IFM Investors

Building robust portfolios with private assets: the importance of macro alpha and beta

August 2024

Executive summary

Elevated geopolitical risks and heightened uncertainty have made it increasingly difficult to anticipate the future and invest accordingly. In our view, traditional portfolio construction approaches yield portfolios that are sub-optimally positioned to navigate this new investment paradigm. We apply advanced machine learning techniques to assess the relationship between key macro factors and asset performance to identify strategies to build more robust portfolios. Our approach significantly outperforms traditional factor estimation methods, includes both private and public markets, and takes into account the returns smoothing of private assets to improve comparability across private and public markets. We find clear evidence that higher private market exposures are desirable and result in increased portfolio resilience to broad macro volatility, better insulation against specific macro risks, improved overall portfolio robustness, and enhanced through-the-cycle risk-adjusted returns.

Alex Joiner
Chief Economist

Frans van den Bogaerde, CFA
Economist

Chris Skondreas
Economist

Matthew Tsiglopolous
Analyst, Portfolio Management

1. Introduction

We argued in a previous paper – "*Evolving portfolios for the new paradigm: the case for private infrastructure*" – that elevated geopolitical risks, structural headwinds, and heightened uncertainty have resulted in a more challenging investment landscape than seen in the 30-40 years pre-pandemic. In this paper, we expand on our previous work through a factor investing lens to identify portfolio construction strategies to assist investors in navigating these challenges.

Factor investing – the process of systematically investing in assets to gain exposure to some desirable characteristic – is not a new concept. This is particularly true in public equity markets where factor-based strategies like quality, value, and momentum are common. A drawback to factor frameworks that focus on a single asset class is that it is of limited use when taking a portfolio view.

With a top-down portfolio approach, a macro factor investing (MFI) framework is preferrable. MFI seeks to establish relationships between asset returns and key macro factors such as growth, inflation, and interest rates to inform investors' asset allocation with respect to their own macro views and targets for portfolio risk/return characteristics. MFI is also a well-developed concept, and in this piece we introduce a number of innovations to improve upon the bulk of the existing research.

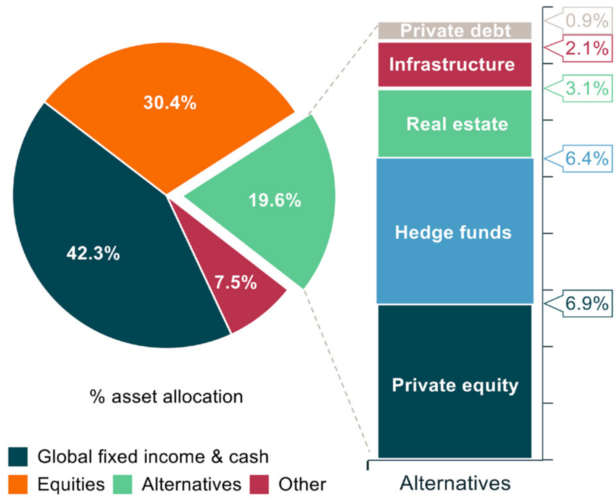
We apply an MFI approach to the multi-asset space, with a focus on private markets in general, and on unlisted infrastructure in particular. This is one of our key innovations as the majority of existing research tends to focus exclusively on public/listed markets. We provide empirical evidence on the macro properties of both private and public asset classes and, in doing so, answer common questions such as whether specific private market assets classes are 'growth' or 'defensive'; how effective different private market asset classes are at immunising against different macro risks; and how adding private market asset classes to a portfolio can improve portfolio robustness.

Greater insights to the return dynamics of private market assets are increasingly being sought by investors seeking to move into this space from what are relatively underweight positions. Globally, unlisted infrastructure in particular is an asset class that is underrepresented in institutional investor portfolios, with a weight of just 2.1% of total allocations on average (see Figure 01). We argue that higher allocations to private markets are desirable and can provide a number of benefits from a portfolio perspective.

Another key innovation in this piece is our use of advanced machine learning techniques to identify more robust macro factor relationships. We create a model that performs significantly better than the traditional modelling techniques which are generally applied in this space (this point is demonstrated at length in the Technical Appendix for interested readers). Finally, we also control for the 'returns smoothing' that is a common criticism of private markets through the use of statistical unsmoothing techniques.

FIGURE 01 **GLOBAL INSTITUTIONAL ASSET ALLOCATION**

Institutional investors are underweight infrastructure



Source: IFM Investors, Preqin. Data as at December 2023 covering 4,255 investors and US$21.1 trillion FUM.

> **Unlisted infrastructure is underrepresented in institutional investor portfolios globally. We argue that higher allocations to this asset class potentially provide a number of benefits to the investor. Specifically, in this paper, portfolio robustness through economic cycles.**

1.1 Key findings

The following are our key findings based on our modelling framework and are as follows[1]:

1. Private markets provide differentiated factor exposures compared to listed markets. This suggests that listed proxies for private market asset classes (e.g. listed infrastructure, listed real estate) should be thought of as complements to – not substitutes for – private markets.

2. Private markets may provide better insulation against macro risks than listed markets. We refer to this as the 'macro beta' of an asset class. Infrastructure (listed and unlisted) tends to have low macro betas. IFM's international infrastructure portfolio (IFM IIP) has the lowest macro beta of the private assets examined here and is only slightly more exposed to macro risks than investment grade fixed income.[2]

3. Listed markets remain the most appropriate avenue to express tactical macro views. But this comes at the cost of much higher downside macro risk. This is particularly relevant in the current context where elevated geopolitical risks and heightened uncertainty have made it harder to anticipate the future and invest accordingly. There is a strong argument to increase exposure to assets that have reduced sensitivity to macro factors to improve the robustness of portfolio returns through-the-cycle.

4. Private markets tend to generate higher real risk-adjusted returns when controlling for macro risk. We refer to this as the 'macro alpha' of an asset class. The ability of an asset to generate risk-adjusted returns independent of macro exposures is central to navigating the complex and volatile investment landscape we find ourselves in. Unlisted infrastructure, private equity (PE), and private credit (to a lesser extent) all provide higher macro alphas than the listed assets examined here.

5. Real assets like infrastructure and real estate tend to provide inflation hedging capabilities that outperform other asset classes in the model. This, however, tends to be associated with a sizeable negative exposure to rates. Effective construction of real asset portfolios is crucial to optimise macro positioning and, if done correctly, can provide the benefits of inflation hedging while limiting interest rate risk. This is the case with IFM IIP, which has been specifically constructed with this in mind and possesses stronger inflation hedging properties than other asset classes while at the same time insulating against the risk of changing interest rates.

6. Adding private assets to a portfolio of listed assets is an effective way to enhance portfolio risk-adjusted returns and to 'immunise' against macro risks. This supports the view that higher allocations to private market assets are central in building more robust portfolios.

Pictured: Aleatica, Global

[1] The conclusions we draw throughout this paper are in the context of our modelling framework, which is based on historical data analysis. We do not assert that these relationships will hold in the same way in future and seek only to inform the reader on this basis.

[2] Investments in infrastructure are subject to various risks including regulatory risk and market risk, which are outlined in further detail on the "Important Disclosures" page.

