ALLOCATING BY RISK FACTOR

Quantifying Private Asset Contributions to Risk Factor Exposures

April 2026

Executive Summary

Factor-Based Portfolio Construction: Using a factor lens, institutions may target explicit exposures to risk factors[1] including growth (equity), interest rates, and credit, as a means of aligning the portfolio with long-term risk and return objectives. In this paper, we demonstrate how these targeted exposures can be quantified using both listed and private asset classes, with private assets proxied by privateMetrics® and infraMetrics® indices. A growth-oriented portfolio targeting 65/25/20 exposure to the equity, interest rate, and credit factors, respectively, is constructed across listed and private assets. We compare a simple portfolio comprised of listed assets with one that incorporates private assets, with both portfolios having the same allocations across the three risk factors.

Diversification Within the Factor Allocation: Private equity, infrastructure equity, and infrastructure debt each exhibit return variation beyond common risk factors, and these unexplained components are uncorrelated with listed asset residuals. This offers potential diversification within the factor allocation and may contribute to improved portfolio Sharpe ratios while maintaining similar factor exposures.

Infrastructure as a Diversifier: Infrastructure equities offer diversification within a factor allocation framework. With statistically significant betas to both the equity factor (~0.36) and interest rates (~1.01), infrastructure equities contribute meaningfully to desired exposures, not easily replicated from equity or bond only assets. Similarly, infrastructure debt provides diversification relative to investment grade bonds, with lower equity beta and credit exposure than IG bonds, and differing rates beta. The uncorrelated residuals suggest that obtaining rates and credit exposure via infrastructure debt may enhance risk adjusted performance.

Time varying Betas and Uncertainty: In our last TPA piece (here: TPA III), we showed that the risk factor betas are time varying. There are periods when private equities and infrastructure equities may have higher/lower sensitivity to risk factors that are defined by tradeable listed assets. This creates a challenge for allocators seeking a certain level of exposure across equities, rates, credit, or other factors. Related to this is the uncertainty around the coefficients. For infrastructure equities, we find an average equity factor beta of ~0.36 using 20 years of monthly (~250 months of returns). At a 5% confidence level, the beta is 0.25 to 0.47. This can make it a challenge to understand true exposure. Extending this across other betas and unlisted asset classes and the confidence in the betas may become an issue. For institutions with large private asset allocation, estimation errors have real consequences. Using privateMetrics and infraMetrics helps reduce this uncertainty, as higher-frequency data that better reflects current private market conditions can provide more accurate estimates.

[1] For this paper risk factors refer to Equity, Rates, and Credit. This distinguishes them from style factors

Data and Methods

Drawing on data from infraMetrics® and privateMetrics®, this paper explores how market-based private asset data can be used to quantify risk factor betas across listed and private asset classes, allowing one to construct a portfolio based on desired factor exposures.

Both infraMetrics® and privateMetrics® databases can be used to download monthly index prices and risk metrics for private infrastructure equities, private infrastructure debt, and private equities. The flagship indices, infra300 and private2000, represent broad market indices diversified by sector, geography, and risk profile, best capturing the systematic risk of their respective markets. Both represent excellent starting points for capturing systematic risk and returns in their respective markets, private equity and infrastructure. Find infraMetrics indices (here) and privateMetrics indices (here). Further, our MSExcel Add-in allows for seamless download of the index data (see here).

A brief description of each index is below:

The infra300 index is a representative set of 300 unlisted infrastructure companies. The companies are selected to form a representative sample by TICCS® categories from an underlying universe of close to 9100+ firms in 27 countries. The index is represented globally in both corporate and project finance companies.

The private2000 index includes the top 2000 private companies by value across 30 countries and diversified by sector. The companies are selected to form a representative sample by PECCS® categories from an underlying universe of close to 1 million firms.

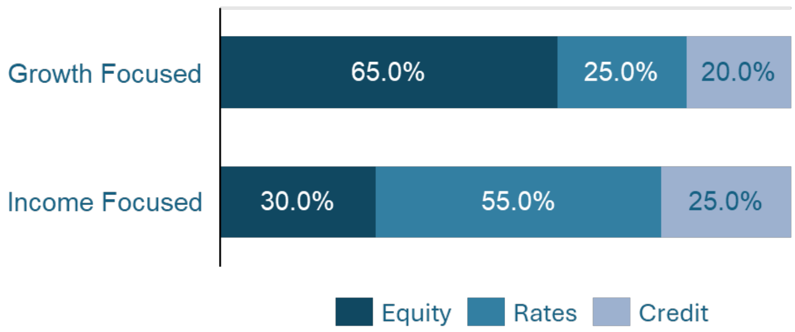
Introduction

In this paper, we consolidate aspects of our previous papers on Total Portfolio Allocation or TPA,[2] and explore portfolio construction based on desired exposures to key risk factors: Growth (equity), interest rates, and credit. We start with listed asset classes to create a simple reference portfolio and then construct a second portfolio that includes private assets, both with the same desired exposures.

