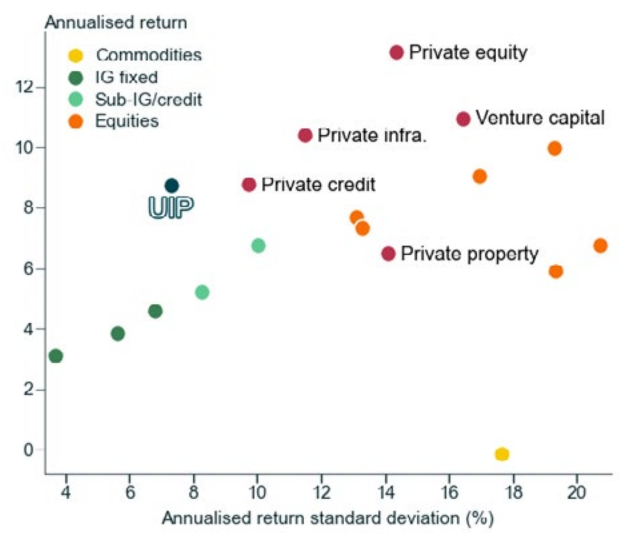
We are also seeking to separate liquidity risk from credit risk where the former is difficult to differentiate from the latter in terms of the impact on returns particularly in stressed markets (where correlations rise). To construct what is a composite indicator for this factor we are guided by two key studies: *Pastor–Stambaugh (2003)* who proxy liquidity via capturing the price impact of order flow, that is how much prices move in response to trades; and *Amihud (2002)* where illiquidity is measured as the price impact per unit of volume – higher values mean less liquid assets. This process is detailed in the Technical Appendix along with a graphical exposition of the factor.

We should note here, somewhat prefacing our results discussion, that this liquidity factor is constructed from identifiable market dynamics. By this definition we are able to get an estimate of how liquidity flows or 'cyclical liquidity' impact returns – this is particularly true of private market asset classes and those in closed-end funds. What is less clear, and less identifiable via a constructable proxy, is the impact on returns of 'structural liquidity', which is the illiquidity premium – again an important concept for private market assets. This is a discussion we will return to based on our results.

2. Asset return overview

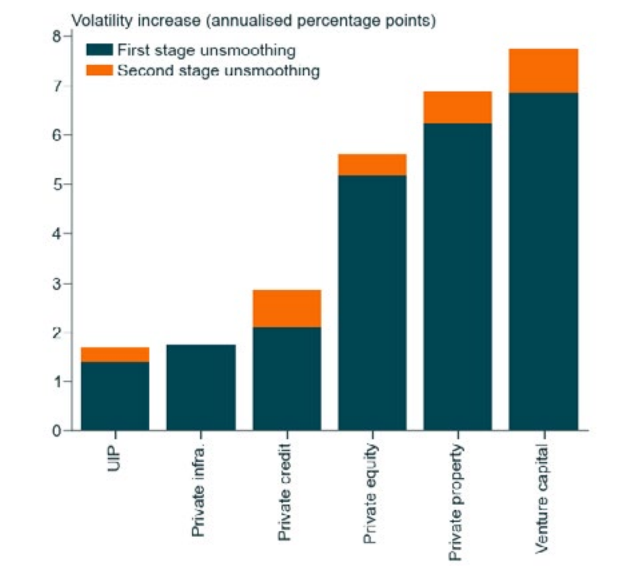
We start with a visual examination of the risk-return characteristics of the asset classes in this analysis. Graph 01 is simply a sense check comparing the average risk-return characteristics of each 'unsmoothed' asset class over the entire window. It is important to emphasize that this view is intentionally broad: performance dispersion within each asset class can be significant, and this chart is not intended to capture those nuances. Rather, it provides an overview of how these asset classes behave on average over the estimate period, Q4 2005 to Q2 2024.

GRAPH 01 **AVERAGE ASSET CLASS RISK/RETURNS**



Source: IFM Investors, Bloomberg, MSCI, Preqin.

GRAPH 02 **UNSMOOTHING IMPACTS***



Source: IFM Investors, Bloomberg, MSCI, Preqin.. *See appendix for unsmoothing parameters and significance estimates for the full private markets sample.

Note: For private credit, private equity, private property and venture capital we use the average volatility increase of the two representative indices for each asset class.

The risk/return profile is broadly as we would expect as an investor accepts higher return volatility. That is to say takes more 'risk'.[2] Despite this analysis taking place after the unsmoothing process (where we expect higher volatilities, higher correlations to public markets, and lower ex-post Sharpe ratios) the more defensive private market asset classes in infrastructure and credit are what we would call 'mid-risk' – that is to say straddling the space between lower risk fixed income and higher risk listed equity market returns. The outlier of these 'mid-risk' assets is private property where returns are uniquely at the centre of two crisis periods: the Global Financial Crisis (re-financing, securitisation and credit issues as well as economic impact); and the COVID pandemic (public lockdowns, changing work arrangements, impact on occupancy, supply-side inflation and rising rates). These high-impact episodes punctuate returns for commercial property and impart a differentiated risk profile when compared to other private market asset classes. For The higher risk-return (upper-right) private market asset classes are identified as being in the private equity (PE) space, again as we would intuitively expect. All unsmoothing parameters are included in the Technical Appendix.

Interestingly private property and PE are most heavily impacted by the unsmoothing process. Private equity valuations are particularly sensitive to unsmoothing because interim NAVs are model-based and updated quarterly, often using lagged public market multiples and conservative assumptions. Applying this methodology risks creating significant valuation inertia, so when actual transactions occur – such as portfolio company sales or new funding rounds – they frequently reveal large deviations from prior appraisals. This impact can be magnified in the venture capital space as an earlier stage, higher risk subset of PE. Property is also very sensitive to unsmoothing as valuations again depend heavily on appraisal cycles and cap-rate assumptions, rather than observable market multiples or contracted cash flows. These methods are well-recognised as potentially imparting a high degree of serial correlation and rely on lagged adjustments from transactions (as noted in Geltner (1993) and Fisher, Geltner & Webb (1994)). In fast repricing episodes (as noted earlier as examples the GFC, COVID-19), appraisal lags can mask the timing and depth of drawdowns – again 'smoothing' returns.

While private infrastructure has similar valuation lags and discount rate assumptions as these two asset classes, the characteristics of returns differ somewhat. Cash flows are often longer-duration, contracted, or regulated, which anchors valuations and stabilises fundamentals. Further, portfolios can be exposed to more defensive aspects of market risk. This seems to be the case with the infrastructure benchmark used in this analysis and IFM's Unlisted Infrastructure Portfolio (UIP) and to some extent may explain the relatively modest impact of the unsmoothing process on these return series.

[2] We have written before and recognize here again that the term 'risk' isn't all encompassing, particularly for private market assets, and is descriptive of the volatility of returns.

3. Examining the macro

3.1 Interpreting the factors

Armed with this framework and our unsmoothed returns series we can now examine how the different asset class returns interact with the macro-factors we have identified. This is achieved by interpreting the coefficients produced from the model. We refer to these coefficients as 'macro elasticities' (previously we referred to these as macro 'betas'). The estimated elasticities are presented in Table 01.

3.1.1 Public market assets driven by pro-cyclical factors

In summary credit, economic growth, and liquidity emerge as the principal drivers of risk asset performance, while higher rate levels act as a broad headwind and inflation offers little support outside of commodities. This risk-on pattern is most evident in listed equities and high yield credit, where the credit–growth–liquidity trio aligns closely with return outcomes and rising discount rates weigh on valuations. These outcomes while seemingly obvious give us confidence that the model is correctly specified.

3.1.2 Private exposures align with their economic narratives

Private equity behaves first and foremost like a spread asset: the sensitivity to credit dominates, with growth and liquidity providing secondary support, and inflation modestly detracting – consistent with valuation compression when price levels rise. **Venture capital** is distinctly growth-led and inflation-averse, reflecting the long-duration nature of its cash flows and the premium investors place on future earnings. These dynamics also reflect the asset class being reliant on leveraged financing and favourable exit environments. **Private property** loads primarily on growth, tracking the occupancy and rent cycle more than rates or inflation

Table 01: Key macro elasticities

	Private markets				
	Credit	Growth	Inflation	Liquidity	Rate level
Private equity* (R^2= 0.61)	4.5 (0.00)	1.1 (0.20)	-1.4 (0.12)	1.6 (0.13)	-0.5 (0.56)
Private equity (growth)* (R^2= 0.61)	2.8 (0.01)	2.0 (0.03)	-1.5 (0.07)	1.4 (0.15)	-0.8 (0.54)
Private equity (buyout)* (R^2= 0.59)	4.6 (0.00)	1.1 (0.23)	-1.3 (0.16)	1.5 (0.16)	-0.4 (0.62)
Venture capital* (R^2= 0.54)	2.4 (0.24)	3.3 (0.02)	-3.7 (0.01)	1.4 (0.32)	-0.4 (0.71)
Private property* (R^2= 0.31)	1.0 (0.27)	2.3 (0.02)	-0.7 (0.37)	1.4 (0.13)	-0.8 (0.36)
Private credit* (R^2= 0.74)	3.2 (0.00)	0.4 (0.48)	-0.5 (0.35)	1.3 (0.12)	0.0 (0.85)
Private infra.* (R^2= 0.32)	1.0 (0.09)	1.2 (0.04)	0.0 (0.80)	0.8 (0.13)	-0.5 (0.51)
IFM's UIP (R^2= 0.22)	0.2 (0.32)	1.0 (0.01)	0.5 (0.08)	0.5 (0.08)	0.3 (0.28)
	Public markets				
	Credit	Growth	Inflation	Liquidity	Rate level
Government IG bonds (R^2= 0.55)	-0.8 (0.00)	0.1 (0.34)	-0.8 (0.00)	0.1 (0.71)	-0.6 (0.00)
Corporate IG bonds (R^2= 0.47)	0.2 (0.35)	0.5 (0.06)	-1.1 (0.00)	0.7 (0.02)	-1.1 (0.00)
EM IG bonds (R^2= 0.43)	1.1 (0.01)	0.3 (0.36)	-1.1 (0.00)	0.8 (0.04)	-0.9 (0.01)
Global HY credit (R^2= 0.82)	3.5 (0.00)	0.6 (0.14)	-1.0 (0.02)	0.8 (0.08)	-1.0 (0.05)
EM HY Credit (R^2= 0.59)	2.1 (0.00)	0.3 (0.28)	-1.3 (0.00)	0.8 (0.06)	-0.9 (0.03)
DM equity (R^2= 0.69)	3.5 (0.00)	2.0 (0.02)	-0.6 (0.32)	3.0 (0.00)	-1.8 (0.02)
Defensive equity (R^2= 0.58)	2.3 (0.00)	1.3 (0.03)	0.3 (0.43)	2.1 (0.01)	-1.4 (0.03)
Cyclical equity (R^2= 0.69)	3.9 (0.00)	2.3 (0.01)	-1.2 (0.12)	3.5 (0.00)	-1.8 (0.04)
EM equity (R^2= 0.72)	4.6 (0.00)	2.7 (0.01)	-1.0 (0.19)	3.3 (0.00)	-1.9 (0.04)
Infrastructure equity* (R^2= 0.45)	1.7 (0.01)	1.4 (0.01)	0.0 (0.84)	1.7 (0.01)	-1.5 (0.01)
Property equity* (R^2= 0.51)	2.9 (0.00)	2.4 (0.01)	-1.0 (0.13)	2.3 (0.01)	-1.6 (0.04)
Commodities (R^2= 0.59)	3.7 (0.00)	2.1 (0.01)	3.2 (0.00)	0.6 (0.28)	-1.3 (0.08)

Source: IFM Investors, Bloomberg, MSCI, Preqin. *Constructed as average of two or more benchmarks, see appendix for full results table.

Note: P-values in brackets. Intensity of highlight corresponds to statistical significance (darker=more significant).
Colour corresponds to direction (green=positive, orange=negative).

in this specification. As we noted in our previous factor paper the GFC and pandemic/work-from-home episodes have materially disrupted intuitive results particularly regarding inflation but also rates. The substantial returns smoothing seen in private property is likely also a factor here. Although unsmoothing provides a much more economically realistic risk profile, the unsmoothing technique employed cannot retrieve the true returns series. Accordingly, confidence in estimated coefficients is lower, ceteris paribus, the more severe returns smoothing is. **Private credit** is – as designed – most exposed to credit with an additional, smaller liquidity component, mirroring spread dynamics and market depth.

Private infrastructure shows moderate growth sensitivity and otherwise muted macro elasticities, which is consistent with the stabilising influence of contracted or regulated cash flows. **IFM's UIP** has a significant positive growth loading, but it is notable that the coefficient is lower than the majority of risk assets. Indeed, this factor exposure is more similar to defensive asset classes. This result re-affirms the result from our previous factor paper that IFM's UIP provides a level of defensive protection from unanticipated swings in the economic cycle. There is also a positive exposure to inflation which implies it remains an effective inflation hedge. An artefact consistent with inflation-linked revenue streams in regulated or contracted assets. Indeed, IFM's UIP is a superior inflation hedge, in this analysis, to all other asset classes considered outside of the energy and commodities complex.

Again, as with our previous paper, there is little identifiable sensitivity to credit or rate level in this model. This pattern is consistent with a diversified portfolio of listed infrastructure operators where earnings grow with economic activity, inflation pass-through is present but partial, trading conditions matter at the margin, and capital structures and contract frameworks temper credit and rate-level sensitivity relative to broad equities.

3.1.3 Listed proxies behave like equities with a sector tint

Listed infrastructure and listed property both exhibit positive exposure to credit, growth, and liquidity, and a negative loading to rate levels, effectively acting as equity-like sleeves with moderated elasticities reflecting underlying asset class dynamics. This is consistent with their position in capital structures and the valuation impact of discount-rate moves.

3.1.4 Liquidity matters

The liquidity factor is an innovation relative to previous work so here we focus on clarifying its interpretation, which is more nuanced than our other factors. Below, we disambiguate between two types of liquidity: cyclical and structural.