2. Under the hood

We identified five macro factors that define key aspects of the investment environment: growth, inflation, interest rates, credit, and commodities (see Figures 09 and 10 in the Data Appendix). We also include two control variables: 1) equity volatility which is intended as a rough proxy for sentiment/uncertainty to control for market movements that are disconnected from the macro fundamentals; and 2) a broad US dollar index that is intended to control for the fact that some indices are US dollar denominated while other indices are local currency denominated[3]. We do not report values for the control variables to keep focus on the macro factors of interest. See Table 02 in the Data Appendix for further details.

We primarily use market-based proxies rather than actual economic data because of the higher frequency of market-based measures. Machine learning techniques require larger volumes of data than traditional approaches for model training and testing and the lower frequency of actual economic figures limits analysis. Another reason to favour market-based proxies is that they are forward-looking and incorporate market expectations of the future, which is an important determinant of asset prices. Lagged economic datasets are less useful in this regard.

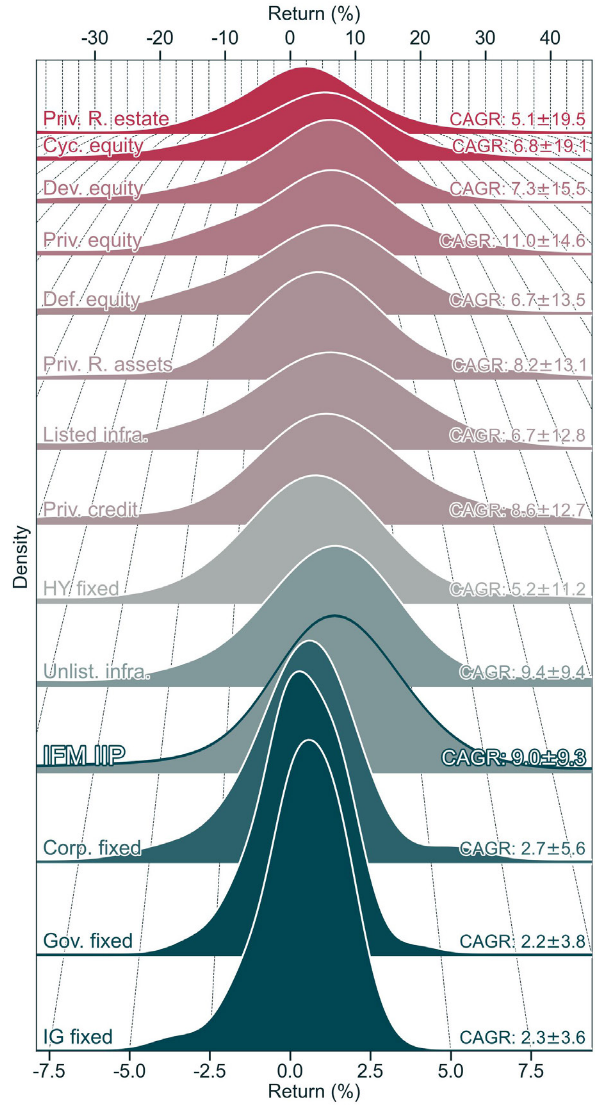
It is worth noting that we have opted to not use a markets-based proxy for inflation and have instead chosen to use actual inflation. This is driven by two primary concerns. Firstly, actual inflation has a direct mechanical link to real returns via the deflation of nominal returns. Secondly, one of the key value propositions of infrastructure as an asset class is its ability to hedge real returns against actual inflation given explicit contractual linkages with realised inflation. This choice does somewhat limit the quantitative approaches available to us, but our analysis suggests that it is a worthwhile compromise. See section 7.2.3 Model Selection in the Technical Appendix.

The majority of the research on factor sensitivities has relied on standard ordinary least squares (OLS) as the basis for estimating factor exposures. In this piece we test the performance of a number of machine learning (ML) algorithms and select the optimal performer from the available candidates. We also test the performance of a traditional OLS model to use as a reference point against which to assess the performance improvements provided by ML approaches.[4]

We include a number of proxies for asset classes across fixed income, equities, and alternatives in both listed and private markets in this investigation. The analysis window covers Q4 2004 to Q4 2023. Figure 02 highlights the risk/return distributions of some key assets included in the analysis over the full window (see Table 03 in the Data Appendix for the full details of the proxies). Note that the distributions for the private assets in Figure 02 are constructed from unsmoothed returns series, and all subsequent analysis uses unsmoothed data for private assets. See section 7.1 in the Technical Appendix for further details about the unsmoothing approach used and the impacts thereof.

FIGURE 02 **QUARTERLY RETURN DISTRIBUTIONS***

Private assets range from mid-risk unlisted infra to higher risk PE/private real estate



Source: IFM Investors, Bloomberg, Burgiss, MSCI, LPX, S&P, FTSE

*The ± following the estimated CAGR represents the annualised return standard deviation.

What is immediately noticeable in Figure 02 is that the publicly listed asset classes that are traditionally linked to 'growth' strategies have significant variation in average returns (as can be see accompanying standard deviations). And those that are defensive have relatively narrow variations. The private market assets tend to sit between these two extremes with unlisted infrastructure falling comfortably into the 'mid risk' zone between equities and fixed income. Private credit and private real assets sit on the upper end of the mid-risk scale with volatility between high-yield (HY) fixed income and defensive equities. We class PE and private real estate as high-risk given the comparable volatility to listed equities. We now seek to ascertain why these dynamics are evident using macro factors.

[3] We have tried where possible to minimise the impact of currencies by preferring local currency indices in the first instance and by using equally weighted combinations of the same underlying index in different currencies where local currency indices were not available.

3. Results

3.1 Isolating macro effects

We begin by examining the coefficients of our model which relate asset returns to factor changes. We refer to these coefficients as 'macro betas'. The estimated macro betas are presented in Figure 03 and align with the well-known properties of listed markets and what we would intuitively expect from the various private market asset classes examined here.

Listed markets:

- **Fixed income (grey box)** returns are negatively impacted by inflation and rising interest rates and are well insulated from growth. HY fixed income has a differentiated macro exposure profile and is much more sensitive to credit conditions and growth than other fixed income instruments. HY fixed income has a near negligible exposure to interest rates after controlling for the other macro factors. HY fixed income behaves like a 'hybrid' between investment grade fixed income and equities.

- **Equities (red box)** benefit from growth and improving credit conditions and are largely immune to interest rate movements when controlling for other important macro factors. Cyclical equities are much more exposed to growth and credit than defensive equities. Cyclical equities also tend to be negatively impacted by rising inflation, whereas defensive equities provide useful inflation hedging characteristics.

- **Listed alternative equities (blue box)** provide a degree of differentiation in terms of macro factor exposures when considering a portfolio of traditional equity and fixed income assets. Listed infrastructure tends to have a higher exposure to interest rates given higher leverage ratios but is more insulated against changing credit conditions and growth. This is likely due to the underlying infrastructure assets having more defensive characteristics. Listed real estate provides inflation hedging properties but is much more sensitive to growth, interest rates, and credit given the more direct valuation implications. It is worth highlighting that both infrastructure and real estate have substantial variation within the overall universe. For example, within infrastructure regulated utilities have different macro exposures from toll roads, and within real estate, retail property will have different exposures to industrial property. As such, representing performance with a single index will likely dilute the potential benefits from a more nuanced investment strategy that takes into account these fundamental differences.