As an illustration, figure 1 shows two hypothetical portfolio exposures. First, a Growth Focused portfolio, typical of pension, endowment and sovereign wealth funds, exhibits a large exposure to growth assets (equities) and meaningful interest rates and credit exposure. Alternatively, an Income Focused portfolio, typical of a life insurer, maximises interest rate sensitive assets, given a greater need to hedge liabilities.

[22] See TPA Part I, TPA Part II, TPA Part III

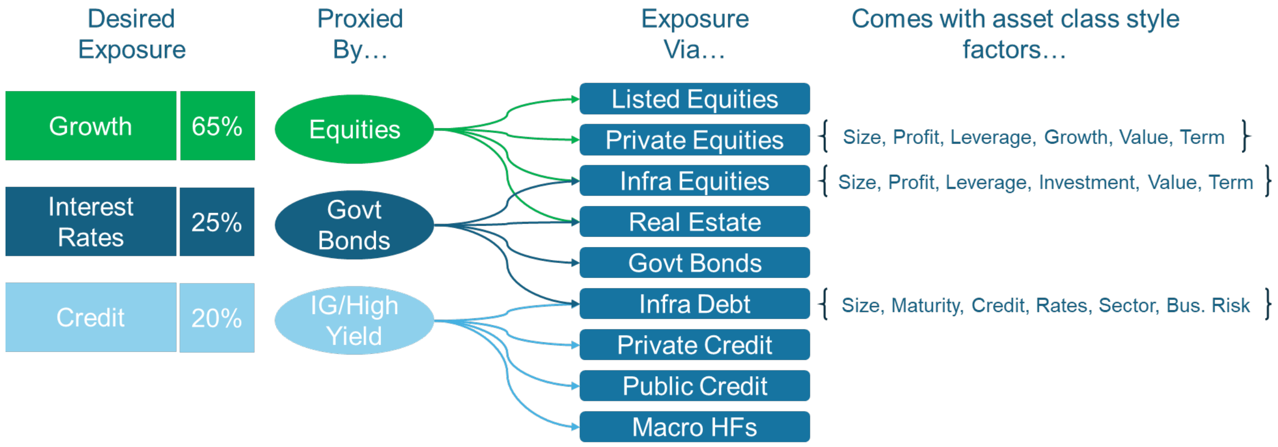
FIGURE 1: POTENTIAL TARGETED RISK FACTOR BETAS TO EQUITY, NOMINAL RATES, AND CREDIT



In what follows, we focus the example on the former case (Growth), though the insights would apply much the same for an income heavy portfolio, particularly for infrastructure equity and debt.

Figure 2 shows schematically how the exposure objectives (equity, rates, and credit betas for the portfolio of 0.65, 0.25, and 0.20) are achieved by allocating across a number of asset classes. Some asset classes contribute to one exposure e.g., government bonds, while other such as infrastructure equities, create exposures to both interest rates and equities. For listed assets, it is straightforward to quantify these exposures. For private asset classes, we use privateMetrics and infraMetrics indices, with monthly data stretching back 13 years and 25 years, respectively, which is enough datapoints to quantify exposures.

FIGURE 2: MAPPING DESIRED FACTOR EXPOSURES TO ASSET CLASSES OR OPPORTUNITIES



Next, table 1 details the asset classes used to construct a portfolio based on the Growth Focused target risk factor exposures.

TABLE 1: ASSET CLASSES AND PROXIES

Asset Class	Proxy or Index
Government Bonds	UST 1-3, 7-10, and TLT
Credit	US Investment Grade Bonds
Inflation Protection	TIPS
Global Equities	MSCI ACWI
Small Cap Equities	Russell 2000
Infrastructure Debt	infra300 debt index
Infrastructure Equity	infra300 equity index
Private Equity	private2000 index

Measuring Factor Contributions

In figure 3, allocations for the reference portfolio and a portfolio diversifying across asset classes are shown. The reference portfolio achieves the desired exposures via listed assets, with equities exposure through a global equities index (MSCI ACWI) and a small cap index, in this case the Russell 2000. Rates exposure comes via government bonds, TIPS, and investment grade bonds. This portfolio would have achieved annualised return and realised volatility of 7.39% and 10.32%, leading to a **Sharpe ratio of 0.55** for the period covering 2014 to 2025.

The target portfolio (rhs) produces the same targeted exposures but achieves greater diversification thanks to its use of private alternatives. Private equity, represented by the private2000 index is given a near 10% weight, while infra equity and debt each have an approximate 6% weight. This portfolio has an annualised return and volatility of 7.72% and 8.91%, and a **Sharpe ratio of 0.67**, as shows in table 2. It should be noted that the improved Sharpe ratio does not come from lower volatility in private asset classes. Volatility of the private2000 index was over 17% during the period, greater than global equities. Infrastructure equities had nearly 12% volatility for the same period. Instead, **the improvement comes from diversification alone**.

