IFM Investors

Evolving portfolios for the new paradigm: the case for private infrastructure

IFM Economics

September 2023

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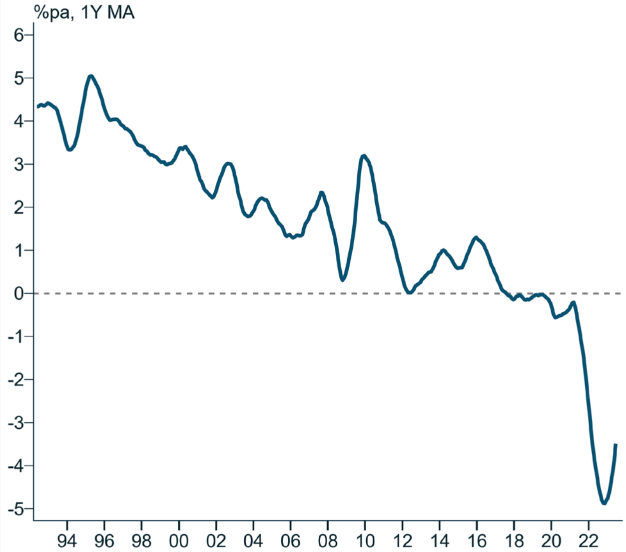
1. A new paradigm

The challenge for asset allocators to maximise risk-adjusted returns continues in the post-pandemic environment as it did in the low interest rate world that preceded it. However, the investment landscape has clearly changed. Economies and markets have faced a series of exceptionally disruptive events in the past few years, and investors must now navigate a new economic and geopolitical paradigm that we believe will require a further evolution of the traditional approach to portfolio construction.

In the following, we briefly discuss some of the most salient economic factors and broader themes affecting the investment outlook and put forward several strategies that might be considered to support overall portfolio risk-return objectives. We find compelling evidence that including private infrastructure can lead to better portfolio diversification, portfolios that are more robust to a range of macroeconomic regimes and higher risk-adjusted portfolio returns. Importantly, we find that optimal portfolio outcomes tend to be achieved when private infrastructure equity and private infrastructure debt are included in the same portfolio because of the complementary nature of the assets: private infrastructure equity tends to act more as a 'return enhancer' and private infrastructure debt tends to act more as a 'risk reducer'.

GRAPH 01 **REAL YIELDS***

Real risk-free rates have fallen for the past 30-40 years



Source: IFM Investors, Macrobond *Real yields proxied by GDP-weighted index of Australia, US, UK, Japan, Germany, France, Spain and Netherlands nominal 10Y government yields less actual headline year-on-year CPI inflation

1.1 The key challenges

- **The secular shift in interest rates:** Risk-free rates have broadly cycled around a declining trend since the peak of the 1980s. To our mind, this trend slowed and concluded in the years following the Global Financial Crisis. And while the COVID-19 pandemic precipitated exceptionally high volatility as policy settings swung from maximum accommodation (to protect economies) to aggressively contractionary (to curtail inflation), a new trend emerged that sees rates cycling around a stationary average. We expect the current tightening phase of interest rates to gradually decline towards this average. This is because more accommodative settings will become appropriate as inflation comes under control. This new average will be anchored by structurally lower neutral interest rates, subdued potential growth rates, and a return of inflation to target.

  Graph 1 highlights the structural fall in real rates.[1] This provided a broad tailwind to the returns of many assets.[2] Ilmanen (2022) estimates that between 1981-2020, the excess return of US treasuries over cash was 3.3%, of which 1.5% is attributable to the sample-specific windfall gains associated with falling yields. Similarly, the excess return of the S&P500 over cash was 7.8%, of which 2.7% is attributable to sample-specific windfall gains driven by the cyclically-adjusted earnings yield falling from 10.3% to 2.9%.

  The 'traditional' "60/40" portfolio that delivered solid returns in the declining rates environment will likely be challenged over the forward view. Furthermore, as the pandemic period demonstrated, this style of asset allocation struggled to cope with the types of supply-side shocks that we suspect may become more common. On this basis, we make three key conclusions for the medium term:

  1 Fixed income investors will need to be more tactical in their allocation to this asset class as rates will likely cycle more around a stationary average, rather than trend lower.

  2 Similarly, the valuation impact on other asset classes up the risk curve will become more variable.

  3 Portfolios will need to further diversify both within and across asset classes to maximise risk-adjusted returns.

- **Central bank balance sheets:** We see the continued withdrawal of liquidity by central banks as prompting investors to become more active both at the intra- and inter-asset levels. Risk will also be repriced within asset classes. A specific example is fixed income spread products, where central bank action artificially compressed yields.

- **Inflation:** There is considerable uncertainty around how persistent the recent surge in inflation will prove. Our view is that underlying inflation will return to central bank targets over the longer term, but we see the risks of inflationary shocks over the next decade

[1] We proxy real rates by using 10-year government yields (given our longer-term investment horizon) less year-on-year changes in headline CPI. Inflation expectations are technically more correct but long histories of inflation expectations across economies are challenging to find and actual CPI still illustrates our point.

[2] This is most obvious in fixed income instruments with a direct linkage to rates but is equally important to other asset classes with positive interest rate duration exposure. In equities, for example, falling real risk-free rates will lower the discount rate applied to future cash flows and lead to higher equity prices, ceteris paribus.

or so as tilted to the upside. We expect these inflation shocks to be disproportionately driven by supply-side issues and see a higher probability of stagflationary periods characterised by tightening monetary policy, above-target inflation, and below-trend growth.

- **Fiscal policy:** Recent years have seen a shift towards increasingly interventionist and populist governments. The main risks around this are 1) the increased likelihood of protectionist trade, industrial, and regulatory policies; 2) the volatility associated with heightened policy uncertainty; and 3) the likelihood of populist expansionary fiscal policy adding to the public debt burden that may overwhelm the appetite of investors for these assets. It may also create opportunities for private capital to invest in spaces previously the purview of governments.

- **Demographics:** Ageing populations and slowing/negative population growth will weigh on potential growth. In the investment space, the demand for low-risk liquid assets will evolve as we pass through the peak of the current generational retirement surge. This may also present a liquidity challenge as this generation moves into the drawdown phase of their pensions.

- **Geopolitics/geoeconomics:** A seemingly more divided and divisive geopolitical backdrop characterised by 1) increasingly confrontational foreign policy towards strategic threats, with heightened risks of conflict; 2) more muscular industrial policy focussed on protecting and the 'de-risking' of supply chains in strategically important domestic sectors; 3) more liberal use of economic 'soft power' towards geostrategic ends; and 4) regionalisation and fragmentation of global trade/investment relationships with a shift in dealings towards geopolitically aligned actors rather than those that might be geographically close or economically attractive.

