An Infrastructure Investment Primer: From Valuation to Allocation and Manager Selection

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KEY FINDINGS

- Unlisted infrastructure investment presents numerous performance measurement challenges due to the paucity of available data. However, extensive data collection and advanced methodologies can palliate these issues and considerably increase the reliability and transparency of performance reporting and benchmarking.
- Unlisted infrastructure investment is not risk free and presents a number of equity-like and bond-like characteristics. The cash flows of infrastructure companies are resilient but not completely independent of the business cycle, while the price of risk for such cash flows is driven by market forces—because investors arbitrage between asset classes—and by their exposure to duration and convexity.
- Unlisted infrastructure can play a powerful role in the portfolio as a diversifier, provider of yield, and as a liability matching or hedging instrument thanks to its high cash yield and duration. Beyond performance and risk measurement, the greatest challenge for investors is to achieve a well-diversified exposure to the infrastructure asset class in order to benefit fully from its investment characteristics. Manager selection and benchmarking are important parts of this question.

ABSTRACT

Infrastructure investments can play several important roles in the portfolio, from generating yield and income to creating diversification and matching or hedging liabilities. They are also relatively large and illiquid and, as such, present valuation and risk measurement challenges. Stale, biased, and limited contributed data have long left investors and regulators only able to make educated guesses. Recent developments in data collection and asset pricing techniques for private assets allow granular market-based valuations and risk-adjusted return calculations. This article introduces standard definitions for infrastructure investments and styles as well as a modern and robust asset pricing framework for the production of fair valuations and useful risk measures. It also presents stylized empirical facts based on 20 years of data for the risk-adjusted performance of unlisted infrastructure equity, systematic and extreme risks, asset allocation, and fund manager selection.

Over the past two decades, unlisted infrastructure equity investment has become a fully fledged asset class, often with its dedicated allocation pocket and asset managers or investment team. This article proposes an introduction to this relatively new and fast-changing asset class, in a context where a shift in investor preferences in favor of unlisted infrastructure after 2008 led to a significant increase in asset prices, while Covid-19 lockdowns in 2020 and the normalization of the yield curve from 2022 reminded investors of the underlying risks of these investments, increasing prudential and fiduciary scrutiny in the valuations and risk-adjusted performance of this asset class.

From a portfolio management perspective, the decision to arbitrage in favor of unlisted infrastructure corresponds to at least three objectives:

1. *Yield*: Infrastructure investments have a well-documented ability to deliver higher cash yield than other asset classes. Infrastructure companies have limited reinvestment options for their free cash and typically pay a high proportion of revenues as dividends. Likewise, infrastructure debt can achieve relatively high levels of yield given its low credit risk profile.
2. *Diversification*: Infrastructure returns are expected to have lower correlation with other asset classes and to be less exposed to market stress. Infrastructure companies offer essential services with a low price-elasticity of demand and derive their value from cash flows that expand far into the future, making asset values less sensitive to short-term variations in the business cycle.
3. *Asset–Liability Management (ALM)*: Infrastructure assets are a source of income and duration in the portfolio. As a result, they can contribute to ALM strategies such as cash-flow matching or liability hedging.

To achieve these objectives, investors need answers to a number of important empirical questions:

1. What distinguishes infrastructure investment from other asset classes?
2. What risk factors explain the fair market value of infrastructure investments?
3. What is the relevant performance benchmark?
4. How does infrastructure compare with other asset classes in terms of returns, cash yield, and duration, including in times of market stress?
5. How much infrastructure should be added to the portfolio?
6. How does one select top-quartile fund managers?

In what follows, we address each one of these questions using the latest research results available. We first describe the unlisted infrastructure investment universe to which institutional investors and their asset managers typically have access. We then focus on key asset pricing challenges and solutions. Indeed, only with a sufficiently robust valuation framework can investors approach the question of risk and the benchmarking of unlisted infrastructure investments. Next, we describe the historical performance of the asset class and the best choice of benchmark for investors and then explore correlations with other asset classes and how infrastructure investments have performed during times of market stress over the past two decades. In the Asset Allocation section, we present a multi-asset allocation case study of the role of unlisted infrastructure in the portfolio, describe the performance of investor peer groups as function of their actual historical allocations to different segments of the infrastructure universe, and finally, we propose an approach to benchmarking and selecting fund managers in a context where manager contributed data are typically too sparse to estimate robust performance quartiles of fund multiples or internal rate of return (IRR).

THE INFRASTRUCTURE INVESTMENT UNIVERSE

In this section, we briefly review recent research on the characteristics of infrastructure companies and how they may be categorized using a taxonomy that reflects their risk and performance profile. We then examine the structure and size of the investible market.

The Anatomy of a Cash Cow

In a description of typical "investment beliefs" about infrastructure, Blanc-Brude (2013) summarizes the "infrastructure investment narrative" including the fact that infrastructure companies are expected to possesses special characteristics such that "investors are expected to benefit from the low elasticity of demand creating pricing power and an inflation hedge, as well as low return covariance with other investments, allowing attractive risk-adjusted returns." As such, infrastructure businesses are often portrayed as "cash cows"—that is, the combination of semi-monopolistic conditions, limited opportunities for growth, high leverage, and steady revenues should result in significant dividend payouts. These dividend payouts could go a long way in explaining why, on a total return basis, infrastructure equity returns are also expected to be less correlated with those of other asset classes while staying attractive.

In a recent paper, Whittaker and Tan (2019) examine the way in which infrastructure companies differ from the rest of the economy and in particular whether or not they tend to pay larger and more frequent dividends—that is, whether infrastructure really is a cash cow. They find that infrastructure companies exhibit key systematic differences with a sample of "matched" firms that are otherwise comparable in size, leverage, revenue growth, or profits. The authors formulate four hypotheses about the differentiating characteristics of infrastructure companies:

1. Infrastructure exhibits higher asset tangibility given its reliance on large capital investments. They adopt two measures of asset tangibility from Berger, Ofek, and Swary (1996) and Campello and Giambona (2013) that estimate the liquidation values of a firm's assets and calculate the intensity of property, plant, and equipment (PP&E) in a firm's total assets.
2. Infrastructure exhibits higher asset illiquidity as infrastructure's large, capital-intensive assets are hard to liquidate in times of firm distress. Infrastructure's large capital investments are relationship specific. We employ three measures from Gopalan, Kadan, and Pevzner (2012) and Ortiz-Molina and Phillips (2014) to gauge asset illiquidity by estimating the liquidation values of the different types of liquid assets a firm has.
3. Infrastructure exhibits higher asset inflexibility due to the firm's inability to reallocate their assets to other activities. Asset flexibility measures the ability of a firm to either expand or contract production in response to market shocks. Infrastructure firms, as a result of their assets being large, durable and with sizable sunk costs, would be unable to adapt as well as firms with greater operational flexibility. We use Gu, Hackbarth, and Johnson's (2018) measure of inflexibility to identify the range bounds for which a firm does not change its production process when hit by a productivity shock.
4. Infrastructure exhibits lower operating leverage as infrastructure firms have a significant asset base, and the level of operating costs in comparison to the size of these assets would be smaller than other capital light businesses. Operational leverage is the theory that a firm's production costs have the same impact on profitability as financial leverage (see Novy-Marx 2011). A firm

EXHIBIT 1

Summary of the Hypotheses Tested in the Study

Hypothesis	Finding	Implications
Infrastructure exhibits higher asset illiquidity	Evidence that infrastructure has lower asset liquidity compared with non-infrastructure	Infrastructure has large capital investments that are relationship specific and hard to liquidate in times of firm distress
Infrastructure exhibits higher asset inflexibility	Strong evidence for unlisted infrastructure having higher inflexibility compared with non-infrastructure	Infrastructure has large and durable assets with sizable sunk costs and cannot adjust production to adapt as well as other firms in response to market shocks
Infrastructure exhibits higher asset tangibility	Strong evidence for unlisted infrastructure firms having a higher intensity of property, plant, and equipment compared with non-infrastructure	Infrastructure assets have high physical tangibility, although they may not necessarily be mobile
Infrastructure exhibits lower operating leverage	Strong evidence for unlisted infrastructure's operating leverage being lower than that for non-infrastructure	Infrastructure differs from other firms by having an asset base so significant that the level of operating costs is small in comparison to the asset size
Infrastructure has special characteristics that can explain dividend payout behavior	Strong evidence for infrastructure paying out more dividends as a proportion of their revenues compared with non-infrastructure; strong relationships found between payout behavior and such characteristics as operating leverage and asset illiquidity	Infrastructure does pay higher dividends than other firms and these higher payout ratios correlate with the identified characteristics

with a large proportion of fixed costs in their cost structure would be impacted more severely in an economic shock than firms with a smaller proportion. We employ Chen, Harford, and Kamara (2019) and Novy-Marx's (2011) measures of operating leverage by scaling operating costs with the size of the firm.

Using propensity score matching controls for endogenous differences between infrastructure and non-infrastructure firms and allows matching firms that are most alike in terms of size, leverage, revenue growth, and profitability. Exhibit 1 provides a summary of the findings and implications: Infrastructure does exhibit different characteristics compared with other firms, such as lower operating leverage or inflexibility. These characteristics result from the nature of infrastructure businesses, specifically the requirement to invest in large, highly specialized assets that cannot be repurposed easily.

Looking at dividend payout behavior using various regression models, Whittaker and Tan (2019) find that:

1. Infrastructure firms pay out a larger proportion of their revenues as dividends compared with other comparable firms;
2. Unlisted infrastructure firms also pay out more dividends relative to asset size, in comparison with unlisted non-infrastructure firms;
3. The higher the operating leverage of an infrastructure firm, the higher its dividend payout as a proportion of total assets. An explanation for this observation is the documented negative relationship between operating leverage and leverage. With lower leverage, a firm is able to pay out more free cash to shareholders.
4. Asset illiquidity has a positive relationship with dividend payout for non-infrastructure firms but a negative relationship with dividend payout for infrastructure firms. This means that an infrastructure firm with more illiquid

assets pays out higher dividends as a proportion of its revenue and assets. This may be due to brownfield infrastructure companies being in a better position to pay out dividends than greenfield infrastructure companies, which have more liquid assets, such as cash.

A Typology of Infrastructure Companies

Thus, infrastructure companies are indeed different from other public or private firms: They tend to exhibit high asset tangibility, asset illiquidity, and asset inflexibility, as well as lower operating leverage, as measured by a range of well-established metrics found in the academic literature. Finally, they find that infrastructure companies do pay higher (but not more frequent) dividends than other firms and that these higher payout ratios correlate well with the characteristics identified. These findings and others (see for example Blanc-Brude et al. 2016) are useful to form a structured view on the fundamental characteristics of infrastructure.

In 2018, the EDHEC Infrastructure Institute published the first version of the infrastructure company classification standard or TICCS, as a way to organize investment data about firms (EDHEC*infra* 2018). The taxonomy has since been updated regularly with the help of an independent review committee headed by prominent investors in infrastructure including asset owners and asset managers. The latest version was published in April 2022 (see EDHEC*infra* 2022b).

TICCS uses a number of fundamental economic criteria to define the boundaries of the infrastructure universe in a way that reflects the findings of Whittaker and Tan (2019):

- *Single-use investment*: Infrastructure assets can be described as “relationship-specific”; that is, the investment required only makes sense in the context of a relationship—typically a contract, license, or concession—that justifies the demand or usefulness of the investment.
- *Sunk or irreversible capital investment*: A relationship must exist for infrastructure investment to take place because the initial capital expenditure is sunk—that is, irreversibly invested and unusable for any other purpose than the one originally intended.
- *Large size requiring a long repayment period*: Not only are infrastructure investments sunk, they must be sizable in absolute terms, making the repayment period necessarily long (multiple decades).
- *Inflexible total cost structure*: Operating infrastructure at its design capacity implies highly predictable fixed (operating, maintenance, and capital) costs and low variable costs, resulting in an inflexible cost structure. In turn, investing in infrastructure requires a higher degree of certainty in future revenue streams, which underpins the requirement for long-term contracts, especially because infrastructure assets have little to no alternative uses.
- *Infrastructure as a service*: Infrastructure companies have value because their assets provide a useful service to its users, the demand for which is the sole justification for the investment. Thus, despite consisting mainly of large tangible, immobile assets, the nature of infrastructure assets and the business of infrastructure companies is to provide a service.
- *Not a store of value*: It follows that, unlike other real assets, such as land, building, commodities, or art, infrastructure investment cannot be considered as a store of value. Infrastructure assets must be useful (and infrastructure companies provide a service) for them to have (social, economic, and financial) value.

Assets and companies that can be categorized under TICCS are expected to meet these criteria, all of which stem from the long-term and durable nature of infrastructure assets and the companies that hold them and the commitment of their owners to only recoup the value of their investment over a long time period.

The classification itself uses a four-pillar multicriteria approach split into the following:

1. A *business-risk classification* takes into account the financial economics of infrastructure companies, in particular the role of contracts and regulation.
2. An *industrial classification* uses a very granular taxonomy of industrial activities, technologies, and asset-level characteristics that captures the potential diversity of infrastructure companies' services and products.
3. A *geo-economic classification* captures the degree of common economic exposure of different infrastructure companies.
4. *Corporate-governance classification* reflects the expected difference of behavior between single-project and multiproject infrastructure ventures.

Business Risk

The first TICCS pillar is the business-risk classification of infrastructure companies. Broad families of business-risk or business-model profiles can be identified on the basis of how standalone, investable infrastructure is created using different forms of long-term contracts. In turn, these families of infrastructure-business risk are fundamental drivers of the financial structure and total risk profile of infrastructure companies. TICCS business-risk profiles are found across various industrial activities classifications (the second TICCS pillar).

While infrastructure assets are usually understood to be tangible assets—physical structures of steel and concrete—from the point of view of financial economics, infrastructure investment is better defined as a high-sunk-cost, long-term investment in immobile, relationship-specific assets. It is contracts, not concrete, that matter.

In other words, the physical characteristics of tangible infrastructure only determine the need for long-term contracts, which in turn determine the investment profile of infrastructure investments. Outside of contractual and regulatory relationships, tangible infrastructure assets have no or little value. This is what fundamentally differentiates infrastructure from other so-called real assets: Infrastructure is never a store of value. It needs to be used to have value. And its usability is entirely determined by a combination of long-term contractual commitments.

The contracts that allow infrastructure investment to take place are characterized by risk-sharing mechanisms embodied by their revenue model. While numerous risk-sharing agreements can be envisaged, in practice, three types of contractual arrangements are used.

The first type is *contracted* or availability-payment schemes, by which a public- or private-sector client commits to paying a fixed income over a pre-agreed period, typically in excess of two decades. In exchange, the investor accepts more or less unlimited responsibility for the investment, operating, debt, and equity cash flows incurred to invest in the delivery of an infrastructure service, according to an agreed output specification. Terminal value can be set to zero and control of the physical assets is returned to public-sector clients at the end of the contract. This model is typically used to deliver social infrastructure projects, such as schools, hospitals, or government buildings. It is also common in the energy sector, including in renewable-energy projects, but it can also be found in a range of other sectors, including such transportation projects as roads or port terminals.

The second type of arrangement is a *merchant* or commercial scheme, by which the public- or private-sector client enters into a similar long-term contract with an investor but in exchange for a risky income stream. This is typically the case with tolled transportation projects, for which an investor is granted the right to collect tolls/tariffs from users. Likewise, terminal value is often zero in most jurisdictions. This model is typically used for transport projects with real tolls but also energy projects connected to a competitive power or gas market, as well as privatized airports or certain rail projects. Merchant telecom companies are also common.

Regulated schemes are the third type and are typically associated with large network industries that benefit from a natural monopoly, such as water or gas utilities or power distribution networks. They require regulation in order to ensure efficient operations at a reasonable cost to end-users, who are typically captive and receiving "essential services" from the companies in question. Terminal value may not always be set to zero; for example, privatized utilities own tangible assets outright and in perpetuity. Regulators set tariffs to achieve multiple economic and financial objectives and often aim to mimic competitive market forces through so-called yardstick competition. Such schemes exist because of the universal tendency of monopolies to overcharge and underinvest (irrespective of public or private ownership). They also create up- and downside limits on business risk, which sets them apart from contracted and merchant infrastructure companies. For a detailed discussion of these three types of arrangements and of the related academic literature, see Blanc-Brude (2013). For a discussion of the role of contracts in infrastructure finance see Brealey, Cooper, and Habib (1996). An empirical analysis of the difference of cost of capital and credit risk between contracted and merchant infrastructure business models is provided by Blanc-Brude and Strange (2007) and Blanc-Brude, Hasan, and Whittaker (2018). For a detailed discussion of regulated infrastructure, see Gomez-Ibanez (2003).

The first TICCS pillar includes three classes and five subclasses of business risk.

Industrial activity. The second TICCS pillar categorizes infrastructure companies by groups of industrial activities. Industrial-sector group classifications (or superclasses) represent broad areas of industrial activity but also transaction or project-development expertise. Industrial sector and subsector classifications (or classes and subclasses) represent specific industrial activities and types of physical assets and technologies.

Standard industrial classification can be ill-suited to represent different types of infrastructure companies. They focus on broad industrial activities only, but do not take into account other aspects of the delivery of infrastructure projects and services. For instance, an airport operator and an airline-catering company are typically bundled together. Thus, under MSCI's Global Industrial Classification Standard, "operators of airports and companies providing related services" are classified together.

Likewise, many road-operating companies are categorized as construction firms, while some project-financing vehicles are found under "financials." Instead, the activities of infrastructure companies can be seen as broad families of technical and financial skill sets that are relevant not only to creating and operating but also to investing in infrastructure companies. Infrastructure investments also require highly specialized knowledge of various industrial processes, such as power generation or the construction and maintenance of major structures but also project management and financial structuring. Transportation projects have common technical and industrial features, as do renewable-energy or social infrastructure projects, which correspond to broad groups of professionals that have the relevant know-how to understand and execute individual transactions.

Within each broad family, infrastructure companies have specific industrial activities typically associated with different types of 1) services, 2) technologies, 3) clients, and 4) structures. For instance, standalone power generation facilities may use different fuel types and water-treatment companies may serve residential (potable water) or industrial clients (ultra-pure water). Wind power generation may be on-shore or off-shore. Such industrial activities can be sufficiently differentiated to warrant individual classifications. For example, different types of power-generation fuel (coal versus gas versus nuclear) have an impact on the level of regulatory risk taken by investors.

The second TICCS pillar includes eight industrial superclasses, corresponding to 35 industry classes of specific industrial activities and 101 industrial asset-level subclasses.

Geo-economic exposures. The third TICCS pillar classifies infrastructure companies into four levels of geo-economic exposure that are relevant to understanding potential correlations between investments. Business-risk families defined in the first TICCS pillar capture the resemblance between infrastructure firms' business models, including how they may or may not covary as contracted or merchant companies. But an additional dimension is the exposure of each company to the different geographic levels of the economy that they serve.

Infrastructure companies operate typically large immobile structures. Their physical position is a lifelong constant. However, the type of economic activity they are involved in can correspond to different economic factors, creating a multitude of possible interactions between infrastructure companies.

A first example is that two merchant toll roads can be expected to be less correlated if they are farther away from each other in space. This assumes that traffic variability is mostly determined by local economic conditions. If the roads in question are part of a regional transport corridor spanning hundreds or thousands of kilometers, however, they would probably exhibit a high level of revenue-risk dependency. Likewise, two contracted infrastructure companies can be expected to be relatively unrelated unless they have a similar or the same counterparty, which could be a local government.

Certain infrastructure companies are part of and exposed to the global economy. These include large transportation hubs, such as major airports and ports, which are not only exposed to the business cycle but, as a result of that, tend to be correlated with one another. Conversely, it's possible for global and regional or national infrastructure companies to be less correlated with each other even when they are relatively close in space and have similar business models. This is the case in the port sector, which can be divided into several categories of global container-shipping hubs: regional ports, which act partly as distribution networks of global port traffic, and national or subnational ports, which cater to the local economy.

Certain infrastructure companies are also exposed to global commodity prices: gas pipelines or coal terminals, even when they have a contracted business model, face highly correlated counterparty risk because commodity price movements can make their off-take contracts uneconomic or bankrupt their sole client.

This third TICCS pillar proposes four geo-economic classifications.

Corporate structure. The fourth TICCS pillar classifies the corporate structure of infrastructure companies into two classes and two subclasses. The behavior of a firm and its managers differs depending on whether it was created to develop a single project or multiple projects. Furthermore, the level of external debt financing impacts the behavior of a firm as well. External debt financing creates a demand for monitoring on the part of creditors, especially with single-project firms. External monitoring impacts the predictability of behavior of the firm and its managers.

Infrastructure companies typically take one of two corporate forms: "projects" or "corporates." Infrastructure project companies are single-project firms or project-financed. Infrastructure corporates are multiproject companies more akin to corporate structures found in other industrial sectors. These two types of firms can be expected to have fundamentally different behaviors.

Infrastructure project companies are created in the context of a long-term contract between an investor (the owner of the project company) and a public- or private-sector client. Project companies are created for the sole purpose of delivering a new tangible infrastructure asset and operating it for the length of the contractual period. Infrastructure project companies are also referred to as special-purpose vehicles (SPVs) or special-purpose entities (SPEs). They typically serve as the focal point of a nexus of contracts between investors, builders, operators, a client, and providers of long-term finance, usually in the form of long-term senior debt.

Debt plays a significant role in project finance because it tends to be the main source of capital. The theoretical literature on project finance and corporate structure (see for example Shah and Thakor 1987) highlights the role of leverage as one of the most counterintuitive dimensions of project financing. Project financing reduces the net financing costs associated with large capital projects (Esty 2004) because external debt plays an important disciplinary role by preventing managers from wasting or misallocating free cash flows and deterring related parties, including the public sector, from trying to appropriate them (Jensen and Meckling 1976; Hart 1995).

Because leverage mitigates these costly incentive conflicts among capital providers, managers, and investors, it increases expected cash flows available to capital providers, thereby establishing a link between financing structure and asset values. In this context, the presence of significant loan financing is a signal of creditworthiness (Fama and French 1997).

Indeed, infrastructure assets have few growth options, which hinders overinvesting in negative-net present value projects and makes investment decisions more easily monitored by external claim holders. When raising financing, infrastructure project companies typically commit to a given capital program and are not able to seek other sources of financing without the explicit involvement of their original creditors. In the event of various credit events, senior creditors have control rights akin to those of majority shareholders and can require a financial restructuring or even take over the company from its original owners.