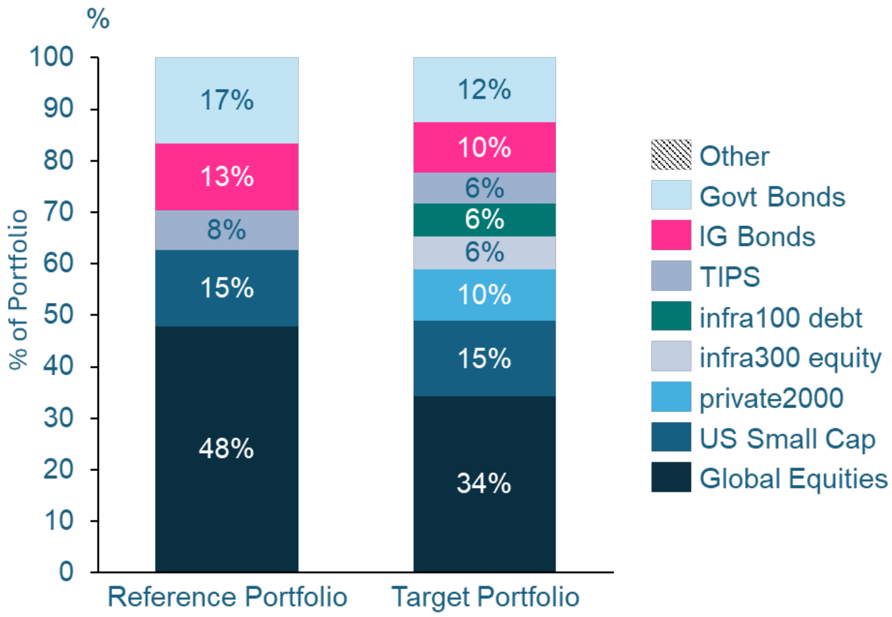
TABLE 2: PORTFOLIO RISK AND RETURN METRICS

Portfolio	Equity %	Rates %	Credit %	Annualised Return	Annualised Volatility	Sharpe Ratio
Target	65	25	20	7.72%	8.91%	0.67
Reference	65	25	20	7.39%	10.32%	0.55

Source: privateMetrics, infraMetrics, Bloomberg, SIPA Calculations.

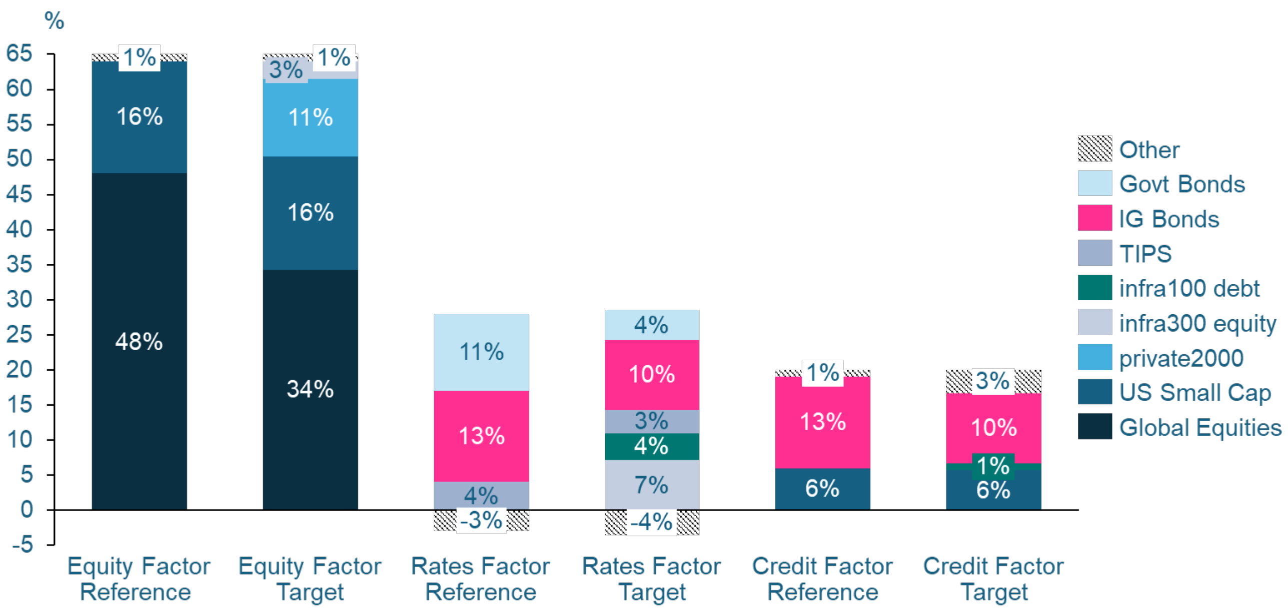
Figure 4 shows how each asset class contributes to the targeted exposures in both the reference and target portfolios.

FIGURE 3: REFERENCE PORTFOLIO ASSET MIX (LEFT) VS TARGET PORTFOLIO (RIGHT)



Source: privateMetrics, infraMetrics.