Private markets:

The unlisted asset models have a broadly lower R^2 when compared to the listed assets. This highlights the higher macro immunity provided by unlisted assets given that a higher proportion of returns are driven by factors not captured by the macro risks examined here. Note that we will disambiguate between the unlisted infrastructure benchmark and unlisted infrastructure as a whole (which includes the benchmark and IFM IIP) by referring to the benchmark as UIB from here on.

- **Private credit (green box)** has similar characteristics to HY fixed income, though it is more exposed to rates and more insulated from credit. This is likely due to the composition of the private credit proxy spanning a wider range of credit ratings than HY fixed. Private credit is also more exposed to growth as borrowers leverage into better growth conditions.

FIGURE 03 **MACRO BETAS**

Factor exposures align with the well-known listed market characteristics and make intuitive sense for the private market asset classes examined.

	Inflation	Growth	Credit	Comm.	Rates	
Short fixed $R^2 = 0.49$	-0.1	0.0	0.0	0.0	-0.3	Fixed income
IG fixed $R^2 = 0.83$	-0.4	0.0	0.4	0.0	-1.4	Fixed income
Gov. fixed $R^2 = 0.85$	-0.4	0.0	0.0	0.0	-1.5	Fixed income
HY fixed $R^2 = 0.79$	-0.4	0.7	3.7	0.5	0.1	Fixed income
Dev. equity $R^2 = 0.78$	0.0	2.6	2.0	0.0	0.0	Equities
Def. equity $R^2 = 0.76$	0.5	0.1	1.6	1.3	0.0	Equities
Cyc. equity $R^2 = 0.80$	-0.3	3.1	2.8	0.1	0.2	Equities
Listed infra. $R^2 = 0.67$	0.3	0.1	1.7	1.9	-0.8	Listed alts
List. RE $R^2 = 0.58$	0.6	2.0	4.2	1.1	-2.0	Listed alts
Listed PE $R^2 = 0.74$	-0.1	3.3	5.0	0.0	0.3	Listed alts
Priv. credit $R^2 = 0.68$	-0.3	1.3	2.5	1.3	1.0	Private/unlisted alts
Priv. R. assets $R^2 = 0.29$	1.3	1.1	0.0	2.0	-0.5	Private/unlisted alts
Priv. R. estate $R^2 = 0.24$	0.2	3.6	0.7	2.7	-2.4	Private/unlisted alts
Priv. equity $R^2 = 0.48$	-0.4	1.9	1.7	0.5	0.0	Private/unlisted alts
Unlist. infra. $R^2 = 0.36$	0.1	0.5	1.2	1.8	-0.6	Private/unlisted alts
IFM IIP $R^2 = 0.21$	1.1	0.2	1.1	0.3	0.0	Private/unlisted alts

Source: IFM Investors, Bloomberg, Burgiss, MSCI, LPX, S&P, FTSE

[4] We find that an elastic net (ENet) specification is optimal in this context and accordingly we use it for our modelling task. For reference, the ENet has an average out-of-sample predictive performance that is approximately 35% better than the reference OLS model. The interested reader is directed to section 7.2 in the Technical Appendix for further specifics about the machine learning algorithms, model selection, and parameterisation.

[5] Diversification cannot ensure positive returns nor protect against negative returns. It is a strategy used to help mitigate risk.

[6] For institutional clients only.

- **Private real assets (green box)** are able to provide substantial differentiation to macro factor exposures when compared to traditional fixed income and equity assets. Real assets (of which real estate, infrastructure, and natural resources are a subset) also have strong inflation hedging properties.

- **Private real estate (green box)** has a large exposure to interest rates, similar to the listed sector. This is unsurprising given the direct valuation effect in the sector and often high leverage ratios. There is also a relatively strong exposure to cyclical growth which is to be expected given clear linkages to GDP. The sector was also hit exceptionally hard in both the global financial crisis and from structural shifts in demand as a result of behavioural changes due to the COVID pandemic. These shocks have had a significant impact on estimated inflation parameters for the asset class. Our full sample estimation finds little exposure of returns to inflation, however given the direct linkages from CPI to rents this anomalous result was worth exploring. Ending the estimation period before the pandemic pushes the inflation coefficient above 1. This inflation linkage is more in line with what we would expect.

- **Private equity (green box)** behaves similarly to cyclical equities but is more insulated from growth/credit. Similarly to private real estate the post-pandemic inflationary spike was associated with a disproportionately large valuation impact on the private equity space and has skewed results somewhat. Excluding this period leaves PE with an inflation coefficient around zero. This may reflect the ability of more innovative firms to pass on price increases and also being at a stage of growth that is self-sustaining beyond the broader set of economic conditions.

- **UIB (green box)** has some positive return relationship with growth and inflation as expected. Both the credit and commodities channels are also important. Credit conditions are likely reflective of investor risk appetite and positive economic conditions and commodities likely reflect the nominal growth environment. Rates have a negative impact on returns with the asset class being viewed as highly leveraged and long duration.

> **Private real assets are able to provide substantial differentiation to macro factor exposures when compared to traditional listed markets**

- **IFM IIP (green box)** has similar qualities to the UIB. However, it has relatively strong inflation hedging characteristics compared to the other asset classes examined here whilst simultaneously providing insulation from changes in interest rates. We tend to find that through periods when rates are rising the nominal growth impacts across the portfolio on average more than offset the potential negative rates impact. We note that IFM IIP assets tend to have lower leverage ratios than the sector more broadly and relatively long-dated interest rate risk management strategies. IFM IIP is also less exposed to growth which is likely due to careful and deliberate geographical and sector diversification within the portfolio. Note that the UIB as at Q4 2023 was based on the aggregate behaviour of nearly 400 closed-end funds with a market capitalisation of over US$800bn. Crucially, this proxy is uninvestable, in contrast to IFM IIP which is both open-ended and investable. The open-ended nature of IFM IIP can provide a number of benefits including 1) vintage diversification; 2) potentially improved liquidity (redemptions can be made from cash yield and queued capital); 3) better opportunities for diversification across sectors/asset age/risk profile associated with the fund accumulating assets over an extended period; and 4) a track record on an existing portfolio which improves visibility on portfolio risk/return characteristics. Further insight into open-ended structures be found here at IFM's Investor Insights page.

Pictured: Vienna Airport, Switzerland

INSIGHT

Deep dive on unlisted infrastructure

Infrastructure assets are broadly positively linked to inflation to some degree. Invariably, core infrastructure assets typically have pricing mechanisms either directly or indirectly linked to CPI. Such arrangements are common amongst regulated utilities, toll roads and ports which generally have sizeable revenue streams which take on little price risk and varying levels of volume or growth risk. Given the positive correlation between interest rates and inflation the usually translates to a partial offset against this risk of rising rates due to the positive impact of inflation on revenues.

There are two important points to note regarding the pressures brought by rising rates. The impact of rising rates can be further ameliorated by managers having laddered, long-term debt that needs to be refinanced, of which a large proportion is fixed. The other consideration of rising rates is the discount rate, and corresponding risk-free rate. Independent valuation firms used by asset managers tend to take a long-term view when setting the risk-free rate, considering historical long-term sovereign bond rates and sustained changes in those rates.