The empirical literature on infrastructure project finance (Brealey et al. 1996; Esty 2002; Blanc-Brude and Strange 2007; Blanc-Brude et al. 2018), shows that project financing typically relies on high levels of nonrecourse external debt financing (typically between 60% and 90%) and concludes repeatedly that project finance loans have different characteristics from corporate debt. In corporate finance, debt can be used to increase returns on equity, creating incentives to take risks. In project finance, because the financial viability of a single project has to be demonstrable ex ante with a high probability, debt is used to minimize the cost of capital and creates incentives to minimize risk.

In contrast, infrastructure "corporates" or multiproject companies have all the usual characteristics of the firm. Managers have more freedom to make various investment decisions and can change course both strategically and financially over time. They can take on new projects, including those in sectors that are not directly related to infrastructure (e.g., utilities investing in media companies) or invest internationally in other infrastructure firms (e.g., European utilities invested in Asian utilities in the mid-1990s), thereby changing their business-risk profile.

Likewise, infrastructure corporates are free to change their financial structures and can use multiple sources of private and public financing. Creditors play a much more limited monitoring role and do not have different control rights in the event of default than with other corporate borrowers. Nor do they play a leading role in the financial structuring of the firm either before or after credit events. As a result, high or increasing levels of indebtedness in infrastructure corporates is typically interpreted as signaling higher credit and equity risk. UK water utilities are a case in point (see Helm 2009).

The fourth TICCS pillar includes two corporate-structure classes (and two subclasses).

Market Size and Structure

Using TICCS, we can examine the investible universe available to investors and identify the relevant universe to track the fair value and the risk-adjusted performance of the unlisted infrastructure asset class. Indeed, the notion of fair value is a market-based measurement rather than an entity-based measurement. It is concerned with how average prices are formed in the most representative markets. In the language of academic finance, fair value is about betas—that is, the combined exposure of each firm to priced risk factors—but not alpha, which represents market outperformance and is the result of proprietary or new information.

In the terminology of IFRS 13, the relevant market is known as the principal (or most advantageous) market. The principal market enables the best possible measurement of average/systematic drivers of prices in unlisted infrastructure investments. This point has direct implications for the definition of the relevant broad market universe: The choice of universe for a broad market reference index aims to include those markets that are representative of the price preferences of independent, knowledgeable, and willing buyers and sellers on the measurement date.

EDHEC*infra* applies a number of market- and company-level inclusion criteria to identify and document the relevant investment universe (see EDHEC*infra* 2022a for details): the result is 6,192 uniquely identified and documented unlisted infrastructure companies representing about USD2.5 billion by total asset book value and about USD3 trillion by market enterprise value. Exhibit 2 shows the split of this universe by TICCS pillars over time until 2021. Exhibit 3 shows the same data by region.

We observe the following:

1. About half of the universe is made of contracted (pillar 1) projects and financed (pillar 4) companies. These "vanilla" types of infrastructure investment form the bulk of the market and are ubiquitous in many infrastructure portfolios. They also consist of most of the new investments that are added to the universe in the form of renewable power projects (wind and solar farms) or data centers.
2. The largest segments of the universe are transport and utilities and, increasingly, renewables.
3. The vast majority of investible infrastructure investments are linked to national or subnational economy and only rarely to transnational or global economic flows.

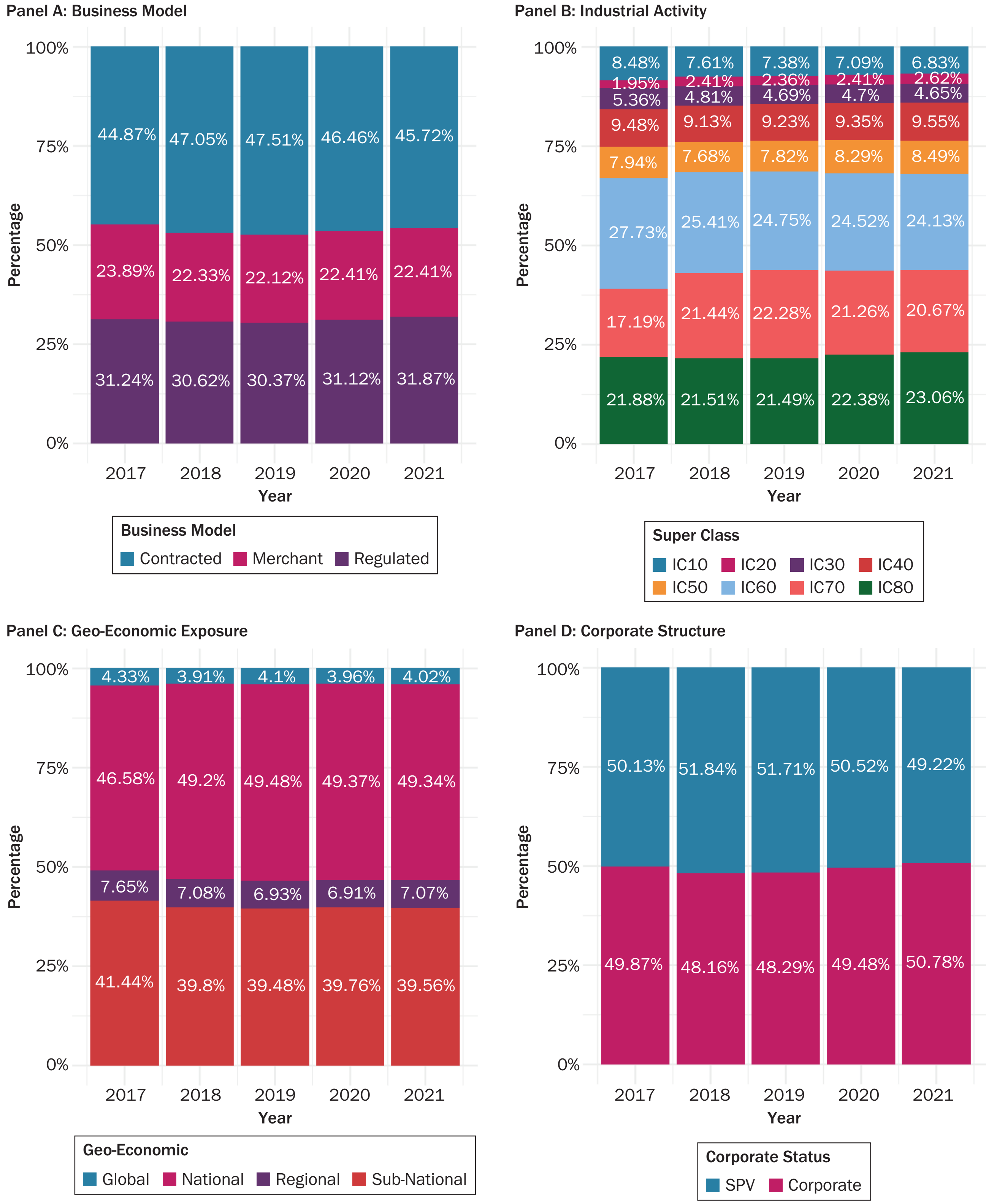
It should be noted that the infrastructure companies described in these results are unlisted and already in private hands. The lion's share of the world's infrastructure remains publicly owned and managed and is not featured in this analysis.

ASSET PRICING

The importance of assessing illiquid assets, such as infrastructure, at their fair market value is often underestimated. Some investors might ask why they should aim to mark illiquid assets (e.g., unlisted infrastructure) at their "fair market value" because there is no liquid market to observe frequent transaction prices and they

EXHIBIT 2

Global Investible Private Infrastructure Market by TICCS Segment—Total Asset Book Value

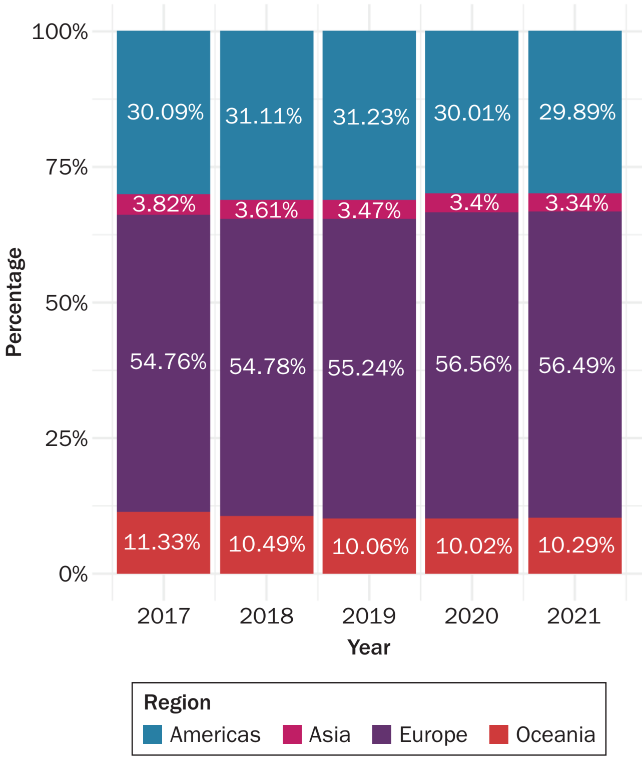


NOTE: For the Industrial Activity panel, TICCS codes are as follows: IC10 = Power; IC20 = Environmental services; IC30 = Social infrastructure; IC40 = Natural resources; IC50 = Data; IC60 = Transport; IC70 = Renewable power; IC80 = Network utilities.

SOURCE: EDHEC*infra*.

EXHIBIT 3

Global Investible Private Infrastructure Market by Region—Total Asset Book Value



SOURCE: EDHEC*infra*.

intend to hold them to maturity. Indeed, one of the reasons for investing in infrastructure is to generate income rather than capital gains, perhaps with a long-term liability-matching objective. Hence the frequent buy-and-hold stance taken by long-term investors in infrastructure, such as large asset owners.

If the reason for holding these investments is to collect revenue over long periods, however, then the present value of these future flows matters. The longer the investment/holding period, the more important it becomes to know how to discount these cash flows to their present value. Because these future cash flows are also dividends and therefore uncertain, their discounting requires knowing what the adequate risk premia should be. Any financial instrument that is purchased to receive cash flows in the future can only be valued by computing the present value of these future cash flows in a manner that incorporates both time value of money and the risk of not receiving these flows.

Moreover, if these future cash flows are used to match liabilities that are themselves discounted to their present value, not discounting the assets at the appropriate rate not only is inconsistent from an economic and accounting perspective but also leads to an inadequate understanding of the asset–liability position of the investor.

For instance, say the risk-free rate used to discount liability side of the balance sheet was to decrease, leading to an upward revaluation of the liabilities. Then not discounting the cash flows of future infrastructure income used to match liabilities on the asset side with equivalent market rates leads to a wrong assessment of the asset–liability position. In effect, this obviates the liability matching (or hedging) role of infrastructure assets.

Infrastructure assets need to be valued at their fair value, whatever the liquidity or strategy. The idea that an asset conserves its historical value because it is difficult to sell does not make sense from a financial point of view. We can draw a very valid comparison with fairly illiquid assets, such as corporate bonds. When valuing such instruments, investors refer to a credit spread and the rate of interest to discount future cash flows. It would not occur to long-term investors not to value their corporate bond portfolio at fair market value. The same logic applies to unlisted infrastructure.

The Limitations of Appraisals

Until recently, the only data available to assess the volatility of unlisted infrastructure investments was the reported net asset values (or NAVs) resulting from regular appraisals of individual assets.

In the case of unlisted infrastructure equity, appraisals are typically produced using the "income" or discounted cash flow approach, by which the value of the asset is

$$P_j = \sum_{t=1}^{T} \frac{D_{j,t}}{(1 + r_t + \gamma_j)^t}$$

EXHIBIT 4

The Smooth Risk and Return Profile of Appraisal NAVs (contracted projects)

	3-Year	5-Year	10-Year
Appraisal discount rate	7.5%	7.6%	8.3%
Appraisal NAV total returns	7.8%	8.4%	8.0%
Appraisal NAV total returns volatility	2.0%	2.0%	1.8%
Implied Sharpe ratio	3.21	3.54	3.8

NOTE: Data as of December 31, 2020.

SOURCE: Annual and quarterly reports, NAV of assets for 14 funds of unlisted infrastructure equity representing about USD22 billion of reported NAV in 2020.

EXHIBIT 5

Market-Implied, Discount Rates, and the More Realistic Risk-Adjusted Return Profile of Unlisted Infrastructure Equity (contracted projects)

	3-Year	5-Year	10-Year
Market-implied discount rates	6.6%	6.7%	8.2%
Total returns	6.5%	8.5%	15.3%
Returns volatility	7.3%	8.2%	11.5%
Sharpe ratio	0.75	0.91	1.2

NOTE: Data as of 31 December 2020, with the last five quarters estimated as of Q1 2021.

SOURCE: EDHEC*infra* Contracted Projects Advanced Economies Index, includes about 260 live investments and represents about USD50 billion of market value at the end of 2020; available at indices.edhecinfra.com.

where T is the investment's expected life, r_t is the risk-free rate at each point in time until date T, and γ is the deal's risk premia. In practice, r_t is typically set to be a moving average of long-term bond yields and γ is also a long-run average usually based on the capital asset pricing model (CAPM). While these estimates do vary over time (see, for example, KPMG 2020), they are typically "smooth"; that is, they do not reflect the current latest market conditions but rather tend to capture a trend. In fact, most private company appraisals aim to represent the value that a company is "expected to be sold for" (i.e., not current market conditions).

Moreover, using the CAPM requires estimating a single asset beta to derive the equity risk premium of a given investment. In the absence of listed proxies for most unlisted infrastructure assets, this estimate of the asset beta is often little more than an educated guess with little to no basis and no scheme for revising it over time.

This approach also assumes that a single public equity risk premium is a fair representation of the all the risks to which unlisted infrastructure assets are exposed. Academic research has long shown that this is not the case even for listed stocks, which are instead exposed to a number of risk factors in different ways.

Investors in unlisted assets are familiar with the issue of "smoothed" returns—that is, reported performance that does not capture the variability of market prices but instead relies on historical discount rates or minimal and lagged changes to the discount rate.

This reporting phenomenon results in the equally familiar "stale" pricing issue: Reported NAVs are not in line with market prices but instead reflect either a valuation at cost or one that has slowly drifted from its historical cost but is not, in the words of the IFRS 13 standard, *calibrated* using the latest market data.

This is well illustrated by looking at data from funds investing in unlisted infrastructure equity. For example, Exhibit 4 reports the average asset-level discount rate of 14 funds investing in unlisted infrastructure equity with a quasi-exclusive focus on "contracted projects," as defined in the TICCS taxonomy, in advanced economies. These data are sourced from the annual and quarterly reports of such funds. The exhibit also shows the asset-level NAV-based total returns, the NAV return volatility, and the implied risk–return ratio of these funds.

This can be compared with the private market-implied discount rates and returns for the same segment in Exhibit 5: The EDHEC*infra* Advanced Economies, Contracted Projects Index includes 257 live constituents and 343 since inception in 2000. Its market capitalization at the end of 2020 was about USD35 billion.

Clearly, when these funds were created about a decade ago, their discount rates were reasonably in line with mark-to-market data, but over time, they have not been adjusted to represent the evolution of the market price of risk. As discussed in the introduction, the demand for such assets has increased considerably and the associated risk premium has decreased (a type of yield compression not unlike that seen in other markets), but this trend is not reflected in the risk premium used to produce appraisals for equivalent assets.

As a result of not updating discount rates to reflect market prices, infrastructure funds may have underreported their private market returns by omitting significant capital gains until 2016 and overreporting returns afterward using smooth discount rates above market implied rates.

Still, the most significant issue arising from smooth discount rates and stale NAVs is the underreporting of risk. We know from empirical research in finance that expected returns are better proxied by risk levels than by historical returns (Merton 1980). If the risk level implied by the reported volatility of appraisals in these funds was true, infrastructure would represent a huge risk-free arbitrage opportunity with a Sharpe ratio of three.

In fact, if the reported volatility was true and fund managers were willing to sell these assets so cheaply on a risk-adjusted basis, they would be generating large negative alpha.

Of course, the conclusion should instead be that the volatility of reported NAVs is not a reflection of the true volatility of these investments, as reported previously and elsewhere (for example, see Amenc et al. 2020). Comparing the volatility of appraisal-based returns with the mark-to-market data shown in Exhibit 5, which reflects the evolution of the fair market value of the infrastructure equity market, confirms that the volatility of appraisal NAVs is off by an order of magnitude.

Therefore, appraisal NAVs are stale, do not capture the fair market value of infrastructure investment, and cannot be used to reflect the risk of the asset class either. Next, we describe how to measure the true variance of unlisted infrastructure market prices and document the volatility of unlisted infrastructure investments.

We have established that reported appraisals and the discount rates used to compute them are not a fair representation of market prices. They are backward-looking, tend to remain at or drift from their historical starting point, and on a risk-adjusted basis, they imply wildly unrealistic valuations given the reported risk. To put it simply and bluntly, they are wrong.

An alternative approach consists of using actual secondary market transactions to recalibrate a model of expected returns on a regular basis. In equilibrium (on average), expected returns equal fair market discount rates. This approach addresses the question of finding enough comparable prices at each point in time, which can be addressed by breaking down the question into a multifactor model of expected returns.

Combined with the largest database of infrastructure investment data built by EDHEC*infra*, the result is a granular estimation of the market price of unlisted investments over time for individual investments as well as entire segments of the universe. In turn, this also enables the measuring of risk in a realistic and consistent manner.

In what follows, we show that such an approach is robust and leads to precise predictions of the observable market prices of unlisted infrastructure equity investments. We then address in more detail what the different the drivers of market prices are and how they relate to the volatility of unlisted infrastructure equity returns.

A Robust Unlisted Equity Valuation Framework

In private asset classes such as real estate, it is possible to use comparable transactions to assess the evolution of the market price of specific types of property. In the unlisted infrastructure space, there are no such “comps”; infrastructure companies are very different from one another, and it is hard enough to find an airport that looks like the one that has to be priced, let alone one that traded in the past three months. To use "comps" as one does in real estate, one would probably need to have more transaction data than there are comparable assets in the world.

However, this does not mean that the valuation of infrastructure companies is not driven by common factors. Simply because each company is quite different from the next, this does not imply that all aspects of its market value are determined by its idiosyncratic features. This is a very fundamental point that is often lost to a more naive understanding of the value of private assets: the belief that they are somehow 100% idiosyncratic and can be benchmarked using an absolute rate of return. This is, of course, wrong. In fact, the impact of the Covid-19 pandemic on infrastructure businesses, which we discuss later, reminded many investors that these companies do not exist in a vacuum and are exposed to a range of risks.

Instead, we approach the valuation of the same illiquid, unique, and heterogeneous infrastructure companies from the point of view of modern finance. While we cannot use comparable transactions to estimate their latest valuation ratios, it is possible to reduce the number of dimensions of the problem and to estimate the price of such assets for the average buyer or seller by *pricing a few systematic risk factors* that are found in each transaction, irrespective of their idiosyncratic characteristics. In other words, while infrastructure companies are different from one another, they still belong to a category of assets that have common valuation factors and these factors are what drives the formation of prices in the market.

The fair market value of any unlisted infrastructure equity investment is a function of three components: a future stream of dividends (cash flows), the term structure of risk-free rates at the relevant horizon (e.g., some investments have pay-offs 20 years into the future, others 35 years, etc.), and a risk premium.

Given a stream of expected cash flows (which can come from the asset owner) and a term structure of rates (which can be built using the yield of risk-free bonds at the relevant horizons), estimating the fair value of illiquid infrastructure assets boils down to measuring the equity risk premium of each asset.

We propose a method of estimating the fair risk premium applicable to any infrastructure investment in three steps. First, using a series of secondary market transaction prices, given the expected stream of dividends, an expected return can be inferred and, using the risk-free curve, a deal risk premium can be extracted for each transaction.

For example, if we observe a secondary market transaction for the equity of infrastructure company j, as before we have,

$$P_j = \sum_{t=1}^{T} \frac{D_{j,t}}{(1 + r_t + \gamma_j)^t}$$

where T is the investment's expected life, r_t is the risk-free rate at each point in time until date T, and γ is the deal's risk premium.

Using a numerical solver, the value of γ_j is obtained and represents the equity risk premia required by investors in transaction j, given expected cash flows D_j, the term structure of rates r_t with $t = 1 \ldots T$, in the relevant country at the time of the transaction, and the price paid P_j.

Second, each observation of a new γ_j is used to calibrate a risk factor model of the risk premia. We can write

$$\gamma_j = \beta_1 \times \lambda_1 + \beta_2 \times \lambda_2 \ldots + \omega = \sum_{k=1}^{K} \beta_{j,k} \times \lambda_k + \omega$$

where β_k represents the exposure of company j to risk factor k at the time of the transaction and λ_k is the price or risk premia associated with factor k at that time and ω is a stochastic process representing the idiosyncratic "noise" in transaction prices.

The risk factor exposures or β_k of each company are based on observable firm financials (e.g., size, leverage, etc.; we will return to this later) or other observable characteristics and the price of each risk factor are re-estimated each time a new transaction takes place.

Before observing each transaction, the set of risk factor prices obtained from the previous transaction is used as the prior value for each λ_k and the value of each risk factor price is then updated using the new information (formally, this is known as Bayesian inference and technically as a Kalman filter).

If the model provides a robust explanation of the variance of observed risk premia in actual secondary market transactions, then it can be said that the K factors provide a good model of the systematic price of risk in these transactions. To obtain a quarterly factor price for each risk factor, the average price implied by each deal of the quarter is used.

Finally, once the price of each risk factor is known at the end of each quarter, all that remains is to multiply the risk factor exposure of any infrastructure company for which we seek a fair equity value by the price of each risk factor, so that the estimated equity risk premia $\hat{\gamma}_i$ of company i is given by

$$\hat{\gamma}_i = \sum_{k=1}^{K} \beta_{i,k} \times \hat{\lambda}_k$$

where $\hat{\lambda}_k$ is the estimated price of risk factor k at the time of valuation. Each firm-specific market risk premium estimated at the end of each quarter is then combined with the term structure of risk-free rates that matches the horizon of the investment and therefore its duration, in the country and on the date of the valuation.