FIGURE 4: FACTOR CONTRIBUTIONS BY ASSET CLASS: REFERENCE VS TARGET PORTFOLIOS



Source: privateMetrics, infraMetrics Bloomberg.

In the target portfolio, equity factor exposure is achieved through a combination of listed and private assets. Private equity contributes 11%[3] and infrastructure equity 3% of the

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[3] The private2000 beta is estimated based on long-term volatility of the private2000 index relative to MSCI ACWI and a long-term horizon correlation of approximately 0.85. Horizon correlations at investment-relevant hold periods of 12 to 16 quarters rise toward this range, providing support for this assumption. See 'Do Private Equities Track Public Markets? Horizon Correlations in Private Equities.'

total 65% exposure. Compared to the reference portfolio, private assets account for over 20% of the equity factor (14%/65%) in the target portfolio.

Table 3 summarises these contributions for both the reference and target portfolios, with target portfolio figures shown in parentheses.

TABLE 3: REFERENCE AND TARGET PORTFOLIO CONTRIBUTIONS TO RISK FACTORS

Risk Factor %	Global Equities	US Small Cap	private2000	infra300 equity	Infra300 debt	TIPS	IG Bonds	Govt Bonds	Other
Equity	48 (34)	16 (16)	0 (11)	0 (3)	--	--	--	--	1 (1)
Rates	--	--	--	7	4	4 (3)	13 (10)	11(4)	-3 (-4)
Credit	--	6 (6)	--	--	(0) 1	--	(13) 10	--	1 (3)

Source: privateMetrics, infraMetrics Bloomberg. SIPA Calculations.

Measuring Factor Exposures

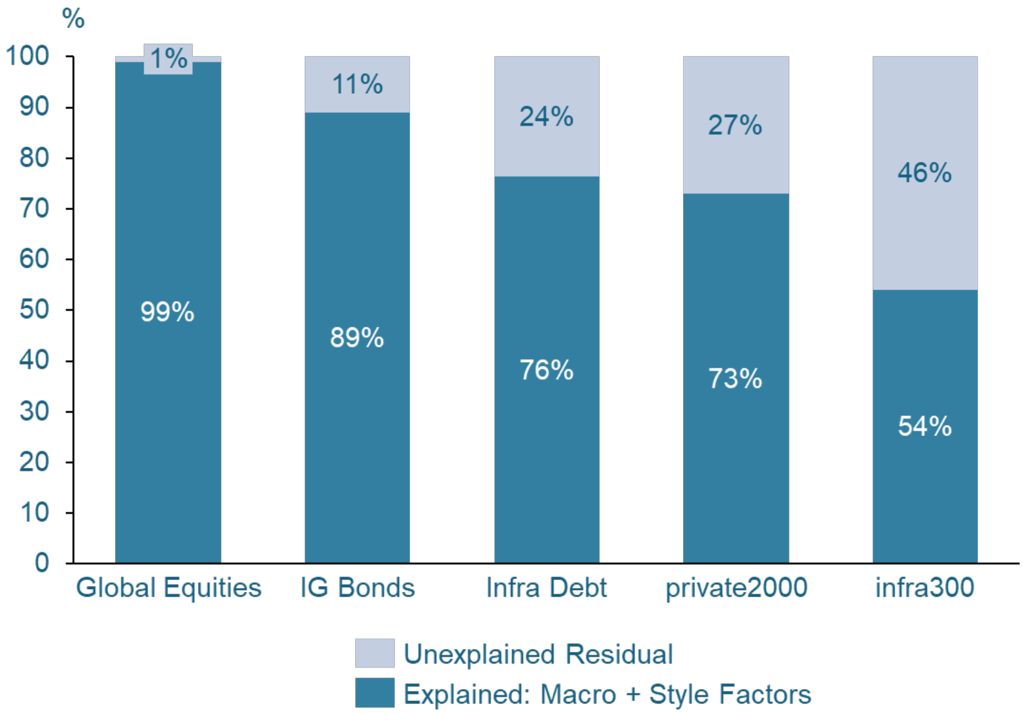
In figure 5, we explore the diversification benefits in more depth by looking at the results from a simple OLS regression with asset class and risk factor returns (equity, rates, and credit), and style returns associated with infrastructure and private equities.

Global equities, by definition, are almost entirely explained by the equity factor. For investment grade bonds (IG bonds), the returns are largely explained by exposure to three risk factors, with an r-squared of 89%. This compares to 76% for infrastructure debt. IG bonds have a greater equity and credit beta than infrastructure debt. Though both IG bonds and infra debt provide rates exposure, their sensitivity to credit spread changes or the equity markets are different. Further, the residual (unexplained portion) for infra debt is larger and is uncorrelated with the residual for IG bonds, suggesting diversification benefits. The risk factor betas, confidence intervals, and significance can be found in table 4.