3.1.4.1 Cyclical liquidity

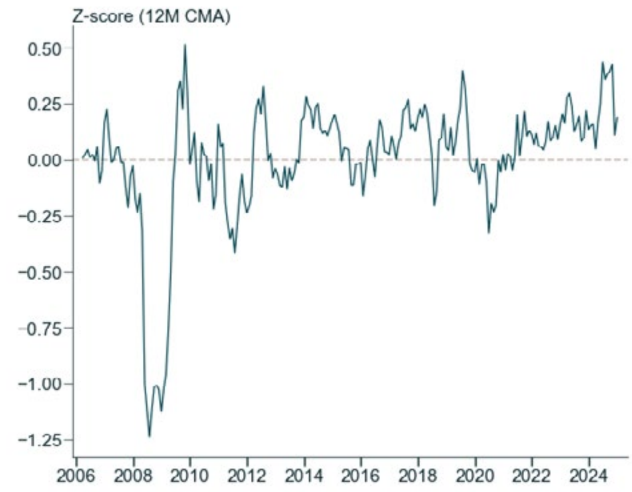
As discussed earlier the liquidity factor captures the concepts of market depth and the ease of financing – those relying on 'cyclical liquidity'. This reflects short-term fluctuations in market conditions, often linked to the business cycle and investor sentiment. It improves during periods of economic expansion and accommodative monetary policy (noting the estimation period is characterised by both very low rates and periods of quantitative policy regimes), when funding is abundant and risk appetite is high. Conversely, it deteriorates in stressed markets, where risk aversion rises and funding tightens, amplifying price volatility and transaction costs.

It is therefore not surprising that in our results the factor loadings behave as a pro-cyclical, pro-risk asset 'accelerant': when trading conditions improve and funding windows are open, assets that depend on external capital, secondary market turnover, or issuance channels tend to outperform. This effect shows up most clearly in listed equities with strong, significant positive factor coefficients. The much lower factor loadings for liquidity, in public market assets, occur in counter-cyclical asset classes, most notably investment grade bonds.


Pictured: Mersin International Port

In private markets, PE, private credit and property returns have some sensitivity to cyclical liquidity, but to a materially diminished extent compared to public markets. This comes as they are structurally less liquid than public markets due to longer investment horizons, limited secondary trading, and bespoke deal structures. Nonetheless, these asset classes benefit in several ways. First, easier refinancing reduces default risk and lowers the cost of capital, supporting higher valuations through improved cash flow certainty and lower discount rates. Second, smoother deal flow, driven by greater availability of financing and active transaction markets, enhances exit opportunities and often results in higher exit multiples. Finally, abundant liquidity compresses the illiquidity premium as investors require less compensation for holding hard-to-trade assets, further boosting valuations. Conversely, when liquidity tightens, refinancing becomes more challenging, transaction activity slows, and the illiquidity premium widens, exerting downward pressure on valuations and increasing dispersion across managers.

GRAPH 03 LIQUIDITY FACTOR



Source: IFM Investors, Bloomberg, MSCI, Preqin.

By contrast, private infrastructure and IFM's UIP exhibit low factor loadings to cyclical liquidity conditions. Possible explanations for this include: infrastructure's long duration; contracted and often regulated cash flow profiles; and reduced reliance on frequent refinancing limiting exposure to short-term funding shocks. Furthermore, these assets often operate under concession agreements or regulated frameworks that provide predictable inelastic revenue streams, insulating valuations from liquidity-driven repricing pressures. While transaction activity in infrastructure can slow during periods of tight liquidity, the fundamental value of these assets is anchored in their essential-service nature and often contracted cash flows, rather than market sentiment or deal flow dynamics. Furthermore, open-ended investment structures like IFM's UIP that either do not transact on a cyclical basis or indeed only transact when liquidity conditions are favourable can materially limit or eliminate pressures from the short term cyclical factor. As a result, the illiquidity premium for infrastructure is likely more structural than cyclical, and valuation volatility linked to liquidity shocks is generally lower compared to other private market segments.

3.1.4.2 Structural liquidity & the illiquidity premium

Structural liquidity is not a factor we have been able to isolate but we intuitively expect it to be a driver of returns and this assertion is supported in the literature.[3] In our analysis while private infrastructure assets and IFM's UIP exhibit far more muted or statistically insignificant sensitivity to the liquidity factor we'd assert that the cyclical liquidity is simply compressed and structural liquidity or the illiquidity premium (two interrelated concepts) remain prominent. This is due to the distinct characteristics of the asset class outlined above. The illiquidity premium exists as investors need to be compensated over the long term for committing capital. While it is a structural component of private infrastructure returns we would argue that the illiquidity premium is time-varying: insofar as it tends to compress in risk-on environments when liquidity is abundant, and widen during market stress when liquidity evaporates. That said the valuation volatility linked to liquidity shocks is significantly lower compared to other private market segments. It is useful for the investor to understand this behaviour to maximise the return available for each marginal unit of illiquidity in their portfolio. We will return to this discussion around structural factors that contribute to excess returns in Section 4.

3.1.5 Model fit is strongest where factor stories are cleanest

We now turn from the factor interpretation to the explanatory power of the model itself for each asset class. What is evident is that the explanatory power is highest for global high yield credit, private credit, and EM/DM equities, where the economic mechanism is clear and the return series are marked frequently. By contrast, private real assets (property and infrastructure) exhibit more moderate fits, suggesting that other factors are at play in 'explaining' returns. Part of this may be a structural liquidity premium, intra-asset portfolio construction with consistent or indeed regulated revenues, underlying asset quality and management, favourable geopolitical tailwinds (stability in terms of governance, regulatory environment, tax efficiencies etc) and investor demand.

[3] Longstaff (1995) applies option-pricing theory to show that the ability to sell a security is economically valuable – losing this "liquidity option" can create large discounts, even for short restriction periods. This insight underpins the concept of an illiquidity premium in private markets, where long lock-ups and limited secondary trading require investors to be compensated for constrained flexibility and exit risk.

4. Bringing it together

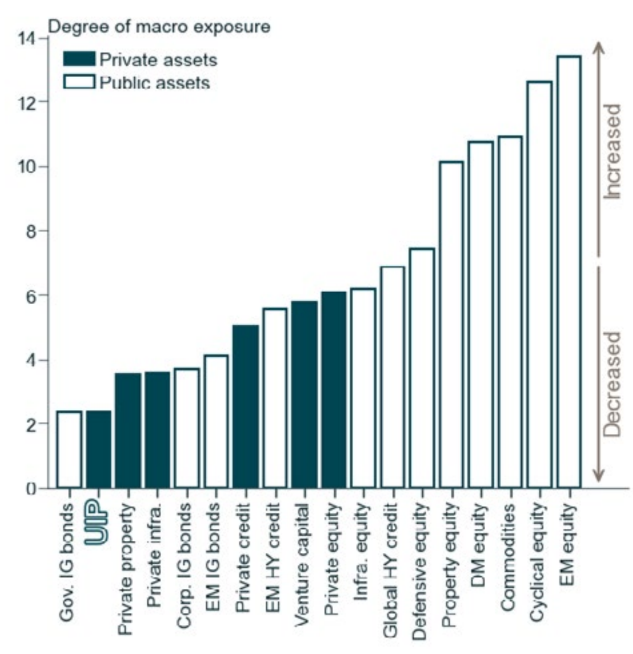
4.1 Macro elasticities

To understand how different asset classes respond to macroeconomic conditions, we sum the absolute values of the estimated factor loadings across the model. This aggregated measure reflects each asset class's overall sensitivity to the macro environment. This is effectively the overall macro elasticity or 'macro beta' of each asset class. For macro-oriented investors, this provides a practical ranking of asset classes by their historical exposure to economic forces – offering insight into which segments may be more or less reactive to shifts in the economic cycle. This allows for the alignment of allocations with macro views, enhances the ability to manage risk more effectively, and enhance diversification across economic regimes.

The macro elasticity framework is summarised in Graph 04 and highlights meaningful differences in macro sensitivity across public and private market asset classes. Public equities – particularly emerging market and cyclical sectors – exhibit high macro elasticities, reflecting strong responsiveness to economic conditions. As we move from growth to defensive public market assets the macro elasticities diminish through HY and private credit to investment grade government bonds. It is notable that asset classes at the lower end of the macro elasticity scale which are defensive in nature have little ability to leverage macro-conditions – this defines defensive – rather than outperforming when the cycle deteriorates. This is reflected in Graph 01 through lower average returns – in public market assets there is a clear correlation between macro elasticity – or economic risk – and returns. We highlight this relatively intuitive result as it is broadly replicated in the private market space. Private equity and VC have relatively high macro elasticities and high expected returns. However, while private infrastructure and IFM's UIP have low macro elasticities, or high insulation from economic cycles, they also have materially higher returns than other asset classes (notably fixed income) which offer these properties. This divergence underscores the role of private infrastructure in dampening portfolio-level macro exposure, offering stability during periods of economic stress whilst retaining the desired return profile.

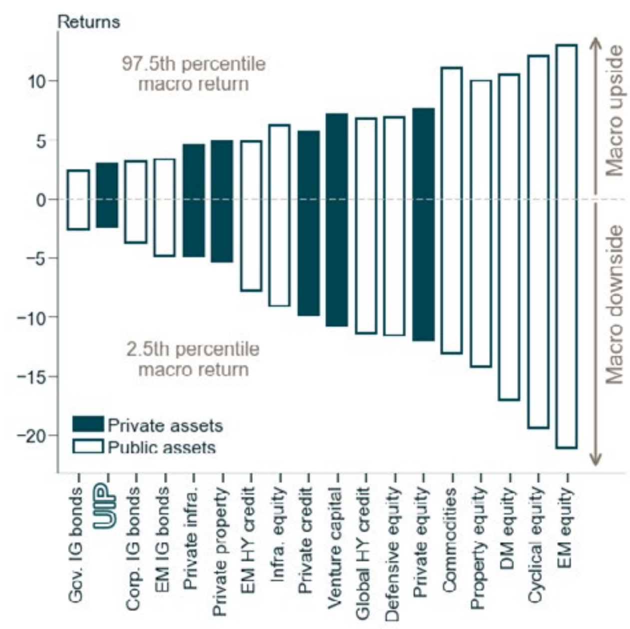
For investors, incorporating macro elasticity into allocation decisions enables more deliberate balancing between growth-sensitive public exposures and defensive private market allocations. It is useful to emphasise that, as Graph 05 illustrates, the elasticities that limit upside to returns from the macro-cycle also from it in a downturn.

GRAPH 04 **MACRO ELASTICITIES**



Source: IFM Investors, Bloomberg, MSCI, Preqin.

GRAPH 05 **MACRO RETURN RANGES**



Source: IFM Investors, Bloomberg, MSCI, Preqin.

Note: Calculated as the sum of model estimated factor-driven returns (i.e. returns predicted by elasticity coefficients only) in each quarter.

4.2 Sharpe ratios decomposition

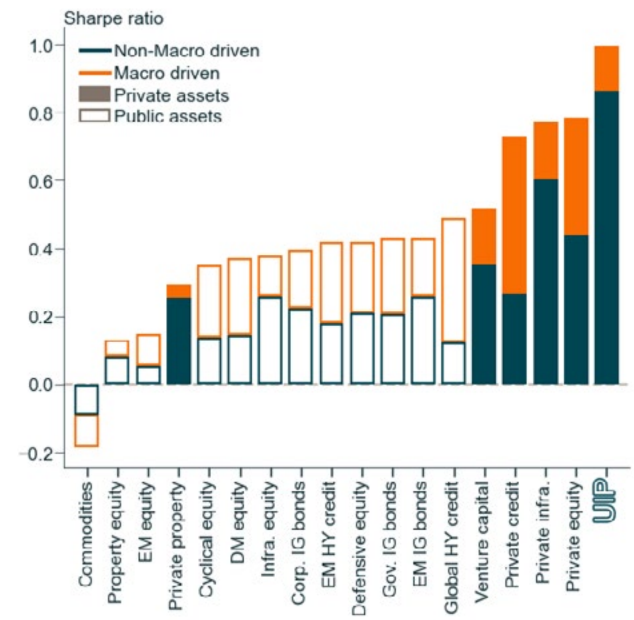
We investigate further in this section a key observation from the above. Certain assets - mostly in private markets - have high expected returns relative to their macro elasticities. This is driven primarily by how well the factors explain the returns in this model.

With this in mind, we apply a variance-based decomposition[4] of each asset's Sharpe ratio to quantify the contribution of macro and 'non-macro' factors on each asset's risk-adjusted return. This methodology aligns with the R^2 based attribution commonly used in multi factor models, enabling a partitioning of risk drivers. We present the results of this partitioning in Graph 06.

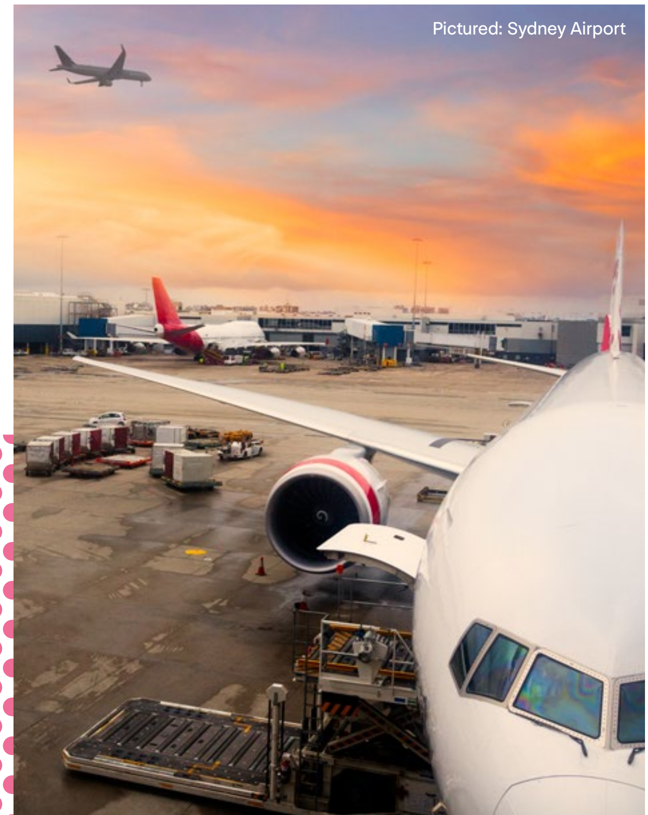
A high 'macro-driven' Sharpe ratio (represented by the orange bars in Graph 06) indicates that an asset's risk-adjusted returns are predominantly explained by the macro-factor set, suggesting strong sensitivity to economic conditions. Such assets are well-suited for expressing macro views and implementing tactical and regime-based allocation strategies. Public market asset classes have a significant proportion of their Sharpe ratio driven by macro-factors. In the private market space private equity and credit have larger macro-factor returns drivers. Of course, the liquidity factor plays a role in both.