These factors are evident in both listed and unlisted markets, where infrastructure valuations tend to be less volatile than the broader equities market in response to negative macro events. Thus, in general, we tend to view infrastructure as being positively correlated to inflation, with a weak negative correlation to rates. Sitting in between the two is economic growth, where returns can be relatively inelastic to demand where the level of elasticity is dependent on the amount of merchant risk and volume risk taken on by assets and their corresponding revenue streams. This general inelasticity is due to the monopolistic nature of the assets that in many cases are in the non-discretionary space.

The challenge for valuers is to factor these dynamics into valuations. Independent firms under well recognised accounting and valuation standards are charged with this task to take in all relevant information at the asset level. This is rather than being subject to broader swings in market sentiment as seen in the listed space.

These dynamics can be harnessed by the fund manager to construct a portfolio with weighting across various sub-sectors and revenue streams to optimise returns characteristics. For example, on the most defensive end of the spectrum, utilities are usually backed by inflation-linked revenue mechanisms along with some inherent downside protection to rising rates due to consideration of the market cost of debt when determining the regulatory cost of capital. This can be seen across our global portfolio at Anglian Water, where regulated capital values and returns are determined by the regulator in real terms, and at Enwave Energy, where revenues are supported by long-term CPI-linked contracts with customers.

At the other end of the infrastructure portfolio spectrum are assets that are more leveraged to economic activity such as ports, airports and toll roads. These assets often have inflation-linked concession pricing, tariff regimes or regulatory weighted average cost of capital calculations but have a higher proportion of revenues which are linked to economic growth and volume throughput. We would expect these to generally have a marginally lower correlation to inflation and higher correlation to reasonable proxies for economic growth.

Further insight into infrastructure's resilience as an asset class can be found here at IFM's Investor Insights page.

Pictured: Mersin International Port, Turkey

3.2 Total macro effects

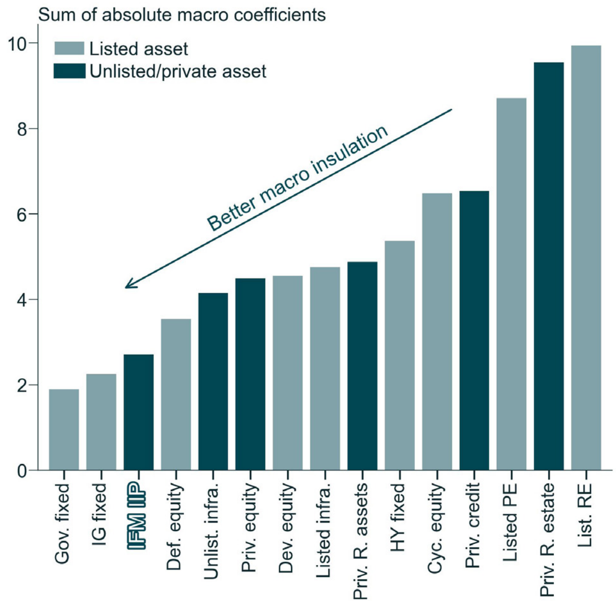
Asset returns are clearly not defined by a singular impact from macro factors but from the broader macro environment. To demonstrate how asset classes performed in the average macro conditions that prevailed over the estimation period, we examine the total macro effects by summing the absolute coefficients of the estimation. What this analysis highlights is, essentially, a ranking of how exposed an asset class might be to the macro environment over time. The outcomes in Figure 04 reinforce a relatively well-recognised risk hierarchy. In the public asset space, the hierarchy moves from defensive fixed income through the risk spectrum to equities and sectoral equites. This is relatively unsurprising. Interestingly, the highest-risk fixed income asset – HY credit – is more exposed to the macro environment than defensive and developed market equities.

Private market asset classes have a range of macro exposures. Private credit and private real estate sit at the more macro exposed part of the spectrum, which is likely driven by both asset classes tending to have direct listed inputs into the valuation process which are exacerbated by sentiment.

At the other end of the spectrum is IFM IIP, which is the private asset class most insulated from macro effects and has the overall macro exposure of more defensive asset classes. Again, this is likely driven by active portfolio and asset management initiatives, bottom-up portfolio construction with a focus on underlying revenue streams and their macro drivers, and the open-ended structure that encourages re-investment and value creation. This highlights again the potential 'through the cycle' properties of an unlisted infrastructure portfolio.

FIGURE 04 **TOTAL MACRO EXPOSURES**

Unlisted infrastructure, private real assets, and private equity have low overall macro exposures.

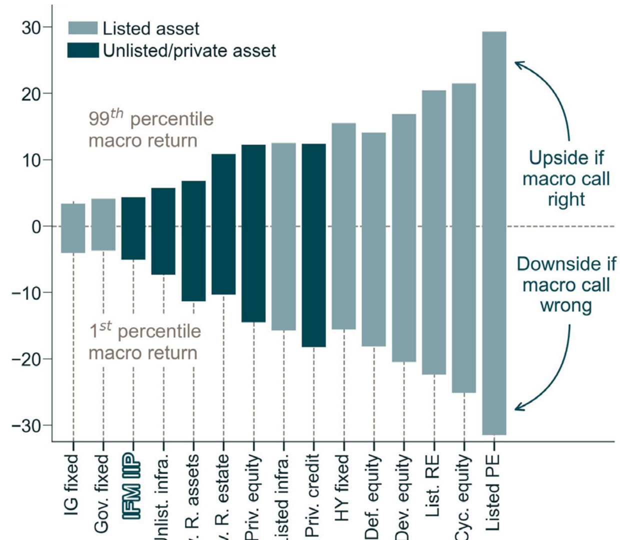


Source: IFM Investors, Bloomberg, Burgiss, MSCI, LPX, S&P, FTSE

The total macro exposure characteristics are important for portfolio construction. Depending on the environment and risk appetite of the investor it may be desirable to take more risk and leverage into the economic cycle. The macro return results in Figure 05 demonstrate the suitability of each asset class to this end. It is clear that public/listed asset classes provide the greatest potential to express a macro view, whether that be defensive or growth. However, with this higher potential reward comes a commensurately higher potential downside. Private market/unlisted asset classes on average provide less opportunity to express views on the macro cycle, as evidenced by their returns properties and liquidity characteristics. This underscores our assertion that a larger allocation to private markets is more appropriate for a strategic asset allocation with tactical views better expressed in more liquid public markets. We'd also note that wherever possible, tactical views and the performance of listed markets should not undermine, via the denominator effect, the objective of setting private market assets as the foundation of portfolio risk-adjusted returns.

FIGURE 05 **MACRO RETURN***

Tactical views are better expressed in public markets



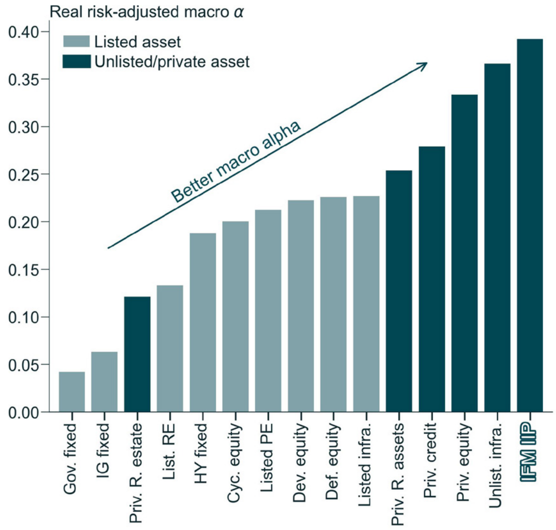
Source: IFM Investors, Bloomberg, Burgiss, MSCI, LPX, S&P, FTSE

*Calculated as the sum of model estimated factor-driven returns (i.e. using beta coefficients only) in each quarter.