Asset classes or opportunities with large residuals that are uncorrelated with core asset classes offers diversification benefits, potentially leading to a higher Sharpe ratio. We observe a similar outcome for private equities and private infrastructure equities in figure 5. Here we extend the regression to include both macro risk and style factors. Listed equities, by definition will be almost entirely explained by the equity factor. The private2000 index has an r-squared of 73%, with a large portion explained by private equities style factor exposures. For infrastructure equities, the r-square is 54%. Both asset classes offer diversification benefits relative to listed assets; however, they are also exposed to significant systematic risks in infrastructure and private equity markets that are not captured by the three core risk factors (equity, credit, and rates).

Table 5 shows the betas more explicitly.

FIGURE 5: OLS REGRESSION EXPLAINED VS UNEXPLAINED BY ASSET CLASS (ADJUSTED R-SQUARED)



Source: privateMetrics, infraMetrics, Bloomberg.

Since uncorrelated residuals across these private asset classes provide diversification at the portfolio level, when several asset classes each contribute modest idiosyncratic returns that are uncorrelated with each other and with listed benchmarks, the portfolio-level diversification benefit is amplified. This is why we observe lower volatility and a higher Sharpe ratio in the portfolio with private assets.

TABLE 4: OLS RESULTS IG BONDS VS INFRA DEBT

	IG Bonds	Infra Debt
Equity Beta	0.12 [0.060,0.175]***	0.033 [-0.010,0.076]*
Rates Beta	1.18 [1.066,1.295]***	0.606 [0.545,0.668]***
Credit Beta	0.42 [0.301,0.531]***	0.118 [-0.003,0.239]***
R-squared	89%	76.3%
Residual	11%	23.7%
Residual Correlation	0.0065	0.0065
N	144	144

Note: p<0.01 = *** and p<0.10=*. Infra debt represented by infra300 index in LCU.

For infrastructure equities, the exposure is differentiated relative to both IG bonds and listed equities. The rates beta is similar to IG bonds, but the equity beta is much larger. Like with infra debt, the residuals are uncorrelated with those of the listed asset class proxies.

It is worth noting that the betas reported here reflect the full sample period (2014–2025, 2004-2025 for infra equities). As discussed in Part III of this series, the betas are time varying and regime dependent. Betas behaved differently for the period 2014–2021 vs 2022-2025. Institutions that want to manage factor exposures dynamically, rather than relying on a longer-term average (implied by the OLS) would need to monitor these betas on a rolling basis and potentially use listed asset classes to adjust the portfolio exposures.

TABLE 5: OLS SUMMARY RESULTS IG BONDS, LISTED EQUITIES, AND INFRA EQUITY

	IG Bonds	**Listed Equities**	**Infra Equity**
Equity Beta	0.12 [0.060,0.175]***	1.00***	0.36 [0.247,0.470]***
Rates Beta	1.18 [1.066,1.295]***	-	1.01 [0.810,1.212]***
Credit Beta	0.42 [0.301,0.531]***	-	0.02
R-squared	89%	100%	54%
Residual	11%	0%	46%
N	144	144	250

Note: p<0.01 = ***.

Conclusion

This paper brings together the key themes of the TPA paper series, demonstrating how higher frequency, market based private assets data can be utilised to measure exposures to risk factors, putting private assets alongside listed securities. This includes the ability to look through to the private asset classes to understand how they contribute to various exposures. For asset classes that have multiple exposures (e.g. infrastructure), this may impact allocations from both the equity and rates buckets.

The approach reinforces a key point from earlier papers: asset allocation weights and risk factor exposures are not the same thing. Even with high-frequency, market-based private asset data, factor exposure estimates carry meaningful uncertainty — betas are time-varying and confidence intervals are wide. An institution's true factor exposures may differ materially from what its allocation weights imply, and that difference is not stable over time.

The results highlight another problem. Private assets operate in their own markets, with distinct buyers, sellers, valuation mechanisms, and return drivers, that at times diverge materially from listed markets, as the post-2022 experience has demonstrated. Private assets cannot be perfectly reduced to a combination of listed market exposures, however well measured. Longer time series of higher-frequency, market-based pricing narrows the uncertainty considerably, but relying on stable long term beta assumptions may lead to imprecise measurement of risk exposure. This challenge is compounded for the many institutions that still rely on infrequent appraisal valuations, which reduce the data available for estimation and introduce additional smoothing that may further misstates true exposures.

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Access all privateMetrics data programmatically and build your own applications for private market investing and reporting

Index Catalogue

Browse our catalogue of hundreds of private equity, infrastructure and infra debt indices, inc. market indices like the infra300 and private2000, and thematic indices representing specific market segments.

Taxonomies

Query the PECCS® and TICCS® taxonomies used to create the privateMetrics universe. Access class codes, names and definitions to build your own index and comps customisations applications.

Index Data

Access a comprehensive set of performance and risk metrics for hundreds of private equity, infrastructure and infra debt indices tracking numerous geographies and segments.