Hence, the quarterly valuations of asset i is obtained by discounting each future dividend at time t at the marked-to-market discount factor $(1 + r_t + \hat{\gamma}_i)^t$.

Several years of research into the determinants of expected returns in unlisted infrastructure companies have led to the selection of several key factors that are found to explain observed transaction prices and their implied expected returns (Bessembinder, Cooper, and Zhang 2019; Bartram and Grinblatt 2018; Blanc-Brude and Tran 2019). We have established that the most relevant, robust, and persistent risk factors that explain transaction prices in unlisted infrastructure transactions are as follows:

1. leverage (senior liabilities over total assets);
2. size (total assets);
3. profitability (return on assets before tax);
4. investment (capex over total assets);
5. country risk (term spread);
6. a range of control variables including business model and industrial activities according to the TICCS taxonomy of infrastructure companies, in particular their business model and corporate structure.

Note that these factors are in line with fundamental concepts in asset pricing and corporate finance. For example, higher leverage should increase the cost of equity as per the Modigliani and Miller theorem, and the size, profits, and investment factors are well-established risk factors in modern equity valuation since Fama and French. It is also important to note that such an approach rigorously follows the IFRS 13

EXHIBIT 6

Average Risk Factor Loadings of the Unlisted Infrastructure Equity Universe, Data as of Q1 2021

Date	Leverage	Size (USD millions)	Term Spread	Profits	Investment
Q1 2020	76.97%	1,387.91	1.15%	11.87%	3.59%
Q1 2018	78.12%	1,314.85	1.80%	11.23%	4.35%
Q1 2016	78.30%	1,264.73	1.70%	11.39%	4.95%
Q1 2011	78.49%	1,110.95	3.48%	10.34%	8.85%

NOTE: Data as of Q1 2021.

SOURCE: EDHEC*infra*, available at indices.edhecinfra.com.

guidance on measuring fair value in unlisted investments, from focusing on principal markets to using contemporaneous market inputs and, crucially, calibrating valuations to market inputs at the time of valuation.

Risk Factor Exposures and Premia

Next, we look at the drivers of the risk premium, the estimation of which was previously described in the asset pricing section. As discussed earlier, the equity risk premium of individual companies is the result of the combination of risk factor loadings (or exposures) denoted as β_k's and risk factor prices known as λ_k for factor $k = 1 \ldots K$.

Exhibit 6 shows the average factor exposure in the EDHEC*infra* broad market universe as of Q1 2021. We see that average leverage is high but stable at 77%–78%, the average size has increased by about 25% since 2011, while the average term spread has decreased consistently as the term structure flattened. Profits have increased from about 10% return on assets to almost 12% and the investment factor in the tracked universe tends to decrease as more and more firms reach the brownfield stage of their life-cycle.

Next, Exhibit 7 shows the marginal impact of each factor on the average risk premia, given the factor loading and the factor premium over time. These results are presented by "buckets" of low, medium, and high exposure to each factor. These buckets are defined in Exhibit A2, and descriptive statistics are provided in Exhibit A3 in the Appendix.

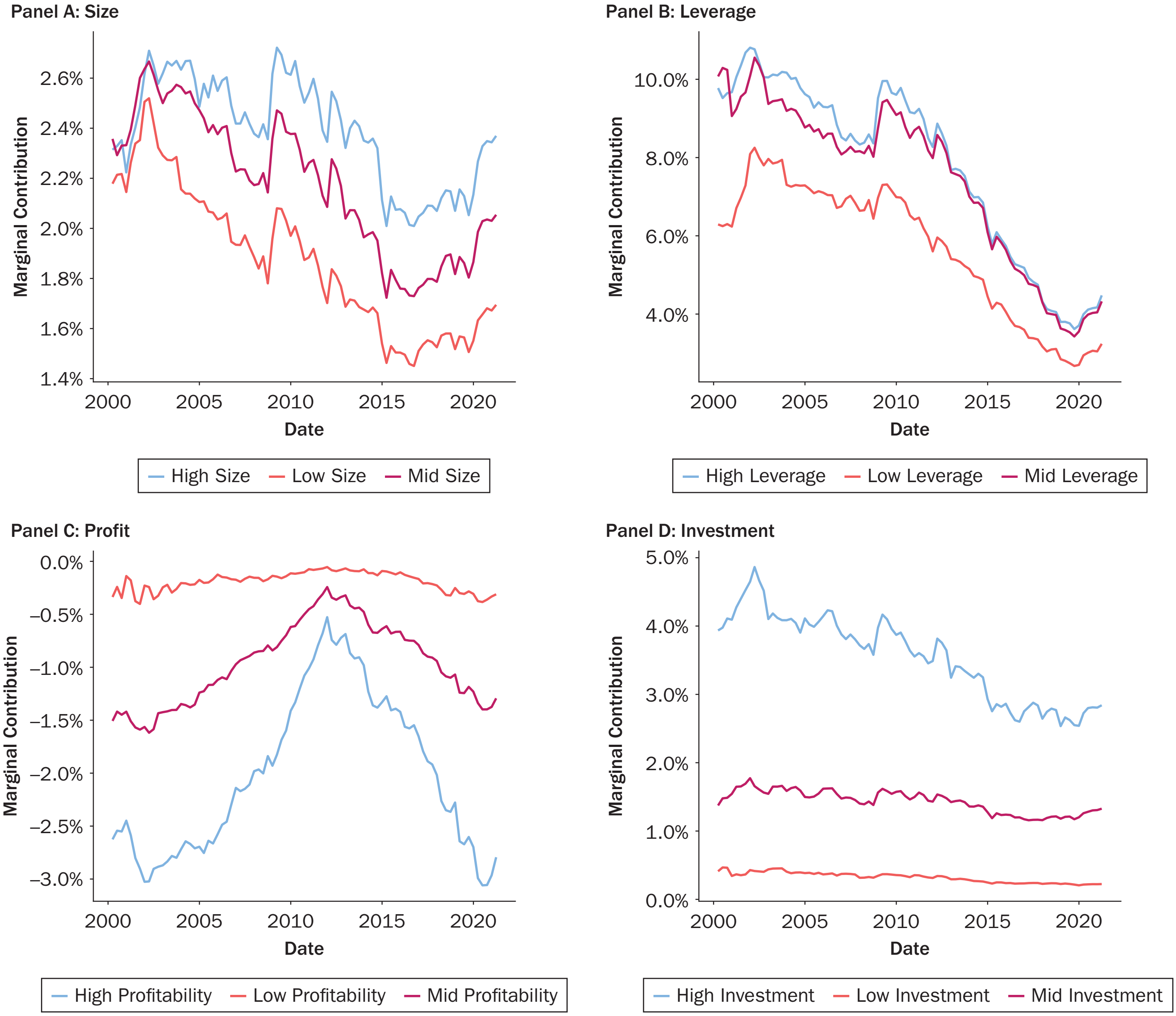
We see that the individual effect of each factor on the risk premia of different infrastructure companies can be quite different.

Size (Exhibit 7, Panel A). As expected, size has a positive impact on the premia. It can be interpreted as a form of "relative liquidity" premium: Infrastructure companies with a high exposure to the size factor have consistently higher risk premia. This factor contributes to the variability of the risk premia over time across all levels of exposure. Small or large investments, all see the contribution of the size factor increase during bad times and trend down until 2017.

Leverage (Exhibit 7, Panel B). Consistent with theory, leverage is one of the key drivers of the equity risk premium and has the highest marginal contribution. An important difference from size is the relative difference between leverage buckets: Higher leverage commands a significantly higher premium when moving from the low to the medium exposure buckets but much less so between the medium and high buckets. This is evidence of a well-known finding in infrastructure project finance research by which high leverage is considered a sign of low asset risk. This is consistent with the most highly leveraged investments, such as renewable energy or

EXHIBIT 7

Marginal Impact of Key Risk Factors on the Risk Premia of Unlisted Infrastructure by High/Medium/Low Factor Exposure Bucket



SOURCE: EDHEC*infra*.

social infrastructure projects, exhibiting the highest leverage (about 90%) because they have a solid contracted business model. The leverage factor is also the main contributor to the decrease of the risk premium in absolute terms over time with a reduction in excess of 50%.

Profit (Exhibit 7, Panel C). Also consistent with the financial economics of infrastructure companies, the profit factor premium (λ_k) has a negative sign; that is, higher profits (β_k) lead to a lower aggregate risk premium and negative profits (greenfield or distressed assets) to a higher premium. However, this effect is more variable over time depending on the exposure level. Unlike the size or leverage factors, the profit factor does not show signs of a secular reduction in the premium. Instead, it appears to have reverted to its pre-2008 level after peaking in 2012. Profitable companies become increasingly less "discounted," that is, requiring higher returns, in the wake of the 2008 and 2012 crises. In other words, their risk premia became relative higher, irrespective of how profitable infrastructure companies were until 2012, before this effect goes into reverse and investors once again "value more" (require a lower premium) the more profitable companies. This effect is minimal for low profitability companies, significant for companies in the median profitability band, and very significant for high profitability investments. Given that positive profits are always valuable, the evolution of this factor over time can be interpreted as a sign of relative risk aversion among investors. In terms of its marginal contribution to the risk premium however, the profit factor has the smallest contribution.

Investment (Exhibit 7, Panel D). Most of the capital expenditure of infrastructure companies takes place during an initial period of development. As expected, a higher loading on the investment factor; that is, a higher capex/total assets ratio leads to a higher risk premium. This factor mainly captures the difference between so-called greenfield and brownfield investments (even though this is also captured by the profit factor). The contribution of the investment factor is higher than that of the size factor but lower than that of leverage. This effect tends to decrease significantly over time only for high exposures to the investment factor. This can be interpreted as a decrease in the premia required to invest in greenfield assets.

Growth or merchant risk (not shown). When infrastructure companies collect risky revenues either based on demand or traffic, they command a higher risk premium than if they do not (and are either contracted or regulated). Thus, this factor (which is binary, companies are either merchant or not) has a positive marginal impact on the premia. We see that while its impact has trended down and exhibits jumps around times of economic crisis (2008, 2020).

Clearly, the dynamic contribution of each factor to the market risk premium of unlisted infrastructure equity over time is an important contributor to the variability of fair market values and to the volatility of returns.

As the infrastructure asset class has developed, its pricing has evolved significantly. From a relatively opaque investment to a sought-after alternative asset, unlisted infrastructure went through a process of "price discovery": Although unlisted infrastructure is an illiquid and segmented market, risks are priced rationally and risk price evolution is consistent with broader market phenomena, including yield compression, leading to relatively easier access to leverage or risk aversion during periods of crisis.

Robustness

Next, the data used to calibrate the EDHEC*infra* model of expected returns were drawn from a dataset of 1,000+ individually validated secondary market transactions of unlisted infrastructure observed over 20 years, 250+ of which are also tracked in EDHEC*infra* indices. Exhibit 8 shows the coverage of the model input data compared with the universe.

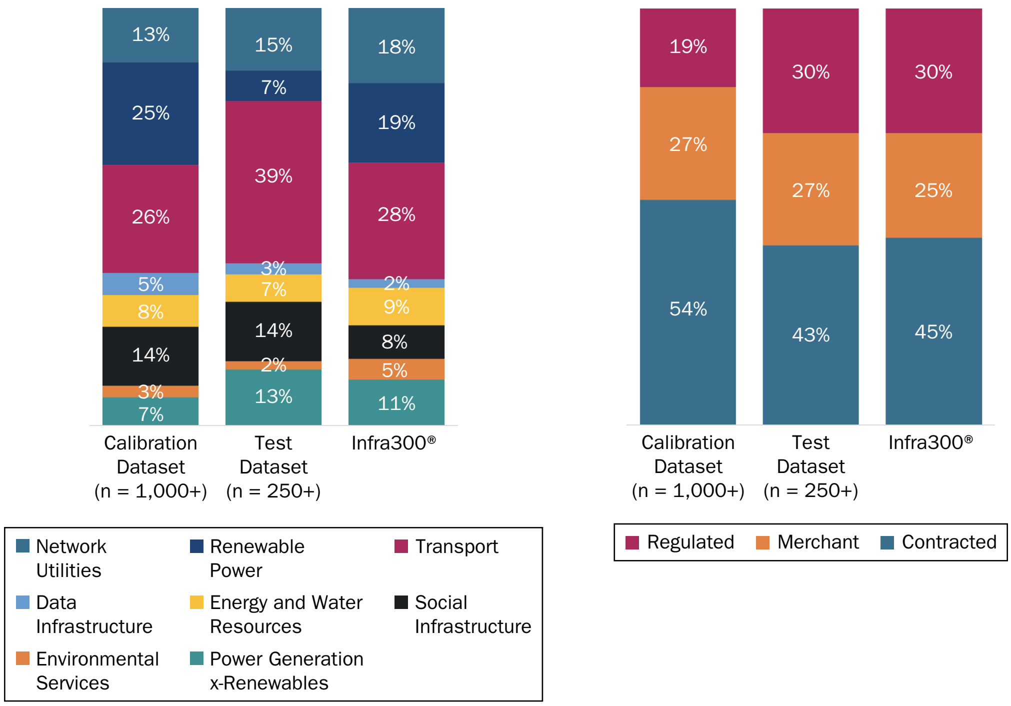
This approach is robust and predicts market prices well. For the 250+ transactions that correspond to companies tracked in the EDHEC*infra* universe and for which observed secondary market prices are available (the test dataset), we can directly compare observed and model-predicted valuations.

Exhibit 9 shows a comparison between model-predicted IRRs, enterprise value/earnings before interest, taxes, depreciation, and amortization (EV/EBITDA), price-to-book, and price-to-sales ratios with actual values for the test dataset of 250+ observed transactions between 2000 and 2020. Model-predicted prices are accurate and the prediction error is typically within 5% of observed prices, as shown in Exhibits 10 and 11.

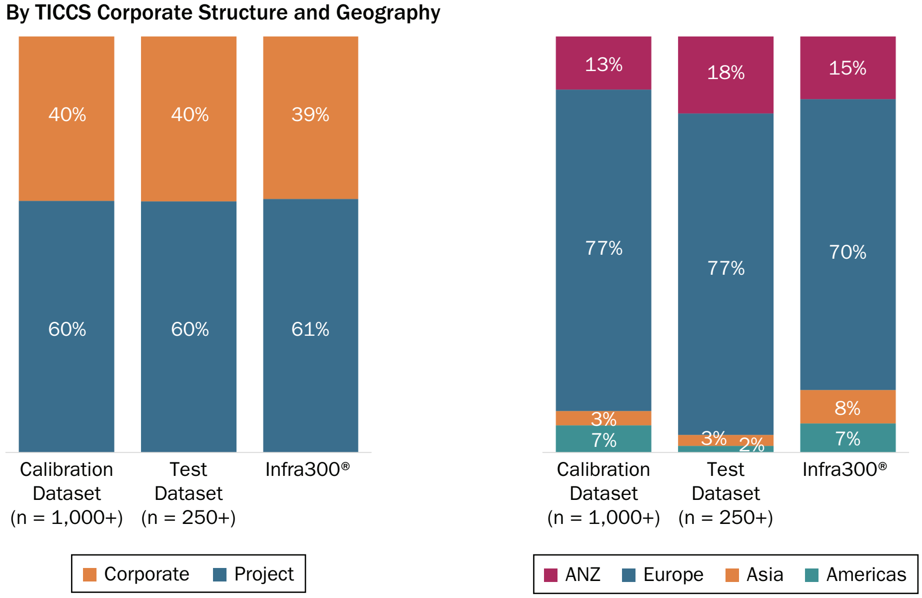
EXHIBIT 8

Distribution of the Model Input Price Data by Segment: Model Calibration Dataset and Model Test Dataset vs. the Infra300 Index Weights (global market, as of year-end 2020)

Panel A: By TICCS Industrial Activity and Business Risk Segment



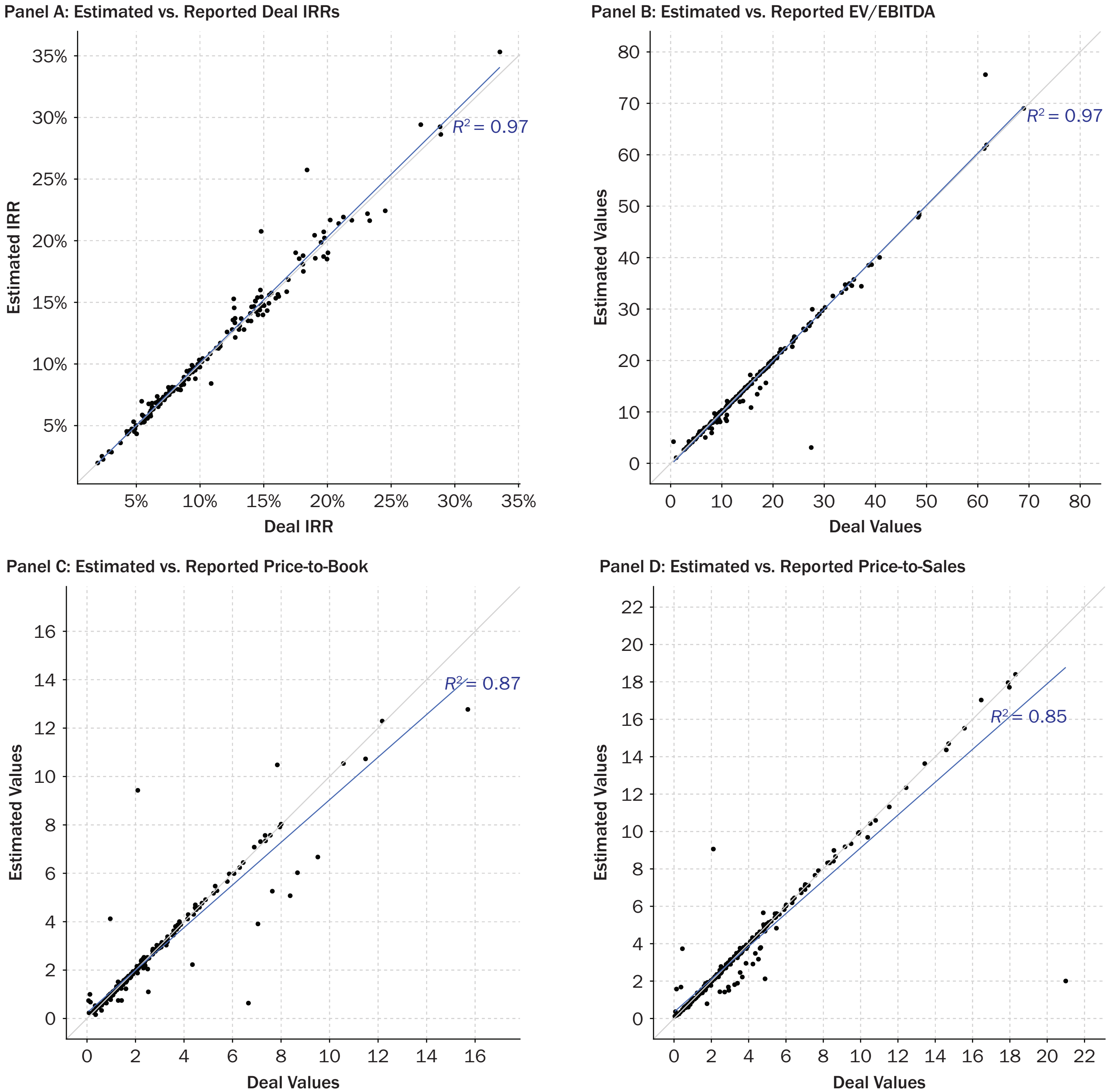
Panel B: By TICCS Corporate Structure and Geography



Thus, we have shown that it is possible to measure the fair value of unlisted infrastructure equity robustly and accurately and that the resulting time series of returns exhibits a nontrivial level of volatility, consistent with the characteristics of the different infrastructure segments as defined by the TICCS taxonomy, as well as the individual exposure of infrastructure assets to certain key risk factors.

EXHIBIT 9

Estimated vs. Reported Asset Pricing Values in the EDHEC*infra* Model of Unlisted Infrastructure Equity



SOURCES: Annual and quarterly reports, EDHEC*infra*.

RISK-ADJUSTED PERFORMANCE AND BENCHMARKING

Having established a robust approach to asset valuation and risk measurement in unlisted infrastructure investments, we turn to the question of benchmarking infrastructure and how the Infra300 market index is built.

EXHIBIT 10
Estimated vs. Reported Valuation Ratios and Model Goodness of Fit

Ratio	Reported Mean	Estimated Mean	Reported Median	Estimated Median	R^2	RMSE*
EV/EBITDA	15.54	15.34	12.98	12.61	0.97	2.27
P/Book	2.37	2.28	1.65	1.59	0.87	0.90
P/Sales	3.35	3.21	2.52	2.32	0.85	1.43

NOTE: *RMSE = root mean squared error.

SOURCE: EDHEC*infra*.

EXHIBIT 11
Quantiles of Model Errors

0% Quantile	25% Quantile	Median	Mean	75% Quantile	90% Quantile
–5.00%	–1.95%	–0.22%	–0.55%	1.64%	3.85%

SOURCE: EDHEC*infra*.

Issues with Absolute Return, Contributed, and Listed Benchmarks

Is infrastructure market-neutral? Investors in private, illiquid assets like infrastructure can be tempted to adopt a so-called "absolute return" benchmark, despite the use of absolute return benchmarks having been vilified in the academic literature with regard to other alternative asset classes, such as hedge funds or private equity. Waring and Siegel (2006) provide a useful summary of these critiques, and Gompers, Kaplan, and Mukharlyamov (2016) review the uses and abuses of absolute performance benchmarks by private equity managers.

By definition, a market-neutral investment strategy is not impacted by market movements. In effect, only a truly market-neutral portfolio would warrant an absolute return benchmark. Indeed, the promise of absolute return strategies is that their performance depends on asset characteristics alone and not on any systematic features, including any influence from the various markets for financial assets.

Likewise, infrastructure assets are often presented as less correlated with the business cycle and notably its main financial proxy, which is the equity market. This belief in the decorrelation of infrastructure leads investors to expect higher returns and limited downside risk from these investments (for a review of the infrastructure investment narrative, see Blanc-Brude 2013). Still, as with any other asset class, unlisted infrastructure is exposed to systematic risks. These may be different from the risks of public equities but nonetheless drive variations in returns. Thus, there is no reason to believe a priori that unlisted infrastructure is a pure absolute strategy, the performance of which would only be due to the inherent characteristics of the assets and, by extension, of the managers or investors who select them.