Further evidence to support the contention that private market assets can be a prominent part of an investors' strategic allocation can be provided by isolating the risk adjusted returns of asset classes in the absence of variation in economic conditions. Figure 06 shows what we have termed the 'macro alpha' of each asset class adjusted for risk (return volatility) and shown in real terms (adjusted for inflation). Macro alpha can be thought of similarly to the traditional investment alpha, though it is not precisely the same concept. Investment alpha measures the performance of an investment relative to some benchmark, whereas macro alpha measures the expected return of an asset after controlling for various

FIGURE 06 **MACRO ALPHAS***

Private assets offer higher risk-adjusted macro alphas



Source: IFM Investors, Bloomberg, Burgiss, MSCI, LPX, S&P, FTSE

*Calculated as the estimated model alpha less inflation divided by return volatility.

macro factors. In other words, macro alpha quantifies the ability of an asset to generate returns without needing to bear macro risk.

Private market assets generally have higher macro alphas[7]. The implication from a portfolio perspective of this modelling result is that increasing exposures to private markets – and to unlisted infrastructure and PE in particular – can result in a portfolio that is better insulated from macro risks and is therefore potentially supportive of higher and more stable returns over time.

> **Private market assets generally have higher macro alphas potentially insulating a portfolio against unanticipated swings in the economic cycle**

INSIGHT

Portfolio optimisation: infrastructure

A key focus for IFM's international infrastructure portfolio is portfolio optimisation and the development of target strategic asset and sector allocations. This is done through bottom-up analysis of revenue streams using InFRAME™, a proprietary risk management system developed to enable IFM Investors to analyse the underlying revenue stream drivers of infrastructure performance.

Revenues are classified according to the price and volume risk inherent in the revenue streams.

1. Contracted revenues are contractually based with one or more commercial counterparties, entailing limited or virtually no price and volume risk. This is common with property leases across airports and ports, or take-or-pay agreements for midstream assets.

2. Regulated revenues which have limited volume and price risk, potentially subject to periodic regulatory reviews as seen in electricity transmission and distribution assets and some road concessions with revenues characterized by a guaranteed return mechanism.

3. Volume-linked revenues which are based on throughput/patronage volumes, with pricing normally set under a medium to long-term contract. These revenue streams are usually linked to GDP with potentially cyclical growth characteristics. The level of volume-risk can be limited depending on the monopoly characteristics of the asset.

4. Market revenues which are typically a revenue stream based upon throughput/patronage, with pricing determined through market forces. Within this though are more defensive market revenue streams which typically exhibit counter-cyclical growth characteristics such as mid-stream oil storage revenues which benefit when economic demand is weak and the fuel market takes on a 'contango' structure, which provides diversification benefits against the GDP exposure of volume-linked revenues such as aeronautical revenue streams at airports.

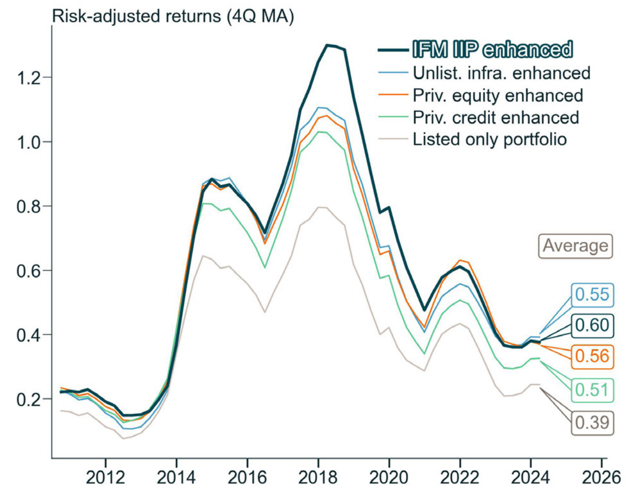
InFRAME was constructed to form a new perspective on how to build a robust diversified portfolio of infrastructure investments which have core qualities that are looked for in infrastructure assets, including monopolistic characteristics, long asset/concession life, stable and predictable cash flows, inflation hedging and exposure to economic growth. The results of InFRAME are routinely included in IFM Investors' decision-making processes and have become powerful tools for our infrastructure investment team.

Further insight into InFrame be found here at IFM's Investor Insights page.

[7] To assess the robustness of this result we fit the model to a rolling 28-quarter window and the results largely hold. Unlisted infrastructure and PE are shown to provide better outcomes over almost the entire rolling window with private credit performing reasonably well in a relative sense.

FIGURE 07 **PRIVATE MARKET PORTFOLIO IMPACT***

Including private assets improves real risk-adjusted returns



Source: IFM Investors, Bloomberg, Burgiss, MSCI, LPX, S&P, FTSE

*Listed reference portfolio composed IG fixed (20%), government fixed (10%), HY fixed (10%), defensive equity (10%), cyclical equity (10%), developed equity (40%). Private market enhanced portfolios include a 30% allocation to private asset and pro rata remaining listed portfolio according to listed reference weights. Real risk-adjusted returns calculated on a rolling 5-year basis.

FIGURE 08 **PRIVATE MARKET MACRO EXPOSURES**

Transforming portfolio characteristics

	Inflation	Growth	Credit	Comm.	Rates
IFM IIP enhanced $R^2 = 0.74$	0.1	1.0	1.3	0.2	-0.2
Unlist. infra. enhanced $R^2 = 0.73$	0.0	1.1	1.4	0.4	-0.2
Priv. equity enhanced $R^2 = 0.72$	-0.1	1.3	1.5	0.3	-0.1
Priv. credit enhanced $R^2 = 0.77$	0.0	1.2	1.7	0.3	0.0
Listed portfolio $R^2 = 0.79$	-0.1	1.3	1.8	0.1	-0.2

Source: IFM Investors, Bloomberg, Burgiss, MSCI, LPX, S&P, FTSE

Table 01: Private market portfolio impacts

Portfolio	Total macro exposure	Risk-adjusted macro alpha
IFM IIP enhanced	2.8	0.50
Priv. infra. enhanced	2.9	0.49
Priv. equity enhanced	3.4	0.48
Priv. credit enhanced	3.2	0.44
Listed portfolio	3.4	0.36

Source: IFM Investors, Bloomberg, Burgiss, MSCI, LPX, S&P, FTSE

4. Portfolio implications

We now demonstrate the beneficial macro insulation and macro alpha properties of private markets in a portfolio context. Figure 07 shows the impact that including various private market assets has on quarterly risk-adjusted returns. The starting point is a standard 60/40 listed-only portfolio, and each private market enhanced portfolio includes a 30% allocation to a given private market asset whilst keeping the relative weights of the listed assets the same. A substantial improvement to risk-adjusted returns is seen with the inclusion of either private credit, PE, or unlisted infrastructure, and on the latter particularly IFM IIP. The overarching point is that private market assets can provide the basis for more robust portfolio returns.

Additionally, a strategic allocation to private market asset can be used to effectively dial up or dial down macro risk exposures in the portfolio. This is demonstrated in Figure 08.