Custom Benchmarks

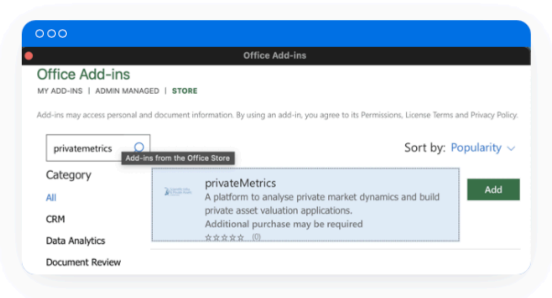
Build custom benchmarks setting target weights by PECCS, TICCS, style and geography that align with your strategy. All index metrics are recalculated for you.

Custom Comps

Create customised comp sets using PECCS® and TICCS® segments, geography and systematic risk profiles. Get metrics like discounts rates and EBITDA multiples.

Yield Curves

Query risk-free rates for a given pricing and maturity date to support discounted cash flow (DCF) calculations, valuation models, and other financial analyses.



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privateMetrics Excel Add-in Documentation

The privateMetrics® Valuation Model

Our approach to the valuation of private companies is designed to maximise the available transaction and financial data in private markets and provide a standardised and systematic manner to update prices with every observed transaction.

First, we construct a multi-factor model of prices using a sample of observed transactions over time which can infer the unbiased and precise factor prices that investors pay for different characteristics of a private asset. Although every transaction is idiosyncratic or unique, in a large sample of transactions, the individual errors in each transaction price can be diversified away to discern the price attributable to each factor. Factor prices refer to the premium (or discount) that an investor is willing to pay to seek exposure to a specific factor of return in private companies. For example, observing the relationship between size and valuation among reported transactions, it can be inferred how much premium or discount an investor is willing to pay for purchasing a larger private company.

Second, an important and key application of this approach is that, with the estimated factor prices, say for size, it would then be possible to price unlisted private companies whose size information is available, irrespective of whether they are traded or not. This approach provides a more robust estimate for FV and enables the creation of representative indices of private companies.

Our approach's novelty is calibrating the model to newly observed transactions obtaining the factor price evolution over time, which allows us to update the valuation for all tracked unlisted private companies.

Common Risk Factors

If investors trade unlisted private companies from each other in mutually negotiated transactions, there must be some common characteristics that at least partially explain prices. For example, private companies that have higher profits or growth opportunities may be more valuable to investors than those that are not.

To arrive at a potential list of factors, we follow simple criteria that there needs to be an economic rationale for the factor to affect valuation. The factor should also be statistically related to the valuation. Moreover, the factor should also be objectively observable or measurable. With a potential list of factors, our factor selection is the result of a statistical approach, where the factors that can satisfactorily explain the variation in observed transaction valuations are included in the final model while trading off being parsimonious with being able to explain a higher variance in valuation. The privateMetrics asset pricing model uses five key risk factors as below:

- **Size**: Larger companies may be more complex, have higher transaction costs, and be less liquid, all of which can make them trade at a lower valuation per $ of revenue.

- **Growth**: As traditional PE strategies rely on growing the entry multiple, that may involve both increasing its top and bottom lines, i.e., revenue and profits. Thus, companies that can grow faster can be more sought after, making them more valuable.
- **Leverage**: Leverage can make a company riskier as it increases the risk of default. However, there is also a signaling effect of leverage, as companies with stable consistent cash flows can support a higher leverage, and vice versa. Thus, leverage is expected to influence the valuation of a company.
- **Profits**: More profitable companies have more predictable (less risky) future payouts and hence attract a lower risk premium, making them more valuable.
- **Maturity**: Younger companies have fewer track records and face higher information uncertainty. Studies have shown that firms with high uncertainty tend to be overvalued and earn lower future returns. Thus, the maturity negatively affects valuation.
- **Country risk**: Investors may require a high return when investing in a high-risk country, thus depressing the current valuation. In other words, in countries with lower risk, investors may be willing to purchase assets at a higher valuation as government policies may be more predictable with lower macroeconomic risks.

TABLE A1: KEY FACTORS, THEIR EFFECT ON VALUATION, & THE ECONOMIC RATIONALE FOR INCLUDING THEM IN THE MODEL

Factor	Definition (Proxy)	Effect on price	Economic Rationale	References
Size	Revenues	Negative	Larger firms are more illiquid and trade a lower price	Fama & French (1993)
Growth	Change in Revenues	Positive	Companies with higher revenue growth trade at a higher price	Fama & French (1992), Petkova & Zhang (2005)
Leverage	Total debt / Revenues	Positive	Companies that can borrow more have a lower cost of capital and a higher value	Gomes & Schmid (2010), George & Hwang (2010)
Profits	Ebitda Margin	Positive	Companies that have higher profits have a higher value	Novy-Marx (2013), Hou et al. (2015)
Maturity	Years since incorporation	Negative	Companies that are mature exhibit less growth potential and trade a at a lower price	Jiang et al. (2005)
Country Risk	Term Spread	Negative	Companies in high-risk countries face more uncertain prospects	Chen & Tsang (2013)

SOURCE: CALCULATED USING OVER 10K DEALS FROM PITCHBOOK, CAPITALIQ, FACTSET, AND OTHER PRIMARY SOURCES BETWEEN 1999-2022

Our factors have been documented in prior academic studies to be associated with valuation. We also include factors that have been identified as key determinants of valuation from a survey of private equity practitioners that we conducted in 2023. Table A1 summarises the key factors that we use in the model, how they are measured, each factor's effect we document in the data on average, the economic rationale for their inclusion, and citations for the work that underpins their inclusion.