- **Climate change:** The transition to a net-zero economy will be disruptive by design. Much will depend on the transition path and policy measures employed to facilitate the transition. The demand for capital through the adaptation/mitigation of the carbon economy over the transition period will likely place upward pressure on costs and downward pressure on growth as resources are directed away from potentially more growth-positive, nearer-term uses. Investor demand for 'green' assets will also continue to push down rates of return that may deter some marginal capital flows. There are also more direct risks insofar as the frequency/severity of extreme weather events, which are expected to increase supply-side shocks. This will impact output and food and energy prices but also raise risks to physical assets in terms of damage and obsolescence.

- **AI and technology:** The nascent AI boom and the importance of technology in the geostrategic landscape present material upside and downside risks to economic growth and inflation. Advances in technology look set to revolutionise the knowledge economy over the next decade with material implications for productivity and growth. However, if the associated labour market destabilisation is not carefully managed, there may be a rise in social/political instability. Furthermore, powerful AI tools can be easily leveraged by malign actors to serve their needs (e.g. a flood of AI-generated disinformation will make it even harder to identify facts, further polarising societies and increasing animus in the political sphere).

2. An evolving approach

There are several approaches that investors can explore to address the above challenges. One popular approach is to include a greater proportion of private market assets in a portfolio. Over recent years, investor demand for these exposures has been notable; in our experience, particularly for private infrastructure. A key characteristic that defines core infrastructure businesses is their long-term, stable revenue streams that may be inflation-linked and which may also benefit from economic growth. This is generally the result of these businesses providing essential services to communities (for example, within energy, utilities, transportation, or telecommunications) whilst inhabiting secure, monopolistic positions with very high barriers to entry and a limited availability of substitutes. Revenue streams for core infrastructure tend to sit in one of four categories – contracted, regulated, volume-linked and market-based revenues, with contracted and regulated revenues exhibiting the greatest downside protection, and volume-linked and market revenues showing correlation to economic activity. Ultimately, a diversified balance across these revenue types is key when building a resilient portfolio while providing meaningful upside in returns. It is worth noting that given the illiquid nature of private infrastructure, this discussion is of most relevance to longer-term investors who can effectively assume the illiquidity risk. Some approaches available to investors are:

Move up the risk/return curve: The most accessible method to increase returns is to take more risk. This may seem straightforward, but simply moving up the risk curve by altering the weights of existing asset exposures will likely not be enough. Indeed, expected risk-adjusted returns are not a monotonic function of expected returns. At some point, the additional volatility will outweigh the additional returns as risk-factor exposures become increasingly concentrated. Private market assets like unlisted infrastructure have a different risk profile than listed assets. As we have argued before, while this is beneficial in a portfolio sense, it is a limited proxy for an asset's real-world

A key characteristic that defines core infrastructure businesses is their long-term, stable revenue streams that may be inflation-linked and which may also benefit from economic growth.

'risk'. However, direct investment into private assets does have the benefit of often allowing for a more complete understanding of risks over and above what is available for listed markets. If the investment is of sufficient scale, it may also afford some degree of control and management of risks. Further, private markets discount shorter-term macro risks, which drive listed asset volatility despite not materially altering underlying valuation drivers. We posit that the mixed growth and defensive properties of private infrastructure, while clearly de-risking volatility of returns, offer a differentiated risk profile with respect to macro-economic factors. Given these factors, we argue for a more prominent place in portfolios for private infrastructure. This represents an acceptable and well-understood method of moving up the risk curve to support returns.

Better diversification: Differentiated risk, volatility, and correlation properties are all desirable factors from a portfolio diversification perspective. Private infrastructure is well-placed to help improve these portfolio properties. The recent stagflation risk and monetary policy response laid bare the limitations of traditional diversification approaches that rely predominantly on public markets. This is particularly true when the extremes of monetary policy stretch markets simultaneously to valuations not reflective of fundamentals, creating asymmetric risks. We assert these 'difficult to price' risks for public markets support a greater allocation to private ones. However, somewhat ironically, the volatility we observe in public markets has the potential to undermine the case for diversifying more aggressively into private markets. This effect has been observed recently (particularly in the Australian market where allocations to private infrastructure are relatively high) - private infrastructure allocations have recently been inflated relative to listed assets via a 'denominator effect'[3]. This pushes private infrastructure allocations closer to the upper end of strategic asset allocation constraints and limits long-term investors from fully capitalising on the potential opportunities and attractive entry points into the asset class.

This underscores two key points around diversification with private infrastructure. Firstly, it is difficult to 'time the cycle', and the diversification benefit comes from building a target allocation over time. We view private infrastructure as a largely buy-and-hold asset class for long-term investors; views on the economic cycle are better expressed in highly liquid public markets. Secondly, it may benefit asset allocators to put systems in place, primarily around liquidity, to 'look through' temporary increases in asset allocation towards unlisted asset classes when it is primarily due to valuations of listed asset classes.

Increase portfolio robustness: The elevated uncertainty regarding the macro and geopolitical outlook also argues in favour of building portfolios that are robust to a range of outcomes rather than simply leveraging into growth and defensive economic environments. The concepts of 'perpetual risk' or 'polycrisis' are increasingly employed to describe the current environment. This view suggests that portfolios will need to be robust enough to perform in changing macro and geopolitical environments and supports the case for more sophisticated portfolio diversification. This point applies both across and within assets. Investors need to be more active in their tactical allocations and thoughtful in their strategic ones to maximise risk-adjusted returns. In our view, selecting skilled managers across portfolios is more important than ever as alpha generation is an increasingly important component of overall returns as expected rewards for bearing systematic risk look lower and uncertainty looks higher.

3. Supporting analysis

Given the above, we now endeavour to explore an analytical framework to support our assertions with regard to private infrastructure. We have done this in a previous work (available online and by request) focusing on private infrastructure equity (PIE). In this paper, we build on that by including a proxy for private infrastructure debt (PID) to sit alongside equity and reflect investor appetite across the asset class and risk spectrum (see data appendix on page 11 for details). This allows us to comment on the role that PID and PIE could play in a portfolio, both individually and in concert.

In our previous approach, we used a traditional constrained mean-variance optimisation framework to highlight the potential benefits from a portfolio perspective of including private infrastructure. Yet we recognise the limitations associated with traditional mean-variance optimisation[4]. To address these limitations, we have developed a more sophisticated framework that leverages practitioner and empirically supported asset allocation algorithms.