Broadly, private market asset characteristics can serve to reduce macro exposures in the growth and rates space and increase inflation hedging properties. Interestingly, the analysis shows that the inclusion in the portfolio of IFM IIP has the potential to significantly improve portfolio inflation hedging properties, a result that was not replicated via the inclusion of other private market assets.

Table 01 shows how the macro alpha properties of the portfolio are also enhanced and susceptibility to overall macro factors is reduced. This is arguably why private market allocations are viewed as being part of the solution to increased geopolitical risk. This risk has more often than not in recent experience imparted increased growth volatility and upside risks to inflation.

5. Conclusions

This paper introduces a number of innovations and applies a modern approach to provide investors with robust empirical evidence on the relationship between key macro factors and asset performance. We find clear evidence that higher private market exposures are desirable and result in increased portfolio resilience to broad macro volatility, better insulation against specific macro risks, improved overall portfolio robustness, and enhanced through-the-cycle risk-adjusted returns. We also find that listed assets are a good way to express cyclical/tactical macro views, but this comes at the cost of much higher downside macro risk.

Of the private assets examined, unlisted infrastructure and PE tend to have a significant positive impact on portfolio performance. Our model shows IFM IIP to be a standout in providing macro insulation, the highest real risk-adjusted macro alpha, the optimal combination of inflation hedging and interest rate insulation, and is the most impactful on risk-adjusted returns when added to a traditional listed-only portfolio. IFM IIP potentially offers more robust returns characteristics for those investors particularly concerned about structural shifts in the inflation outlook.

The combination of characteristics provided by PE/unlisted infrastructure is particularly attractive in the current context. Higher geopolitical risks and elevated uncertainty make it harder to anticipate the macro environment and to position a portfolio accordingly. The lower overall macro exposures and higher risk-adjusted macro alphas of PE/unlisted infrastructure suggests that investors who add PE/unlisted infrastructure to their portfolios are potentially better positioned to weather unanticipated volatility in the economic environment. And are therefore potentially maximising portfolio returns through economic cycles.

One limitation of this paper is that a single representative index for was used to assess the performance of infrastructure and real estate. Both infrastructure and real estate have substantial variation within the overall universe and, as such, representing performance with a single index will likely dilute the potential benefits of a more nuanced investment strategy that takes into account these fundamental differences. In future research we will examine infrastructure and property in more detail, taking into account these differences.

6. Data appendix

The macro factor data are adjusted to address some common concerns in investigations of this type. Specifically, we Winsorise and standardise the macro factor data. Winsorisation mitigates the impact of outliers by removing any observations above/below some specified percentile and replacing them with that percentile value. In this case, we specify the 99.5th percentile as the upper limit and the 0.05th percentile as the lower limit to only remove the most significant of outliers.

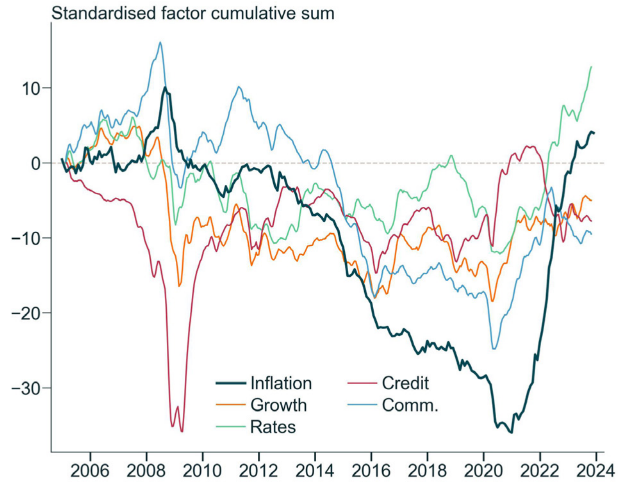
Standardisation is useful to enhance comparability across factors. This is particularly true with the penalised regressions of the type we employ in this investigation – the penalty applied in penalised regressions is dependent on scale and may therefore unfairly penalise variables with a large scale, or unfairly favour variables with a small scale. We did not standardise the asset return data in this analysis because – unlike with the macro factor data – the scale of asset returns is a feature, not a bug, and contains critical information in assessing overall asset performance and sensitivity to macro factors.

Table 02: Macro factor proxies

Risk factor	Proxy
Growth	Return on a portfolio long cyclical equities and short defensive equities.
Inflation	Actual advanced economy CPI
Rates	Yield on 10-year US government bonds
Credit	Return on a portfolio that is long corporate IG bonds and short IG government bonds
Commodities	Returns on a broad commodities index
Volatility	VIX
US dollar	DXY

FIGURE 09 **MACRO FACTORS**

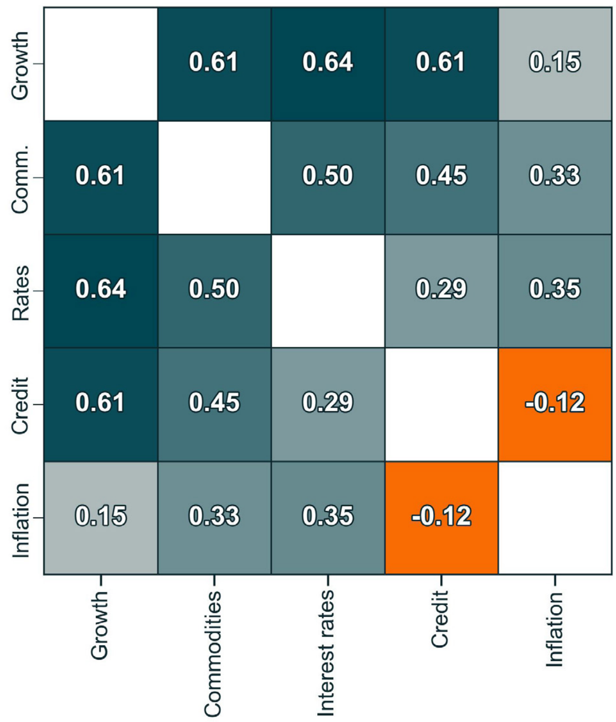
Controlling for scale improves comparability substantially



Source: IFM Investors, Bloomberg, World Bank

FIGURE 10 **FACTOR CORRELATIONS**

Assessing macro exposures in a multi-variable context is more appropriate than a univariate context given relationships between macro factors.