There is no infrastructure investing strategy today that could be considered market neutral in the sense that it would not be related to any systematic source of volatility. Moreover, there is no market to short unlisted infrastructure equity or debt. Nor are derivative contracts written against unlisted infrastructure assets widely available. Thus, unlike hedge fund strategies, any claim of the market neutrality of infrastructure investments would have to rely entirely on the intrinsic characteristics of the business of infrastructure companies.

While it is reasonable to assume a degree of independence from the business cycle for most types of infrastructure assets in good times, this may not apply in all states of the world, as the Covid-19 lockdowns perfectly illustrated. Moreover, some types of infrastructure companies can be expected to be correlated with the business cycle even in good times, such as large airports or toll roads. We return to this in the next section.

A cursory analysis of the potential outcomes of infrastructure investments also suggests that they are can be impacted by the state of the economy. For instance, in the 630+ companies tracked in the EDHEC*infra* broad market universe, over the past 20 years we observe more than 150 events of default or dividend lock-up, several dozen events of bankruptcy, and more than a dozen events of termination by the public sector. These defaults and bankruptcies are typically found in companies that are exposed to the economy because they have a merchant business model (e.g., after a recession) or because of structural shifts affecting an entire industrial sector (e.g., electricity market prices permanently lower than the marginal production cost of older power plants).

Nor should the financial performance of unlisted infrastructure investments be expected to have no relation with asset prices in capital markets. Indeed, the key point of modern finance theory since Markowitz (1952) and Sharpe (1963) is that the excess return of any given portfolio of financial assets can always be decomposed into at least two parts: a systematic one that is related to the market for financial assets (usually referred to as beta) and a portfolio-specific one which is not (and is usually called alpha). In its simplest form, this is the well-known capital asset pricing model or CAPM.

The systematic part represents the average future exposure to market returns and is necessarily expressed relative to a benchmark (the portfolio beta captures the correlation of portfolio returns with market returns). Treating infrastructure as an absolute return investment implies that the systematic part of the infrastructure portfolio does not exist, that is, the beta in the portfolio return equation always equals zero.

Instead, in line with modern financial theory, we can show that a series of risk factors systematically explain expected returns observed in secondary markets for unlisted infrastructure equity or debt (we return to this below). The nature of infrastructure assets and of the risks that determine their future returns are such that the systematic part of portfolio returns is always there.

In theory, the beta part of the portfolio can be expected to explain most of its expected returns. In Sharpe's CAPM, alpha always equals zero and, on average, betas explain all asset returns. While it can be reasonable to assume non-zero alpha because of the presence of market inefficiencies and of investment skills to exploit these, the notion that any portfolio includes a large systematic part is impossible to escape, even for unlisted infrastructure assets. This last point boils down to the fundamental nature of a market for any asset. Investors are not alone. Even infrastructure investors buy and sell assets (from each other) in a market, where they tend to behave in certain, correlated ways. What is more, the same infrastructure investors are active in the markets for other asset classes, where they express the same preferences for risk and have the same investment objectives than the ones they bring with them to the market for infrastructure assets.

Finally, the reasons (call them factors) for which investors value financial assets are found in many markets at once. For instance, if an investor values highly profitable listed tech companies, she also values highly profitable unlisted infrastructure companies. The same goes for liquidity or leverage. When investors speak of a liquidity premium in private assets like infrastructure, they implicitly recognize that all assets are priced in part as a function of their liquidity and thus that asset prices are formed together in a market for all assets.

Thus, not only do many infrastructure investments often exhibit *prima facie* a degree of correlation with the business cycle, but the fact that infrastructure investors are increasingly large asset owners and managers expressing the same risk preferences across multiple asset classes at the same time necessarily implies that a long-only unlisted infrastructure portfolio cannot possibly be market neutral.

The hypothesis of the market neutrality of infrastructure investment cannot be retained as a good reason to use absolute return benchmarks in infrastructure investment. However, one final reason for their continued use is the perceived absence of an alternative, which we discuss next.

The lesser evil? One may argue that absolute return benchmarks have simply been inherited from other private asset classes, such as private equity or real estate, for lack of a better alternative. The use of absolute return benchmarks is a fallback option in a context where there is very little data available to benchmark investor portfolios. Investors might say that while they acknowledge that absolute return benchmarks are not adequate, they have no alternative but to treat unlisted infrastructure *as if* it was an absolute return investment. Until recently, alternatives to absolute benchmarks in infrastructure portfolios have been so limited that using absolute benchmarks could be considered the *lesser evil*.

The two other common choices to benchmark such unlisted and illiquid investments as infrastructure are appraisal-based indices or listed proxies. In the case of infrastructure, both are fraught with such serious problems that ultimately a simple "cash+" benchmark adjusted for an ad-hoc premium for the specific, and especially illiquidity, risks of private assets could appear more relevant than these flawed relative benchmarks. *Appraisals* are collected from a limited number of asset managers, causing the indices built with such data to have two fundamental flaws:

1. *Lack of representativeness*: The constituents included in appraisal-based indices (which are typically not revealed) are not chosen according to any rule or logic other than being the data reported by certain investors at one point in time. The composition of such indices thus keeps changing randomly. Moreover, appraisal-based indices suffer from survivorship biases: Only the investments of reporting funds are still present in the portfolio of the reporting investors, hence the index fails to include past bankruptcies and terminations that nevertheless exist in the universe. Exhibit 12 shows the sector composition of the MSCI Global Unlisted Infrastructure index compared to the investible universe across the 25 largest markets in the world and highlights the lack of coverage of certain sectors and the excessive weights placed on others due to the selection bias introduced by contributions.
2. *No measure of risk*: The net asset values used to compute appraisal-based indices exhibit very low return volatility and no return correlation with other asset classes (see Exhibit 4). This is because valuation methods rely on smooth time series of interest rates and the "equity risk premium" to arrive at a discount rate that changes very little over time. If expected cash flows are indeed stable, then valuations barely change from one period to the next, even though market participants may be willing to pay very different multiples from one valuation date to the next. This smoothing of the volatility of private assets is reflected in the significant serial correlation of returns reported in appraisal-based datasets (see Exhibit 13).

It can be noted that if infrastructure investment really was as appraisal-based indices suggest it is, then an absolute return benchmark could be justified. Indeed, taking these data seriously implies a complete lack of correlation with other asset

EXHIBIT 12
MSCI Unlisted Infrastructure Index: Sector Weights vs. the Unlisted Universe

	MSCI Global Unlisted Infrastructure	Over/Underweight	Unlisted Infrastructure Universe[a]
Transport	54.6%	160%	21%
Network utilities	6.4%	–69.5%	21%
Renewables	0%	–100%	18%
Power	32.8%	118.6%	15%
Energy resources	0%	–100%	11%
Data	2.3%	–67.1%	7%
Social infrastructure	0%	–100%	4%
Environmental services	0%	–100%	2%
Other	3.4%	N/A	

NOTE: [a]EDHEC*infra* Universe Standard 2020.

SOURCE: MSCI; no sector exposure data are available for the Preqin Infrastructure Index.

EXHIBIT 13
Statistical Characteristics of the Preqin, MSCI, and Infra300 Unlisted Infrastructure Indices over a 10-Year Period

Index	Total Return	Total Return Volatility	Sharpe Ratio (Rf = 1%)	Max Drawdown	Return Correlation with MSCI World	Return Correlation with 30-Year Treasuries	Serial Correlation of Returns
Preqin Unlisted Infrastructure	10.41%	3.11%	2.99	1.37%	–5%	–7%	Statistically significant
MSCI Unlisted Global Infarstructure	13.42%	3.26%	3.78	0%	4.6%	–5.7%	Statistically significant
Infra300	12.03%	13.90%	0.78	14.67%	24.2%	20.4%	No serial correlation

NOTES: Correlation data from 2009 to Q3 2019 (latest data available for the Preqin infrastructure index). All computations use quarterly USD returns. Serial correlation test statistics in the appendix (Exhibit A1).

SOURCES: Preqin, MSCI, EDHEC*infra*.

classes.[1] However, this absence of correlation is only the result of the low quality and lack of market representativeness of the inputs used to produce such indices. The 10-year annualized Sharpe ratio on the appraisal-based-index is obviously too high to be real.

Finally, *listed infrastructure* indices and proxies have been studied extensively and have always been found to pose a different kind of challenge for investors in need of an unlisted infrastructure benchmark. While some listed firms are indeed infrastructure companies and qualify as such under the TICCS taxonomy, only a handful exist (we estimate about 100 globally), and these firms are concentrated in the energy, utilities, and airport sectors in a small number of jurisdictions. Crucially, existing listed infrastructure indices and products usually include many other types of firms that are not infrastructure (Amenc et al. 2017). Hence, listed infrastructure data are either too narrow for most investors in infrastructure or too noisy. As a result, listed infrastructure indices and products have been shown time and again to be highly correlated with listed equities and to have a similar risk and drawdown profile (see Exhibit 14).

[1] Incidentally, it would make the appraisal-based index itself irrelevant by the same token.

EXHIBIT 14

Statistical Characteristics of Listed Infrastructure

Index	Total Return Volatility	Sharpe Ratio	Correlation with Equities
MSCI World	15.2%	0.33	N/A
S&P Global Listed Infrastructure	15.45%	0.19	90%
EDHEC*infra* Listed Infrastructure Managers Proxy	14.9%	0.4	84%

SOURCES: Datastream; EDHEC*infra*–USD return data for Q1 2000 to Q1 2020.

It can be noted that if infrastructure investment really was as listed infrastructure indices suggest it is, then there would not be much point for investors to seek an exposure to infrastructure because they are already exposed to the same risk–return profile through their listed equity positions. A portfolio optimizer given both listed equities and listed infrastructure as inputs would exclude one of the two from the portfolio because they are equivalent.

Thus, because both appraisals and listed proxies fail to produce convincing benchmarks, it can be argued that until now *investors have been left with the sole option of using absolute return benchmarks*, despite significant evidence that infrastructure investment cannot be considered market neutral.

A Mark-to-Market Index of the Performance of Unlisted Infrastructure Equity

Following the approach described in section to value unlisted infrastructure companies, we now describe how the market index for the asset class—the Infra300 Index—is designed.

A representative sample of the universe. To build a representative view of the investible universe we follow a *scientific* approach to identify the relevant markets and pick the relevant constituents of a broad-market index.

- Data are collected and structured using TICCS, an objective and consensual taxonomy that is the industry standard, and the complete investible universe is identified in each country through market research, leading to a list of several thousand private infrastructure companies and projects vehicles categorized by TICCS that corresponds to the 25 most active (principal) markets globally.
- A representative sample of the universe is built that matches its characteristics over time in terms of each TICCS segment (business risk, industrial activity, corporate governance).
- This sample is then used to create the list of constituents of the Infra300.

Each firm included in the Infra300 Index is studied in detail by a team of financial analysts who collect, aggregate, and validate their financials; understand their history and prospects; and produce quarterly updated revenue forecasts on the basis of sector and company specific information. Each year, the investible universe is updated and the sampling recalibrated. Each quarter, the broad-market index constituents are updated for new financial data, new business information and new revenue forecasts.

With this approach, we avoid two major pitfalls of contributed indices like the ones based on appraisals. We avoid selection bias because the constituents of the broad-market index are sampled from a well-defined and most relevant population of investments and based on the structure of the market at each point in time.

EXHIBIT 15

Infra300 Equity Risk Premia and Market Discount Rate

We also avoid any survivorship bias because there is no backfilling of the broad-market constituents, instead we “fill forward” as new infrastructure companies become investible or have to leave the index. This is well illustrated by the number of adverse events in the history of the sampled universe: In the 630+ companies tracked in the EDHEC*infra* broad market universe, over the past 20 years we observe more than 150 events of default or dividend lock-up, several dozen events of bankruptcy, and more than a dozen events of termination by the public sector. These defaults and bankruptcies are typically found in companies that are exposed to the economy because they have a merchant business model (e.g., after a recession) or because of structural shifts affecting an entire industrial sector (e.g., electricity market prices permanently lower than the marginal production cost of older power plants).

Thus, we can build a representative set of investible unlisted infrastructure companies in all the major markets where such investors as superannuation funds are active. This approach allows us to compute a market-implied discount rate for several hundred investments over the past 20 years. Exhibit 15 shows the average discount rate and market risk premia for the 300 constituents of the Infra300.

We see that in periods of stress like the 2008 financial crisis, the 2012 European debt crisis and the Covid-19 pandemic, the average risk premium of unlisted infrastructure equity investments tends to increase. We also see that it keeps varying as the price of risk changes over time (the λ_k’s discussed earlier) and the exposure to different risk factors (the β_k’s) also changes as individual infrastructure companies follow their cycle and the business cycle. Hence, the infrastructure risk premium not only increases in times of crises but may also be higher because, in aggregate, infrastructure companies take on more leverage or see their profits decline. Changes in country risk also impact these investments’ exposure to the term spread factor. (This is the main reason for the 2012 spike for all assets in southern Europe, which make up about one fifth of the Infra300 by weight.)

EXHIBIT 16

Total Returns, Risk and Expected Returns of the Unlisted Infrastructure Asset Class and Selected TICCS Segments, Data as of Q1 2021

	1-Year Total Return	5-Year Total Return	5-Year Volatility	10-Year Total Return	10-Year Volatility	99.5% 1-Year VaR	Max Drawdown	Duration	Expected Returns
Infra300	–3.92%	4.08%	9.79%	13.46%	12.69%	21.21%	13.75%	8.69%	8.8%
Global Infrastructure	–1.15%	6.42%	9.68%	14.64%	12.35%	18.97%	13.70%	8.03%	8.6%
TICCS Segment									
Contracted	2.81%	6.62%	8.13%	14.79%	11.26%	14.98%	10.35%	7.67%	7.7%
Merchant	–3.37%	5.82%	11.77%	14.38%	14.63%	27.18%	21.60%	7.70%	10.6%
Global Transport	–4.22%	6.16%	11.45%	15.17%	14.93%	26.90%	22.41%	8.56%	8.7%
Airports	–19.79%	-0.92%	16.22%	11.85%	17.78%	36.00%	34.89%	11.63%	8.9%
Global Projects	0.97%	7.88%	9.07%	15.73%	12.03%	17.02%	13.93%	7.66%	8.2%
Global Wind	–0.25%	7.86%	8.19%	15.22%	10.48%	11.37%	9.55%	7.40%	6.6%
Global Core	0.96%	9.43%	7.33%	15.04%	10.36%	12.46%	11.16%	7.73%	6.2%
Global Core+	–1.88%	10.95%	9.67%	17.94%	12.40%	14.62%	11.86%	9.19%	9.1%
Mid-Market	–0.11%	11.13%	9.40%	16.88%	10.94%	12.07%	10.88%	7.70%	8.8%
Range in Basis Points	2,260	1,210	890	610	740	2,460	2,530	420	440

NOTES: Returns shown are local currency returns as of Q1 2021. Expected returns shown as of Q1 2021. The 99.5% 1-Year VaR is Cornish–Fisher value at risk. Global Range in basis points is determined by maximum value—minimum value. Global Core is based on the first and second quantiles, and Global Core+ is based on the third quantile of expected returns; Mid-Market is defined as the second and third size quantiles in the universe.

SOURCE: EDHEC*infra*.

The general trend is, unsurprisingly, one of declining yield. Over the past 20 years, the market-implied discount rates of unlisted infrastructure investments have declined from the 12%–14% range to a more modest 6%–8% range.

This phenomenon is driven by a number of factors, including a higher demand for such assets and declining interest rates. Indeed, the risk premia has also declined steadily during that period but less than discount rates, as also shown in Exhibit 15.

We also note that this re-pricing of unlisted infrastructure equity drew to a halt at the end of 2016. Since then, yields have stabilized and the average risk premia increased in the wake of continuously decreasing lower interest rates until the end of 2020. In Q1 2021, a significant increase across the term structure of rates led to a higher discount rate and negative returns across most infrastructure segments.

By definition, this secular change in the average value of unlisted infrastructure (the compression of yields) also adds variance to infrastructure returns, even though it tends to be the result of significant capital gains as unlisted infrastructure turned into a fully fledged asset class during that period. Once this "great repricing" had taken place after 2016, the valuation of unlisted infrastructure companies, while still exposed to changes in the market price of risk, became less variable—that is, returns became less volatile.

Exhibit 16 shows the risk and return metrics for a selection of segments of the infrastructure universe, including the Infra300, the broad market, and TICCS segments, such as global contracted infrastructure or global airports. The table also shows the value range (maximum value minus minimum value) for each metric across the different segments, which helps to highlight the differences between them but also the ability of our approach to capture these differences. Results are updated as of Q1 2021.

First, we see that the risk measures, including the volatility of returns, value-at-risk, or maximum drawdown, are in line with the nature of the different segments: Contracted infrastructure is less volatile than merchant infrastructure, Core less volatile than Core+, and so on. Similarly, despite higher interest rates in Q1 2021, purely contracted infrastructure exhibits positive total returns whereas most other segments do not. In effect, the only two segments in Exhibit 16 with positive returns in Q1 2021 are the ones with the lowest duration.

The range of extreme risk measures is also significant, with a difference of about 2,500 basis points (bps) between the lowest and the highest value at risk (99.5%) and maximum drawdown measures across these segments.

Consistent with the finding that the upward change in valuations that started after 2009 ended in 2016, the five-year volatility of total returns is significantly lower than its 10-year equivalent in a number of sectors, especially Contracted and Global Core infrastructure (which overlap significantly). On average, total return volatility is 20% lower in the five-year window as of Q1 2021.

Likewise, returns are also much lower because part of the variance of prices that occurred between 2011 and 2021 was driven by capital gains that abated after 2017. On average, realized total returns are 50% lower in the five-year window. We also note that the range of realized returns has increased, with a spread between the highest and lowest five-year returns in excess of 1,200 basis points, which is twice as large as the spread between the best and the worst 10-year returns (610 basis points).

Next, we turn to the determinants of return volatility in unlisted infrastructure.

Return drivers. We now consider the role of each individual component of the market value of infrastructure assets in explaining the change in net asset value; that is, how much market prices have changed because of a change in expected dividends, a change in risk premium, or a change in the term structure of interest rates, as well as performance differences between segments of the infrastructure universe, as defined by the TICCS taxonomy.

Exhibit 17 shows the cumulative impact on the NAV of the actual (realized) change of dividend forecast, interest rates (across the term structure), and risk premia, over one-, three- and five-year windows as of Q1 2021, which is during the more recent period when valuations appear to have stabilized following a period of significant re-pricing. These impacts are computed to isolate the effect of each factor.

Thus, we see that the aggregate NAV of the global infrastructure segment tracked by EDHEC*infra* (about 600 live firms in 2021) has increased in aggregate by 2.1% since Q1 2016 due solely to changes in expected dividends. In the more recent period, however, lower expected dividends due to the consequences of the Covid-19 lock-downs have had a negative impact on the aggregate NAV.

As expected, this effect is less strong (almost zero) for contracted infrastructure and much larger for merchant assets. Also because of Covid-19, the impact on airports of lower dividends is significant (mostly booked in Q1 2021, hence in the three-year window), but because airports have very long lives it remains limited—the sum total of all future dividends is large relative to the lost dividends of 2020–2022/23.

The cumulative impact of changes in rates is shown in the third column of Exhibit 17. This is the aggregate effect of all rate changes in the segments across two dozen countries and can include simultaneous upward and downward movements of the yield curve in the same quarter in different countries. We see that over a five-year window, the effect has been consistent and large, however, explaining between 9% and 10% of the increase in the NAV of assets.

However, this impact is at least partially offset by an increase in the risk premium. In merchant infrastructure and airports, the impact of higher risk premia driven by lower profits in particular is larger than the positive impact of lower rates, and therefore, on aggregate, NAV has decreased.

EXHIBIT 17

Average Impact on Market NAV of Change in Rates, Future Dividends, and Market Risk Premia on Different Segments of the Unlisted Infrastructure Equity Universe, Data as of Q1 2021

	Average Change in NAV		
	…Due to Change in Dividend Forecast	…Due to Change in the Term Structure of Rates	…Due to Change in Equity Risk Premia
Global Infrastructure			
1-Year	–4.0%	–1.2%	–3.9%
3-Year	–2.0%	7.4%	–8.2%
5-Year	2.1%	9.9%	–9.4%
Contracted			
1-Year	–0.2%	–1.0%	–2.7%
3-Year	–0.3%	7.3%	–5.6%
5-Year	3.6%	9.9%	–7.0%
Merchant			
1-Year	–7.20%	–1.30%	–6.90%
3-Year	–5.20%	7.20%	–12.50%
5-Year	–2.20%	8.50%	–13.20%
Global Transport			
1-Year	–6.10%	–0.50%	–5.60%
3-Year	–6.70%	8.80%	–11.70%
5-Year	–0.40%	11%	–11.70%
Airport			
1-Year	–4.40%	–5.20%	–13.70%
3-Year	–8.30%	10.20%	–26.40%
5-Year	12.40%	13.80%	–27.20%
Global Projects			
1-Year	–2.90%	–0.50%	–3%
3-Year	–1.70%	7.40%	–7%
5-Year	2.80%	9.70%	–8%
Global Core			
1-Year	–2.60%	0%	–2.20%
3-Year	–0.50%	7.20%	–5.10%
5-Year	2.70%	9.40%	–6%
Global Core+			
1-Year	–4.70%	–1.60%	–4.40%
3-Year	0.10%	8.10%	–9.10%
5-Year	8.80%	9.40%	–9.60%

SOURCE: EDHEC*infra*.

In the global segment however, and particularly in the contracted one, a higher risk premium less than offsets lower interest rates and reasonably stable expected dividends, leading to low but positive or close to zero changes in the NAV of assets.

Thus, we see that the impact of changes in rates and risk premia on the variance of the fair value of unlisted infrastructure equity (and thus on the volatility of returns) is at least as large as that of changes in expected dividends. By focusing only on changes in the cash flows and not on the market price of risk, investors risk seriously mispricing their assets and fail to recognize large changes in market value, both positive and negative.

An important result is that the volatility of unlisted infrastructure investments is driven by changes in expected dividends only to a point. With a long investment horizon, the role of duration or sensitivity to changes in the discount rate is much more significant in explaining the variance of market prices. This discount rate is the combination of the evolution of interest rates and of a risk premium that compensates investors for the uncertainty of future cash flows. Thus, investments in unlisted infrastructure equity can be characterized as investing in a combination of exposures to a time-varying (infrastructure) equity risk premium, as well as a significant amount of interest rate risk.