Our updated framework[5] includes five separate asset allocation algorithms, of which three are non-clustering-based, and two are clustering-based[6]. Using different algorithms is intended to produce more robust estimates and to highlight the impact of model uncertainty[7]. Within each algorithm, we vary parameter estimation procedures such that a total of 54 optimal portfolios are produced for each data sample. These portfolios are then aggregated (taking into account algorithm characteristics) to produce range estimates of optimal portfolio weights, which reflect parameter uncertainty[8]. We also introduce an additional bootstrap-like layer: we sample from partially overlapping data windows and then estimate optimal weight ranges that take parameter instability into account, by performing

[3] The denominator effect: private asset valuations tend to be more stable than listed asset valuations such that the recent downtrend in listed asset valuations has driven private assets to account for an increasingly large proportion of overall asset allocations.

[4] For example, instability of outputs, sensitivity to inputs, overly concentrated portfolios, assumptions around investors objectives, etc. See also Frankfurter, Phillips & Seagle (1971); Chopra & Ziemba (1993); Jobson & Korkie (1980); Kallberg & Ziemba (1984); Michaud (1989) etc.

[5] See Technical Appendix on page 12 for details.

[6] Based on hierarchical clustering algorithms taken from the machine learning literature.

[7] Model uncertainty refers to the uncertainty introduced by using a given type of model to approximate reality.

[8] Parameter uncertainty refers to the uncertainty associated with estimating key input parameters due to measurement/sampling errors etc that may cause the estimated parameter to deviate from the true parameter value.

two-step aggregation[9]. We use this approach because it is important to consider the impacts of model uncertainty, parameter uncertainty, and parameter instability in this context. This allows us to highlight the risk associated with forward-looking asset allocation decisions.

We use eight asset classes in this investigation,[10] including investment grade (IG) fixed income, high yield (HY) fixed income, listed equities, listed property, listed infrastructure, commodities, PIE, and PID. We should note that we have used standard benchmarks to represent non-infrastructure asset classes. For infrastructure, we have taken a composite approach to reflect methodological differences in benchmark construction across the asset class. Also, while it would be possible to increase the granularity of this analysis (e.g. by breaking IG fixed income into different duration buckets or by splitting equities by geography/sector), there would be little benefit because we want to focus more on the alternatives space. Broadly, IG fixed income, listed equities, and HY fixed income are intended to cover the more traditional asset allocation space, whereas listed property, listed infrastructure, commodities, PIE and PID are intended to occupy the 'alternatives' investment space, which we are more concerned with. We also exclude cash from this analysis as we view the decision to invest in cash as more of a capital allocation rather than an asset allocation decision[11]. Where risk-free rates are required for portfolio optimisation, we use GDP-weighted 3-month government borrowing rates for the US, UK, Japan, France, and Germany. We use short-term rather than long-term sovereign debt instruments to minimise the impacts of non-default related risks like market risk, inflation risk, and duration risk (Mukherji, 2011).

Our analysis starts with the correlation matrix in Graph 2 that shows the aggregated correlation estimates[12]. As expected, PIE and PID both have low correlations with the remaining six assets. PID is also the only asset with negative correlations to the more equity-like assets (equities, listed property, listed infrastructure, HY fixed income). It is worth emphasising that PIE and PID have a correlation of just 0.1 with each other as well. This initial evidence suggests that these assets can improve portfolio efficiency individually and together.

Graph 3 shows the hierarchical relationship between asset groups. It visualises how the different asset classes are 'clustered' together and can be thought of as an analogue to the correlation matrix (Graph 2). The lower down the split between two assets on the dendrogram, the more 'similar' those assets are. The similarity of assets is quantified based on a combination of co-dependence and linkage metrics[13]. Although we use four combinations of co-dependence and linkage metrics in the complete framework, here we show one example to highlight asset characteristics where co-dependence is calculated as distance correlation and linkage is calculated using Ward's method (see Technical Appendix on page 12 for details). In

GRAPH 02 **MODELLED ASSET CORRELATIONS**

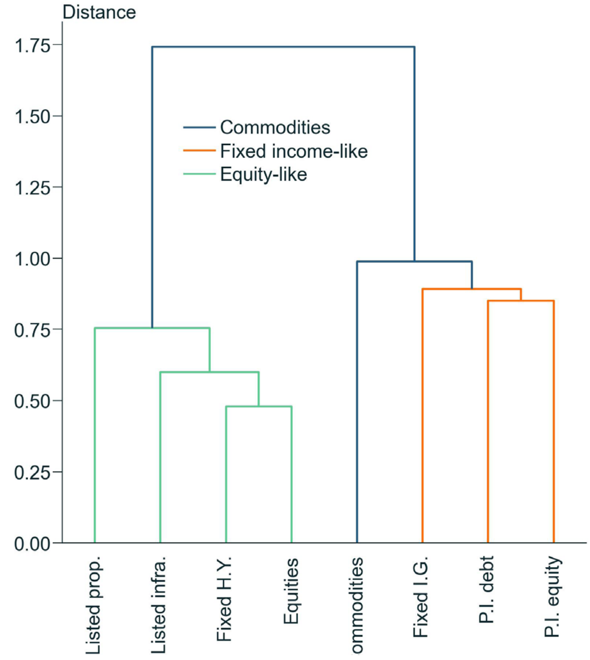
PIE/PID have desirable correlation profiles

	Equities	Fixed H.Y.	Listed infra.	Listed prop.	P.I. equity	Fixed I.G.	Commodities	P.I. debt
EQU		0.7	0.7	0.5	0.1	0.1	0	-0.1
FHY	0.7		0.5	0.5	0.1	0.3	0.1	-0.1
LIN	0.7	0.5		0.5	0.2	0.2	0	-0.1
LPR	0.5	0.5	0.5		0.2	0.1	0	-0.1
PIE	0.1	0.1	0.2	0.2		0.1	0.1	0.1
FIG	0.1	0.3	0.2	0.1	0.1		0.1	0.1
COM	0	0.1	0	0	0.1	0.1		0.1
PID	-0.1	-0.1	-0.1	-0.1	0.1	0.1	0.1	

Source: IFM Investors

GRAPH 03 **ASSET DENDROGRAM**

PID/PIE sit in the more fixed income-like cluster and remain distinct from one another



Source: IFM Investors

[9] Parameter instability refers to the variability in estimated parameters across data windows. Parameters may be dynamic (i.e. change over time) such that the true parameter values in different data windows may vary substantially.

[10] See Data Appendix on page 11 for details.

[11] Capital allocation is the distribution of funds across risk-free assets and risky assets, whereas asset allocation is the distribution of funds across risky assets.

[12] Correlations based on three robust covariance estimation procedures: Ledoit-Wolf; graphical lasso; oracle approximating shrinkage that are used in the non-clustering-based algorithms.