Conversely, a high 'non-macro' Sharpe ratio reflects performance driven by idiosyncratic or structural premia outside the macro model – such as manager skill, deal sourcing, operational value creation and sector or geographical exposures. Returning to our previous discussion the illiquidity premium is also part of this non-macro Sharpe. At the high end of Sharpe ratio rankings in Graph 06 private infrastructure and IFM's UIP have very high attribution of their Sharpe ratios from these idiosyncratic factors. Our model suggests that these asset classes offer access to persistent alpha or structural risk premia and can enhance portfolio diversification by reducing exposure to systematic macro risk. This may justify to investors that exposure to these asset classes puts their illiquidity budget to good use as they are accessing returns drivers that are far less available in public markets.

GRAPH 06 **RISK-BASED PERFORMANCE ATTRIBUTION**



Source: IFM Investors, Bloomberg, MSCI, Preqin.



[4] Decomposition is based on the ratio of predicted variance to total variance. Note that the decomposition is approximate as 1) Sharpe ratios are not linearly additive and 2) the PLRAs employed do not guarantee that residuals are orthogonal to the fitted factors. This approach also assumes expected return contributions scale with risk contributions. On balance, this approach remains a useful practical tool to get a sense of what is driving risk-adjusted performance.

5. Portfolio implications

5.1.1 The allocator's challenge

Building resilient portfolios in today's environment and one that will be well-placed to produce robust returns in a highly uncertain future requires an evolution of traditional asset allocation principles. This is towards a Total Portfolio Approach (TPA) that integrates macroeconomic sensitivities, structural premia, and liquidity considerations into a unified framework. Our analysis of factor exposures across public and private markets provides actionable insights for positioning portfolios under different economic regimes, while ensuring that scarce resources – risk and illiquidity – are deployed where they deliver the greatest marginal benefit.

The following guidance translates these insights into a range (that is far from exhaustive) of practical portfolio construction choices for institutional investors. It is facilitated by Graph 07 that is a visualisation of the broad macro-elasticity and illiquidity trade-offs with each asset class.

5.1.2 Positioning for macro-views

Our factor model enables targeted expression of macro-views via assets with higher macro elasticities. This is most appropriate for tactical asset allocation in response to short term fluctuations in the economic cycle.

- **Spread tightening/risk-on environments**
  Best positioned: High yield credit, private credit, buyout private equity, cyclical equities, and commodities (especially petroleum and industrial metals).

  Why: These assets have strong positive loadings on credit and liquidity, benefiting when spreads tighten and financing/trading conditions improve (see Table 01 and Graph 06 for macro vs. non macro drivers).

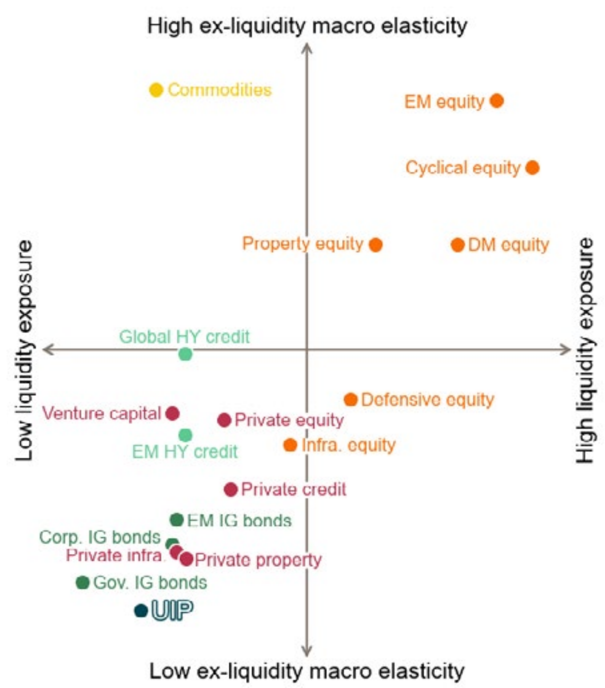
- **Growth acceleration**
  Best positioned: Growth oriented private equity, venture capital, cyclical equities, and industrial commodities.

  Why: These assets show significant positive sensitivity to the growth factor, reflecting dependence on economic expansion and capital availability.

- **Downturn/recession risk**
  Best positioned: Government and IG bonds, particularly long duration.

  Why: These assets have the strongest negative loading on rates level and inflation that would likely fall in a recessionary environment.

GRAPH 07 FACTOR SENSITIVITY QUADRANT



Source: IFM Investors, Bloomberg, MSCI, Preqin.

5.1.3 Inflationary environments

The persistence of inflation in the future is a key consideration for many investors, our model supports two key approaches to this potential environment:

- **Natural inflation hedges**
  In **public markets** energy and commodities exhibit strong positive inflation elasticities and act as direct cyclical hedges. However, strong linkages to growth present a risk should the cycle turn. This is also true of a stagflationary environment where a high exposure to growth risks eroding the effectiveness of the inflation hedge.

  In **private markets** infrastructure, and in particular IFM's UIP, offers potential inflation protection with a relatively low overall macro elasticity, making this asset class a useful hedge against inflation without adding large cyclical growth/credit exposure. We would normally expect property to be a good long term inflation hedge (due to CPI-linked rents) however that relationship has been clouded in our model as the supply-side inflation of the post-pandemic period corresponded with negative valuations compounded by higher interest rates.

- **Vulnerable assets**
  In **public markets** long duration IG/government bonds struggle in inflationary regimes and this impact is more pronounced as duration increases – this is well understood. Listed equities outside the energy space tend to find inflation a weak headwind to returns, though cyclical and consumer equities understandably are more exposed to higher rates of inflation. A key transmission to the listed space is via the higher rates inflation would bring and the negative impact from rates on returns is more pronounced and significant.

  In **private markets** growth/VC strategies display a strong negative inflation sensitivity due to valuation compression at higher discount rates that also impacts financing costs. Higher inflation also impacts that exit environment with M&A activity tending to slow when inflation uncertainty is high, reducing exit opportunities and pressuring valuations.

5.1.4 Diversification & resilience

A key theme for investors is seeking to improve portfolio 'robustness' in an increasingly uncertain geopolitical and investment environment. The focus here is on strategic rather than tactical allocation to set the portfolio up to best cope with unanticipated shifts in the investment landscape rather than to either predict or react to them as an investor might with short term tactical 'tilts'. Our analysis highlights two key approaches to improve portfolio robustness via:

- **Low macro elasticity assets**
  Private infrastructure and IFM's UIP, private real estate, and defensive equity sectors exhibit lower macro explanatory power (lower overall macro-elasticities and R^2 based macro-Sharpe contribution). This implies diversity in return drivers. We'd argue that private market assets comprise a material allocation of a portfolio depending on an investors risk tolerance. We'd also note our two stage unsmoothing shows higher true volatility; diversification benefits are thus more about distinct return drivers than simple volatility dampening.

- **Idiosyncratic drivers in private markets**
  The non macro Sharpe captures residual performance from manager skill, deal structuring, operational improvements, sector/region composition, and structural premia (including illiquidity). Private infrastructure and IFM's UIP ranks highly on this dimension (Graph 06), supporting its role as a diversifier with persistent non macro return drivers – a key facet of portfolio design to improve robustness.

5.1.5 Risk and illiquidity budgets

Investors applying a total portfolio approach are guided in their portfolio construction by explicit budgeting of both economic risk and illiquidity.

- **Macro risk budgeting**
  Our framework can inform the investor on how they might apportion their macro elasticities to calibrate exposure to growth, credit, rates, inflation, and liquidity. Investors can balance macro sensitive allocations (for return capture and tactical views) with macro insulated allocations (for drawdown control and regime diversification). Further, an investor can explore factor based scenario analysis and macro return ranges (Graph 05) to quantify tail risks and avoid concentration in pro cyclical exposures.

- **Illiquidity budgeting**
  Also in a total portfolio context we can consider the strategic role of illiquidity. This is as illiquidity is treated as its own risk factor constrained by portfolio needs (pension payments, rebalancing flexibility), stress scenarios (periods of market dislocations and redemption pressures) and governance tolerance (appetite for valuation uncertainty and long term commitment of capital). In doing so the investor treats illiquidity as a scarce resource to be deployed where compensation and diversification benefits are greatest.

  - **Private equity and private real estate:** Higher expected returns but more exposed to cyclical liquidity (refinancing/exit risk); allocate from the growth risk budget.

  - **Private infrastructure and IFM's UIP:** Delivers structural illiquidity premia with low cyclical liquidity sensitivity, plus inflation linkage – well suited to the defensive/real income budget. Ensuring the investor is compensated for extended investment horizons.

  - **Prioritise low macro elasticity,** high non macro Sharpe strategies for marginal illiquidity to allow for flexibility at the margin of the portfolio allocation.

5.1.6 Multi asset portfolio construction

Based on the assessments above the below are examples of how different asset classes may be thought of in a portfolio context.

- **Macro heavy assets:** Allocate towards HY credit, private credit, cyclical equities, and select commodities to express risk on and growth views; trim or hedge when targeting macro neutrality.
- **Macro resilient assets:** IFM's UIP and select private infrastructure provide predictability and potential inflation protection without adding large growth/credit elasticity; consider as strategic portfolio anchors.
- **Balanced inflation hedge:** Pair commodities/energy (high inflation elasticity) with UIP (inflation linked cash flows; low overall macro elasticity) for a hedge that limits cyclical amplification.
- **Private real estate:** Recognise that low measured inflation elasticity may reflect smoothing and structural breaks (GFC, COVID). Treat as a partial, lagged inflation hedge, not a tactical inflation tool.

5.1.7 Key takeaways for investors

- **Balance macro sensitive and macro insulated exposures** to improve resilience across regimes. To take advantage of cyclical views but also guard against them.
- **Deploy illiquidity strategically** – favour structural premia and non-macro Sharpe over headline returns.
- **Use factor insights tactically** to position for spread tightening, growth acceleration, or inflation shocks while keeping long term objectives intact.
- **Private infrastructure (and IFM's UIP in particular)** stand out as a defensive anchor with potential and non-macro return drivers.

5.2 Geopolitical risk

5.2.1 Why geopolitical risk matters

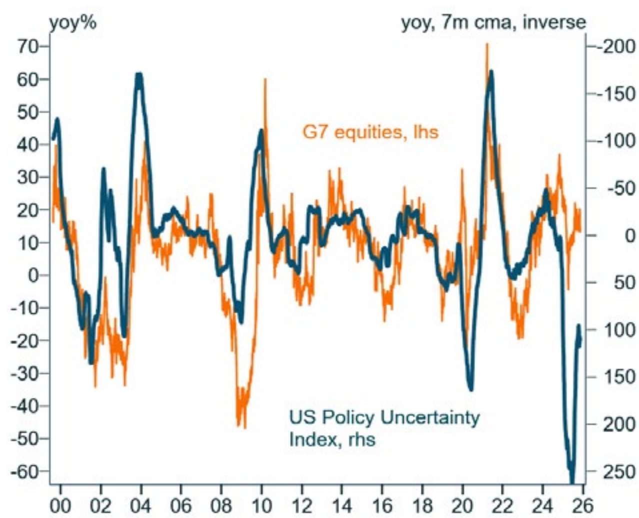
A highly uncertain geopolitical environment is at the forefront of investors' concerns as they look to asset allocate globally. This is not only recognising heightening risk of different jurisdiction but also the uncertainty that has risen in what would be described historically as low risk investment destinations. Geopolitical risk is increasingly recognised as a structural and asymmetric force in global markets. Within a Total Portfolio Approach (TPA), it is not treated as a standalone asset class but as a cross-cutting influence on macroeconomic factors such as growth, inflation, real rates, liquidity, and FX. This section outlines how geopolitical risk affects portfolio sensitivities and strategic responses, and how it can be embedded into macro-factor risk budgeting.

5.2.2 Macro-factor interaction

Geopolitical risk is a structural and asymmetric force that influences macroeconomic conditions through multiple transmission channels. While not a standalone factor in our model, these risks interact with the five macro factors – growth, inflation, rates, credit, and liquidity – in the following ways:

- **Growth:** Heightened geopolitical uncertainty (e.g., trade wars, sanctions, military conflicts) can dampen global trade, disrupt supply chains, and reduce investment confidence, leading to slower economic growth.
- **Inflation:** Supply-side shocks from conflicts or trade disputes/tariffs (via the energy space or more broadly) can drive cost-push inflation, even in weak demand environments.
- **Rates:** Central banks may respond to geopolitical shocks with policy easing to support growth or tightening if inflationary pressures dominate, altering real rate dynamics.
- **Credit:** Risk premiums widen during geopolitical stress as investors demand compensation for uncertainty, tightening credit conditions and raising borrowing costs.
- **Liquidity:** Market depth deteriorates in periods of heightened uncertainty, reducing risk appetite and amplifying volatility. Conversely, policy responses (e.g. quantitative measures or fiscal support) can temporarily offset these effects.