Finally, we see that the realized volatility of infrastructure equity includes a significant period of repricing between 2009 and 2016, during which infrastructure assets became more expensive and their yield lower. This "regime shift" in the pricing of unlisted infrastructure was the result of the asset class coming of age and becoming priced in capital markets. As a result, the 10-year volatility stands between 10% and 15%, and 10-year returns are also high, reflecting the significant capital gains of that period. The forward-looking volatility of these investments is more likely to resemble that of the five-year period immediately afterward, typically ranging between 8% and 12%.

INFRASTRUCTURE AND MARKET STRESS

We compare the behavior of unlisted infrastructure equity investments with traditional assets in capital markets and focus on the role of such shocks as recessions, financial market crises, or policy shocks. We compare the return correlations and drawdown characteristics of geographically comparable indices of unlisted infrastructure equity, listed equity, treasuries, and corporate bonds and examine their return drawdown and covariance, as well as higher co-moments of returns (coskewness and cokurtosis) to determine the presence or absence of joint extreme risks.

There are several reasons why infrastructure equity returns could become more correlated with capital markets at times of economic or financial distress. Three factors play a role in the covariance of infrastructure valuations: future cash flows and the two components of their market discount rate—the (unlisted) infrastructure equity market risk premia and the bond yield curve at the relevant horizon. The extent to which infrastructure asset prices are impacted by market downturns is a combination of changes in these three quantities. In particular, interest rates and risk premia shocks can be expected to drive any extreme comovements of returns between unlisted infrastructure and public asset classes.

In terms of future cash flows, because infrastructure companies provide essential services, demand can be expected to be resilient in bad times. Moreover, infrastructure companies derive their value from a long-term business model and payback period. Hence, their value should be less sensitive to short-term fluctuations in demand for services and revenues. Still, even if the value of long-term and essential assets is not materially impacted by small or brief downturns in economic activity, infrastructure is the backbone of the economy and derives its value from its continued future activity. Hence, large economic or policy shocks could have a significant impact on the future cash flows of some infrastructure businesses, precisely when other asset classes also exhibit large losses.

Next, the present value of infrastructure equity investments is a function of a risk premium that represents the market price of the risk of future cash flows. This premium is in part a reflection of the supply and demand for unlisted infrastructure investments, which in itself is dependent on investors' arbitrage choices between different asset classes (including between alternative asset classes), the evolution of their risk preferences, and the market price of the various risk factors that drive this premium. In times of market stress, the listed equity market premium and the unlisted infrastructure equity market premium can be expected to become more correlated, as investors' preferences for low risk and liquid assets increase concurrently.

Likewise, the level of interest rates is a conduit through which unlisted infrastructure and capital markets could become more correlated in times of crisis. The long-term nature of infrastructure investments implies a significant duration—that is, a higher sensitivity of asset values to changes in discount rates and in particular to shifts in the yield curve—when interest rates are already very low. Such duration alone can be expected to create correlations between infrastructure investments and bonds.

Finally, certain types of infrastructure are also more exposed to downturns than others: infrastructure companies with a so-called "merchant" business model, such as toll roads or merchant power plants, see their revenues fluctuate with the business cycle. Not only is their equity risk premium higher than that of infrastructure companies with a more predictable business model, such as contracted infrastructure projects, but it is also more likely to co-vary with the equity risk in capital markets. However, merchant and regulated assets are also more likely to exhibit future cash flow growth, including through tariff indexation and monopoly pricing power, partly offsetting the impact of higher interest rates on their valuation and returns. Contracted assets, however, may only hedge movements in discount rates if they have contractually defined inflation pass-through. Thus, for a given duration, contracted infrastructure investments may be more exposed to interest rate risks, including inflation-driven rate increases, while merchant and regulated infrastructure may better protect real returns through cash flow growth.

Risk Profile

We examine 22 years of monthly returns for our capital market benchmarks and the Infra300.[2] Exhibits 18 and 19 show the performance, volatility, and risk-adjusted returns for each asset class.

Unlisted infrastructure has higher return volatility than bonds but lower than listed equities, which is consistent with its economic characteristics. Note that the risk (annualized standard deviation of returns) of the Infra300 is lower on a total return basis than when using price returns. This is not the case for the capital market benchmarks and a testament to the importance of cash yields in infrastructure returns, including as a source of return stability.

On a risk-adjusted basis, unlisted infrastructure equity has a more attractive in-sample Sharpe ratio than other asset classes. As shown in a previous paper (Blanc-Brude et al. 2021), the significant increase in infrastructure asset valuations that occurred during the 2010–2017 period, as demand for this type of assets increased rapidly, led to substantial but finite capital gains that explain the high historic risk-adjusted performance of the unlisted infrastructure asset class and its very high realized Sharpe ratio.

On a forward-looking basis, the 2022 Sharpe ratio of infrastructure equity is lower. Using infraMetrics data, average expected returns in 2022 for global unlisted infrastructure equity are around 8%. Using historical volatility as a proxy of forward-looking risk, the forward-looking Sharpe ratio of unlisted infrastructure is close to 0.6, which remains attractive in comparison with capital markets, especially equities.

Exhibits 18 and 19 also show the skewness and excess kurtosis of the distribution of returns, which are indicators of asymmetric and extreme risks. Unlisted infrastructure

[2] Note that such an analysis, however simple, was not possible until recently because monthly performance data were not available for research until infraMetrics started publishing monthly data in Fall 2021.

EXHIBIT 18

Total Returns (monthly local currency), 2000–2022: Benchmark Portfolios and Infra300 Index

	Equities	Government Bonds	Corporate Bonds	Infra300
Annualized return	0.0548	0.0503	0.0493	0.1354
Annualized standard deviation	0.1409	0.0509	0.0612	0.0826
Annualized Sharpe ratio (R_f = 1%)	0.3148	0.7838	0.6362	1.5052
Monthly standard deviation	0.0407	0.0147	0.0177	0.0238
Skewness	–0.6941	–0.0110	–0.6608	–0.5689
Kurtosis	4.7712	2.9061	5.2433	3.2662
Excess kurtosis	1.7712	–0.0939	2.2433	0.2662
Sample skewness	–0.7017	–0.0111	–0.6680	–0.5753
Sample excess kurtosis	1.8253	–0.0737	2.3061	0.2943

SOURCES: Datastream, infraMetrics.

EXHIBIT 19

Price Returns (monthly local currency), 2000–2022: Benchmark Portfolios and Infra300 Index

	Equities	Government Bonds	Corporate Bonds	Infra300
Annualized return	0.0204	0.0088	0.0002	0.0433
Annualized standard deviation	0.1415	0.0544	0.0608	0.0947
Annualized Sharpe ratio (R_f = 1%)	0.0729	–0.0214	–0.1591	0.3481
Monthly standard deviation	0.0408	0.0157	0.0176	0.0273
Skewness	–0.6766	–0.0714	–0.6337	–0.4783
Kurtosis	4.7354	3.1042	5.2033	2.7451
Excess kurtosis	1.7354	0.1042	2.2033	–0.2549
Sample skewness	–0.6840	–0.0722	–0.6406	–0.4838
Sample excess kurtosis	1.7889	0.1279	2.2653	–0.2368

SOURCES: Datastream, infraMetrics.

exhibits less extreme risk (absence of fat tails) than equities or corporate bonds, as suggested by their respective excess kurtosis. Likewise, infrastructure exhibits lower negative skewness than equities or corporate bonds. Very negative returns are clearly possible with infrastructure equity, but there is a 10–20 basis point difference between the skewness of equities and corporate bonds returns and that of the Infra300.

In aggregate, the risk-adjusted profile of unlisted infrastructure can be described as "between equities and bonds" with common negative skewness with equities (we return to large drawdown analysis in a later section) but an absence of fat tails (lower kurtosis) that is more akin to treasuries.

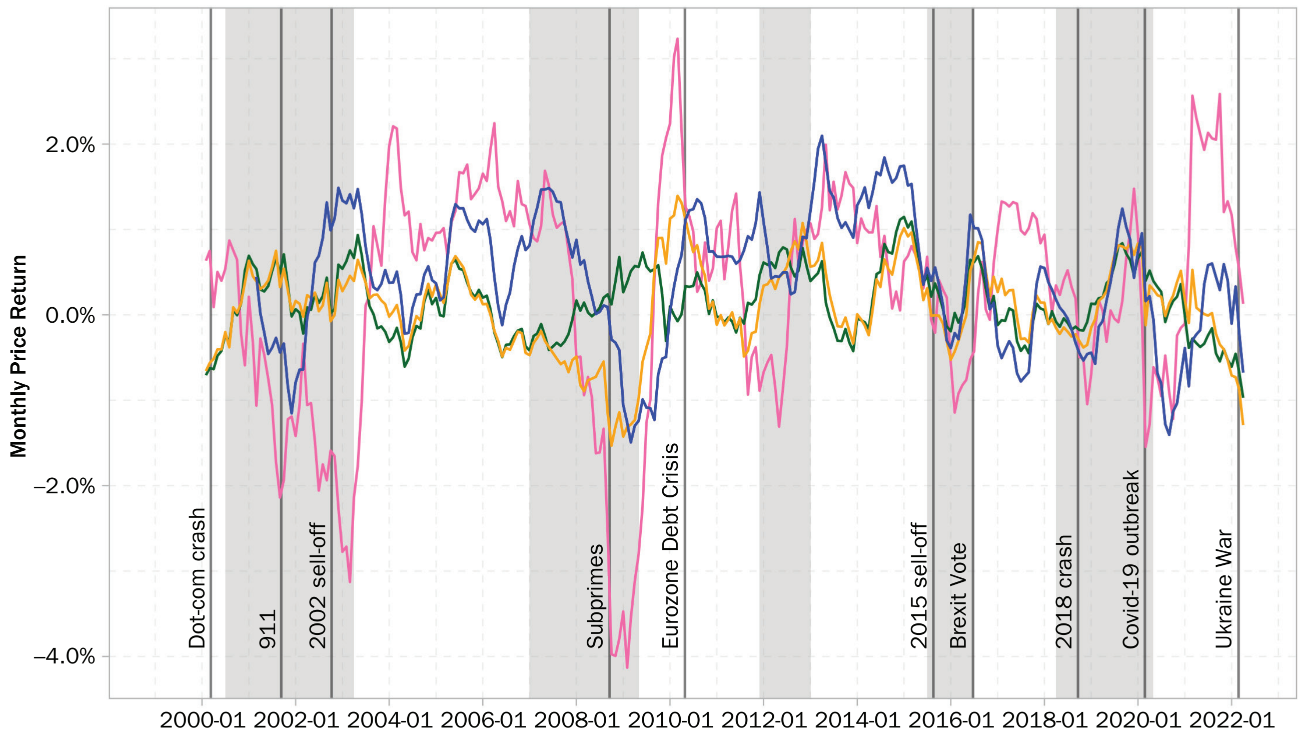
Performance during Shocks

In effect, whether infrastructure investments behave more like bonds or equities depends on the time period and type of market stress. Exhibit 20 shows the price, total, and cash returns of the Infra300 and its three comparators over time. The figures also show periods of economic recession in grey and a number of start dates for financial market and policy shocks.

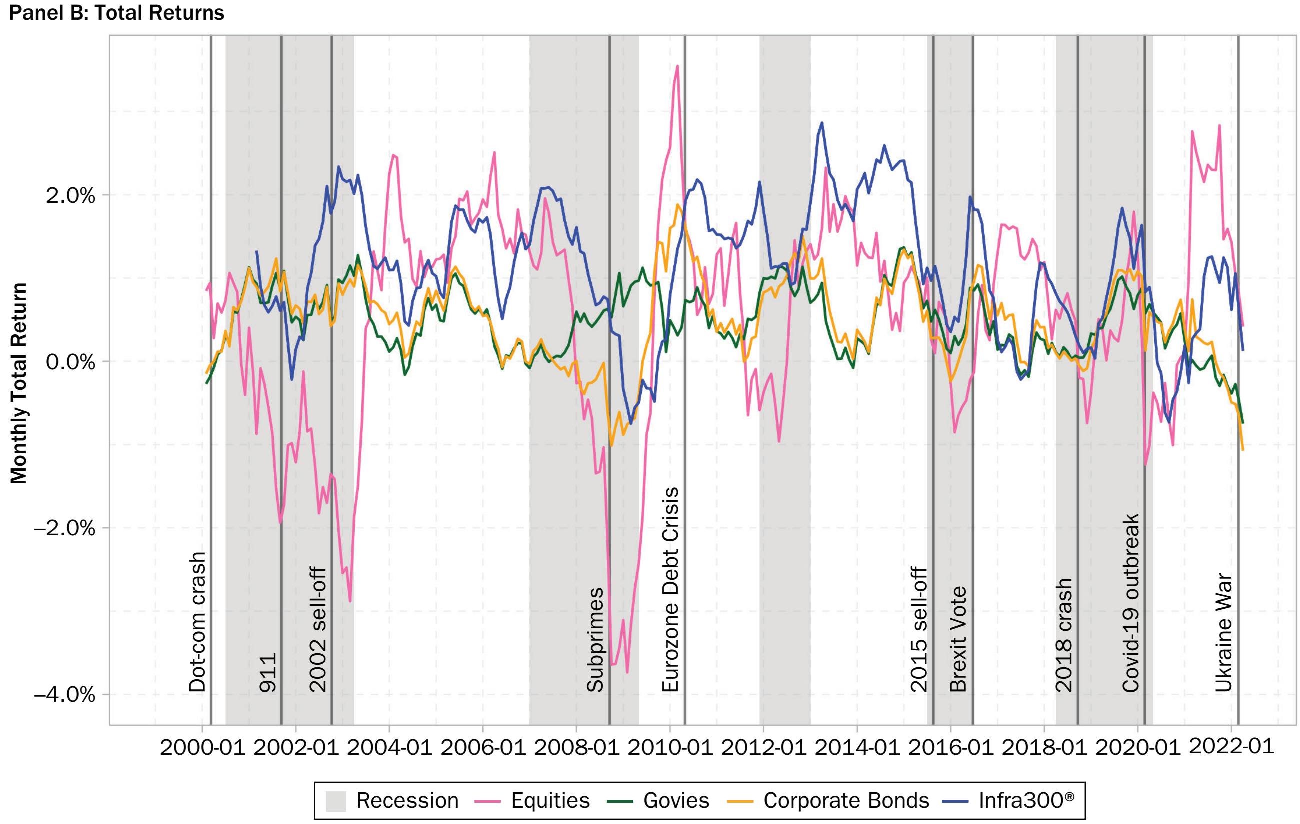
EXHIBIT 20

12-Month Average Returns, Reference Market Benchmarks, and Infra300

Panel A: Price Returns



Panel B: Total Returns



SOURCES: Datastream, infraMetrics.

Casual observation of these charts reveals that the comovements of infrastructure returns (in blue) with other asset classes change over time and can be both positive or negative. The performance of infrastructure and bonds can seem largely related, presumably via the interest rate channel, but this is not always the case, especially in times of economic contraction.

For instance, we see evidence of higher comovement with equities in times of recession, especially during the first part of the 2000–2003 recession episode (note that large parts of OECD countries came out of recession earlier in 2002), the 2007–2009 recession, as well as the 2012 and 2016 recessions. However, during the 2018–2020 recession period, infrastructure performed well until the end of 2019 and only started to experience lower returns from December 2019 as economic activity bounced back and interest rates increased.

A number of financial shocks led to very visible comovements between infrastructure and equities, such as the dot-com crash, the subprime crisis, or the 2015 sell-off. However, not all financial crises seem to affect the private infrastructure sector. The 2002 sell-off or the Eurozone debt crisis for instance do not coincide with large losses in the Infra300, despite their impact on capital markets.

Some policy shocks are also sources of downside for infrastructure, especially the Covid-19 lockdowns, which went on to trigger inflation and interest rate shocks, and the Ukraine war of February 2022. However, events like 9/11 or Brexit do not seem to increase downside risks for infrastructure investors. Indeed, infrastructure and equities also exhibit minimal and sometimes seemingly negative correlations, especially in periods of economic expansion.

In order to better document the impact of recession, financial, and policy shocks on infrastructure as proxied by the three capital market benchmarks, we conduct the following analyses:

1. The next section presents a comparative drawdown analysis.
2. We then examine return correlations and co-moments over time.
3. We examine the role of movements in the yield curve and the equity risk premia in explaining the impact of various shocks on infrastructure investments.

Drawdown Analysis

To further document the behavior of infrastructure investments in times of shock, we consider the maximum drawdown behavior of the Infra300—that is, the maximum observed loss or drop in value from a peak to a trough until a new peak is reached—compared with that of listed equities and bonds. We examine whether infrastructure equity drawdowns are more likely during period of capital market drawdowns.

Drawdown profiles. We report the drawdown profile of the Infra300 and the reference asset classes in Exhibits 21 and 22. We see that on a price return basis, infrastructure with about 7% average drawdown is less exposed to losses than stocks (about 13%) and more than government bonds (about 4%) but is on par with corporate bonds. On a total return basis, consistent with Exhibit 18, infrastructure sits between stocks and bonds in terms of expected loss.

When it comes to maximum or worst drawdowns, on a price return basis, infrastructure comes in second with 23% observed maximum loss, behind governments bonds (16%) and ahead of corporates bonds (29%) and equities (50%). On a total return basis, infrastructure again retains the second place with (15%) maximum observed loss, behind government bonds (12%), and ahead of corporate bonds (16%) and equities (47%).

EXHIBIT 21
Drawdown Statistics: Price Returns, 2000–2022

	Equities	Government Bonds	Corporate Bonds	Infra300
Average Drawdown	0.1287	0.0506	0.0683	0.0749
Worst Drawdown	0.4976	0.1573	0.2884	0.2291
Average Length	18.3571	13.9474	19.2857	11.7895
Average Recovery	11.8571	6.8421	9.5000	4.6842
Conditional Drawdown 5%	0.3896	0.1003	0.1609	0.1833

EXHIBIT 22
Drawdown Statistics: Total Returns, 2000–2022

	Equities	Government Bonds	Corporate Bonds	Infra300
Average Drawdown	0.0745	0.0263	0.0293	0.0462
Worst Drawdown	0.4689	0.1235	0.1600	0.1466
Average Length	8.8148	6.2424	6.3235	6.2308
Average Recovery	5.2963	3.3636	2.8824	3.5385
Conditional Drawdown 5%	0.1665	0.0523	0.0591	0.1073

The average length of drawdowns is also the shortest for infrastructure: 11.7 months on a price return basis and 6.2 months on a total return basis. Likewise, average drawdown recovery (from trough to peak) is the shortest on a price return basis for infrastructure and the second shortest on a total return basis, with only government bonds recovering faster on average.

Finally, we look at the conditional drawdown at risk (CDaR) of Chekhlov, Uryasev, and Zabarankin (2003). For some value α (here, 5%), the CDaR is the mean of the worst $(1 - \alpha) \times 100\%$ drawdowns.[3] Hence, the 5% CDaR is the average of the worst 5% drawdowns over a given time period using the average and maximal drawdown as boundaries, thus including the magnitude and duration of drawdowns. In comparison, maximum or worst drawdown measure focuses on a single loss event.

On this measure, which is more robust than the worst drawdown, infrastructure equity maintains its between-equity-and-bonds profiles, with a clear tilt toward bond-like extreme risk characteristics. In aggregate, over the considered period, infrastructure appears more resilient to drawdowns than equities and bonds.

Drawdown shocks. Next, we look at the behavior of the Infra300 during various periods of drawdown in capital markets. Exhibit 23 shows drawdowns of monthly price and total returns over a period of 22 years. The worst unlisted infrastructure equity drawdowns appear to occur during periods of equity and corporate bond market drawdown and economic recessions.

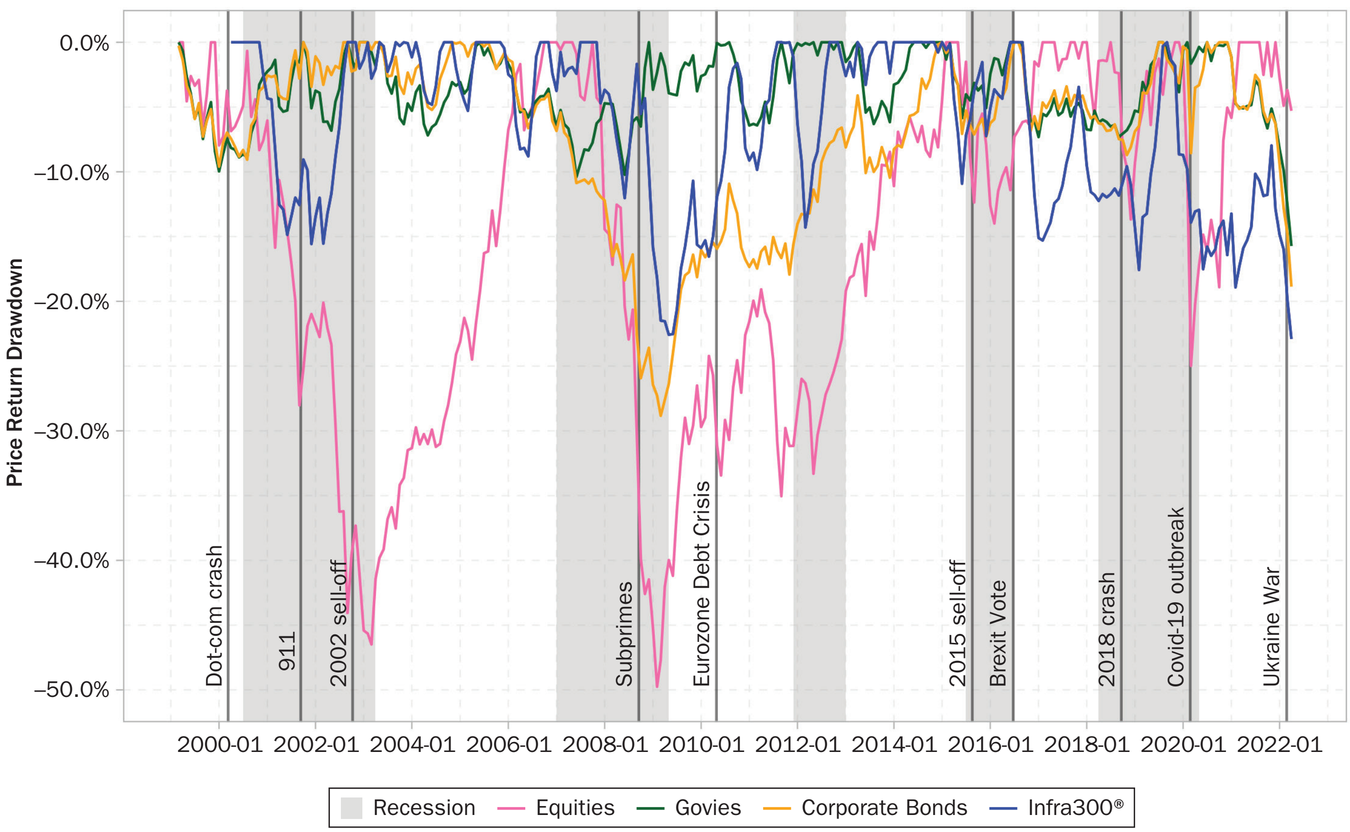
On a price return basis, the Infra300's two worst drawdowns include the subprime crisis and the October 2019 downturn triggered by higher interest rates, which was still unfolding in 2022, as the longest and worst drawdown for this asset class. This is due to higher risk premia, including since the Covid lockdowns, higher interest rates, and in some sectors like transport, especially airports and ports, lower expected cash flows.