[13] See Technical Appendix on page 12 for more details on co-dependence and linkage metrics used in this analysis.

this example, HY fixed income and equities are the most similar as they have the lowest split. This relationship can also be seen in Graph 2 where the modelled correlation between HY fixed income and equities is relatively high. We see three clusters, which we will refer to as 'equity-like', 'fixed income-like' and commodities. The fixed income-like cluster is more like the commodities cluster than the equity-like cluster. This structure is also visible in the correlation matrix. Within the fixed income-like cluster, PIE and PID are only modestly more closely related to each other than they are to IG fixed income (and to a slightly greater extent, commodities). PIE and PID are also more different from one another than equities are from HY fixed income/listed infrastructure, for example.

Graphs 2 and 3 strongly suggest that PIE and PID have distinct characteristics from, and low correlations to 1) each other 2) the range of assets investigated here. This is evidence that including either PIE or PID will lead to improved diversification but that the assets are not substitutes for one another and that for the best diversification outcomes both PIE and PID should be included.

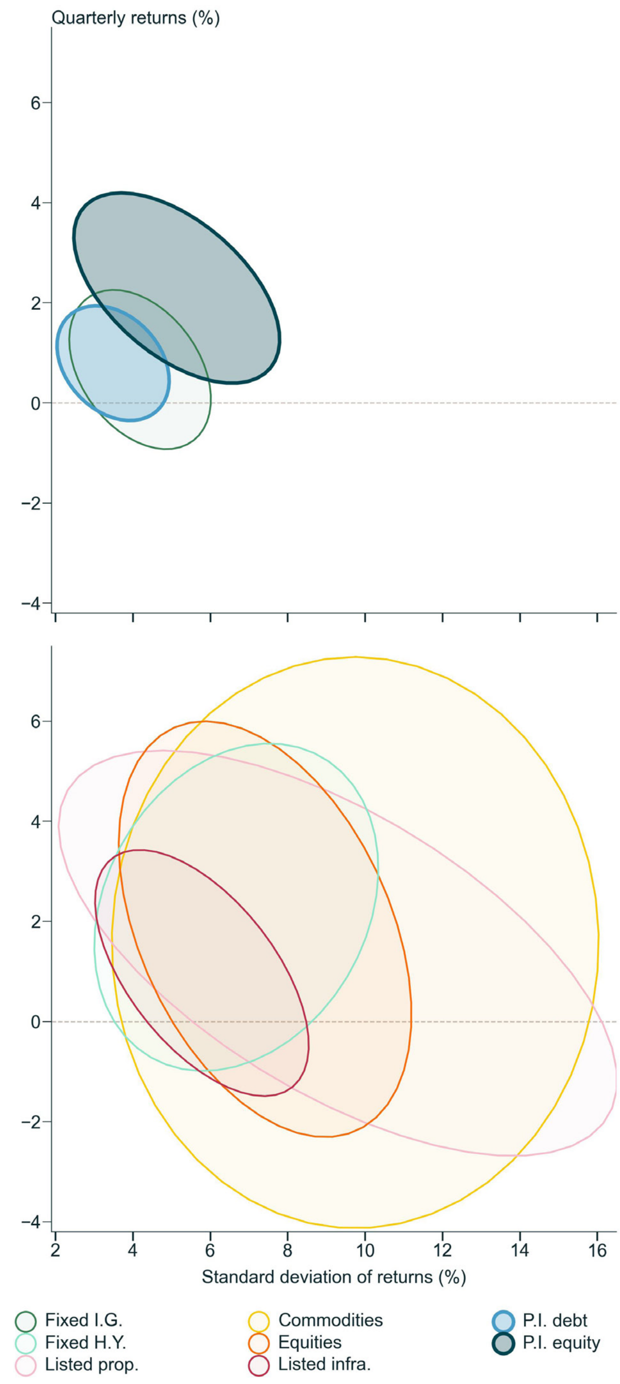
In Graph 4 we bring estimated returns[14] into the analysis and use the return standard deviations implied by the correlation chart (Graph 2) to create a variation of the popular risk/return scatter plot. We replace point estimates with ellipses that show the risk/return 'footprint' for each asset based on bootstrapped samples[15]. Compared to the traditional single-point risk/return scatter chart, this approach carries more information and allows the visualisation of estimated parameter instability. Higher parameter instability (larger ellipses) suggests higher sensitivity to various macro and idiosyncratic risk factors.

This chart highlights several important characteristics of PIE and PID returns that support what we intuitively suspected:

1. PID has a more limited risk/return footprint than IG fixed income, suggesting that PID may have more desirable defensive characteristics despite routinely being assigned greater credit risk.
2. PID has a significantly smaller risk/return footprint than HY fixed income despite having similar credit risk in many cases. This is likely due to defensive characteristics such as returns being more insulated from growth risks and more strongly linked to inflation.
3. PIE occupies a space between IG fixed income and listed equities, suggesting that it leverages growth but retains some defensive properties – the definition of mid-risk in this asset universe.
4. PIE tends to have higher and less volatile returns than listed infrastructure. Listed infrastructure shares the defensive properties of the underlying assets but has higher sensitivity to macro factors and sentiment-induced volatility.
5. PIE and PID have different risk/return characteristics, suggesting they should be viewed as complements rather than substitutes from a portfolio perspective.

GRAPH 04 **ASSET RISK/RETURN ELLIPSES**

Smaller risk/return footprints of PID/PIE are beneficial, particularly for portfolio robustness



Source: IFM Investors

[14] We use a combination of historical and Bayes-Stein return estimates.

[15] 12-quarter data window, rolling ahead 2-quarters each iteration for a total of 30 observations.

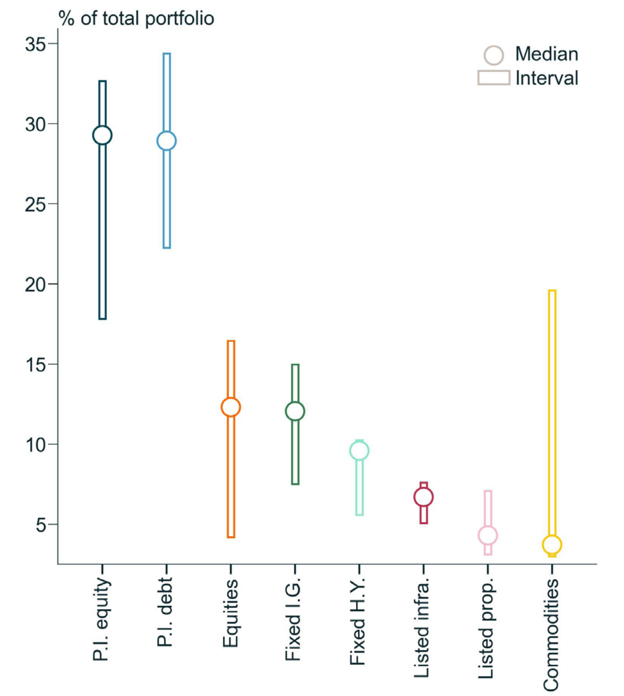
The generally attractive and relatively more stable risk/return characteristics of PIE and PID argue for the incorporation of the assets from a portfolio robustness perspective, while their distinct risk/return characteristics suggest that PIE and PID are not substitutes for one another and should both be included to maximise portfolio robustness. The favourable comparisons of PID and PIE to IG fixed income and listed equities, respectively, suggest that substitution into PID and PIE will support portfolio robustness. Furthermore, PIE's stable, mid-risk nature suggests that the asset can be an appropriate substitute for lower-risk/lower-return assets like IG fixed income where appropriate. This approach can be employed by investors who want to move up the risk/return curve whilst keeping overall portfolio risk well contained by avoiding the need for excessive risk concentrations in traditional, higher-returning assets like equities.