Model Set Up

The privateMetrics asset pricing model uses the Price-to-Sales ratio of observable transactions (the entry price multiple) as the modelled variable. The model is estimated as the linear sum of the product of factor exposures and factor prices. The estimation can then separate the systematic part of the valuation while leaving out “noise” in each valuation.

$$\frac{P}{S} = a + \sum_{k=2}^{K} b_k l_k + e$$

Following standard asset pricing notation, the factor exposure or factor loading is called a beta (β), and the factor premium is called a lambda (l) for the *k* factors in the model. a is the intercept and e is the noise or idiosyncratic part of the valuation.

Model Calibration

The privateMetrics model uses a carefully curated dataset of more than 10k+ unlisted private company investments going back two decades sourced from a wide variety of datasets including PitchBook, Factset, Capital IQ, fund manager reports, and other publicly available data sources.

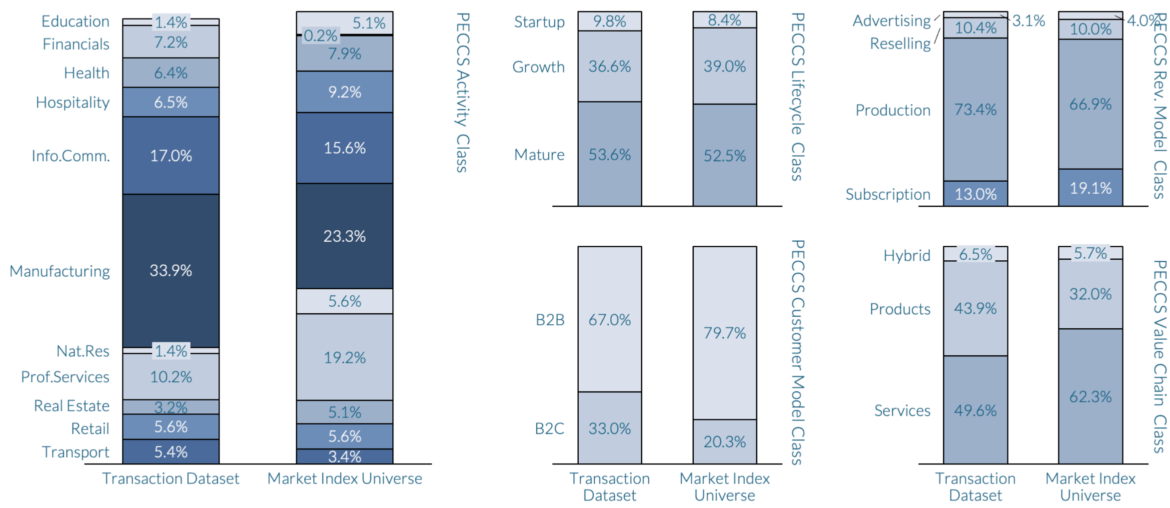
We calibrate this model using new observations monthly to update its estimation of the price of risk of each factor. In other words, each transaction observed is then used to ‘update’ this model (i.e., obtain new ls) through a dynamic estimation (using a Kalman filter), which retains the memory of past ls while also allowing the new transaction to influence the relationship while keeping the average e close to zero. More details on the implementation of the model are available in our online documentation and Selvam and Whittaker (2024). The dataset covers all key segments of the market as shown in Figure1.

A good application of using the model to value unlisted private companies is to create a representative marked-to-market index of private companies that are regularly valued. The privateMetrics index universe in Figure 1 includes the constituents of the private2000® index constructed by Scientific Infra and Private Assets, which is developed on this shadow pricing idea and captures the performance of private companies in 30 countries globally that are important for private equity investors (read more about the index here).

How Precise are the Predictions across PECCS® Pillars?

To examine how closely the predicted valuations track the raw modelled valuations in transactions, we compute the average estimation errors of the full sample, and also by classes within each PECCS® pillar. What stands out is that although the model by design is expected to have lower estimation errors in the full sample, the within PECCS® class estimation errors are also very small. All the errors are within ±10%, reassuring that the model predictions on average even within each segment of PECCS® are reasonable. The errors are summarised in Table A2.

FIGURE A1: PRIVATEMETRICS TRANSACTION DATASET COMPARED TO THE PRIVATEMETRICS INDEX UNIVERSE BY PECCS PILLAR & CLASS



The most commonly used metric of valuation in private markets is EV/EBITDA as PE owners have the flexibility to alter the capital structure of their holding company and hence are more interested in operational profitability without factoring interest costs. However, our model is based on P/S because P/S is statistically better, stable, and not affected by loss-making companies. Thus, one may be concerned whether our predictions for EV/EBITDA might be biased.