Source: IFM Investors, Bloomberg, World Bank

Table 03: Asset proxies	
Asset	**Proxy**
Investment grade (IG) fixed	Bloomberg Global Aggregate Total Return (average of USD, GBY, EUR, and JPY hedged indices)
Government fixed	Bloomberg Global Treasury Total Return (average of USD, GBY, EUR, and JPY hedged indices)
Corporate fixed	Bloomberg Global Corporate Total Return (average of USD, GBY, EUR, and JPY hedged indices)
High yield (HY) fixed	Bloomberg Global High Yield Total Return (average of USD, GBY, EUR, and JPY hedged indices)
Short fixed	Bloomberg Global Aggregate 1-3 Year Total Return (average of USD, GBY, EUR, and JPY hedged indices)
Mid fixed	Bloomberg Global Aggregate 3-5 Year Total Return (average of USD, GBY, EUR, and JPY hedged indices)
Long fixed	Bloomberg Global Aggregate 7-10 Year Total Return (average of USD, GBY, EUR, and JPY hedged indices)
World equity	MSCI ACWI Net Total Return Local Index
Developed equity	MSCI World Net Total Return Local Index
Emerging equity	MSCI Emerging Net Total Return Local Index
Developed defensive equity	MSCI World Defensive Sectors Net USD Index
Developed cyclical equity	MSCI World Cyclical Sectors Net USD Index
Developed small cap equity	MSCI World Small Cap Net Total Return USD Index
Listed PE	Equal weighted combination of S&P Listed PE Net Total Return, LPX50 Listed Private Equity Index Total Return, and FTSE Private Equity Buyout Index
Listed real estate	Equal weighted combination of S&P Global REIT USD Total Return Index and MSCI World Real Estate Net Total Return USD Index
Listed infra.	Equal weighted combination of MSCI World Infrastructure Sector Capped Net Total Return Local Index and Dow Jones Brookfield Global Infrastructure Total Return Index
Private credit	Equal weighted combination of Burgiss Global Private Credit (average of EUR and USD indices) and Bloomberg Debt PE Index. Back-cast using Burgiss Global Private Credit for data prior to Q1 2007.
Private real estate	Equal weighted combination of Burgiss Global Private Real Estate (average of EUR and USD indices) and Bloomberg Real Estate PE Index. Back-cast using Burgiss Global Private Real Estate for data prior to Q1 2007.
Private real assets	Equal weighted combination of Burgiss Global Private Real Assets (average of EUR and USD indices) and Bloomberg Real Asset PE Index. Back-cast using Burgiss Global Private Real Assets for data prior to Q1 2007.
Private equity	Equal weighted combination of Burgiss Global Venture Capital (average of EUR and USD indices), Burgiss Global Buyout (average of EUR and USD indices), Burgiss Global Expansion Capital (average of EUR and USD indices), Bloomberg Fund-of-Funds PE Index, Bloomberg Venture Capital Index, Bloomberg Buyout PE Index, and Bloomberg Growth PE Index. Back-cast using Equal weighted combination of Burgiss Global Venture Capital (average of EUR and USD indices), Burgiss Global Buyout (average of EUR and USD indices) and Burgiss Global Expansion Capital (average of EUR and USD indices) for data prior to Q1 2007.
Unlisted infra.	Burgiss Private Infrastructure Index (average of USD and EUR indices)
IFM's international infrastructure portfolio	IFM international unlisted infrastructure portfolio net return local currency index

7. Technical appendix

7.1 Robustness – unsmoothing returns

A common criticism of private markets is that they exhibit ‘returns smoothing’ and therefore lead to downward biased returns volatility and covariances. To address these concerns, we use a statistical approach to ‘unsmooth’ the private market data.

A thorough investigation of various unsmoothing techniques is beyond the scope of this paper. Accordingly, we focus on the unsmoothing technique developed by Geltner (1993). This approach utilises an autoregressive model of order 1 – AR(1) – to estimate unsmoothed returns according to the below equation:

$$R_t^* = \frac{R_t - \phi_1 R_{t-1}}{1 - \phi_1} \qquad (1)$$

Where R_t^* is the unsmoothed return at time, R_t is the observed return at time, and $\emptyset_1$ is the first-order autoregressive coefficient estimated in the below model:

$$R_t = \phi + \phi_1 R_{t-1} + \epsilon_t$$

We note that AR(2) models can also be used in unsmoothing but in this particular case we find no evidence that would argue in favour of an AR(2) model over an AR(1) model.

To test the validity of the various AR models we first examine the validity of the stationarity assumption required for the AR models. In this instance there is sufficient evidence to reject the null hypothesis of non-stationarity above the 1% level of confidence for all assets (see Table 04).

Table 04: Stationary test

Asset	Augmented Dickey-Fuller test (constant only)
PE	p<0.00
Private credit	p<0.00
Real estate	p<0.00
Real assets	p<0.00
UI	p<0.00
IFM IIP	p<0.00

Source: IFM Investors, Bloomberg, Burgiss

With this established, we fit both an AR(1) and AR(2) model to each quarterly returns series and find that the AR(1) model is most appropriate for this case (see Table 05). All of the private markets assets have statistically significant first order autoregressive coefficients above the 1% level in the AR(1) model. The second order autoregressive coefficients in the AR(2) model are for the most part insignificant.

Table 05: Autoregressive model testing*

	AR(1)	AR(2)	
Asset	ϕ_1	ϕ_1	ϕ_2
PE	0.47 (0.00)	0.42 (0.00)	0.11 (0.32)
Private credit	0.47 (0.00)	0.50 (0.00)	-0.10 (0.38)
Real estate	0.63 (0.00)	0.50 (0.00)	0.20 (0.07)
Real assets	0.46 (0.00)	0.39 (0.00)	0.14 (0.23)
Unlisted infra.	0.31 (0.00)	0.25 (0.02)	0.09 (0.43)
IFM IIP	0.30 (0.01)	0.27 (0.01)	0.07 (0.50)

Source: IFM Investors, Bloomberg, Burgiss

*Numbers in brackets represent p-values.

The impacts of the unsmoothing approach are showed in Table 06 below.

Table 06: Unsmoothing results

	Original volatility	Unsmoothed volatility
PE	8.4	14.0
Private credit	7.6	12.6
Real estate	9.2	19.2
Real assets	7.8	13.0
Unlisted infra.	6.8	9.4
IFM IIP	6.8	9.3

Source: IFM Investors, Bloomberg, Burgiss

7.2 Machine learning

7.2.1 Algorithms

We test five supervised linear regression machine learning (ML) models in this investigation. We include a standard ordinary least squares multiple linear regression as a reference point against which to assess model performance. The ML models we use include ridge, elastic net, lasso, Bayesian ridge regression, and automatic relevance determination.

- **Lasso regression:** standard linear regression model combined with an L1 (linear) regularisation penalty based on the absolute value of the regression coefficients. The algorithm solves for coefficients such that the combination of 1) the sum of squared differences between predicted and actual values and 2) the L1 penalty term is minimised. The intensity of the L1 penalty term is a hyperparameter that must be selected by the modeller. The L1 penalty term guides the algorithm towards fewer non-zero coefficients and therefore is useful for feature selection/creating sparse models. For further information see Efron, Hastie, Johnstone, & Tibshirani (2004).

- **Ridge regression:** standard linear regression model similar to lasso but with an L2 (quadratic) regularisation parameter based on the square of the regression coefficients. The algorithm solves for coefficients such that the combination of 1) the sum of squared differences between predicted and actual values and 2) the L2 penalty term is minimised. The intensity of the L2 penalty term is a hyperparameter that must be selected by the modeller. The L2 penalty term guides the algorithm towards smaller coefficients but does not perform feature selection or assist in the production of sparse models like the L1 penalty. For further information see Rifkin & Lippert (2007).

- **Elastic net:** a combination of lasso and ridge models which combines L1 and L2 penalty terms. The elastic net has the benefit of being able to create sparse models as with a lasso model while maintaining the regularisation properties of a ridge model. Elastic net models require the modeller to set two hyperparameters: one that controls the shrinkage intensity of the penalty term and another that controls the balance of penalisation between the L1 and L2 penalty terms. The algorithm solves for coefficients such that the combination of 1) the sum of squared differences between predicted and actual values and 2) the weighted aggregate of the L1 and L2 penalty terms is minimised. For further information see Zou & Hastie (2005) and Friedman, Hastie, & Tibshirani (2010).