Corporate and government bonds (govies) were also still going through their latest drawdown period in April 2022, also the worst one in the 22-year period

[3] The CDaR family of risk functions is related to the conditional value-at-risk (CVaR) measure.

EXHIBIT 23

Return Drawdowns for Reference Asset Classes and Infra300 Index



for government bonds and the second worst one for corporate bonds. On a total return basis, the current drawdown of the Infra300 is the sixth worse in the last two decades, and it only started in January 2022 with the latest spike in interest rates. In comparison, as of May 2022, corporate and government bonds were undergoing their worst total return drawdown since 1999. Thus, we see that when capital markets are impacted by shocks, these losses often coincide with losses in the private infrastructure market, albeit not perfectly and not always.

There are three possible mechanisms through which a capital market drawdown might coincide with a drawdown in the private infrastructure portfolio.

1. *Cash flows*: Recessions that depress asset values in stocks and bond markets also mean lower revenues for certain infrastructure companies, especially if they have a merchant business model. Policy shocks, such as travel bans during the Covid-19 pandemic or sanctions related to the war in Ukraine, can also have a significant impact on the cash flows of some infrastructure investments.
2. *The equity risk premium*: The price of cash flow risk—that is, the expected excess return—of infrastructure investments is a function of investor preferences and is not independent across asset classes. For example, if a financial shock increases the equity risk premium in public equity markets, it is likely to coincide with a high equity risk premium in private asset markets such as infrastructure.

3. *The yield curve*: Whether interest rates vary as a result of macro-economic or macro-prudential causes, all asset values are ultimately impacted by movements in the yield curve, as a function of the investment's duration.

To examine the coincidence of drawdowns between the Infra300 and capital markets, we look at return correlations and co-moments in the next section.

Co-Moment Analysis

In this section, we first examine the return correlations of unlisted infrastructure equity with capital markets over time. Correlations are an expression of the covariance of returns, that is, whether mean infrastructure returns tend to covary more with markets in different periods. Next, we look at higher co-moments of returns, coskewness and cokurtosis, which reflect the tendency of multiple asset classes to experience extreme returns at the same time.

Return correlations. The correlation of 12-month average monthly returns between unlisted infrastructure and the reference asset classes over a 22-year period are highly statistically significant. On a price return basis, infrastructure has a higher correlation with corporate bonds and equities (above 30%) and a lower correlation with government bonds (about 20%). On a total return basis, infrastructure correlations with government bonds are the highest (about 40%), followed by corporate bonds and equities. This confirms that the co-movement of infrastructure with markets is rather different whether one takes the cash yield into account or not. To understand the impact of downturns purely on asset prices, price return correlations provide a more direct comparison.

Next, Exhibit 24 shows the 60-month (5 year) rolling correlations of monthly returns between the Infra300 and the three reference asset classes. We see that on both a price and a total return basis, monthly return correlations are high and positive with bonds,. However, they tend to decline during recessions and after financial shocks, such as the subprime crash or the start of the 2015 or 2018 sell-offs. Conversely, return correlations increase during period of economic expansions or inflationary shocks such as the start of Ukraine conflict.

Correlations with equities also follow a different pattern: On average over the entire period, monthly return correlations are not statistically different from zero because they change sign several times. The correlation between the Infra300 and equities increases sharply in times of financial stress, especially the subprime crisis but also policy shocks like the Brexit vote and the Covid-19 lockdowns. Such shocks coincide with a change of sign in correlations, which turn positive before declining over several years until they return to zero or negative territory.

In all likelihood, a combination of comovements in equity risk premia, corporate credit spreads, and the yield curve is driving correlation dynamics between unlisted infrastructure equity. Before looking at these, we report the higher-order return co-moments of the Infra300 with capital markets in the next section.

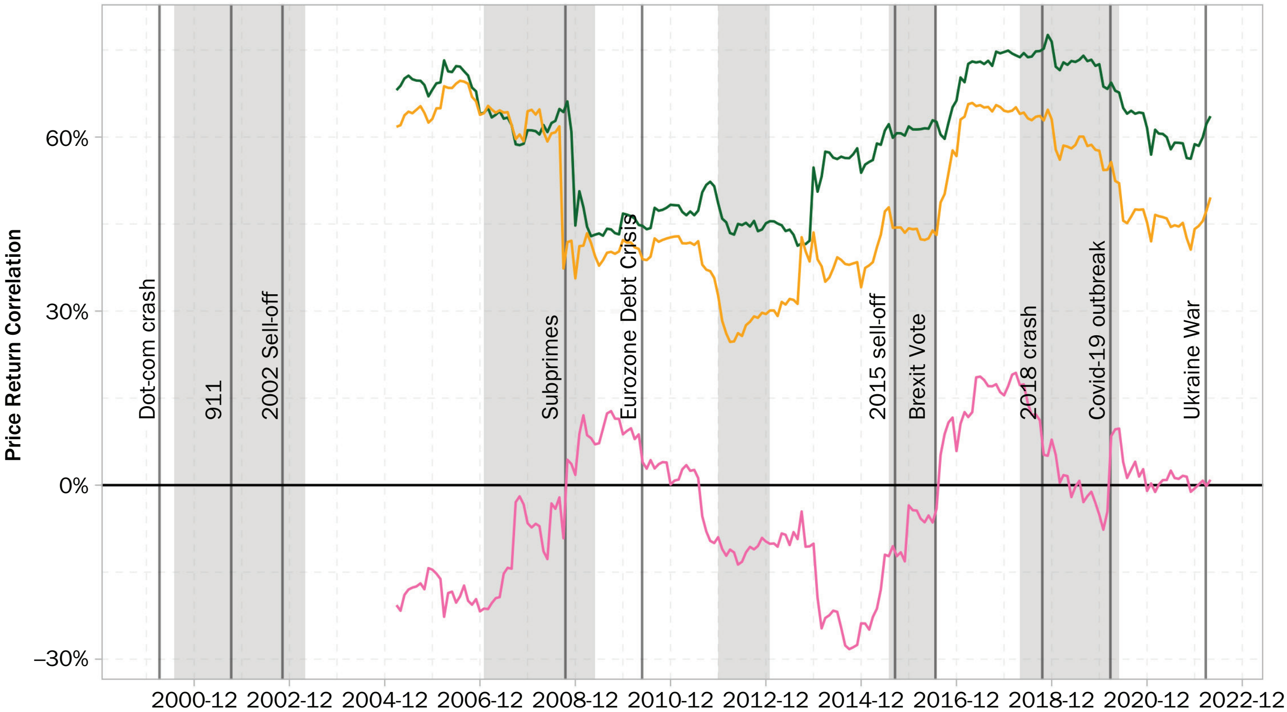
Higher return co-moments. The third and fourth moments of the distribution of returns are known as its skewness and kurtosis and characterize its shape. High skewness is the result of extreme asymmetric positive or negative returns (far from the mean), while high positive excess kurtosis (a.k.a. a leptokurtic return distribution), indicate a flatter shape and fat tails. This also contributes to extreme risk.

In turn, coskewness and cokurtosis denote the tendency of two distributions to exhibit extreme values at the same time, and provide a measure of codependence in extreme or crisis scenarios. Exhibit 25 shows the 60-month rolling coskewness and cokurtosis of the Infra300 price returns with each of the reference asset classes.

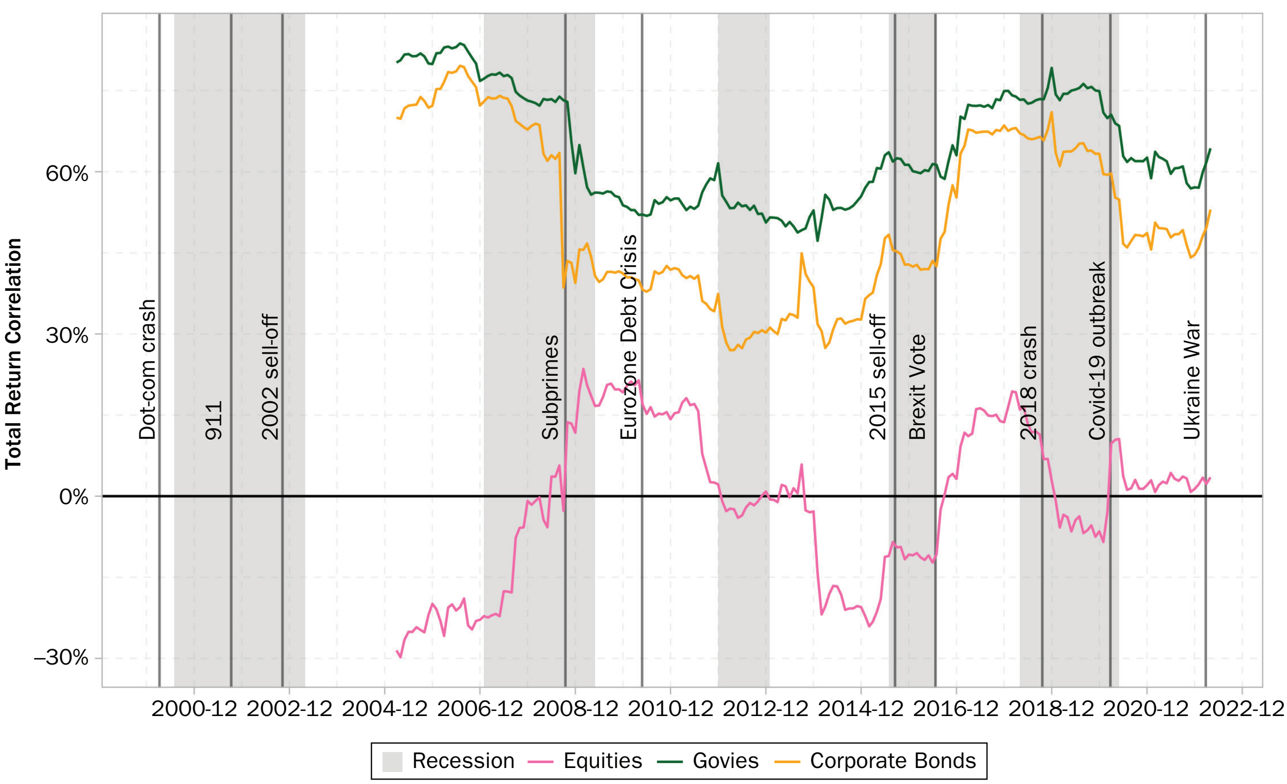
EXHIBIT 24

60-Month Rolling Correlations of Returns between Reference Market Benchmarks and Infra300

Panel A: Price Returns



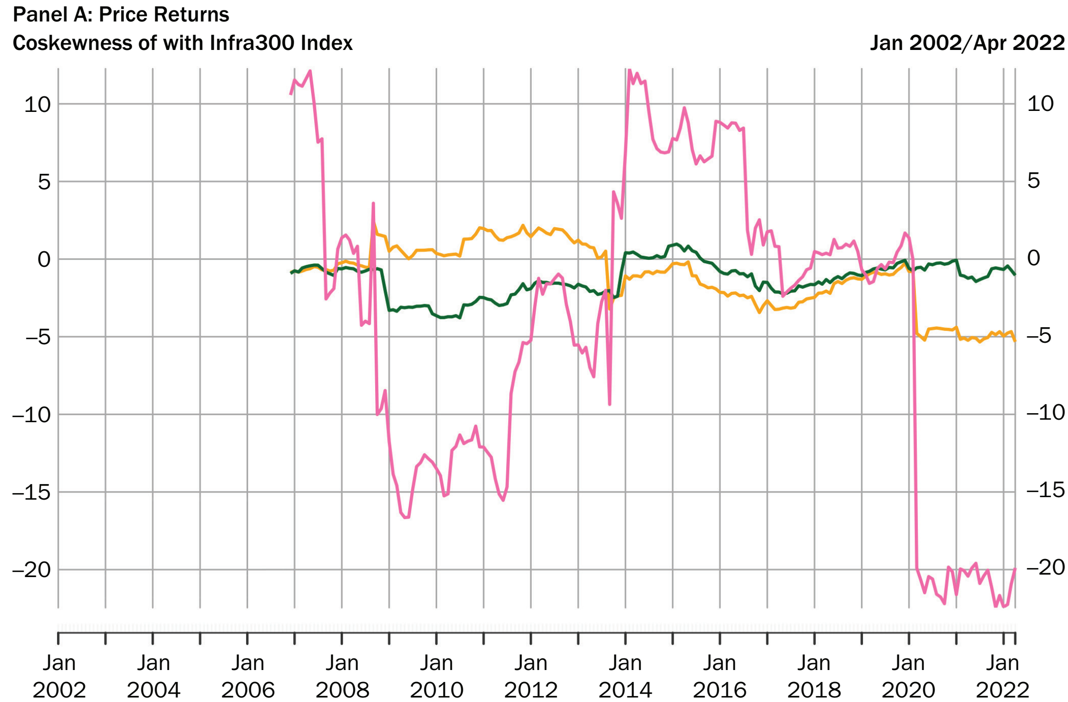
Panel B: Total Returns

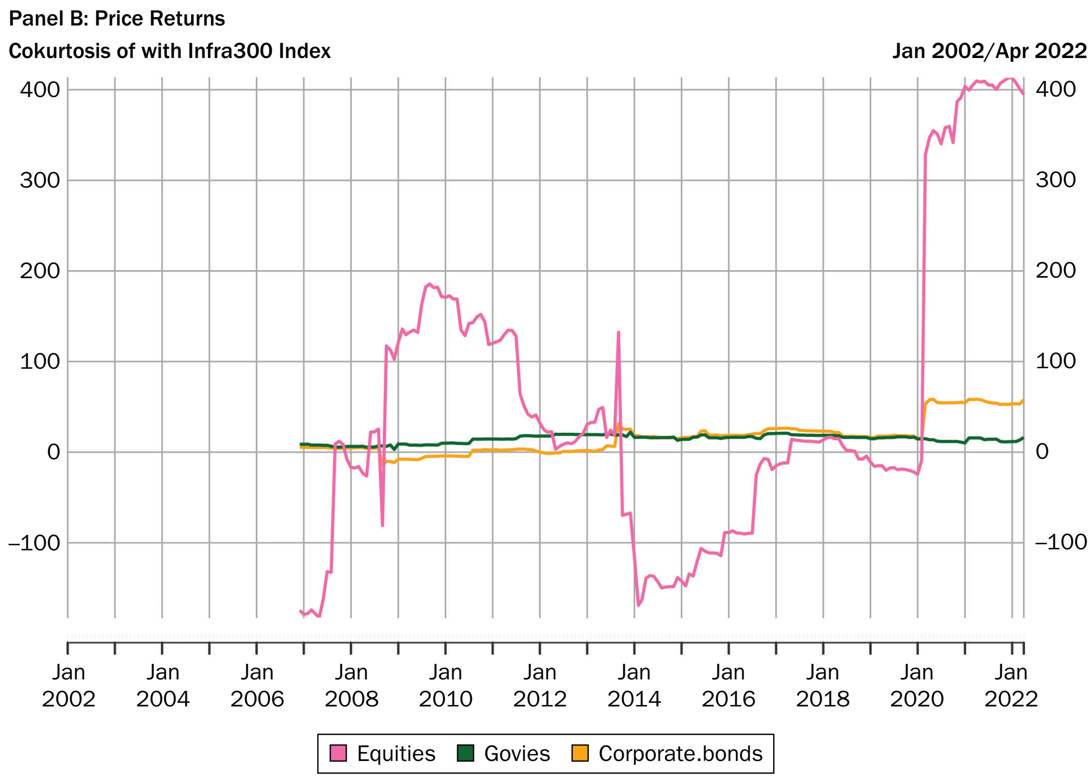


SOURCES: Datastream, infraMetrics.

EXHIBIT 25

60-Month Rolling Coskewness and Cokurtosis of the Infra300 Index Price Returns with Capital Markets





SOURCES: Datastream, infraMetrics.

Coskewness takes the same sign than extreme returns: Positive coskewness indicates that both asset classes are likely to simultaneously exhibit extreme positive returns and vice versa. We see that the subprime crisis in particular triggers a period during which unlisted infrastructure and equities share extreme risk characteristics at least until 2012. From 2014 to 2017, a period of exceptional performance for unlisted infrastructure, the coskewness of the Infra300 and equities is positive until it drops to about zero in 2017. In March 2020, the Covid-19 shock triggers another period of negative coskewness between unlisted infrastructure equity and listed equities.

The cokurtosis of the Infra300 with equities tells a similar story. Here, high kurtosis and cokurtosis indicates a "flatter" distribution and fatter tails. The same pattern is visible, with extreme risk coincidence triggered by certain financial or policy shocks. We note that not all shocks trigger changes of co-moment regimes. These shifts are indicative not only of changes in the price but also of the exposure of investment to risk.

Corporate bonds exhibit similar but considerably lower coskewness and cokurtosis with infrastructure than equities. The shift in co-moment regime triggered by the Covid-19 shock is notable because the impact of the subprime shock on the likelihood of extreme risk in both infrastructure and corporate bonds was much smaller and short-lived.

When it comes to government bonds, their extreme comovements with infrastructure are much smaller in comparison and not statistically different from zero. Thus, while infrastructure and government bonds are highly correlated through the impact of the yield curve on asset values, the two asset classes do not share extreme risk characteristics.

Finally, we look at the link between each asset class in terms of extreme risk. Indeed, return co-moments like covariance, coskewness, and cokurtosis do not allow measuring the marginal impact of one asset class on another.

Martellini and Ziemann (2007) have shown that higher moment betas can provide estimates of how the risk of a benchmark asset class is impacted by adding a second asset class to the portfolio. In the portfolio diversification theorem, adding a test asset class to a benchmark reduces the portfolio's variance if the second-order beta of the asset with respect to the portfolio is less than one. The same can be shown for the third and fourth moments of the return distribution. Higher moment betas thus provide measures of the diversification potential of an asset (for details, see Martellini and Ziemann 2007).

A beta greater than one indicates that no diversification benefits should be expected from the introduction of that asset into the portfolio. Conversely, a beta of less than one indicates that adding the test asset reduces the resulting portfolio's volatility and extreme risk. The lower the beta, the higher the diversification effect on extreme risks.[4]

Exhibits 26 and 27 shows the co-moment betas defined in the literature for price and total returns respectively. We see that adding unlisted infrastructure equity to an equity or corporate bond portfolio does have diversification benefits, including extreme risk diversification. The reverse is true with government bonds: Unsurprisingly, infrastructure adds total risk to a public bond portfolio.

[4] The addition of a small fraction of a new asset to a portfolio leads to a decrease in the portfolio's second moment (respectively, an increase in the portfolio's third moment and a decrease in the portfolio's fourth moment) if and only if the second moment (respectively, the third moment and fourth moment) beta is less than 1. If the skewness of the portfolio is negative, we would expect an increase in portfolio skewness when the third moment beta is lower than 1. When the skewness of the portfolio is positive, then the condition is that the third moment beta is greater than, as opposed to lower than, 1.

EXHIBIT 26

Price Return Co-Moment Beta of Reference Benchmarks with Infra300

	BetaCovariance	BetaCoSkewness	BetaCoKurtosis
Equities	–0.0354	0.0829	0.0451
Govies	1.0735	11.2642	1.0029
Corporate Bonds	0.7629	0.5093	0.4529

EXHIBIT 27

Total Return Co-Moment Beta of Reference Benchmarks with Infra300

	BetaCovariance	BetaCoSkewness	BetaCoKurtosis
Equities	–0.0130	0.1499	0.0533
Govies	1.0722	62.6169	1.0199
Corporate Bonds	0.7033	0.5992	0.4408

Thus, unlisted infrastructure exhibits correlations with other asset classes in terms of both mean returns and extreme returns. Mean returns are correlated with bonds, but extreme returns correlate with equities during period of financial and economic stress. In the next section, we return to the role of risk premia and the yield curve in driving return correlations between these asset classes.

Next, we examine in more details the common factors that can explain the coincidence of large losses in capital markets and private infrastructure equity with a focus on the two main components of the discount rates: interest rates and the equity risk premia.

Discount Rate Shock Analysis

Until now we have empirically examined how the unlisted infrastructure asset class and capital markets co-vary in terms of risk adjusted returns, drawdowns, including the likelihood of facing extreme losses at the same time in periods of economic or financial stress. In this section, we look at the role played by the equity risk premia and interest rates in the coincidence of these losses.

Risk premia shocks. The equity risk premium plays a key role in the performance of an asset class during a shock. The equity risk premium is the aggregate price of the risks of the cash flows (dividends) that the owners of a company expect to receive in the future. It combines the inherent uncertainty of future economic activities, which underpins the ability of firms to pay dividends, with investors' aversion for risk to form a price—that is, a risk premium. This risk premium is also the embodiment of investors' expected (excess) returns: the higher it is, the lower the bid price for an asset and vice versa. A lower risk premium indicates that investors are willing to pay a higher price because they value holding the asset in question and thus accept a lower return.