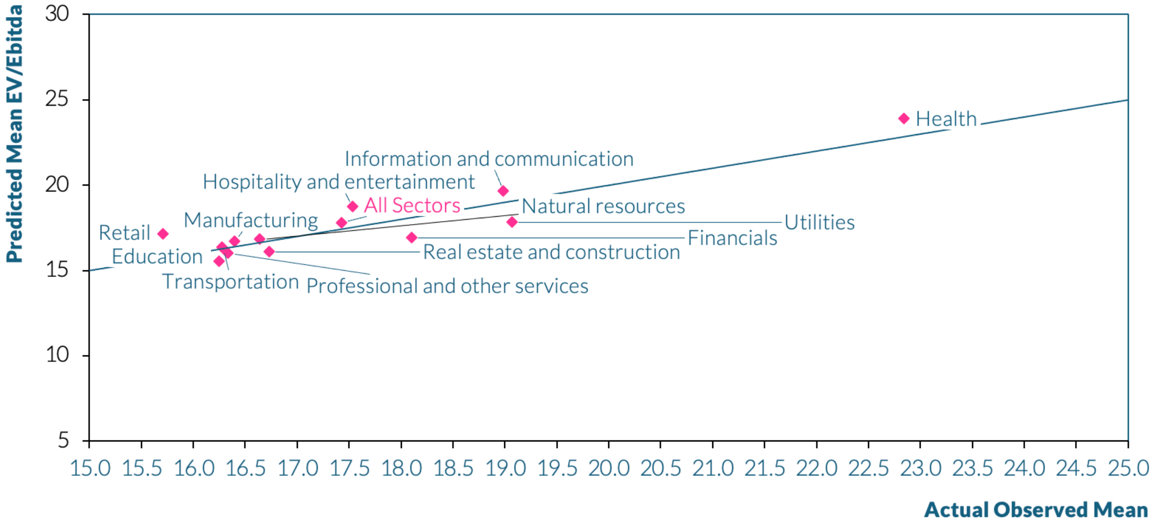
To ensure that is not the case, we compute the EV based on the book value of debt and predicted equity valuation and divide the sum by the EBITDA to get a predicted EV/EBITDA and compare it to transaction implied ratios. Figure A2 presents the average predicted and observed EV/EBITDA by PECCS® activity classes. We find that the predictions are very close to the observed values, thus mitigating this concern.

TABLE A2: AVERAGE ESTIMATION ERRORS ACROSS PECCS® CLASSES, BASED ON THE DIFFERENCE BETWEEN TRANSACTED VALUATIONS AND FACTOR MODEL PREDICTIONS

PECCS Pillar	**PECCS Class**	**Mean Estimation Error**	**PECCS Class**	**Mean Estimation Error**	**PECCS Pillar**
PECCS Activity	Education and public	0.9%	Startup	0.1%	PECCS Lifecycle Phase
	Financials	1.8%	Growth	-1.7%	
	Health	2.6%	Mature	2.8%	
	Hospitality and entertainment	-1.1%	Advertising	1.2%	PECCS Revenue Model
	Information and communication	-4.4%	Reselling	4.6%	
	Manufacturing	2.5%	Production	2.9%	
	Natural resources	9.4%	Subscription	-6.9%	
	Professional and other services	3.3%	B2B	1.5%	PECCS Customer Model
	Real estate and construction	1.9%	B2C	0.9%	
	Retail	0.5%	Hybrid	0.6%	PECCS Value Chain
	Transportation	7.2%	Products	1.1%	
Full Sample		**1.1%**	Services	3.4%	

SOURCE: CALCULATED USING OVER 10K DEALS FROM PITCHBOOK, CAPITALIQ, FACTSET, AND OTHER SOURCES BETWEEN 1999-2022

Figure A2: Predicted versus actual EV/EBITDA ratios by PECCS® activity classes



Source: Calculated using over 10k deals from PitchBook, CapitalIQ, Factset, and other sources between 1999-2022

About Scientific Infra & Private Assets

Our products come from the cutting-edge R&D of the EDHEC Infrastructure & Private Assets Research Institute, established in 2016 by EDHEC Business School. In 2019, we transformed this academic research into a commercial enterprise, providing services like private market indices, benchmarks, valuation analytics, and climate risk metrics. We take pride in our unique dual identity, bridging scientific research and market applications.

The EDHEC Infrastructure & Private Assets Research Institute (EIPA) continues to advance academic research and innovate with technologies in risk measurement and valuation in private markets, especially utilising artificial intelligence and language processing. Our company, Scientific Infra & Private Assets (SIPA), supplies specialised data to investors in infrastructure and private equity.

Merging academic rigor with practical business applications, our dedicated team excels in integrating quantitative research into private asset investing. Our products, infraMetrics® and privateMetrics®, are unique in the market, stemming from thorough research rather than being ancillary services of larger data providers. We are the Quants of Private Markets, leading with innovation and precision.

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