GRAPH 08 EQUITIES & ECONOMIC UNCERTAINTY



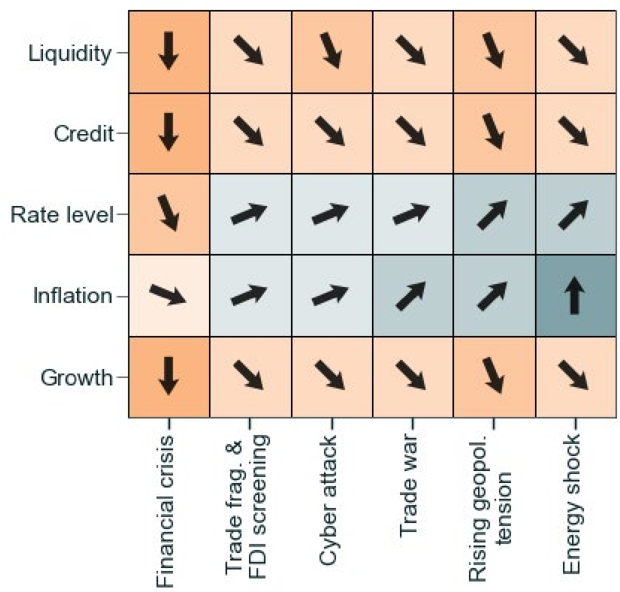
Source: IFM Investors, Bloomberg, PolicyUncertainty.com

5.2.3 Geopolitics and macro-factors

Understanding how geopolitical shocks propagate through macroeconomic channels and affect asset class performance is critical for robust portfolio design. To investigate this relationship through our framework we've constructed two complementary Scenario Impact Matrices (Graph 09 and 10) that translate qualitative risk narratives into quantitative insights grounded in our macro-factor model. While the qualitative aspect of this exercise is clearly an aspect that can be challenged the read through via our factor modelling to asset class returns is more robust. And indeed, the flexibility with which we can modify the qualitative assumptions and scenarios allows great flexibility to explore hypothetical scenarios and how portfolios may perform within them

Our first step is to define six plausible geopolitical scenarios – such as energy supply shocks, trade wars, and financial crises[5] – and mapped their expected impact to our five macroeconomic factors: growth, inflation, real rates, credit, and liquidity. Each scenario was calibrated using a qualitative scale (–2 to +2) to reflect the direction and relative severity of shocks. This matrix (Graph 09) provides a clear view of how geopolitical risks transmit through economic channels.

GRAPH 09 **SCENARIO FACTOR IMPACTS**



Source: IFM Investors, Bloomberg, MSCI, Preqin.

Note: Arrow angle represents magnitude of impact (up represents a +2SD shock, down represents a -2SD shock, and right represents no change).

Next, we quantified the sensitivity of asset classes to these scenarios using the macro elasticities estimated in our factor model. For each scenario, we calculated an impact score by multiplying the scenario's factor shocks by each asset's factor betas, preserving the economic structure of the model. Scores were normalized for visualization, highlighting relative winners and losers while retaining raw values for deeper analysis.

The asset-level matrix (Graph 10) reveals clear patterns in how different segments respond to geopolitical shocks. We briefly discuss highlights here:

- **Defensive asset classes:** Government bonds and high-grade corporate credit rank as relative 'winners' across scenarios. Their positive or least-negative scores reflect flight-to-quality dynamics and policy easing during stress events. For example, in a financial crisis scenario, government bonds benefit from falling real rates and widening credit spreads. Of private market assets, IFM's UIP also shows a relatively high degree of resilience due to its low macro elasticity and inflation-linked cash flows. These characteristics make such assets effective anchors for portfolio stability.

- **Moderately resilient assets:** Private infrastructure and defensive listed equities exhibit muted sensitivity to macro shocks. Their contracted or regulated revenue streams and lower reliance on refinancing reduce exposure to liquidity and credit tightening. These assets provide diversification benefits and help dampen portfolio-level volatility during geopolitical stress

- **Most vulnerable asset classes:** Cyclical equities, emerging market equities, and private growth strategies (venture capital and buyout private equity) show the largest negative scores under scenarios involving liquidity and credit shocks. For public markets this comes as the uncertainty contained in each scenario is immediately priced into markets. For private markets the transmission is likely through their dependence on external financing, high duration cash flows, and sensitivity to global trade and growth make them particularly exposed in risk-off environments. For instance, venture capital strategies suffer disproportionately in financial crises due to valuation compression and constrained exit opportunities.

The matrix underscores the importance of balancing macro-sensitive exposures with macro-insulated allocations. Defensive assets act as structural hedges, while high-beta strategies require careful sizing and liquidity planning to avoid concentration risk during geopolitical stress.

[5] Decomposition is based on the ratio of predicted variance to total variance. Note that the decomposition is approximate as 1) Sharpe ratios are not linearly additive and 2) the PLRAs employed do not guarantee that residuals are orthogonal to the fitted factors. This approach also assumes expected return contributions scale with risk contributions. On balance, this approach remains a useful practical tool to get a sense of what is driving risk-adjusted performance.

5.2.4 Key Takeaways on Geopolitics

- **Integrate geopolitical risk into macro risk budgeting,** treating geopolitical risk as a cross-cutting influence on macro factors (growth, inflation, rates, credit, liquidity), akin to an exogenous factor that needs to be considered. Allocate macro risk budgets with awareness that shocks can propagate through multiple channels simultaneously.

- **Diversify across geographies and jurisdictions** to reduce concentration in regions with correlated geopolitical risks. Prioritise assets with stable legal frameworks and predictable regulatory environments.

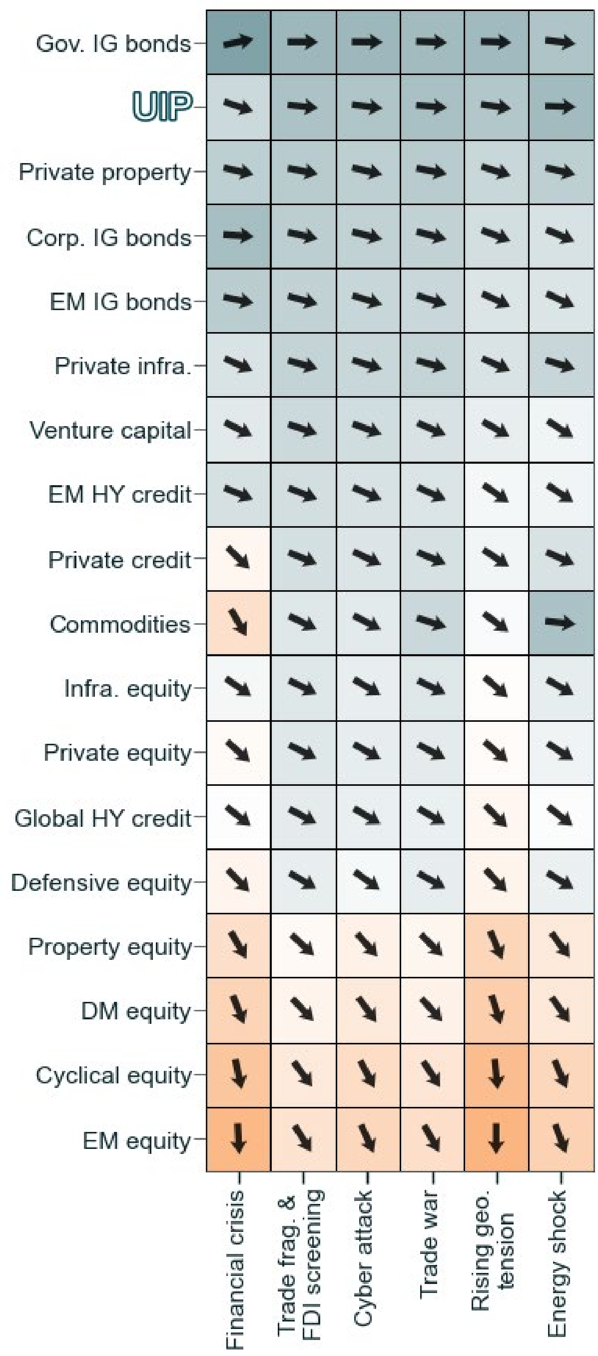
- **Balance macro sensitive and macro insulated exposures** employing macro-sensitive assets (e.g., EM equities, HY credit) for tactical positioning when geopolitical risks are low. Maintain macro-insulated allocations (e.g., core infrastructure, defensive private markets) as structural anchors for resilience.

- **Liquidity and credit buffers** which recognise that geopolitical shocks often tighten liquidity and widen credit spreads. Maintain liquidity buffers and credit-quality tilt to manage refinancing and funding risks.

- **Inflation and rate hedging** can be impactful as geopolitical disruptions can trigger cost-push inflation and policy rate volatility. Pair inflation-linked assets (for example infrastructure with CPI-linked revenues) with rate-sensitive hedges (e.g., duration management).

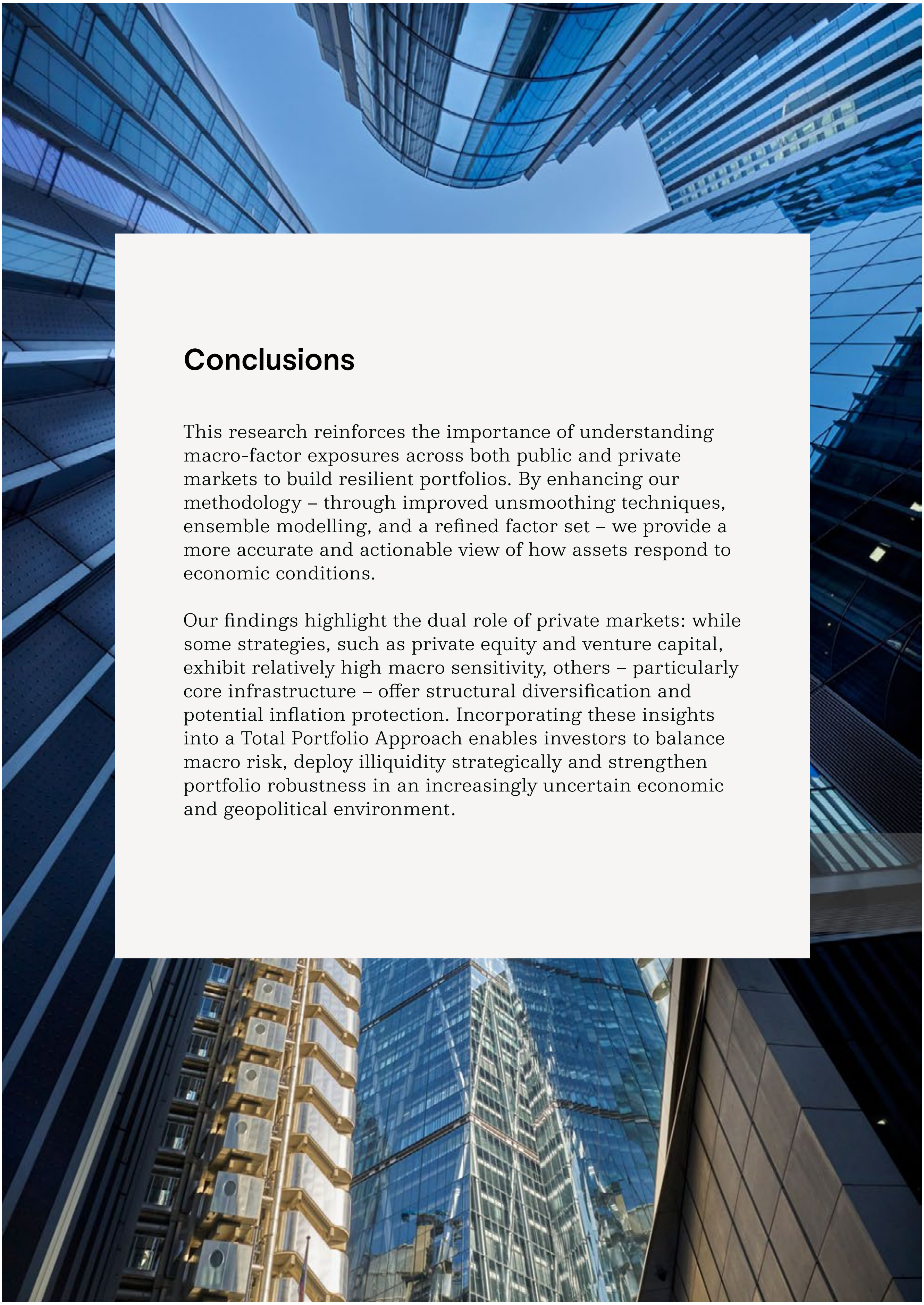
- **Scenario analysis and stress testing** by incorporating geopolitical scenarios into portfolio stress tests (e.g., conflict escalation, trade war, sanctions). Quantify tail risks and ensure drawdown resilience under asymmetric shocks. Within the Total Portfolio Approach this may assist in improving portfolio resilience and clarifies tactical versus strategic role definitions.

GRAPH 10 **SCENARIO FACTOR IMPACTS**



Source: IFM Investors, Bloomberg, MSCI, Preqin.

Note: Arrow angle represents magnitude of impact.



Conclusions

This research reinforces the importance of understanding macro-factor exposures across both public and private markets to build resilient portfolios. By enhancing our methodology – through improved unsmoothing techniques, ensemble modelling, and a refined factor set – we provide a more accurate and actionable view of how assets respond to economic conditions.

Our findings highlight the dual role of private markets: while some strategies, such as private equity and venture capital, exhibit relatively high macro sensitivity, others – particularly core infrastructure – offer structural diversification and potential inflation protection. Incorporating these insights into a Total Portfolio Approach enables investors to balance macro risk, deploy illiquidity strategically and strengthen portfolio robustness in an increasingly uncertain economic and geopolitical environment.