In previous sections, we have seen that in times of stress, in particular the subprime crisis and the onset of the Covid-19 pandemic, unlisted infrastructure equity and listed equity share some of their tail risk, that is, they incur higher losses at the same time. An obvious place to look for the source of this coincidence of losses is the risk premia.

Indeed, if investors become more averse to risk in public equities after or during a shock, they are likely to also have higher risk aversion to the risks of unlisted equity, especially illiquid assets like infrastructure.

We source the unlisted infrastructure equity risk premia from infraMetrics and the risk premia for the four listed equity markets mentioned earlier from Datastream. For equities, we create a weighted risk premia using the same geographic weights we used earlier to create an equity market proxy that has the same geographic characteristics as the unlisted infrastructure universe.

Next, we create a measure of shocks to the infrastructure and equities risk premia sourced respectively from infraMetrics and Datastream: We take the one-month difference in risk premia and compute its six-month moving average.

Listed equities exhibit a slightly higher level of shocks to the risk premium on average and also more extreme shocks than unlisted infrastructure. The rolling correlation between shocks to the relevant equity risk premium and the returns of either listed equities or unlisted infrastructure are shown in Exhibit 28 for price returns (Panel A) and total returns (Panel B). The correlations are negative: Higher positive shocks to the risk premium or either listed equities or unlisted infrastructure equities coincide with a negative return (it increases the discount rate).

Equities and infrastructure have different returns and different risk premia but they follow a comparable pattern in terms of the relationship between the shocks to their risk premia and returns. These correlations increase (become more negative) in time of stress, such as the subprime crisis or Covid lockdowns. This explains why equities and infrastructure have a highly negative coskewness and highly positive cokurtosis of returns at the time of these events, as we showed in the previous section.

Interest rate shocks. To look at the role of changes in interest rates as a driver of the return co-moments in private infrastructure and capital markets, we compute the monthly change in the 10-year government bond yield. The distribution of interest rate shocks in the four key regions that we defined earlier to build capital market benchmarks between 1999 and 2022. We see that the monthly change in yield exhibits comparable distributions. Thus, we define interest rate shocks as the six-month rolling average change in 10-year bond yields.

Next, Exhibit 29 shows the 60-month rolling correlations between monthly returns and interest rate shocks as defined earlier for price (Panel A) and total returns (Panel B). We see that:

- Government bond returns (green line) are always negatively correlated with interest rate shocks; that is, higher rates always mean lower bond returns because higher discount rates decrease the net asset value of assets with fixed cash flows.
- Listed equity returns (pink line) are positively correlated with rate shocks until 2017; that is, higher rates signal positive economic prospects and higher future cash flows, which more than offsets the increase in the discount rate implied by higher rates. After 2017, the positive correlation disappears. Unconventional monetary policies mean that rates are very low, hence asset values become more sensitive to increases in rates (which dominate cash flow effects). Moreover, rate increases from the lower-zero bound after 2017 are not necessarily a signal of economic growth.
- Corporate bond returns (orange line), like government bonds, tend to have a negative correlation with rate shocks. Between 2008 and 2013, however, the correlation becomes positive; that is, higher 10-year bond yields coincide with higher corporate bond returns. This is less straightforward to interpret: During that period corporate bonds go through a period of yield compression due to high levels of demand for these instruments. Excess demand is such that prices increase more during that period than they decrease whenever rates increase. This excess demand eventually disappears after 2014.

EXHIBIT 28

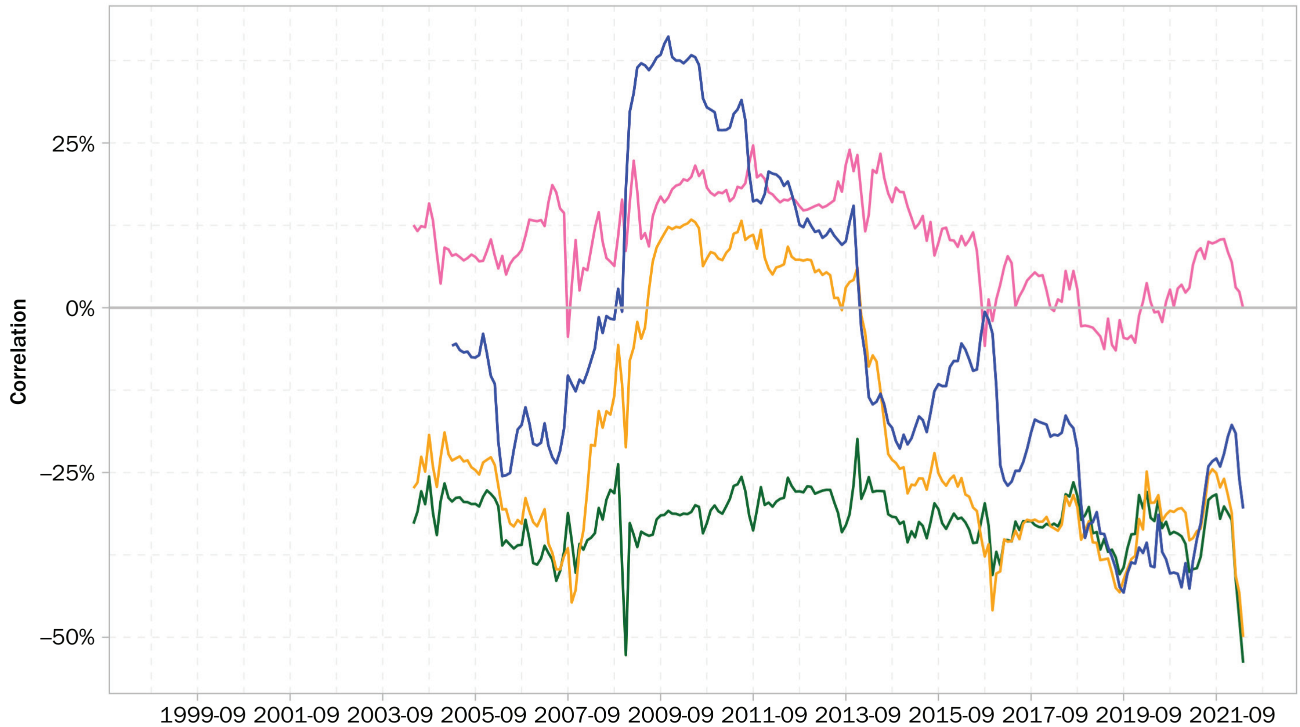
60-Month Rolling Correlations of Returns with Equity Risk Premium Shocks

SOURCES: Datastream, infraMetrics.

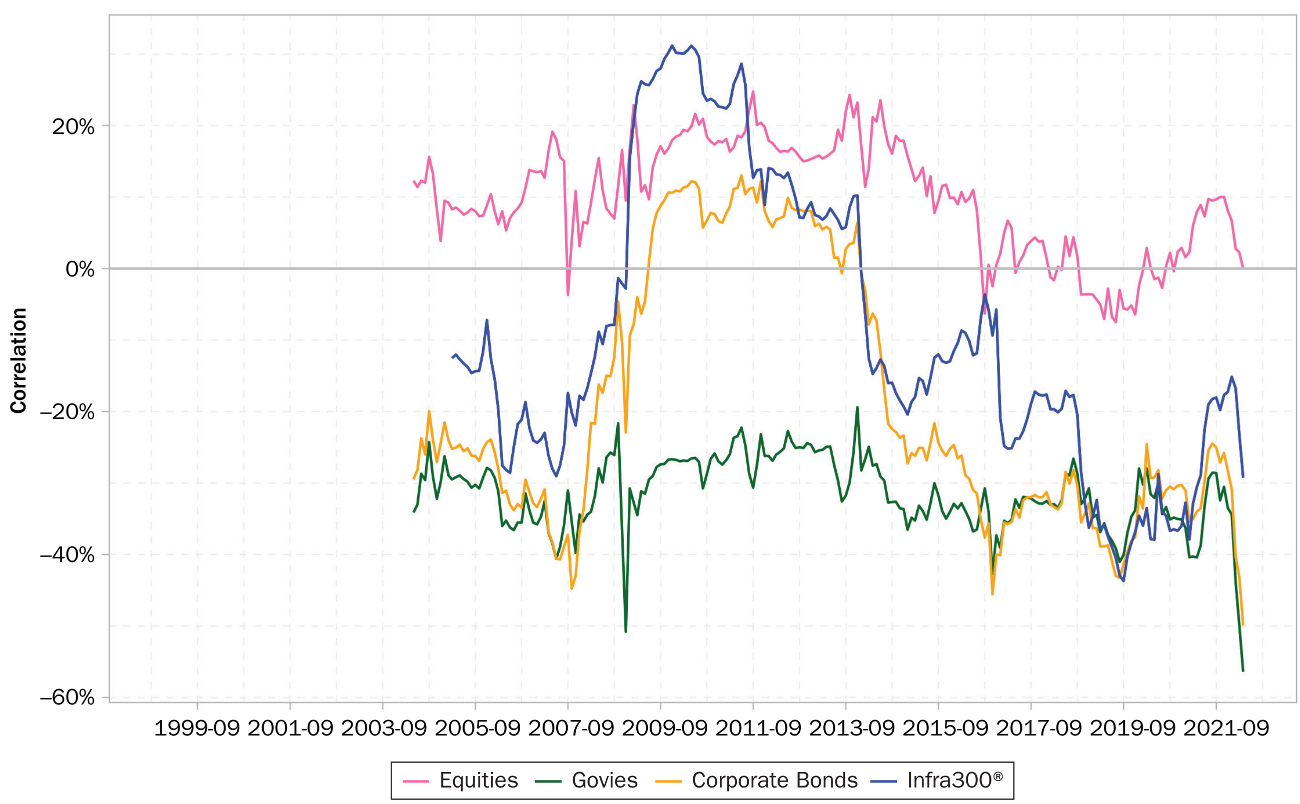
EXHIBIT 29

60-Month Rolling Correlations of Returns with Interest Rate Shocks

Panel A: Price Returns



Panel B: Total Returns



SOURCES: Datastream, Re.

- Unlisted infrastructure equity returns (blue line) follow a similar pattern than corporate bonds during the same time period: In general, the value of infrastructure investments is based on long-dated cash flows and higher rates that tend to increase discount rates also decrease net asset values. This is very much the case in 2022—a significant rate shock is associated with a large drop in returns for all asset classes, even equities. Indeed, the rise in rates is inflation driven and the real value of long-term cash flows is also more highly discounted. During the 2008–2014 period, however, unlisted infrastructure goes through a similar period of excess demand combined with low policy rates, meaning that the correlation between rate shocks and returns becomes positive during that period.

ASSET ALLOCATION

In this section, we address a more normative but also essential question: What is the role of unlisted infrastructure in the multi-asset portfolio allocation?

We look at 10 asset classes. In practice, most investor portfolios contain multiple asset classes in a portfolio including traditional and alternative investments. We start with four traditional asset classes: US equity, emerging markets equity, corporate bonds, and government bonds. We also include six alternative asset classes: private equity, real estate, hedge funds, commodities, unlisted infrastructure equity, and infrastructure debt.

We introduce the distinction between unlisted infrastructure equity and infrastructure debt because there are important differences in their investment characteristics and EDHEC*infra* also produces private infrastructure debt indices, for which there exists, to our knowledge, no appraisal-based or listed proxy.[5]

Private infrastructure debt is exposed to duration and credit risks as well as a combination of risks specific to its TICCS segments. These unique characteristics imply that infrastructure debt can play a different role in an asset–liability framework than unlisted infrastructure equity, which may be more attractive for its return-seeking properties.

In what follows, we first describe the forward-looking data used in this exercise, then define two typical investor profiles to compare different allocation results. Finally, we report strategic asset allocation results using a range of portfolio optimization methods.

Forward-Looking Data

In the first part of this article, we have used in-sample data in combination with a return targeting optimization exercise, which by definition focuses on return estimates. The results obtained were thus highly dependent on the sample itself. And as we have mentioned previously, the available historical sample, which includes a period of significant valuation appreciation for unlisted infrastructure equity, may not be a fair representation of forward-looking risks and returns. Forward-looking estimates of return, volatility, and correlations are a better way to address the question, What should the role of unlisted infrastructure be in a multi-asset portfolio today?

For asset classes other than infrastructure, we rely on the industry estimates, representing a wide spectrum of financial institutions, which are formed as a combination of long-term historical observations and forward-looking views based on

[5] More details on the data and methodology used to compute EDHEC*infra* debt indices can be found on the EDHEC*infra* website: docs.EDHEC*infra*.com.

EXHIBIT 30

Average Industry Consensus for Expectations of Risk and Return, Year-End 2019

Asset Class	Return	Risk	Sharpe Ratio
Infrastructure equity	7.2%	12.8%	0.56
Private Infrastructure debt	2.9%	3.6%	0.81
US equity	5.9%	15.5%	0.38
Emerging equity	8.0%	21.2%	0.38
Corporate bonds	2.0%	6.0%	0.32
Government bonds	1.2%	5.0%	0.23
Real estate	6.7%	10.8%	0.61
Private equity	8.7%	21.1%	0.41
Hedge funds	4.1%	6.9%	0.60
Commodity	3.2%	16.5%	0.19

NOTES: Infrastructure equity is Infra300, and infrastructure debt is the broad market private debt index. Infrastructure returns are calculated as the average expected returns over the 2015–2019 period. Infrastructure volatility is based on in-sample total return volatility over the 2015–2019 period. The Sharpe ratio assumes a risk-free rate of zero. All returns in USD.

SOURCES: EDHEC*infra*. Other asset class expectations are based on the estimates of investment managers and consultants: Blackrock, JP Morgan, Morgan Stanley, BNY Mellon, Invesco, Schroders, Northern Trust, State Street, Callan, and Envestnet.

short-term variations in risk and return of each asset class. We consider the forward-looking data provided by the leading consultants and asset managers—Blackrock, JP Morgan, Morgan Stanley, BNY Mellon, Invesco, Schroders, Northern Trust, State Street, Callan, and Envestnet—reported at the end of 2019/beginning of 2020. We use the average of these views as our forward-looking estimate. The averages of the data provided by each organization are presented in Exhibits 30 and 31. These estimates are supposed to be a guiding point. In practice, investors may have their own preferred benchmarks to develop these forward-looking views.

For infrastructure, we use the expected returns estimated by EDHEC*infra*. As described previously, EDHEC*infra* indices are driven by a valuation methodology that consists of estimating market expected returns (equity risk premia and debt credit spreads) at each point in time, using the latest primary and secondary market transaction prices.

Each quarter, the market discount rates of hundreds of equity investments and debt instruments are estimated by updating a multi-factor model of expected returns, given 1) what the estimates were until then, and 2) how new market price data suggest they have evolved since the last estimation.

Because, in equilibrium, discount rates are equivalent to expected returns, the EDHEC*infra* methodology boils down, in effect, to estimating expected returns each quarter. Moreover, because they represent the average price of a combination systematically rewarded risks, as shown previously, these expected returns can be considered net of any alpha and therefore also net of any fees. We use the Infra300 for unlisted infra equity and the EDHEC*infra* broad market index to represent private infrastructure debt market.

As noted earlier, the infrastructure asset class went through a transition from lower to significantly higher valuations in the years immediately following the 2008 financial crisis. These expected returns have remained, on average, stable since 2015 at around 7%–8% for unlisted infrastructure equity and around 2%–3% for infrastructure debt. In what follows, we use an average of the expected returns over the past five years as the estimate of forward-looking return, as shown in Exhibit 19. Likewise, expected risk estimates of unlisted infrastructure equity and private infrastructure debt are based on the historical volatility of quarterly total returns over the same five-year period, which represents a reasonable estimate for forward-looking risk.

For correlations, we take a longer time period and use the correlations between infrastructure and other asset classes from 2003 to 2019 as the best estimate. Furthermore, due to the lack of any appropriate long-term benchmarks for private equity, we assume the correlations between infrastructure and private equity are the same as with US equities. These correlations are presented in Exhibit 21.

Next, we define two standard investor profiles.

Investor Profiles

Portfolio allocations are a direct function of the investment objectives of investors, including their risk and return targets, time horizon, investment focus, and so on.

EXHIBIT 31

Industry Expectations of Asset Class Correlations

	Infra. Equity	Infra. Debt	US Equity	Emerg. Equity	Corp. Bonds	Gov. Bonds	Real Estate	Private Equity	Hedge Funds	Commodity
Infrastructure Equity	1	0.25	0.2	0.2	0.25	0.35	0.45	0.2	0.15	0.1
Infrastructure Debt	0.25	1	–0.35	–0.3	–0.1	0.4	–0.1	–0.35	–0.4	–0.3
US Equity	0.2	–0.35	1	0.71	0.27	–0.16	0.43	0.78	0.72	0.3
Emerging Equity	0.2	–0.3	0.71	1	0.32	–0.15	0.36	0.65	0.67	0.39
Corporate Bonds	0.25	–0.1	0.27	0.32	1	0.65	0.08	0.17	0.44	0.13
Government Bonds	0.35	0.4	–0.16	–0.15	0.65	1	–0.23	–0.41	0.02	–0.14
Real Estate	0.45	–0.1	0.43	0.36	0.08	–0.23	1	0.45	0.35	0.19
Private Equity	0.2	–0.35	0.78	0.65	0.17	–0.41	0.45	1	0.65	0.31
Hedge Funds	0.15	–0.4	0.72	0.67	0.44	0.02	0.35	0.65	1	0.35
Commodity	0.1	–0.3	0.3	0.39	0.13	–0.14	0.19	0.31	0.35	1

NOTE: Infrastructure equity is Infra300 (USD), and infrastructure debt is the broad market private debt index (USD). Infrastructure correlations are based on long-term in-sample data over the 2003–2019 period. Correlations between infrastructure and private equity are assumed to be the same as with equity. All estimations using USD returns. For unlisted infrastructure equity and private infrastructure debt, we use EDHEC*infra*'s estimates, which are updated each quarter using an explicit Bayesian approach, thus reducing sample dependency.

SOURCES: EDHEC*infra*. Other asset class expectations are based on the estimates of investment managers and consultants: Blackrock, JP Morgan, Morgan Stanley, BNY Mellon, Invesco, Schroders, Northern Trust, State Street, Callan, and Envestnet.

EXHIBIT 32

Typical Investor Profiles Used to Compare Optimal Allocations

	Conservative: 20/80 Investor	Aggressive: 60/40 Investor
Funding Status	Overfunded	Underfunded
Objective	Hedge liabilities	Invest in growth portfolio
Proxy	20/80 portfolio (20% allocation to equity and 80% to bonds)	60/40 portfolio (60% allocation to equity and 40% to bonds)
Target Return	2.8%	4.3%
Target Risk	6.8%	10.6%

SOURCE: Risk and return estimates are based on the average industry expectations of US equity and corporate bonds.

In the following discussion, we compute optimal portfolio weights for a range of risk, return, and diversification targets. Hence, to improve the interpretation of the results we begin by defining two typical investor profiles, shown in Exhibit 32.

The first type is a conservative investor equivalent to a 20/80 portfolio style; that is, a 20% allocation to US equities and 80% allocation to corporate bonds. This profile is akin to a well-funded pension plan and with a focus on liability-driven investment. Their asset allocation goal would typically be to protect the existing fund contributions and hedge liabilities at the lowest possible cost. Traditionally, the conservative investor uses bonds due to their natural ability to hedge the liabilities through interest rate exposure, However, alternative investments such as infrastructure debt could allow such investors to achieve more cost-effective liability hedging thanks to superior returns in private debt. As shown in Exhibit 26, this portfolio has an expected return of 2.8% and an expected risk of 6.8%, using the inputs from Exhibit 21.

The second profile is that of a more aggressive investor with a 60/40 style—a 60% allocation to US equities and 40% allocation to corporate bonds. This profile is commonly associated with an underfunded pension plan focused on seeking growth in order to limit the increase of member contributions. Such an investor would have a higher risk tolerance and want to achieve higher returns. The annualized expected return and risk of this portfolios stands at 4.3% and 10.6%, also using the Exhibit 21 inputs.

Next, we implement several portfolio optimization methods and report the resulting allocations to unlisted infrastructure equity and debt for each investor profiles.

Portfolio Optimization

An optimal portfolio is an "efficient" combination of the assets available on the risk–return spectrum. It should satisfy the requirement that no other set of weights exists with a higher expected return given a certain level of risk.

This approach, which is at the heart of modern finance, requires a robust estimate of expected returns. Unfortunately, such robust return estimators can be difficult to obtain, as Robert Merton famously put it, "even if the expected return on the market were known to be a constant for all time, it would take a very long history of returns to obtain an accurate estimate." (Merton 1980, p. 5). In the same paper, Merton continues, "the unanticipated part of the market return should not be forecastable by any predetermined variables. Hence, unless a significant portion of the variance of the market returns is caused by changes in the expected return on the market, it will be difficult to use the time series of realized market returns to distinguish among different models for expected return."

In other words, unlike with estimates of risk, we cannot necessarily rely on return data converging toward a true long-term estimate as more return data is being observed.

Hence, we compute a range of possible allocations given an explicit range of return or risk targets. Moreover, investors may have a range of different objectives, and the classic return maximization optimization problem is not always the best suited to a strategic asset allocation. In what follows, we implement two types of mean–variance optimization—return-targeting and risk-targeting—and a risk-only optimization technique, which avoids using returns altogether and is instead based on the risk contributions of each asset class to the portfolio.

Return Targeting

The objective of this portfolio optimization approach is to find the allocation that achieves a portfolio return equal to or greater than a fixed target while minimizing portfolio risk, with no shorts and no cash (fully invested portfolio). We add two more constraints:

- the effective number of asset classes (ENC)[6] must be at least equal to 6 (out of 10);
- the cumulative allocation to all illiquid asset classes (infrastructure, real estate, private equity, and hedge funds) cannot exceed 20% of the portfolio.

We compute optimal weights for a range of portfolio return targets from 2% to 5.5%.[7] The results are shown in Exhibit 33 and Exhibit 34, which detail the optimal weights and portfolio characteristics of the two investor profiles previously described.

First, we compare the portfolio with or without any infrastructure. As shown at the bottom of the table in Exhibit 33, using the same optimization setup and

[6] Effective number of asset classes or ENC is a measure of diversification and is given by the reciprocal of the sum of the squared weights of each asset class in the portfolio.

[7] The range of 2% to 5.5% covers all possible portfolios under the given constraints.