- **Bayesian ridge regression:** similar to the ridge regression but the regularisation parameter is not set manually, it is treated as a random variable and tuned to the data at hand. Model estimation is achieved by iteratively maximising the marginal log-likelihood of the observations under the assumption of a spherical Gaussian prior. For more information see Bishop (2006) and MacKay (1992).

- **Automatic relevance determination:** similar to the Bayesian ridge regression but the prior is assumed to be a centred elliptic Gaussian distribution. Automatic relevance determination models lead to sparser coefficients than Bayesian ridge regressions. Automatic relevance determination is also known as the relevance vector machine which has similar properties to, and a number of advantages over, a similar and popular approach known as the support vector machine. For more information see Tipping (2001) and Wipf & Nagarajan (2007).

7.2.2 Cross-validation

Cross-validation (CV) serves a number of purposes including tuning machine learning models to prevent overfitting, building models that generalise better to unseen data, and comparing the performance of competing models. It is an important step in both model parameterisation and selection. There are a number of different CV methods available but methods like k-fold CV and random permutation CV rely on the assumption that data are independent and identically distributed which is unlikely to be the case with time series.

Time series data have a temporal dependency between observations which we need to preserve with CV. Accordingly we build a CV method that we will refer to as "walk forward blocking time series CV". This approach uses a moving window of training data of fixed size and tests performance against a validation sample of fixed size. The training sample comprises 70% of the data and the validation sample comprises 30% of the sample. Within the walk forward blocking time series CV we specify two related methodologies:

- **Overlapping:** For each CV iteration the window 'overlaps' with the previous window – part of the validation sample from the previous iteration is used in the training sample for the following iteration.

- **Non-overlapping:** For each CV iteration the window is 'non-overlapping' – the training data for the following iteration begins at the end of the validation data for the previous iteration.

7.2.3 Model selection

Model selection is based on two tests. In the first test we compare the performance of each model based on the model mean CV score (see Figure 11). The CV score is the highest out-of-sample R^2 found during the CV process for each model and ranges between zero (no better than the mean) and one (perfect predictions). We fit a model of the specified type to each asset using both overlapping and non-overlapping CV with a train/test split of 70%/30% and fixed windows of three sizes for each frequency. We then average the scores to compute the mean CV score. The ENet outperforms (see Figure 11) in all cases and most importantly has an out-of-sample R^2 that is 22% higher than the competing OLS model at a monthly frequency.

Another key result from this is that the ENet maintains predictive performance better when moving to lower frequencies than OLS. Specifically, the OLS out-of-sample R^2 drops by about 6ppts moving from weekly to monthly data whereas the ENet out-of-sample R^2 falls by approximately 1ppt.

FIGURE 11 **CROSS-VALIDATION PERFORMANCE**

The ENet method clearly outperforms

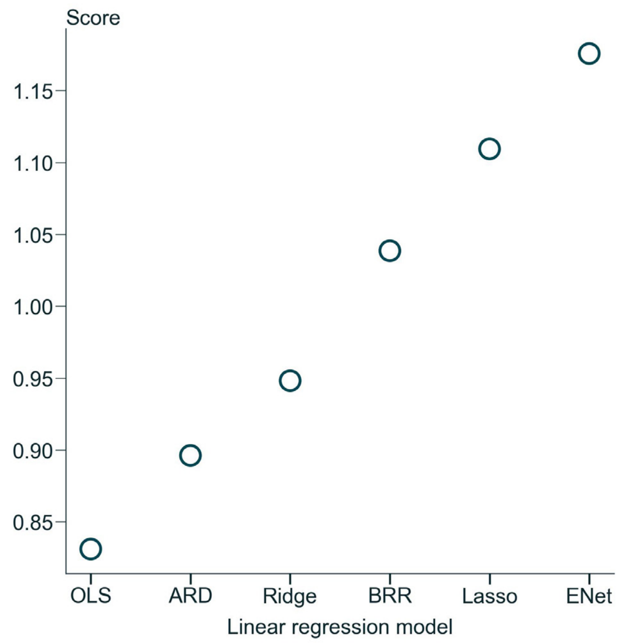
Source: IFM Investors, Bloomberg, World Bank

While this result suggests higher-frequency data are better – as is usually the case with ML – we are limited by two considerations. Firstly, the monthly frequency of the actual inflation data prohibits us from using weekly or semi-monthly data. And secondly, the quarterly frequency of the private market returns data argues in favour of training the model on monthly data as opposed to weekly or semi-weekly data. The reasoning behind this is that different data frequencies may lead to different model specifications, and the greater the change in frequencies, the more substantive the potential for deviation between models. Unfortunately, training the model on quarterly frequency data is problematic as there are only 77 quarterly observations (vs 226 monthly observations) which severely limits CV.

The compromise we have chosen is to train the model using monthly data and then use that model to fit the quarterly frequency data. Note that we use hyperparameters estimated on listed proxies for the private market assets in this investigation. For example, we use the hyperparameters estimated on monthly frequency listed infrastructure data as the assumed hyperparameters for private infrastructure in the quarterly frequency model.

FIGURE 12 **COMPOSITE OUT-OF-SAMPLE PREDICTIVE SCORE**

The ENet generates improved variance-adjusted standardised risks scores



Source: IFM Investors, Bloomberg, World Bank

In the second test we use monthly data only given the limitations discussed previously, and fit the optimal model suggested by CV and test that on a set of data unseen by the model (see Figure 12). We use a minimum of 50 training observations using the non-overlapping CV method with a train/validation split of 70%/30%. We then test predictions on a testing sample of 20 observations. We repeat this process in a rolling manner increasing the training sample by five observations each time and store a range of scores for each iteration including the predicted , mean squared error, mean absolute error, and median absolute error. It is important that we repeat the train/test process a number of times to prevent a spurious result in terms of the optimal model. Given that we are also interested in the consistency with which the models are able to generalise on unseen data, the final model selection decision is based on a composite score that depends both on predictive performance and the volatility of the predictive performance (similar in concept to risk-adjusted returns). The ENet model is shown to outperform with a score 47.5% better than the competing OLS model.

7.2.4 Model parameterisation

We were unable to directly tune and train our ENet model on the full data set (including listed and private assets) as the quarterly frequency of the private assets left us with an insufficient sample size for reasonable CV. In order to address this issue, we used a two-step parameterisation approach.

In the first step, we tuned model hyperparameters on the monthly listed asset data using overlapping walk-forward CV with 3 splits and a 70%/30% train/test split. We used a total of 2,500 hyperparameter combinations with the hyperparameter (shrinkage intensity) ranging from 0.05 to 3 and the L1 ratio hyperparameter (balance between L1 and L2 penalty) ranging between 0.05 and 0.95.

In the second step, we fit an ENet model to the quarterly data using the tuned hyperparameters from listed proxies as the hyperparameters for the private assets. See Table 07 for proxies.

Table 07: Listed hyperparameter proxy

Private asset	Listed proxy
Private credit	Average of HY fixed and IG fixed
PE	Average of listed PE and developed equities
Private real estate	Listed real estate
Private real assets	Average of listed real estate and listed infrastructure
UI	Listed infrastructure
IFM IIP	Listed infrastructure

Source: IFM Investors

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