Appendix: Full asset class elasticities

Table 02: Model outputs – private markets

	Credit	Growth	Inflation	Liquidity	Rate level
Private equity* (R^2= 0.61)	4.5 (0.00)	1.1 (0.20)	-1.4 (0.12)	1.6 (0.13)	-0.5 (0.56)
MSCI PE ex-VC (R^2= 0.61)	4.4 (0.00)	1.1 (0.20)	-1.4 (0.12)	1.5 (0.12)	-0.5 (0.51)
Preqin PE ex-VC (R^2= 0.60)	4.6 (0.00)	1.1 (0.20)	-1.5 (0.11)	1.6 (0.13)	-0.4 (0.62)
Private equity (growth)* (R^2= 0.61)	2.8 (0.01)	2.0 (0.03)	-1.5 (0.07)	1.4 (0.15)	-0.8 (0.54)
MSCI PE (growth) (R^2= 0.58)	2.3 (0.01)	1.5 (0.03)	-1.2 (0.06)	1.5 (0.06)	0.0 (0.93)
Preqin PE (growth) (R^2= 0.64)	3.2 (0.01)	2.5 (0.02)	-1.9 (0.07)	1.3 (0.25)	-1.6 (0.15)
Private equity (buyout)* (R^2= 0.59)	4.6 (0.00)	1.1 (0.23)	-1.3 (0.16)	1.5 (0.16)	-0.4 (0.62)
MSCI PE (buyout) (R^2= 0.60)	4.5 (0.00)	1.2 (0.17)	-1.2 (0.16)	1.5 (0.15)	-0.6 (0.51)
Preqin PE (buyout) (R^2= 0.57)	4.7 (0.00)	0.9 (0.29)	-1.4 (0.15)	1.5 (0.16)	-0.3 (0.74)
Venture capital* (R^2= 0.54)	2.4 (0.24)	3.3 (0.02)	-3.7 (0.01)	1.4 (0.32)	-0.4 (0.71)
MSCI VC (R^2= 0.48)	0.7 (0.45)	2.9 (0.01)	-3.0 (0.02)	1.6 (0.17)	-0.4 (0.68)
Preqin VC (R^2= 0.59)	4.1 (0.03)	3.6 (0.02)	-4.5 (0.01)	1.2 (0.48)	-0.5 (0.74)
Private property* (R^2= 0.31)	1.0 (0.27)	2.3 (0.02)	-0.7 (0.37)	1.4 (0.13)	-0.8 (0.36)
MSCI real estate (R^2= 0.33)	1.3 (0.17)	2.0 (0.04)	-1.0 (0.22)	1.2 (0.19)	-0.6 (0.44)
Preqin real estate (R^2= 0.29)	0.7 (0.38)	2.7 (0.00)	-0.4 (0.52)	1.6 (0.07)	-0.9 (0.27)
Private credit* (R^2= 0.74)	3.2 (0.00)	0.4 (0.48)	-0.5 (0.35)	1.3 (0.12)	0.0 (0.85)
MSCI private credit (R^2= 0.77)	3.3 (0.00)	0.4 (0.48)	-0.5 (0.37)	1.1 (0.16)	-0.1 (0.89)
Preqin private credit (R^2= 0.70)	3.1 (0.00)	0.4 (0.48)	-0.5 (0.33)	1.4 (0.08)	0.2 (0.80)
Private infra.* (R^2= 0.32)	1.0 (0.09)	1.2 (0.04)	0.0 (0.80)	0.8 (0.13)	-0.5 (0.51)
MSCI private infra. (R^2= 0.43)	1.1 (0.01)	0.6 (0.06)	0.0 (0.84)	0.9 (0.03)	0.0 (0.91)
EDHEC infra300 (R^2= 0.20)	0.8 (0.17)	1.7 (0.02)	-0.1 (0.76)	0.8 (0.23)	-1.0 (0.10)
IFM's UIP (R^2= 0.22)	0.2 (0.32)	1.0 (0.01)	0.5 (0.08)	0.5 (0.08)	0.3 (0.28)

Source: IFM Investors, Bloomberg, MSCI, Preqin. *Constructed as average of two or more benchmarks.

Note: P-values in brackets. Intensity of highlight corresponds to statistical significance (darker=more significant). Colour corresponds to direction (green=positive, orange=negative).

Table 03: Model outputs - public markets

	Credit	Growth	Inflation	Liquidity	Rate level
Government IG bonds (R^2= 0.55)	-0.8 (0.00)	0.1 (0.34)	-0.8 (0.00)	0.1 (0.71)	-0.6 (0.00)
Corporate IG bonds (R^2= 0.47)	0.2 (0.35)	0.5 (0.06)	-1.1 (0.00)	0.7 (0.02)	-1.1 (0.00)
IG bonds (1-3Y) (R^2= 0.29)	-0.1 (0.01)	0.0 (0.94)	-0.1 (0.01)	0.0 (0.21)	-0.1 (0.00)
IG bonds (3-5Y) (R^2= 0.43)	-0.2 (0.06)	0.1 (0.34)	-0.4 (0.00)	0.0 (0.71)	-0.4 (0.00)
IG bonds (5-7Y) (R^2= 0.46)	-0.3 (0.08)	0.2 (0.16)	-0.7 (0.00)	0.1 (0.41)	-0.6 (0.00)
IG bonds (7-10Y) (R^2= 0.45)	-0.6 (0.04)	0.3 (0.18)	-1.0 (0.00)	0.2 (0.29)	-0.8 (0.00)
IG bonds (10Y+) (R^2= 0.48)	-1.5 (0.00)	0.5 (0.21)	-1.9 (0.00)	0.5 (0.17)	-1.3 (0.00)
EM IG bonds (R^2= 0.43)	1.1 (0.01)	0.3 (0.36)	-1.1 (0.00)	0.8 (0.04)	-0.9 (0.01)
Global HY credit (R^2= 0.82)	3.5 (0.00)	0.6 (0.14)	-1.0 (0.02)	0.8 (0.08)	-1.0 (0.05)
US HY credit (R^2= 0.81)	3.1 (0.00)	0.7 (0.08)	-0.8 (0.04)	0.8 (0.05)	-0.8 (0.05)
European HY credit (R^2= 0.78)	3.4 (0.00)	0.4 (0.19)	-1.2 (0.01)	1.5 (0.01)	-0.4 (0.25)
EM HY Credit (R^2= 0.59)	2.1 (0.00)	0.3 (0.28)	-1.3 (0.00)	0.8 (0.06)	-0.9 (0.03)
DM equity (R^2= 0.69)	3.5 (0.00)	2.0 (0.02)	-0.6 (0.32)	3.0 (0.00)	-1.8 (0.02)
Defensive equity (R^2= 0.58)	2.3 (0.00)	1.3 (0.03)	0.3 (0.43)	2.1 (0.01)	-1.4 (0.03)
Cyclical equity (R^2= 0.69)	3.9 (0.00)	2.3 (0.01)	-1.2 (0.12)	3.5 (0.00)	-1.8 (0.04)
EM equity (R^2= 0.72)	4.6 (0.00)	2.7 (0.01)	-1.0 (0.19)	3.3 (0.00)	-1.9 (0.04)
Telecoms equity (R^2= 0.29)	0.6 (0.06)	0.8 (0.03)	-0.1 (0.43)	1.2 (0.01)	-1.4 (0.00)
Consumer staples equity (R^2= 0.33)	0.8 (0.05)	1.0 (0.03)	-0.2 (0.32)	1.6 (0.00)	-0.5 (0.14)
Consumer discretionary equity (R^2= 0.61)	3.9 (0.00)	1.9 (0.03)	-2.0 (0.02)	2.9 (0.00)	-0.6 (0.35)
Energy equity (R^2= 0.64)	4.9 (0.00)	0.7 (0.38)	3.9 (0.00)	2.0 (0.09)	-3.1 (0.01)
Financials equity (R^2= 0.61)	4.3 (0.00)	2.3 (0.02)	-0.4 (0.46)	3.1 (0.01)	-0.9 (0.22)
Healthcare equity (R^2= 0.36)	1.6 (0.00)	0.3 (0.25)	-0.3 (0.30)	1.9 (0.00)	-0.3 (0.28)
Industrial equity (R^2= 0.69)	3.5 (0.00)	2.3 (0.01)	-0.6 (0.25)	3.3 (0.00)	-1.5 (0.05)
IT equity (R^2= 0.54)	2.7 (0.01)	1.2 (0.10)	-1.3 (0.08)	4.1 (0.00)	-1.1 (0.13)
Materials equity (R^2= 0.76)	4.4 (0.00)	1.9 (0.04)	0.1 (0.81)	3.7 (0.00)	-2.0 (0.03)
Utilities equity (R^2= 0.29)	0.4 (0.10)	1.0 (0.01)	0.0 (0.84)	1.4 (0.00)	-0.7 (0.04)
Infrastructure equity* (R^2= 0.45)	1.7 (0.01)	1.4 (0.01)	0.0 (0.84)	1.7 (0.01)	-1.5 (0.01)
Infrastructure equity 1 (R^2= 0.47)	1.6 (0.01)	1.6 (0.01)	0.0 (0.93)	2.0 (0.00)	-1.6 (0.01)
Infrastructure equity 2 (R^2= 0.48)	2.5 (0.00)	1.4 (0.01)	0.1 (0.78)	1.5 (0.01)	-1.6 (0.02)
Infrastructure equity 3 (R^2= 0.40)	0.8 (0.02)	1.1 (0.02)	0.0 (0.82)	1.6 (0.00)	-1.2 (0.01)
Property equity* (R^2= 0.51)	2.9 (0.00)	2.4 (0.01)	-1.0 (0.13)	2.3 (0.01)	-1.6 (0.04)
Property equity 1 (R^2= 0.46)	3.0 (0.00)	2.5 (0.01)	-0.7 (0.23)	2.0 (0.02)	-1.6 (0.04)
Property equity 2 (R^2= 0.52)	3.0 (0.00)	2.4 (0.01)	-1.1 (0.11)	2.4 (0.01)	-1.6 (0.04)
Property equity 3 (R^2= 0.56)	3.0 (0.00)	2.3 (0.01)	-1.1 (0.09)	2.6 (0.00)	-1.5 (0.03)
Property equity 4 (R^2= 0.49)	2.7 (0.00)	2.2 (0.01)	-1.0 (0.11)	2.3 (0.00)	-1.5 (0.04)
Commodities (R^2= 0.59)	3.7 (0.00)	2.1 (0.01)	3.2 (0.00)	0.6 (0.28)	-1.3 (0.08)
Precious metals (R^2= 0.15)	0.6 (0.12)	0.4 (0.21)	0.1 (0.66)	0.4 (0.16)	-1.8 (0.00)
Industrial metals (R^2= 0.51)	5.0 (0.00)	2.5 (0.01)	0.5 (0.35)	1.6 (0.07)	-2.0 (0.04)
Agriculture (R^2= 0.26)	1.9 (0.01)	1.8 (0.01)	1.9 (0.01)	0.0 (0.93)	-0.2 (0.53)
Petroleum (R^2= 0.66)	7.4 (0.00)	1.4 (0.28)	9.0 (0.00)	1.8 (0.22)	-3.2 (0.04)

Source: IFM Investors, Bloomberg, MSCI, Preqin. *Constructed as average of indented benchmarks beneath headline result.

Note: P-values in brackets. Intensity of highlight corresponds to statistical significance (darker=more significant).
Colour corresponds to direction (green=positive, orange=negative).

Data appendix

The following table lists the asset class benchmarks used in our analysis.

Table 04: Asset proxies

Asset	Proxy
Risk-free rate	ICE BofA US 3-Month Treasury Bill Index
Investment grade (IG) fixed income	Bloomberg Global Aggregate Corporate Total Return Index (Hedged, USD)
	Bloomberg Global Aggregate Government Total Return Index (Hedged, USD)
	Bloomberg Emerging Markets Investment Grade Total Return Index (Unhedged, USD)
	Bloomberg Global 1-3 Year Total Return Index (Hedged, USD)
	Bloomberg Global Aggregate 3-5 Year Total Return Index (Hedged, USD)
	Bloomberg Global Aggregate 5-7 Year Total Return Index (Hedged, USD)
	Bloomberg Global Aggregate 7-10 Year Total Return Index (Hedged, USD)
	Bloomberg Global Aggregate 10+ Year Total Return Index (Hedged, USD)
Sub-investment grade fixed income/Credit	Bloomberg US Corporate High Yield Total Return Index (Unhedged, USD)
	Bloomberg Pan-European High Yield Total Return Index (Hedged, USD)
	Bloomberg EM Hard Currency Aggregate Total Return Index (Hedged, USD)
	Bloomberg Global Aggregate Credit Total Return Index (Hedged, USD)
Listed equity	MSCI World Diversified Telecommunication Services Net Total Return Local index
	MSCI World Consumer Staples Net Total Return Local Index
	MSCI World Consumer Discretionary Net Total Return Local Index
	MSCI World Energy Net Total Return Local Index
	MSCI World Financials Net Total Return Local Index
	MSCI World Health Care Net Total Return Local Index
	MSCI World Industrials Net Total Return Local Index
	MSCI World Information Technology Net Total Return Local Index
	MSCI World Materials Net Total Return Local Index
	MSCI World Utilities Net Total Return Local Index
	MSCI World Core Infrastructure Net Total Return USD
	Dow Jones Brookfield Global Infrastructure Total Return Index
	MSCI World Infrastructure Net Total Return Local Index
	S&P Global REIT U.S. Dollar Net Total Return Index
	Bloomberg Developed Market Real Estate Large, Mid & Small Cap Net Return Index
	Bloomberg World Real Estate Large, Mid & Small Cap Net Return Index
	Nasdaq Developed Markets Real Estate Large & Mid Cap Net Total Return Index
Commodities	Bloomberg Commodity Index Total Return
	Bloomberg Precious Metals Subindex Total Return
	Bloomberg Industrial Metals Subindex Total Return
	Bloomberg Agriculture Subindex Total Return
	Bloomberg Petroleum Subindex Total Return
Private credit*	MSCI Global Private Credit Closed-End Fund Index
	Preqin Private Debt Index
Private equity*	MSCI Global Private Equity ex-Venture Capital Closed-End Fund Index
	MSCI Global Private Equity Buyout Closed-End Fund Index
	MSCI Global Private Equity Growth Closed-End Fund Index
	Preqin Private Equity excl. VC Index
	Preqin Growth Index
	Preqin Buyout Index
Venture capital*	MSCI Global Venture Capital Closed-End Fund Index
	Preqin Venture Capital Index
Private real estate*	MSCI Global Private Real Estate Closed-End Fund Index (USD)
	Preqin Real Estate Equity Index
Generic infra.*	MSCI Global Private Infrastructure Closed-End Fund Index (USD)
	EDHEC infra300 index (USD)
UIP	IFM unlisted infrastructure portfolio net return local currency index

* MSCI Closed-End Fund Indices are constructed using the average of USD and EUR denominated indices to reduce currency impacts unless otherwise noted

Technical Appendix

Unsmoothing parameters

Below we report the parameters from our unsmoothing estimation. Please see our April 2025 paper for a more detailed discussion of the methodology we employ.