Graph 5 shows the median optimal allocations and optimal allocation intervals[16] based on our framework. Notably, this analysis is agnostic in terms of other constraints placed on a portfolio, particularly around liquidity, for example. This chart highlights how the distinct characteristics of PIE and PID argue for substantial weights to be invested in private infrastructure: even by conservative estimates, roughly 20-30% of the optimal portfolio is invested in each of PIE and PID. While we are cognisant that this exceeds what is practically achievable for most investors and would represent an unacceptable concentration of liquidity risk, it strengthens the case for these assets to be included more prominently in a portfolio. To further highlight the potential benefits of private infrastructure, we compare the optimal portfolio including private infrastructure (IO) to the optimal portfolio excluding private infrastructure (EO). The EO (see Graph 6) allocates approximately 50% to equity assets (including listed infrastructure and listed properties), 40% to fixed income assets, and 10% to commodities. It is also worth highlighting the significant interval around some of the optimal allocations – one of the key motivations for

> **Their distinct risk/return characteristics suggest that PIE and PID are not substitutes for one another and should both be included to maximise portfolio robustness.**

GRAPH 05 **MEDIAN OPTIMAL ALLOCATIONS AND INTERVALS**

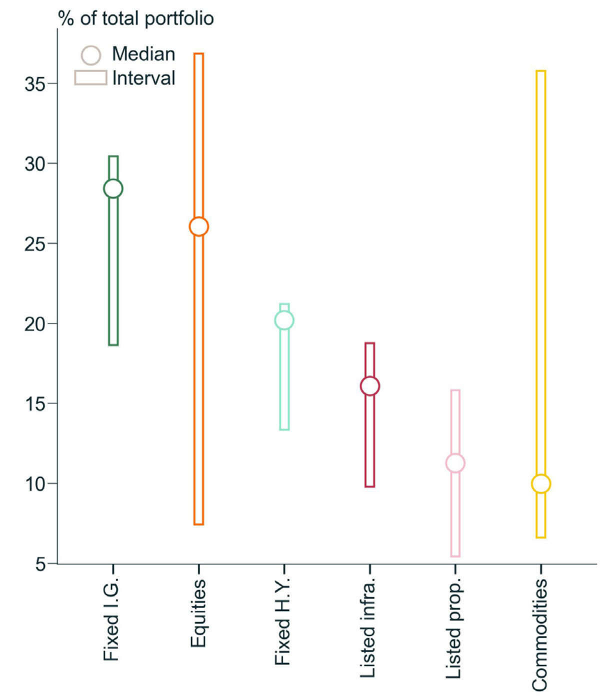
PIE/PID have sizeable allocations and modest allocation intervals relative to the high median allocations suggested



Source: IFM Investors

GRAPH 06 **EXCLUDING PRIVATE INFRASTRUCTURE OPTIMAL PORTFOLIO**

EO optimal looks similar to IO optimal but asset allocation intervals tend to be wider



Source: IFM Investors

[16] The optimal allocation interval is defined as the interval between the 20th and 80th weight percentiles suggested by the model.

TABLE 1

CHARACTERISTICS OF OPTIMAL PORTFOLIOS INCLUDING AND EXCLUDING PRIVATE INFRASTRUCTURE

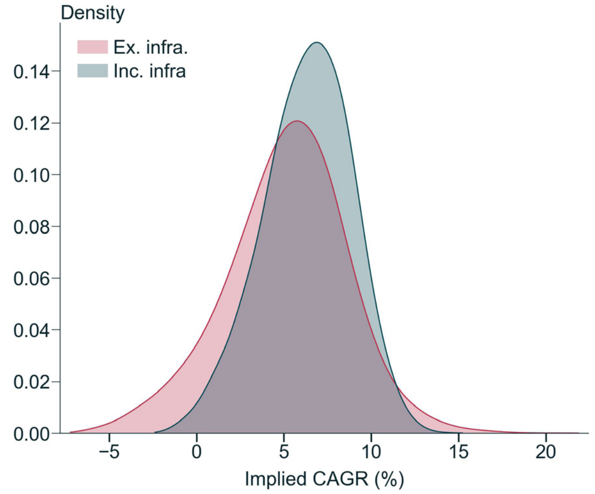
Portfolio CAGR statistic	Ex. Infra.	Inc. Infra.
Median (%)	5.25	6.48
Mean (%)	5.08	6.27
Standard deviation (%)	3.45	2.53
Downside deviation (%)	2.52	1.86
Sharpe ratio*	1.18	2.08
Sortino ratio*	1.62	2.83
Coefficient of variation	0.68	0.40
P(CAGR>10%) (%)	6.36	5.42
P(CAGR<0%) (%)	7.96	0.94
E[CAGR|CAGR<0%] (%)	-1.79	-0.85

Source: IFM Investors

*Risk-free CAGR over full data window implied by GDP weighted proxy is 1% and is used as the risk-free rate. Mean returns are used.

GRAPH 07 **OPTIMAL PORTFOLIO RETURNS**

Including PID/PIE shifts distribution to the right and lowers dispersion



Source: IFM Investors

our updated model framework. Equities and commodities are both standouts here, with optimal intervals that extend from around 5% on the low end to around 30% on the high end.

Comparing graphs 5 and 6 highlights that including private infrastructure tends to shrink overall allocation intervals. This is because private infrastructure tends to have stable allocations relative to its median and displaces the relatively less stable public market assets. This is further evidence in favour of the potential stabilising effects of including private infrastructure in a portfolio.

To compare characteristics between the IO and EO we employ a 'bootstrapped geometric Brownian motion Monte Carlo' approach[17]. This method has the benefit of capturing parameter instability to some degree. We use this technique to generate a total of 5,000 portfolio paths over a period of 10 years and focus on the implied portfolio compound annual growth rates (CAGR) at the end of the holding period. Looking at the CAGR distributions produced by this model, we find that including private infrastructure has material positive effects on portfolio risk/return characteristics (see Graph 7 and Table 1).

Including private infrastructure is associated with:

1. Higher average returns
2. Lower return volatility
3. Better risk-adjusted returns
4. Lower probabilities of negative returns
5. Marginally lower probabilities of CAGRs in excess of 10%
6. Smaller expected losses in the event of negative portfolio returns

In summary, an asset allocator who increases exposure to private infrastructure would likely be required to sacrifice some probability of higher-return outcomes but should receive meaningfully higher, and materially more stable returns with much lower risks of a negative portfolio return over the holding period.

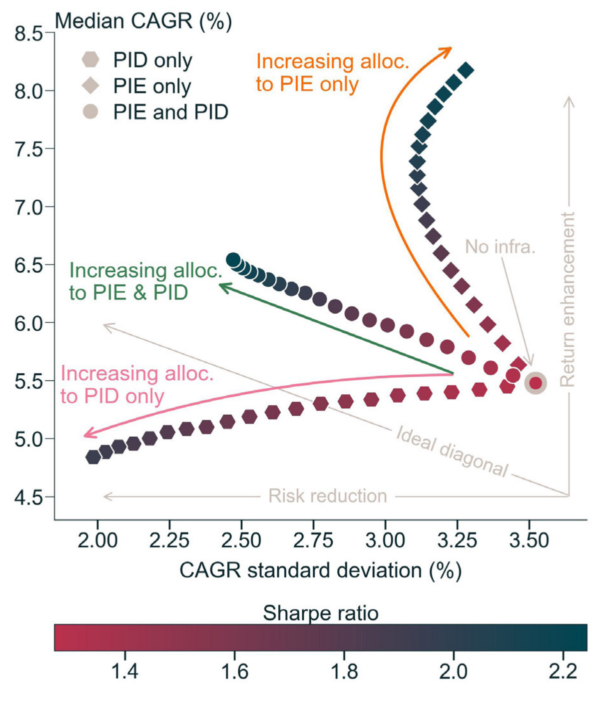
To further highlight the potential positive impacts of PID and PIE, we set the IO allocations for PIE/PID to zero and pro rata weights to the remaining asset classes. Note that this yields a portfolio very similar to the EO optimal portfolio. We then create three portfolios where we gradually increase allocations to PIE only, PID only, and PIE/PID together from 0% to 60% to highlight the relationship between private infrastructure allocations and portfolio risk/return characteristics. Graph 8 shows that adding private infrastructure to the EO portfolio has positive risk/return impacts. As expected, the idiosyncratic risks associated with excessive concentration to a single asset dominate at private infrastructure allocations above approximately 50%. Again, this level is substantially higher

[17] See Technical Appendix on page 12 for details.

than most investors' liquidity risk tolerances would allow but highlights some of the benefits associated with private infrastructure. Looking at PID/PIE in isolation, we see that PID tends to serve as mostly a 'risk reducer' and pulls portfolio risk down with only a limited impact on overall returns. PIE tends to act mostly as a 'return enhancer' and pushes portfolio return up with a more modest impact on overall portfolio risk. As other analysis in this paper has shown, benefits are most pronounced when PIE/PID are both included. A movement up and to the left in Graph 8 can loosely be thought of as the 'ideal diagonal' as it will improve portfolio risk/return characteristics more than an equivalent move only up or to the left. We see that including PIE and PID moves portfolio risk/return broadly along the ideal diagonal: portfolio risk is reduced approximately as much as portfolio return is increased.

GRAPH 08 **IMPACTS OF MORE PRIVATE INFRASTRUCTURE**

PIE mainly enhances returns, PID mainly reduces risk, PID/PIE together are optimal and move risk/return along the ideal diagonal



Source: IFM Investors

> **Including PIE and PID moves portfolio risk/return broadly along the ideal diagonal: portfolio risk is reduced approximately as much as portfolio return is increased.**

4. Conclusion

There are structural headwinds and significant uncertainties impacting the outlook for the investment landscape. This suggests more moderate expected returns and wider confidence intervals around longer-term return expectations such that investors will likely have to evolve portfolio construction strategies to achieve real risk-adjusted returns similar to the 30-40 years pre-pandemic – if they can do so at all.

In this paper, we have highlighted three key strategies that investors may consider to mitigate some of these effects. These include 1) moving up the risk/return curve, 2) better portfolio diversification, and 3) constructing more robust portfolios. We have demonstrated, via the application of an advanced asset allocation framework, how private infrastructure is well placed to help investors implement these three strategies. Our key findings include:

1. PIE and PID have distinct characteristics compared to 1) a range of other assets and 2) each other. This suggests that including either PIE or PID will increase portfolio diversification but that the best diversification outcomes will be achieved by including both PIE and PID in the same portfolio.
2. Private infrastructure tends to have more stable and more attractive risk/return characteristics than similar assets. Private infrastructure also tends to have relatively stable allocations through business cycles. This suggests that including PIE and/or PID in a portfolio will support portfolio robustness and diversification.
3. Private infrastructure can be an attractive substitute for more traditional equity and fixed income asset classes, with PIE best placed to substitute for listed infrastructure/equities, and PID best placed to substitute for HY/IG fixed income. Accordingly, substitutions away from more traditional assets and into private infrastructure can be an effective way to move up the risk/return curve and to facilitate meeting portfolio return targets.
4. Including private infrastructure can have substantial positive impacts on portfolio characteristics over the long term, including higher expected returns, lower return volatilities, better risk-adjusted returns, lower probabilities of portfolio losses, and smaller expected losses in the event of a negative return.
5. Moving from an optimal portfolio without infrastructure we find that including either PID or PIE improves risk-adjusted returns (up to a point). PID acts mainly as a 'risk reducer' and PIE acts mainly as a 'return enhancer'. The combination of PIE and PID provides both risk reduction and return enhancement characteristics and has the most beneficial impact from a portfolio perspective.

5. Data Appendix

We use a total of 10 return indices in this analysis (see Table 2) with quarterly data from Q1 2005 to Q4 2022 for a total of 72 observations.