Table 05: Unsmoothing parameters

	θ_0	θ_1	θ_2	θ_3	ϕ
MSCI PE ex-VC	0.58	0.21 (0.00)	0.21 (0.00)	-	0.20 (0.01)
Preqin PE ex-VC	0.49	0.30 (0.00)	0.21 (0.00)	-	0.34 (0.00)
MSCI PE (growth)	0.75	0.25 (0.00)	-	-	0.11 (0.22)
Preqin PE (growth)	0.47	0.23 (0.00)	0.17 (0.00)	0.13 (0.01)	0.23 (0.00)
MSCI PE (buyout)	0.58	0.20 (0.00)	0.22 (0.00)	-	0.19 (0.01)
Preqin PE (buyout)	0.49	0.29 (0.00)	0.22 (0.00)	-	0.31 (0.00)
MSCI VC	0.53	0.23 (0.00)	0.24 (0.00)	-	0.30 (0.01)
Preqin VC	0.35	0.19 (0.00)	0.28 (0.00)	0.17 (0.00)	0.42 (0.00)
MSCI real estate	0.42	0.33 (0.00)	0.25 (0.00)	-	0.30 (0.00)
Preqin real estate	0.44	0.28 (0.00)	0.27 (0.00)	-	0.36 (0.00)
MSCI private credit	0.68	0.32 (0.00)	-	-	0.19 (0.00)
Preqin private credit	0.66	0.34 (0.00)	-	-	0.28 (0.00)
MSCI private infra.	0.77	0.23 (0.00)	-	-	0.04 (0.59)
IFM's UIP	0.80	0.20 (0.00)	-	-	0.09 (0.23)

Source: IFM Investors, Bloomberg, MSCI, Preqin.

Note: P-values in brackets . theta_0 has no p-value as it is not independently estimated, it is derived from the other parameters based on a constraint assumed within the model.

Constructing the liquidity factor

We create a composite global liquidity factor based on the methodology introduced in Pastor & Stambaugh (2003) and Amihud (2002). We source daily stock price and volume data from key equity indices the US (S&P 500, S&P 400 MidCap, S&P 600 SmallCap), UK/Europe (FTSE All-Share, STOXX Europe 600, Bloomberg Europe Developed Markets Mid & Small Cap), and Japan (Nikkei 225, Bloomberg Japan Mid & Small Cap) over our analysis window and then construct both the Pastor-Stambaugh (PS) and Amihud liquidity measures for each country before constructing a market-cap weighted average PS and Amihud measure to represent global liquidity conditions. We then use PCA to extract the first principal component of the average liquidity measures to serve as our global composite liquidity indicator.[6] We have opted to use both liquidity measures together as liquidity is difficult to measure and the approaches look at liquidity from different perspectives such that combining the factors is likely to better capture the aggregate cyclical liquidity exposure of the assets examined.

Amihud:

The Amihud liquidity measure is based on the idea that more illiquid stocks experience larger price movements for a given trading volume than more liquid stocks. The Amihud liquidity measure $L_{i,t}$ for stock i on day t is calculated according to:

$$\mathcal{L}_{i,t} = \frac{|R_{i,t}|}{V_{i,t}}$$

Where $|R_{it}|$ is the absolute return of stock i on day t and V_{it} is the dollar trading volume (i.e. the stock price multiplied by the number of shares traded) of stock i on day t.

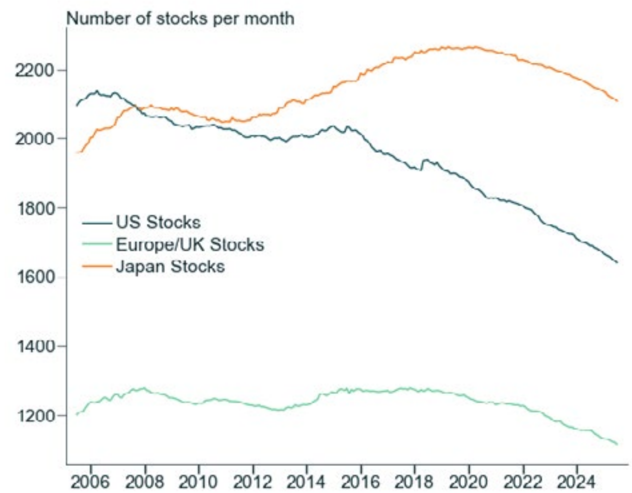
We then estimate the monthly Amihud liquidity measure for each stock i as the mean of that stock's daily Amihud liquidity measure in each month m as below:

$$\hat{\mathcal{L}}_{i,m} = \frac{1}{T}\sum_{t=1}^{T} \hat{\mathcal{L}}_{i,t}$$

Where T is the number of days in each month that a given stock has observations for. We then estimate the market-wide monthly Amihud liquidity measure, $\hat{L}_m$, in month m as the median of the cross sectional Amihud liquidity measures, $\hat{L}_{i,m}$, in the sample. Note that we have opted to aggregate using the median rather than the mean as there are often a number of sizeable outliers which dramatically skew the data such that the median-based measure tends to be more stable and robust. The number of stocks used to estimate the liquidity measure for the US range from 1,641-2,137, Europe/UK from 1,116-1,278 and Japan from 1,959-2,264 (see Graph 11).

[6] Please refer to the multicollinearity discussion in the appendix for further discussion regarding the appropriateness of using this PCA-based approach.

GRAPH 11 LIQUIDITY FACTOR STOCK UNIVERSE



Source: IFM Investors, Bloomberg.

Pastor-Stambaugh:
The Pastor-Stambaugh (PS) liquidity measure is based on return reversals following volume-driven price changes. In this context the authors define liquidity as the ease with which a stock can be traded without affecting the price of the stock. The key variable of interest in our analysis context is the market-wide liquidity innovation factor. This factor, L_t, is calculated in several steps. Firstly, for stock i in month t the authors estimate Y_{it} from the OLS regression below:

$$r^e_{i,d+1,t} = \theta_{i,t} + \phi_{i,t} r_{i,d,t} + \gamma_{i,t} \text{sign}\left(r^e_{i,d,t}\right) \cdot v_{i,d,t} + \epsilon_{i,d+1,t}, \quad d = 1, \dots, D$$

Where:

- $r_{i,d,t}$ is the return of stock i on day d in month t
- $r^e_{i,d,t}$ is given by $r_{i,d,t}$-$r_{m,d,t}$ where $r_{m,d,t}$ is the market return on day d in month t
- $v_{i,d,t}$ is the dollar volume for stock i on day d in month t

The market-wide estimate $\hat{Y}_t$ in month t is calculated as the average of the estimated coefficients:

$$\hat{\gamma}_t = \frac{1}{N} \sum_{i=1}^{N} \hat{\gamma}_{i,t}$$

To construct the liquidity innovation factor, the authors then define a scaled monthly first differenced series according to:

$$\Delta\hat{\gamma}_t = \frac{m_t}{m_1} \left(\hat{\gamma}_t - \hat{\gamma}_{t-1}\right)$$

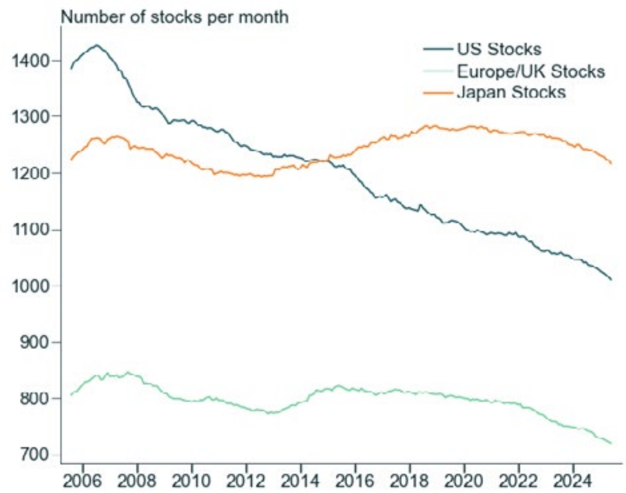
Where m_t is the total dollar volume of the stocks at the end of month t-1 that have been included in the average in month t. The authors then regress $\Delta\hat{Y}_t$ on its lag and the lagged value of the scaled level series as follows:

$$\Delta\hat{\gamma}_t = \alpha + \beta_1 \Delta\hat{\gamma}_{t-1} + \beta_2 \left(\frac{m_t}{m_1}\right) \hat{\gamma}_{t-1} + \epsilon_t$$

And from there the factor of interest, the innovation in liquidity, L_t, is estimated according to:

$$\mathcal{L}_t = \frac{\hat{\epsilon}_t}{100}$$

GRAPH 12 POST-FILTERING PS STOCK UNIVERSE



Source: IFM Investors, Bloomberg.

We make a number of methodological adjustments on the filtering criteria used by PS in order to minimise the potential impact of outlier stocks. Specifically, PS excluded stocks with prices under $5 and over $1,000, required at least 15 observations per month, and required stocks to have at least 12 months of valid observations to be included. Our modifications are as follows

- Exclude stocks whose prices fall outside of the bottom 1% and above the top 99% of prices each month (likely a better exclusionary criteria given the non-stationarity of aggregate stock prices over time)
- Exclude stocks in the bottom 10% of dollar trading volumes in each month (thinly traded stocks may bias results)
- We require at least 16 observations per month
- We require at least 12 consecutive months of valid monthly observations to improve the stability of included stocks throughout the estimation procedure

Once this filtering has been applied, the number of stocks for the US range from 1,010-1,425, Europe/UK from 720-846 and Japan from 1,193-1,282 (see Graph 12).

Multicollinearity examination:

Summary: We compare OLS to penalized linear regression algorithms (PLRAs) and we use a PCA approach to construct a composite liquidity factor to to diagnose and mitigate multicollinearity. The key challenge is the strong co-movement between the Amihud illiquidity measure and credit, which materially inflates variance and undermines interpretability. Our evidence suggests that (i) PLRAs reduce coefficient volatility relative to OLS, and (ii) replacing separate Amihud/Pastor–Stambaugh liquidity measures with a PCA-based liquidity factor further stabilises the credit and liquidity coefficients. We therefore proceed with our Ensemble (PCA) specification as the primary, multicollinearity robust model. See the model comparison section below for further discussion of how we selected our model.

Details: Multicollinearity occurs when two or more independent variables in a regression model are highly correlated, suggesting that the correlated variables contain overlapping information about the variation in the dependent variable. This is problematic for inference as it can lead to unstable coefficients and inflated standard errors (among other issues).

We find evidence that problematic multicollinearity likely exists in some model and factor specifications. Specifically, we find high Variance Inflation Factors[7] (VIFs) and concerningly strong correlation between the Amihud liquidity factor and the credit factor.[8] VIFs are presented in Table A1.

There is no universally accepted cutoff for what constitutes an unacceptably high VIF as this question is dependent on context, but for the purposes of this piece we opt to take a more conservative approach and aim to keep VIFs below three. We consider three candidate factor sets which we will refer to as factor sets A, B, and C. Factor sets B and C regularly breach our VIF threshold with the Amihud liquidity and credit factor VIFs of particular concern. This further motivates our decision to avoid the inclusion of the VIX, DXY, and commodities factors and also to consolidate the liquidity measures via a single PCA-based liquidity factor (see liquidity factor construction section for more information).

We quantify the practical impacts on coefficient stability of using our PCA-based liquidity factor and PLRA ensemble by comparing the dispersion of bootstrapped coefficients across four model variants:

- **OLS** (Amihud + PS),
- **OLS (PCA)** (PCA liquidity replaces Amihud/PS),
- **Ensemble** (PLRA with Amihud + PS), and
- **Ensemble (PCA)** (PLRA with PCA liquidity).

We apply the Levene test – a robust statistical test for comparing variances across groups – to assess the statistical significance of changes in bootstrapped coefficient instability across the four model variants. Unlike tests that assume normality, the Levene test is less sensitive to departures from normality, making it well-suited to this context. We apply a block bootstrap (1,000 samples of 20 consecutive observations with replacement) and report a standardised measure of dispersion (standard deviation divided by median absolute effect size) with the p-values from the Levene test (see Table A2). Our results suggest that:

Table A1: VIFs

	Factor set A	Factor set B	Factor set C
Inflation	1.93	2.22	4.43
Inflation lag	2.18	2.57	3.54
Growth	2.9	4	4.47
Growth lag	1.69	2.16	2.6
Credit	1.78	4.39	4.79
Credit lag	2.43	4.43	4.84
Rate level	1.37	1.48	1.99
Rate level lag	1.34	1.39	1.79
PCA liquidity	1.84	-	-
PCA liquidity lag	1.9	-	-
Pastor-Stambaugh liquidity	-	1.2	1.3
Pastor-Stambaugh liquidity lag	-	1.51	1.55
Amihud liquidity	-	4.52	6.74
Amihud liquidity lag	-	6.53	8.37
VIX	-	-	4.13
VIX lag	-	-	4.33
DXY	-	-	1.7
DXY lag	-	-	1.59
Broad commodities	-	-	3.74
Broad commodities lag	-	-	3.35

Source: IFM Investors, Bloomberg.