TABLE 2

Asset	Proxy
Investment grade fixed income	Bloomberg global aggregate total return USD unhedged index
High yield fixed income	Bloomberg global high yield Total return USD unhedged index
Listed property	FSTE EPRA NAREIT developed total return USD index
Commodities	S&P GSCI index
Listed equities	MSCI large cap total return local currency index
Listed infrastructure	MSCI mid and large cap infrastructure total return index Local Currency
Private infrastructure debt	IFM sub-IG composite total return index USD
	EDHECinfra infraDebt300 total return local currency index
Private infrastructure equity	IFM's International unlisted infrastructure portfolio net return local currency index
	EDHECinfra infra300 total return local currency index

The PIE and PID proxies we use are constructed from two PIE and two PID return indices, respectively. For the PIE proxy, we combine the IFM International unlisted infrastructure portfolio and the infra300 index. Our primary motivation behind including the infra300 index in our PIE proxy is to ameliorate concerns around understated volatility in unlisted indices that are driven by the accepted valuation processes. The infra300 index is substantially more volatile than IFM's International unlisted infrastructure portfolio, in fact the quarterly sample standard deviation of the infra300 index for our full data window is 6.1%, compared to a quarterly sample standard deviation of 5.6% for the listed infrastructure proxy. We do have some concerns around using the infra300 index as a proxy for PIE (e.g. the index is not investable, is gross return and doesn't take into account the generally higher fee structure associated with private investments, is subject to potentially significant revisions as additional information is incorporated into the model). But given the sensitivity of allocation algorithms to input parameters, we opt for the conservative approach of including the higher volatility of the estimated infra300 index in our proxy, rather than solely using the actual realised returns of IFM's International unlisted infrastructure portfolio.

Our approach to combining IFM's International unlisted infrastructure portfolio and the infra300 index explicitly accounts for the variance-reducing impacts of aggregating indices. Specifically, the variance of the average of two returns series will almost always be lower than the average variance of each of the individual series:

$$\mathrm{Var}\left(\frac{\mathrm{X}+\mathrm{Y}}{2}\right) \leq \frac{\mathrm{Var}(X)+\mathrm{Var}(Y)}{2}$$

To address this issue, we calculate each side of the above inequality separately to estimate a variance scaling parameter that we apply to the demeaned aggregate index prior to re-meaning to increase volatility and further limit concerns around understated volatility in private markets. Specifically, we estimate the scaling parameter $\epsilon \geq 1$ as below:

$$\hat{\epsilon} = \frac{\mathrm{SD}(X)+\mathrm{SD}(Y)}{2} \times \mathrm{SD}\left(\frac{\mathrm{X}+\mathrm{Y}}{2}\right)^{-1}$$

Where SD(•) is the standard deviation.

For the full sample, we find $\hat{\epsilon}=1.24$, which corresponds to a 24% increase in volatility for the aggregate index. Note that we assume a quarterly fee of 0.5% for the infra300 index to reflect a reasonable estimate of roughly 2% annual fees for PIE. The complete set of calculations used to calculate the PIE index are given below:

$$\mu_i = \frac{x_i + y_i - \mathcal{F}}{2}$$

$$\sigma_A = \sqrt{\frac{\sum_{i=1}^{N}(\mu_i - \bar{\mu})^2}{N-1}}$$

$$\sigma_B = \frac{\sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}} + \sqrt{\frac{\sum_{i=1}^{N}(y_i - \bar{y})^2}{N-1}}}{2}$$

$$\hat{\epsilon} = \frac{\sigma_B}{\sigma_A}$$

$$\mathrm{PIE} = \prod_{i=1}^{N}[1 + (\hat{\epsilon}(\mu_i - \bar{\mu}) + \bar{\mu})]$$

Where:

x_i,y_i: quarterly return of IFM's International unlisted infrastructure portfolio and infra300, respectively, in quarter

F: quarterly fee (only infra300 is gross and therefore needs fee adjustment)

$\bar{\mu}$: average quarterly return of equal weighted index

$\bar{x}$,$\bar{y}$: average quarterly return for IFM's International unlisted infrastructure portfolio and infra300, respectively

N: Number of quarters in the sample

We use a similar, but more conservative, approach for PID. Firstly, we assume a reasonable 0.25% quarterly fee (~1.0% annually) for both the IFM sub-IG composite and infraDebt300 indices. Secondly, the IFM sub-IG index only goes back to 2014 so we backfill using the longer history of the infraDebt300 index. To reflect the uncertainty associated with one of the data series being shorter, we calculate for the PID proxy based on the maximum rather than average variance and we re-mean the data based on the minimum rather than average return. Specifically, we make the following calculations:

$$\mu_i = \frac{(x_i + y_i)}{2} - \mathcal{F}$$

$$\sigma_A = \sqrt{\frac{\sum_{i=1}^{N}(\mu_i - \bar{\mu})^2}{N-1}}$$

$$\sigma_B = \max\left(\sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}}, \sqrt{\frac{\sum_{i=1}^{N}(y_i - \bar{y})^2}{N-1}}\right)$$

$$\hat{\epsilon} = \frac{\sigma_B}{\sigma_A}$$

$$\text{PID} = \prod_{i=1}^{N}[1 + (\hat{\epsilon}(\mu_i - \bar{\mu}) + \min(\bar{x}, \bar{y}))]$$

Where:

x_i,y_i: quarterly return of IFM sub-IG composite and infraDebt300, respectively, in quarter

F: quarterly fee (both indices are gross and need adjustment)

$\bar{\mu}$: average quarterly return of equal weighted index

$\bar{x}$,$\bar{y}$: average quarterly return for IFM's International unlisted infrastructure portfolio and infra300, respectively

N: Number of quarters in the sample

6. Technical Appendix

This framework includes five separate portfolio optimisation algorithms, three of which are non-clustering-based and two of which are clustering-based. These approaches are widely used in industry and/or have empirical evidence that support their application in this context.

6.1 Portfolio optimisation models:

6.1.1 Mean-variance (MV)
MV optimisation seeks to solve for a set of asset weights that maximise portfolio risk-adjusted return subject to a set of constraints. The MV approach we use is based on methods introduced by Markowitz (1952). The set of constraints imposed here are that weights must sum to 1 (i.e. all capital must be invested in the available assets) and all weights must be greater than or equal to zero (i.e. no short positions are permitted).

6.1.2 Risk parity (RP)
RP optimisation seeks to distribute risk equally across assets. It can be viewed as risk diversification rather than dollar diversification. The RP approach we use is based on methods discussed by Bruder & Roncalli (2012). The approach is 'return naïve' (returns are not considered when calculating optimal allocations) and rests on the assertion that when assets equally contribute to portfolio risk, the portfolio can be more resistant to downturns and can achieve a higher Sharpe ratio.

6.1.3 Relaxed risk parity (RRP)
RRP seeks to improve on RP by incorporating return considerations that permit the portfolio to violate RP conditions in search of higher portfolio return. This is intended to address criticisms that the standard RP portfolio is too conservative. The RRP algorithm we use is based on the approach introduced by Gambeta & Kwon (2020). This approach requires the user to specify two key constraints: a return target and a regularisation parameter. The return target is usually expressed as some multiple of the standard RP return.

6.1.4 Hierarchical risk parity (HRP)
HRP is another return naïve allocation algorithm and seeks to address the issues of instability, concentration, and underperformance associated with MV optimisers. The HRP algorithm we employ is based on the approach discussed by Lopez de Prado (2016). This method uses graph theory and machine-learning techniques to construct portfolios based on information contained in the covariance matrix. Specifically, agglomerative hierarchical clustering is used on the asset returns matrix to construct a hierarchical tree. This requires the user to specify what measures of codependence and linkage are used (see Parameter estimation sub-section). HRP then quasi-diagonalises/seriates the assets based on the constructed hierarchical tree and performs a top-down recursive bisection of the tree. At each bisection step, the algorithm allocates weights to the two 'child clusters' such that each cluster contributes an equal amount of 'risk' based on some user-specified risk metric. This continues until no more clusters remain.

6.1.5 Hierarchical equal risk contribution (HERC)

HERC is similar to HRP (also return naïve, also machine-learning based) but seeks to improve upon HRP. The method we use is based on an approach introduced by Raffinot (2018). The initial steps in HERC are the same as HRP – agglomerative hierarchical clustering builds a hierarchical tree. At this point, however, the tree is 'pruned' by selecting the optimal number of clusters based on the Gap Index developed by Tibshirani, Walther & Hastie (2001). This step helps ameliorate concerns associated with overfitting and computational complexity. After pruning, the recursive bisection procedure discussed in HRP is used to weight clusters such that risks are allocated equally across each bisected child cluster. Once all clusters have been assigned weights, the standard risk parity weights are calculated for all assets in a given cluster and then scaled by bisected cluster weights to get individual asset weights.

6.2 Parameter estimation:

We use parameter estimation techniques that are used by practitioners and/or have empirical evidence supporting their use in this context. We do not select one estimation technique per parameter but instead opt to vary estimation procedures. This is intended to reflect some degree of parameter uncertainty in the estimation procedure and to highlight the uncertainty inherent in allocation optimisation techniques.

6.2.1 Return estimates:

- **Historical returns:** The first moment of the various return indices.

- **Bayes-Stein returns:** An empirical Bayes estimator as discussed by Jorion (1986). The estimator is intended to reduce the degree of estimation error and to decrease the likelihood that optimal allocation algorithms arrive at corner solutions. Empirical evidence suggests that the Bayes-Stein approach leads to improved out-of-sample portfolio performance (Jorion (1985); Chopra, Hensel & Turner (1993); Grauer & Hakansson (1995).

6.2.2 Covariance estimation:

- **Ledoit-Wolf shrinkage:** Robust covariance matrix estimation procedure first described in Ledoit & Wolf (2004a). This approach has been shown to reduce tracking error and increase realised information ratios Ledoit & Wolf (2004b).

- **Graphical lasso sparse inverse covariance estimation:** A machine-learning based method of estimating return covariances taken from the Biostatistics paper by Friedman, Hastie & Tibshirani (2008). The approach induces sparsity in the inverse covariance to better capture conditional independences between different assets to improve the robustness of portfolio optimisation (e.g. Millington & Niranjan, 2017).

- **Oracle approximation shrinkage:** Introduced by Chen, et al. (2010), this approach is well-suited to robust covariance estimation for high-dimensional, small sample problems and has been shown to have lower mean-squared error than Ledoit-Wolf shrinkage.

6.2.3 Risk measure estimates:

- **Standard deviation:** The most popular risk metric used in portfolio optimisation. The square root of the average squared distance between each observation and the arithmetic average of all observations.

- **Mean absolute deviation (MAD):** The average absolute difference between each observation and the arithmetic average of all observations. Konno & Yamazaki (1991) show that using MAD leads to portfolios similar to Markowitz's model but are calculated in a fraction of the time. Furthermore, Yu & Wang (2012) find that a MAD model is consistent with second-degree stochastic dominance when considering a bounded set of mean-risk trade-offs, and Konno & Koshizuka (2007) show that a MAD model is more consistent with rational decision-making than more traditional mean-variance approaches.

- **Gini's mean difference (GMD):** The average absolute difference between all pairs of individual observations. Yitzhaki (2003) has argued that Gini's mean difference has desirable characteristics over variance as a measure of variability.

6.2.4 Codependence metrics:

- **Pearson correlation:** Well-known measure of linear association between two vectors. Based on variances and covariances, the coefficient is bound between -1 and 1.

- **Distance correlation:** Measure of dependence first discussed by Szekely, et al. (2007) that uses Euclidian distance to assess the similarity between two vectors (bound between 0 and 1). Distance correlation is a measure of both linear and non-linear association, in contrast to the more widely used Pearson correlation, which measures only linear association.

6.2.5 Linkage metrics:

- **Unweighted pair group mean averaging:** Method attributed to Sokal & Michener (1958) that defines the distance between two clusters as the average distance between data in the first cluster and second clusters. Clusters with the smallest average distance are combined at each stage of the process.

- **Ward:** Approach described by Ward (1963) that calculates one-way univariate ANOVAs for each variable. Clusters are combined at each stage based on which combination yields the smallest increase in the combined error sum of squares.

6.3 Aggregation of estimates:

For each allocation algorithm (MV, RP, RRP, HRP, HERC), we find the median optimal allocations for each asset as suggested by the algorithms and parameter estimation variations. We weigh the median allocations, taking into account the characteristics of each algorithm. Specifically, the RP, HRP, and HERC algorithms are all return-neutral and receive lower weights than MV and RRP – we do not want the framework to be dominated by return-neutral allocation algorithms. Due to the well-documented issues around extreme allocations suggested by MV, we weigh that approach slightly less than the RRP approach. We repeat this process for each sub-sample using 21 quarters of data. Each successive sample moves forward 3 quarters. We then take the median, 20th and 80th percentiles of all the sub-sample medians to calculate the bootstrapped estimate of optimal allocation and optimal allocation range.

6.4 Bootstrapped Monte Carlo (BMC)

BMC differs from traditional Monte Carlo approaches because rather than estimating parameters across the full dataset, the BMC algorithm randomly samples a subset of quarters from the full dataset a total of times and then applies standard Monte Carlo approaches to each random sample for a total of runs. This yields asset price paths that capture the impacts of parameter instability to some degree. Asset price paths are modelled using geometric Brownian motion, as is commonplace in quantitative finance applications. Given the importance of covariances to overall portfolio performance, we ensure the geometric Brownian motion implementation explicitly includes covariances between all assets when generating price paths.

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IFM-21September2023-3116564