- OLS vs OLS (PCA): Statistically significant reductions in coefficient variability primarily for credit and liquidity, consistent with removing shared variance via PCA.
- OLS vs Ensemble: Significant reductions for four of five factors using separate liquidity measures, highlighting the stabilizing effect of penalization under multicollinearity.
- Ensemble vs Ensemble (PCA): A further, economically meaningful reduction in liquidity coefficient volatility (and some spillover improvement in credit), supporting the PCA-based consolidation even after penalisation.

[7] The VIF is a is a measure used in regression analysis to detect multicollinearity and quantifies how strongly an independent variable is linearly related to the other independent variables.

[8] Regressing the Amihud liquidity factor on the credit factor results in an R_2 of 0.81.

Table A2: Comparing coefficient volatility in different model specifications

Factor	OLS vs OLS (PCA)	OLS vs Ensemble	OLS vs Ensemble (PCA)	OLS (PCA) vs Ensemble	OLS (PCA) vs Ensemble (PCA)	Ensemble vs Ensemble (PCA)
Inflation	0.07 (0.15)	-0.43 (0.11)	-0.32 (0.06)	-0.49 (0.00)	-0.4 (0.02)	0.11 (0.22)
Growth	-0.12 (0.07)	-0.56 (0.00)	-0.64 (0.00)	-0.47 (0.03)	-0.56 (0.00)	-0.1 (0.28)
Credit	-0.22 (0.02)	-0.68 (0.00)	-0.6 (0.00)	-0.45 (0.09)	-0.42 (0.02)	0.00 (0.11)
Rate level	0.08 (0.07)	-0.48 (0.01)	-0.31 (0.06)	-0.56 (0.04)	-0.39 (0.08)	0.25 (0.19)
Liquidity	-0.64 (0.00)	-0.57 (0.00)	-0.99 (0.00)	-0.01 (0.04)	-0.45 (0.00)	-0.45 (0.00)

Source: IFM Investors, Bloomberg.

Note: Values represent the standard deviation divided by median absolute effect size to improve comparability across tests.
Highlights indicate statistically significant difference in coefficient volatility at the 10% level. Orange indicates higher volatility in the second model, green indicates higher volatility in the first model.

Taken together, these results are consistent with multicollinearity between credit and the Amihud liquidity factor being the main driver of instability, and with PCA and penalization providing complementary remedies. These results suggest that the ensemble (PCA) specification is the least impacted by multicollinearity and delivers the most stable and interpretable coefficient set overall. We therefore use the ensemble (PCA) as our baseline model.

Model comparison:

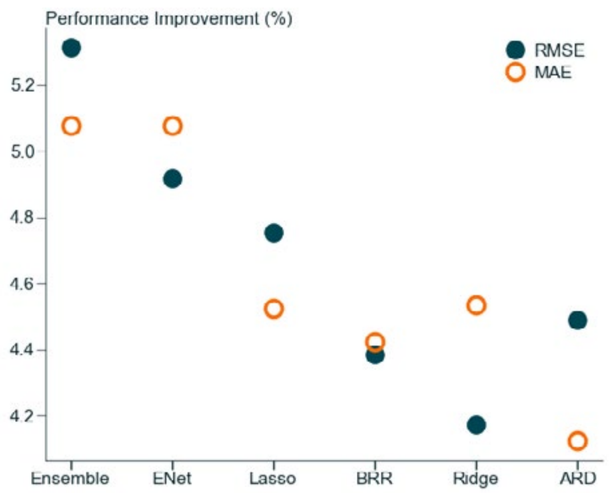
We use resampling techniques to evaluate the out-of-sample predictive performance of the candidate penalised linear regression algorithms (PLRAs) relative to the ordinary least squares (OLS) benchmark. Specifically, we draw 200 bootstrap samples from our monthly dataset, each consisting of 65 sequential training observations followed by 20 sequential testing observations. For each sample, we fit the candidate PLRAs and OLS to the training data and compute the root mean square error (RMSE) and mean absolute error (MAE) on the test set.

The choice of a relatively small number of observations in each sample (65 training and 20 testing observations) reflects a practical balance between statistical reliability and the constraints imposed by our dataset. With 225 total observations, this setup is intended to allow for sufficient data to estimate model parameters and evaluate predictive performance, while maintaining a reasonable number of resamples. Although perfect independence is not achievable in time series data, this sample size helps preserve to some degree the assumption of approximate independent and identically distributed (IID) samples, which underpins the validity of bootstrap-based inference. By avoiding excessive overlap between resamples, we reduce the risk of bias and ensure that the variability captured across simulations reflects true underlying relationships rather than artefacts of repeated data.

Importantly, all models are trained and evaluated on the same resampled datasets, which allows us to treat the resulting performance metrics as paired observations. This pairing means that models are compared within the same data context, controlling for sample-specific variation. Paired designs increase the statistical power of hypothesis tests by reducing within-group variability and focusing the comparison on the within-sample differences, rather than across-sample noise.

To assess the significance of RMSE and MAE differences we employ the Wilcoxon signed-rank test as our primary statistical test. This non-parametric test is particularly well-suited to our context as it does not assume normality of the error distribution and is robust to outliers and skewed data. The Wilcoxon test is commonly described as testing for differences in medians but, more precisely, the test evaluates whether the distribution of paired differences is symmetrically centred around zero by ranking the absolute differences and considering their signs. For simplicity, however, we present the median percentage differences in RMSE and MAE and associated significance in Table A3. See Graph 13 for a visualisation of median performance improvements versus OLS for each of the PLRAs.

GRAPH 13 **PERFORMANCE IMPROVEMENT (MEDIAN BASED)**



Source: IFM Investors, Bloomberg.

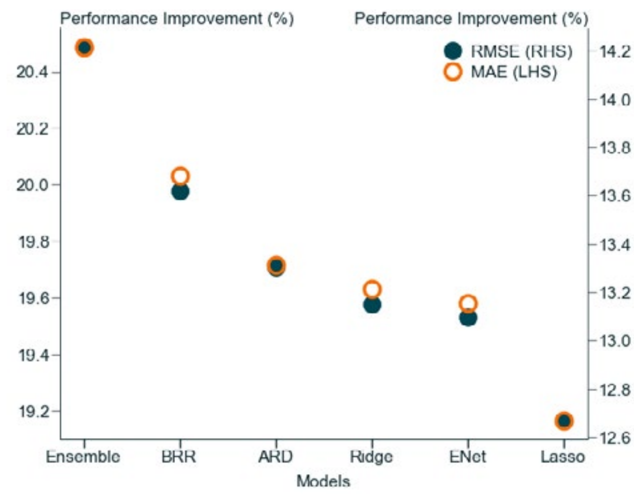
As a robustness check, we also conduct a paired t-test on bootstrapped differences. Specifically, we generate 1,000 bootstrapped samples of size 30 and compute the mean difference in performance metrics between the candidate PLRAs and OLS. This approach leverages the central limit theorem (CLT), which suggests that the sampling distribution of the mean difference will approximate normality even if the underlying data are not normally distributed, provided the sample size is sufficiently large. While the t-test is parametric and sensitive to distributional assumptions, the bootstrapping procedure mitigates this to some degree by empirically estimating the sampling distribution, lending some credibility to the inference drawn, though we use it only as a secondary test here. We present the mean percentage RMSE and MAE differences and significance in Table A3. See Graph 14 for a visualisation of the mean performance improvements versus OLS for each of the PLRAs.

In addition to individual model comparisons, we introduce a parameter-level ensemble model, constructed by averaging the estimated coefficients and intercepts from the five PLRAs. This ensemble approach aims to capture the shared signal across models while smoothing out idiosyncratic noise. We assess whether this aggregated model offers further predictive benefits beyond those provided by each PLRA in isolation.

To account for the multiple hypothesis tests conducted across assets we apply the Benjamini-Hochberg (BH) correction to control the false discovery rate (FDR). The FDR represents the expected proportion of false positives among all statistically significant results. The BH procedure adjusts p-values in a way that balances the need to identify true effects while limiting the risk of spurious findings. This is particularly appropriate in our context, where numerous hypothesis tests increase the likelihood of Type I errors. By applying the BH correction, we ensure that our inferences about model performance remain statistically valid and robust.

Note that for readability we aggregate assets by asset class and show the mean performance improvement and BH-adjusted p-values in the tables. This aggregation approach is more appropriate than calculating the average across all assets for two reasons: 1) assets within a class tend to behave more similarly than assets in

GRAPH 14 **PERFORMANCE IMPROVEMENT (MEAN BASED)**



Source: IFM Investors, Bloomberg.

Table A3: Comparing PLRA out-of-sample performance to OLS

		RMSE						MAE					
		Ensemble	Enet	Ridge	Lasso	BRR	ARD	Ensemble	Enet	Ridge	Lasso	BRR	ARD
Wilcoxon (median-based)	Equity	-5.41 (0.00)	-5.88 (0.00)	-5.63 (0.00)	-5.61 (0.00)	-4.58 (0.00)	-4.30 (0.00)	-5.08 (0.00)	-5.49 (0.00)	-5.76 (0.00)	-5.14 (0.00)	-4.63 (0.00)	-3.85 (0.00)
	Commodities	-4.65 (0.00)	-3.85 (0.13)	-3.95 (0.05)	-3.58 (0.09)	-4.38 (0.00)	-3.86 (0.00)	-3.53 (0.00)	-3.01 (0.23)	-2.74 (0.03)	-2.23 (0.13)	-3.63 (0.00)	-3.44 (0.00)
	Sub-IG/credit	-5.14 (0.00)	-5.38 (0.00)	-3.22 (0.00)	-4.62 (0.00)	-3.85 (0.00)	-3.84 (0.00)	-5.28 (0.00)	-5.83 (0.00)	-4.32 (0.00)	-4.33 (0.00)	-4.04 (0.00)	-2.90 (0.17)
	IG fixed	-6.06 (0.00)	-4.56 (0.00)	-3.90 (0.00)	-5.22 (0.00)	-4.73 (0.00)	-5.96 (0.00)	-6.41 (0.00)	-5.98 (0.00)	-5.31 (0.00)	-6.39 (0.00)	-5.39 (0.00)	-6.30 (0.00)
T-test (mean-based)	Equity	-15.74 (0.00)	-15.55 (0.00)	-15.62 (0.00)	-14.74 (0.00)	-15.35 (0.00)	-14.08 (0.00)	-11.06 (0.00)	-10.86 (0.00)	-10.99 (0.00)	-10.23 (0.00)	-10.63 (0.00)	-9.42 (0.00)
	Commodities	-21.52 (0.00)	-20.38 (0.00)	-20.19 (0.00)	-19.76 (0.00)	-21.32 (0.00)	-20.41 (0.00)	-15.07 (0.00)	-13.80 (0.00)	-13.60 (0.00)	-12.80 (0.00)	-14.84 (0.00)	-14.24 (0.00)
	Sub-IG/credit	-23.02 (0.00)	-22.16 (0.00)	-22.11 (0.00)	-21.95 (0.00)	-22.38 (0.00)	-22.40 (0.00)	-15.49 (0.00)	-14.64 (0.00)	-14.46 (0.00)	-14.10 (0.00)	-14.93 (0.00)	-14.39 (0.00)
	IG fixed	-21.66 (0.00)	-20.06 (0.00)	-20.39 (0.00)	-20.22 (0.00)	-20.85 (0.00)	-21.95 (0.00)	-15.24 (0.00)	-13.33 (0.00)	-13.79 (0.00)	-13.54 (0.00)	-14.32 (0.00)	-15.20 (0.00)

Source: IFM Investors, Bloomberg.

Note: Values are the percentage improvement in average performance metrics using OLS as the benchmark (negative number indicates improvement). Green indicates statistically significant improvement over OLS at or above the 1% level.

different classes such that aggregating across classes may obscure important differences in model performance between asset classes; and 2) the all-asset averages will be skewed because there are differing numbers of assets within each class (e.g. 21 equities and 5 commodities).

Empirically, all individual PLRAs outperform the OLS benchmark at or above the 1% level of statistical significance, with strong evidence of economically meaningful effect sizes in the vast majority of cases (see Table A3). The Wilcoxon test – being median based and non-parametric – provides more conservative estimates of improvement while the t-test – being mean based and parametric – shows larger average gains. These results suggest that penalisation not only improves predictive accuracy but also yields more stable and generalisable models.

We also find evidence that the ensemble model tends to outperform the individual PLRAs. This is consistent with ensemble learning theory, which suggests that aggregating predictions from diverse models can reduce variance and improve generalisation performance. By averaging across different penalised estimators, the ensemble smooths out idiosyncratic errors and captures more stable patterns in the data. To formally assess whether the ensemble offers statistically significant improvements over its individual components, we repeat the same testing procedure as above, this time using each individual PLRA as the benchmark instead of OLS (see Table A4). The results indicate statistically significant outperformance by the ensemble model in many cases. However, the magnitude of these improvements is generally more moderate than the gains observed when comparing PLRAs to the OLS benchmark, reflecting the already strong performance of the individual penalised models.

Another benefit of the PLRA-based approaches is their ability to reduce coefficient volatility relative to OLS. This is primarily due to the regularisation penalties which constrain the size of the estimated coefficients. By discouraging extreme values, regularisation reduces sensitivity to noise and multicollinearity, leading to more stable and interpretable models. This stability is desirable for several reasons: it improves generalisation to new data, enhances model robustness, and increases confidence that the estimated coefficients are close to the true underlying parameters. To formally assess differences in coefficient variability between the ensemble and OLS approaches, we apply the Levene test, a robust statistical test for comparing variances across groups. Unlike tests that assume normality, the Levene test is less sensitive to departures from normality, making it well-suited to this context.

To aid interpretation, we standardise the difference in coefficient standard deviations by the median absolute coefficient size, allowing for comparability across factors with different scales. Many of the reductions in volatility are not only statistically significant but also economically meaningful (see Table A5). For example, values below –1 for growth in IG fixed income and inflation in equity suggest that the average reduction in coefficient variability is large relative to the typical effect size – highlighting the stabilising impact of regularisation.

Table A4: Comparing ensemble out-of-sample performance to individual PLRAs

		RMSE					MAE				
		Enet	Ridge	Lasso	BRR	ARD	Enet	Ridge	Lasso	BRR	ARD
Wilcoxon (median-based)	Equity	-0.17 (0.25)	0.08 (0.27)	-0.54 (0.17)	-0.41 (0.22)	-1.22 (0.11)	-0.24 (0.34)	0.15 (0.37)	-0.48 (0.21)	-0.23 (0.25)	-1.44 (0.08)
	Commodities	-0.93 (0.05)	-1.42 (0.00)	-1.56 (0.01)	-0.17 (0.01)	-0.40 (0.14)	-1.11 (0.08)	-1.41 (0.00)	-2.04 (0.00)	-0.36 (0.20)	-0.19 (0.00)
	Sub-IG/credit	-0.74 (0.01)	-1.05 (0.04)	-1.08 (0.01)	-0.92 (0.00)	-0.57 (0.19)	-0.78 (0.00)	-0.80 (0.32)	-1.62 (0.00)	-0.64 (0.28)	-1.33 (0.14)
	IG fixed	-1.19 (0.00)	-1.47 (0.03)	-0.49 (0.13)	-0.88 (0.17)	0.75 (0.24)	-1.17 (0.00)	-1.44 (0.10)	-0.64 (0.04)	-0.89 (0.11)	1.04 (0.28)
T-test (bootstrapped mean-based)	Equity	-0.23 (0.00)	-0.14 (0.00)	-1.17 (0.01)	-0.46 (0.02)	-1.94 (0.00)	-0.23 (0.01)	-0.07 (0.04)	-0.92 (0.04)	-0.48 (0.00)	-1.81 (0.00)
	Commodities	-1.44 (0.03)	-1.67 (0.00)	-2.19 (0.00)	-0.26 (0.00)	-1.40 (0.00)	-1.47 (0.09)	-1.70 (0.00)	-2.60 (0.00)	-0.27 (0.00)	-0.97 (0.00)
	Sub-IG/credit	-1.11 (0.00)	-1.16 (0.00)	-1.37 (0.00)	-0.82 (0.00)	-0.80 (0.00)	-1.00 (0.00)	-1.21 (0.11)	-1.62 (0.00)	-0.66 (0.00)	-1.28 (0.00)
	IG fixed	-2.01 (0.00)	-1.59 (0.00)	-1.81 (0.00)	-1.02 (0.08)	0.37 (0.00)	-2.20 (0.00)	-1.67 (0.00)	-1.96 (0.00)	-1.07 (0.00)	-0.05 (0.10)

Source: IFM Investors, Bloomberg.

Note: Values are the percentage improvement in average performance metrics using the indicated PLRA as the benchmark (negative number indicates improvement). Green indicates statistically significant result at the 10% level where the ensemble outperforms the indicated PLRA.

Table A5: Comparing coefficient volatility of ensemble vs OLS

	Credit	Growth	Inflation	Liquidity	Rate level
Equity	-0.190 (0.22)	-0.648 (0.00)	-1.068 (0.00)	-0.484 (0.00)	-0.569 (0.00)
Commodities	-0.479 (0.00)	-1.491 (0.00)	-0.637 (0.00)	-1.033 (0.00)	-0.309 (0.01)
Sub-IG/credit	-0.082 (0.48)	-0.739 (0.00)	-0.297 (0.00)	-0.328 (0.08)	-0.127 (0.02)
IG fixed	-0.148 (0.16)	-1.005 (0.00)	-0.256 (0.00)	-0.641 (0.00)	-0.096 (0.04)

Source: IFM Investors, Bloomberg.

Note: Values represent the standard deviation divided by median absolute effect size to improve comparability across factors.

Levene test comparing ensemble coefficient volatility to OLS coefficient volatility. Green indicates statistically significantly lower volatility in ensemble at 5% level or above.

Cross-validation approach:

In our previous paper we applied a time-series aware cross-validation approach called walk-forward blocking time series cross-validation (WFCV) which uses non-overlapping, fixed-size training windows to estimate hyperparameters. This contrasts with the more commonly used time series cross-validation (TSCV) approach which uses a growing training window. While TSCV benefits from larger training sets, it may introduce bias if early data are not representative of later dynamics. The main drawback to both of these approaches, however, is that they are relatively 'data greedy' given that they are specifically designed to preserve the temporal dependence of time series data. This can be problematic if CV splits have a small number of observations and limited fold diversity. Here we more formally investigate whether there are any economically or statistically significant impacts on performance between WFCV and TSCV. As a robustness check we also explore whether a non-time series aware approach can improve performance given the higher data efficiency afforded by relaxing the restriction on preserving temporal dependency in the training set. The non-time series aware approach we use is random permutation cross-validation (RPCV) where the data are shuffled and then split into training and testing sets.

We apply the same testing procedure as in the model comparison section above and present the results in Table A6 below.

There is some weak evidence that the TSCV approach outperforms both the RPCV and WFCV, though the magnitude of the improvements is small (well below 1% improvement in the median-based test) and is not economically significant. We proceed with TSCV as our preferred CV method.

Table A6: Comparing out-of-sample performance of CV methods

		RMSE			MAE		
		RPCV vs TSCV	RPCV vs WFCV	TSCV vs WFCV	RPCV vs TSCV	RPCV vs WFCV	TSCV vs WFCV
Wilcoxon (median-based)	Equity	0.089 (0.12)	0.090 (0.14)	-0.005 (0.11)	0.093 (0.10)	0.121 (0.19)	-0.005 (0.29)
	Commodities	-0.087 (0.30)	-0.100 (0.26)	-0.002 (0.16)	-0.012 (0.12)	-0.106 (0.21)	-0.002 (0.31)
	Sub-IG/credit	-0.018 (0.49)	0.013 (0.49)	-0.006 (0.38)	-0.008 (0.20)	-0.027 (0.56)	-0.029 (0.18)
	IG fixed	0.001 (0.43)	-0.198 (0.18)	-0.069 (0.13)	-0.018 (0.42)	-0.170 (0.16)	-0.056 (0.23)
T-test (mean-based)	Equity	0.334 (0.00)	0.329 (0.00)	-0.005 (0.01)	0.375 (0.01)	0.353 (0.00)	-0.022 (0.00)
	Commodities	0.143 (0.00)	0.065 (0.00)	-0.078 (0.10)	0.172 (0.00)	-0.024 (0.00)	-0.196 (0.00)
	Sub-IG/credit	0.282 (0.00)	0.283 (0.00)	0.001 (0.00)	0.380 (0.00)	0.331 (0.00)	-0.049 (0.00)
	IG fixed	0.128 (0.09)	-0.269 (0.00)	-0.397 (0.00)	0.337 (0.14)	-0.040 (0.01)	-0.376 (0.00)

Source: IFM Investors, Bloomberg.

Note: Values are the percentage improvement in average performance metrics using the second CV method as the benchmark (negative number indicates improvement).

Green indicates statistically significant improvement over benchmark at or above the 10% level.

Testing validity of hyperparameter estimation approach:

We are somewhat constrained in our approach to hyperparameter estimation given the limited number of observations (75 quarterly observations). As we highlighted earlier, the TSCV method which we use is relatively data greedy and so hyperparameters estimated directly on the quarterly data may not be sufficiently stable. We take a two-step approach to model estimation in order to deal with this issue. In the first step we estimate the hyperparameters based on the monthly data (225 observations) and then we save the estimated hyperparameters and apply those to our quarterly models (75 observations). The improved fold diversity and size of CV splits based on the higher-frequency monthly data should lead to more stable hyperparameter estimates. Here we formally test the validity of this approach.

To test the validity of this approach, we construct a proxy dataset using a selection of high-frequency factors, including the cyclicals-less-defensives growth proxy from our previous work, the credit factor from the main model, the VIX, the DXY, nominal interest rate levels (via PCA), and breakeven inflation rates (also via PCA). The objective here is not to validate the factors themselves, but to assess whether hyperparameters estimated from high-frequency data can enhance predictive performance when transferred to lower-frequency settings.

We simulate 200 bootstrapped samples, each consisting of 65 consecutive 3-weekly training observations and 20 testing observations. To replicate the structure of the final model – where a one-quarter lag is applied to variables for private markets – we include a 3-week lag for each factor. This adjustment is crucial, as it ensures the model

Table A7: Comparing out-of-sample performance of two-stage hyperparameter estimation vs direct OLS

		RMSE	MAE
Wilcoxon (median-based)	Equity	-4.1 (0.00)	-4.1 (0.00)
	Commodities	-5.9 (0.00)	-6.1 (0.00)
	IG fixed	-4.7 (0.00)	-4.2 (0.00)
	Sub-IG/credit	-5.5 (0.00)	-6.6 (0.00)
T-test (bootstrapped mean-based)	Equity	-4.9 (0.00)	-5.2 (0.00)
	Commodities	-6.7 (0.00)	-7.0 (0.00)
	IG fixed	-7.6 (0.00)	-8.4 (0.00)
	Sub-IG/credit	-6.6 (0.00)	-7.7 (0.00)

Source: IFM Investors, Bloomberg.

Note: Ensemble with two-stage hyperparameter estimation approach vs direct OLS. Values are the percentage improvement in average performance metrics using OLS as the benchmark (negative number indicates improvement).

structure reflects to some degree the temporal dynamics present in the main model. For each sample, we fit both the OLS benchmark and the ensemble model using the saved hyperparameters, and record RMSE and MAE on the test set. Hyperparameters for the lasso, elastic net, and ridge models are estimated using approximately 225 weekly observations mapped to the training period; ARD and BRR do not require tuning. We then apply both the Wilcoxon signed-rank test and a central limit theorem-based t-test to assess statistical significance, with Benjamini-Hochberg corrections applied to control for the false discovery rate. Results show that the two-step hyperparameter estimation approach yields statistically significant improvements over direct OLS, and that the ensemble model consistently delivers the strongest performance gains in this test case as well (see Table A7).

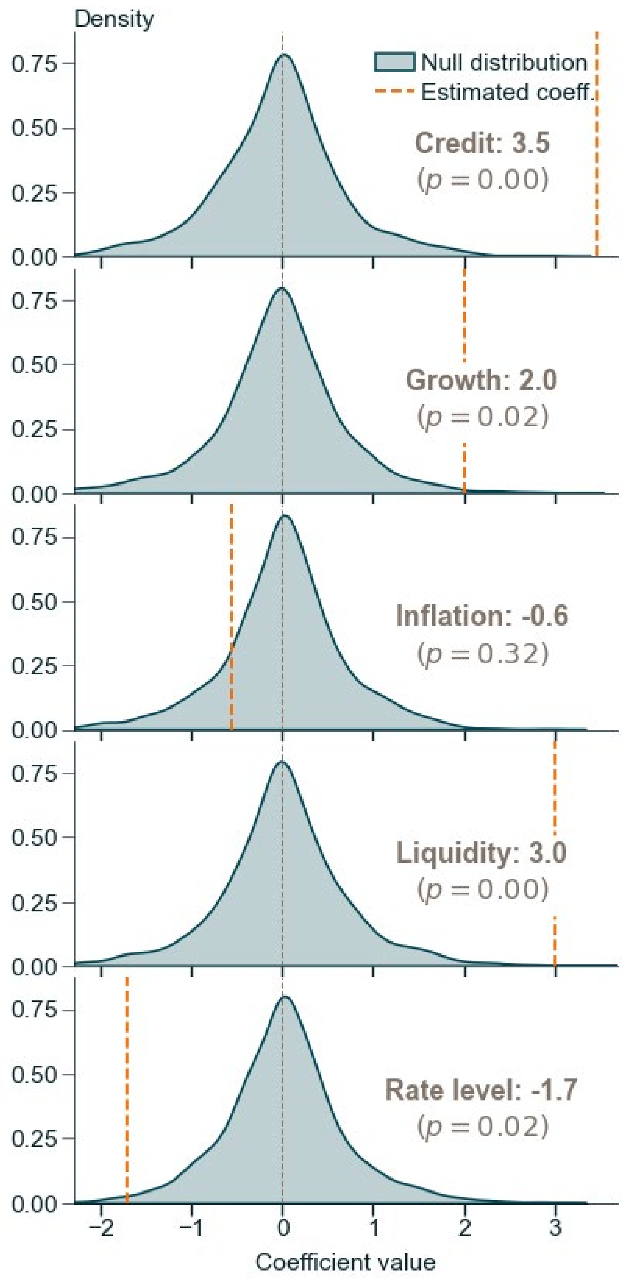
Target shuffling:

Target shuffling (also known as permutation testing) is a non-parametric method used to assess the significance of model coefficients. With target shuffling, the target/dependent variable is shuffled randomly while the features/dependent variables are left in the original order. This process breaks any real underlying relationship between the features and target. The model is then fit to the shuffled data and the estimated coefficients are saved. This process is repeated a number of times (2,500 in our case) to construct a null distribution of the various coefficients under the assumption of no relationship. The true coefficients are then compared to the null distribution to assess the strength of any relationship between the features and target.

Note that target shuffling has some characteristics that make it a powerful approach in this context. No distributional assumptions are required unlike with more traditional approaches like t-tests. This improves robustness to outliers and violations of model assumptions. Additionally, this approach works with PLRAs where traditional t-testing is inappropriate because of the impact of the penalty terms in the PLRAs on coefficient estimation.

We use the DM equity results as an example below to highlight visually how target shuffling works. With reference to Graph 15, we can see that the credit, growth, liquidity and rate level coefficients are all significantly different from the permuted null distributions as the estimated coefficients are located well into the tails of the distributions. The estimated inflation coefficient, however, does not appear significantly different from the permuted null distribution as the estimated coefficient sits near the centre of the distribution.

GRAPH 15 **DM EQUITY TARGET SHUFFLING**



Source: IFM Investors, Bloomberg.

We estimate empirical p-values according to the below formula:

$$p = \frac{1 + \sum_{i=1}^{N} \mathbb{I}(|\beta_i'| \geq |\beta|)}{1 + N}$$

Where p is the indicator function which returns 1 if the condition is true and 0 otherwise, β_i' is the coefficient estimated in the i^{th} shuffle process and β is the actual coefficient estimated on the original unshuffled data.

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