EXHIBIT 33

Multi-Asset Portfolio Including Infrastructure Equity and Debt while Targeting a Return Level

	Asset Class	20/80 Investor	60/40 Investor
Return target		2.78%	4.34%
Weights	Infra equity	2.4%	10.7%
	Infra debt	10.6%	0.0%
	US equity	12.3%	16.7%
	Emerging equity	6.3%	13.6%
	Corporate bonds	22.2%	18.2%
	Gov bonds	25.6%	25.1%
	Real estate	4.0%	9.3%
	Private equity	0.0%	0.0%
	Hedge funds	3.0%	0.0%
	Commodity	13.6%	6.4%
Portfolio return		3.29%	4.34%
Portfolio risk		5.41%	7.10%
Sharpe ratio		0.608	0.611
Sharpe ratio without infra[a]		0.573	0.581

NOTE: [a]Same optimization problem but excluding infra equity and infra debt from the portfolio.

SOURCE: EDHEC*infra*.

constraints, we find that adding infrastructure to a multi-asset class portfolio can improve the Sharpe ratio by up to 6%.

Next, we find that the total allocation to infrastructure (debt and equity) is quite stable, between 10% and 13%, irrespective of the return target used (Exhibit 34).

The two investor profiles shown in Exhibit 33 both have a total infrastructure allocation of more than 10%, but the composition of this infrastructure allocation varies depending on the investor profile. Both achieve quite comparable portfolio Sharpe ratios. For the more conservative (20/80) investor style, infrastructure debt dominates and substitutes the need to have more bonds in the portfolio. In fact, with a better risk-adjusted return than corporate or government bonds, it can help reduce the cost of hedging liabilities significantly while providing the desired duration. This profile also invests less in listed equities and real estate.

The 60/40 investor style, which is more focused on return-seeking investments, invests more in listed equities, including emerging markets, and also receives an infrastructure allocation of about 10%, but it is exclusively dedicated to unlisted infrastructure equity.

The absence of private equity from most optimal portfolios results, except for the ones with a very high return target, is the result of the consensus risk and return estimates used and described previously. As shown previously in Exhibit 19, private equity has an average expected volatility of more than 21%, the highest among all alternative asset classes considered, and has a correlation with equities above 75%, thus reducing its diversification potential. In a way, infrastructure, with a better risk-adjusted return and lower correlations with other asset classes, substitutes the role of private equity in the portfolio.

As a confirmation of this point, in the exercise excluding infrastructure from the mix of asset classes, we find private equity does play a role in the portfolio with an allocation of up to 8.6% for the high return targets.

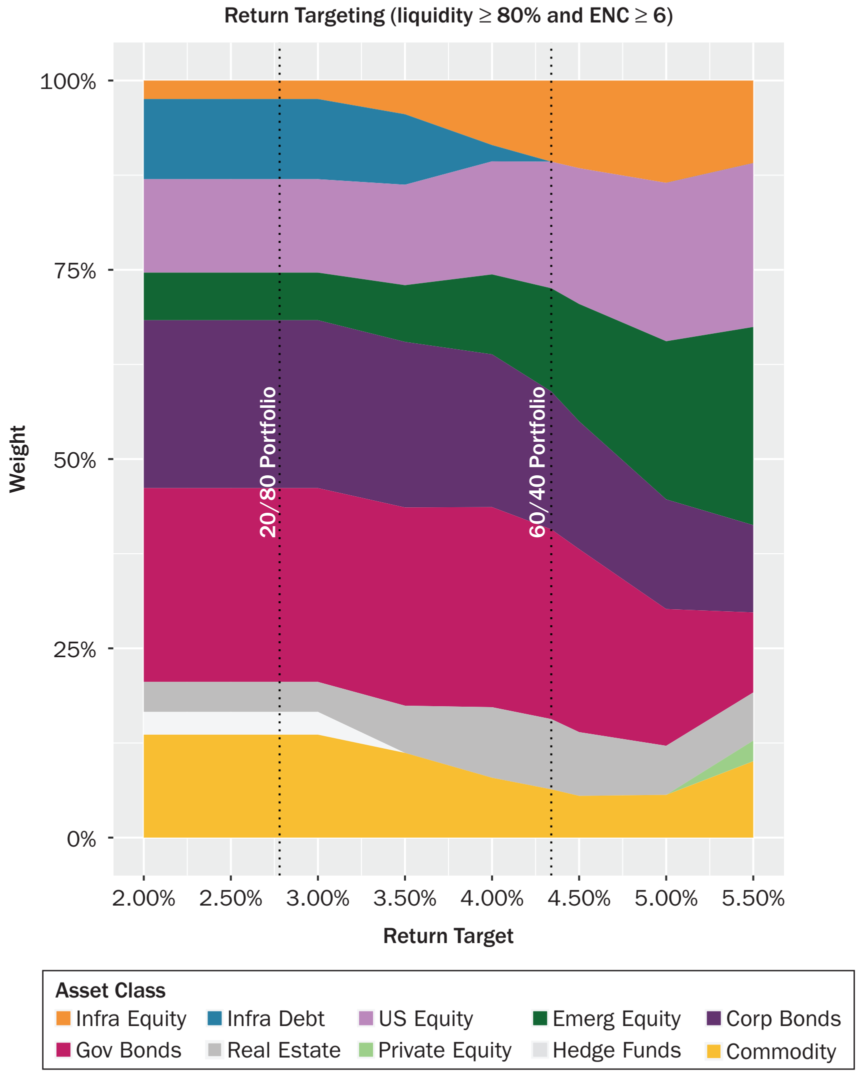
Risk Targeting

This approach requires defining an explicit portfolio risk target before finding the optimal portfolio weights: the objective is to find the allocation that keeps the portfolio risk level below the target while maximizing portfolio returns. We use the same constraints as earlier: a diversification constraint of at least six effective asset classes and an illiquidity constraint of less than 20%. We implement this exercise using volatility targets ranging from 5.5% to 12%, which span all possible portfolio volatilities under the predefined constraints. The volatility targets of the two investor profiles are the ones indicated in Exhibit 26. The results are presented in Exhibit 35, and the details for the two investor profiles in Exhibit 36.

Unsurprisingly, with a higher risk tolerance, the allocation shifts from fixed income assets to riskier assets. As with the previous approach, we find that the total allocation to infrastructure remains stable and significant in all portfolios irrespective of the chosen risk target. With both the 20/80 and 60/40 investor profiles, we again

EXHIBIT 34

Optimal Allocation with Return-Targeting Approach under Different Target Return Constraints



SOURCE: EDHEC*infra*.

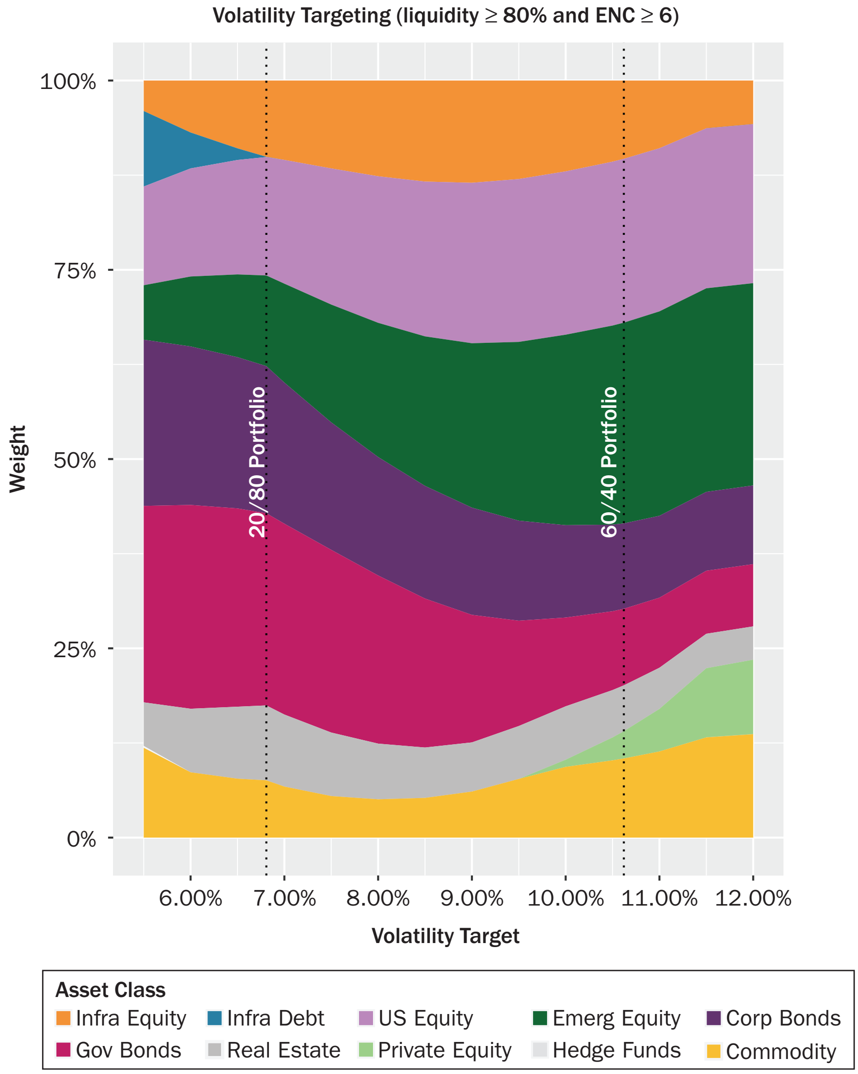
find an infrastructure allocation of around 10%, largely consistent with the results of the return-targeting approach.

Infrastructure debt, however, disappears from the portfolio for risk targets greater than 6.5%, including for our two investor profiles: The objective of maximizing returns while keeping portfolio risk below a target privileges infrastructure equity, which has a higher return than infrastructure debt, given the 20% illiquidity constraint, forces the substitution of infrastructure debt for infrastructure equity. In tests using a relaxed illiquidity constraint, we find a greater participation from both infrastructure equity and debt, with the latter replacing a large allocation away from bonds. The 60/40 investor profile achieves a much lower portfolio Sharpe ratio than the 20/80 profile in this setting.

As we can therefore observe, and beyond the quantities, which always depend on the risk or return assumptions, by using the same set of return, correlation, and risk data, the objectives of the allocation can have a strong influence on the composition

EXHIBIT 35

Optimal Allocation with Risk-Targeting Approach under Different Risk Targets



SOURCE: EDHEC*infra*.

of the optimal portfolios that meet the objectives. These observations show that when we can use true policy benchmarks to represent the infrastructure class, it is genuinely possible to avoid being limited to a segregated sleeve whose value is defined without any link to the investor's expectations in terms of the risk–return combination of their portfolio, and it is possible to be able to integrate this asset class into the allocation menu.

Equal Risk Contribution

In this section, and as we have already underlined, in order to avoid the allocation depending on return estimations that are always sample-dependent, we implement a risk contribution approach that uses only the volatilities and correlations of each asset class to determine their contribution to the risk of the portfolio. The objective is to find the portfolio weights that minimize the risk contribution from all asset classes

EXHIBIT 36

Multi-Asset Portfolio Including Infrastructure Equity and Debt while Targeting a Risk Level

	Asset Class	20/80 Investor	60/40 Investor
Risk target		6.81%	10.62%
Weights	Infra equity	10.1%	10.3%
	Infra debt	0.0%	0.0%
	US equity	15.6%	21.6%
	Emerging equity	12.0%	26.5%
	Corporate bonds	19.4%	11.3%
	Gov bonds	25.4%	10.1%
	Real estate	9.9%	6.1%
	Private equity	0.0%	3.6%
	Hedge funds	0.0%	0.0%
	Commodity	13.6%	10.5%
Portfolio return		4.21%	5.54%
Portfolio risk		6.81%	10.62%
Sharpe ratio[a]		0.62	0.52

NOTE: [a]Same optimization problem but excluding infra equity and infra debt from the portfolio.

SOURCE: EDHEC*infra*.

while achieving a minimum effective number of asset classes defined as an explicit target in the problem.[8]

We also test the sensitivity of the final allocations to the ENC target by letting it vary from 3 to 7 (out of 10 asset classes) and keeping a liquidity constraint set to a maximum of 20% illiquid assets. This approach deviates from the standard "equal risk contribution" approach due to the added constraints. In an unconstrained setting, the same optimization objective would lead to an equal risk contribution from all asset classes.

In this setting, we do not resort to investor profiles because no expected return level is set. Exhibit 37 shows the results for varying ENC targets and Exhibit 38 the detailed results for three specific cases: low (5), medium (6), and high (7) ENC targets.

With a low ENC target of 3, fixed income has the highest allocation in the portfolio, in line with the focus of this approach to minimize the risk contributions. As the ENC target increases, the weights of other asset classes must increase in order to satisfy the ENC constraint, making the individual risk contribution less equal. Thus, the volatility of the portfolio increases from 5.31% for the low ENC target to 6.95% for the highest ENC target, as shown in Exhibit 38.

Consistent with the previous results, for ENC targets of 5 or above, the allocation to infrastructure is in the same range of about 10% in total, evenly split between infrastructure equity and debt.

Thus, we have compared optimal allocation results using three different optimization techniques focusing on targeting returns, risk levels, and risk contributions. We find a consistent allocation to unlisted infrastructure with varying allocations between equity and debt depending on the type of investor profile. Clearly, infrastructure always has a role to play in a multi-asset portfolio as a strategic asset class in the sense that it completes the other allocation classes and due to the proper appreciation of this completeness by policy benchmarks that are appropriate, notably in terms of correlation with the other classes, which allows the infrastructure allocation to be seen as the investor's core investment rather than a satellite sleeve.

PEER GROUPS

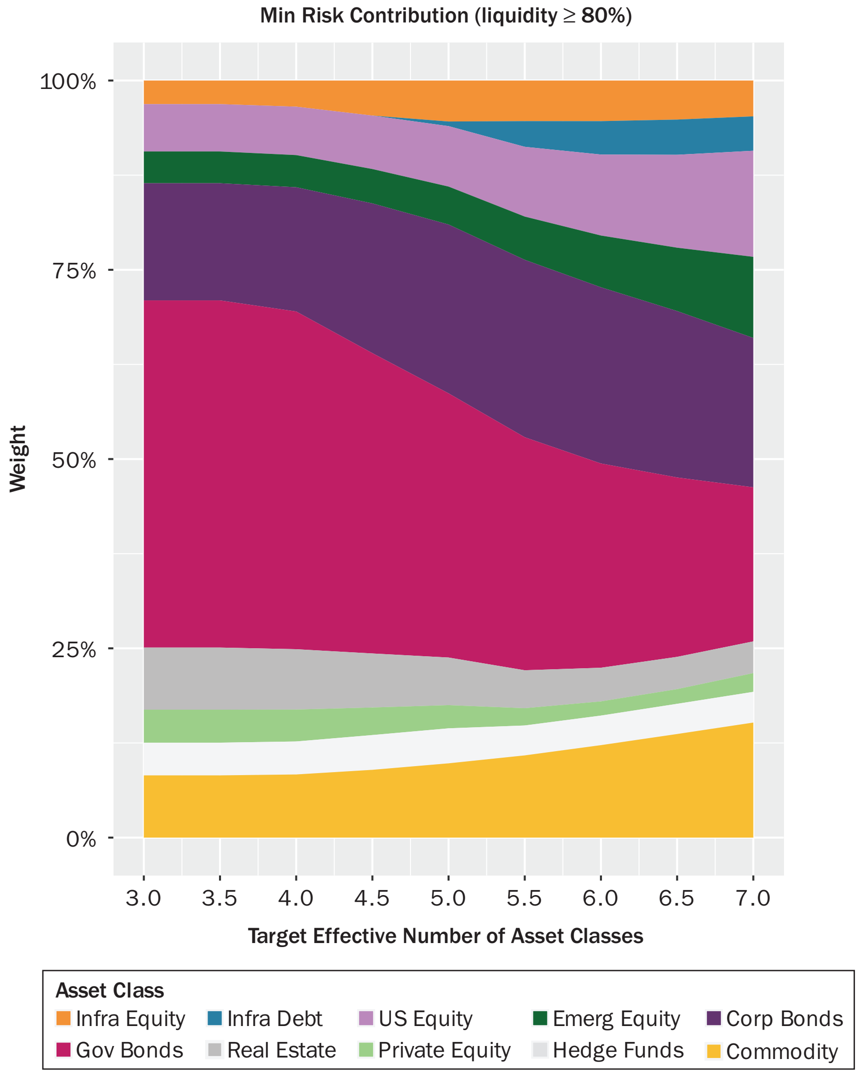
In this section, we present the results of the first global study of infrastructure investment and performance by peer group style.[9] Over the past two decades, pension funds and insurance companies, boutique specialist managers and larger multi-asset managers have all entered the infrastructure asset class with different priorities and focus: Some investors have tended to invest more in renewable energy projects, while others have become more exposed to transport companies, social infrastructure, or regulated utilities.

[8] Both risk contribution objectives and ENC target constraints can be used for diversification purposes, with the former directly diversifying the risk and the latter doing it indirectly through weights.

[9] This survey was done in partnership with the Boston Consulting Group.

EXHIBIT 37

Optimal Allocation using an Equal Risk Contribution Approach under Different ENC Targets



SOURCE: EDHEC*infra*.

To draw up 16 infrastructure investor peer groups, we examined the portfolio allocations through 2021 of 359 infrastructure equity and bond holders using the TICCS taxonomy of infrastructure companies and documented their exposures or tilts. These peer groups capture different types of investors, investment objectives, geographies, and regulatory or prudential frameworks. Infrastructure investor peer group style benchmarks use the latest average allocations to the different segments of the infrastructure universe of each group to compute their risk and total returns and rank them based on their risk-adjusted returns. Exhibit 39 shows the profiles of 16 infrastructure investor peer groups as well as all peer groups pooled together (all investors), for the year 2021.

While investors only achieved higher returns by taking on more risk, there is a range of realized returns for different peer groups for a given level of volatility. This is because certain investors have gained exposure to different segments of

EXHIBIT 38

Multi-Asset Portfolio Including Infrastructure Equity and Debt while Minimizing Risk Contributions

	Asset Class	High ENC Target	Mid ENC Target	Low ENC Target
ENC target		7	6	5
Weights	Infra equity	4.7%	5.3%	5.4%
	Infra debt	4.5%	4.5%	0.6%
	US equity	14.0%	10.7%	8.0%
	Emerging equity	10.7%	6.8%	5.0%
	Corporate bonds	19.7%	23.3%	22.3%
	Gov bonds	20.4%	27.0%	34.9%
	Real estate	4.2%	4.4%	6.3%
	Private equity	2.5%	1.9%	3.1%
	Hedge funds	4.1%	3.9%	4.6%
	Commodity	15.2%	12.2%	9.8%
Portfolio return		3.94%	3.53%	3.34%
Portfolio risk		6.95%	5.75%	5.31%
Sharpe ratio[a]		0.57	0.61	0.63

NOTE: [a]Same optimization problem but excluding infra equity and infra debt from the portfolio.

SOURCE: EDHEC*infra*.

the infrastructure universe over time, and each segment has performed differently. Exhibit 39 shows that North American pensions funds have the highest risk-adjusted returns in 2021 and are in fact the top-ranked peer group. Other peer groups took more risk to achieve lower average returns (e.g., superannuation funds), while Canadian investors are very close to the all-investor average. At the bottom of the risk-adjusted rankings, EU and UK pension funds take less risk but also achieve comparatively lower returns.

Next, we reviewed each of these peer groups and their investment styles and examined what explains their risk-adjusted performance.

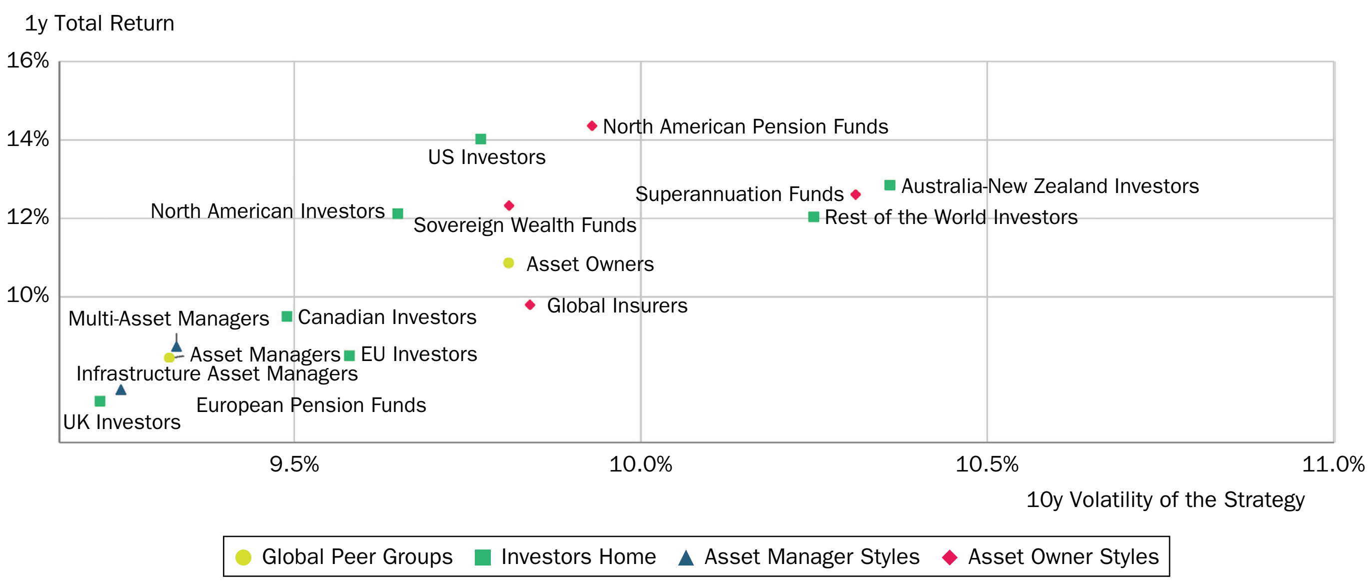
Peer Group Styles, Design, and Ranking Approach

Peer group styles are not target allocations but represent current, as of year-end 2021, realized direct and indirect investments in unlisted infrastructure equity. This inaugural Infrastructure Investment Strategy Report excludes private debt and publicly traded infrastructure investments, but future versions will aim to cover these segments as well.

The 16 peer group styles are summarized in Exhibits 40 to 43 according to industrial activity, business risk, and corporate structure pillars, as well as geographic segments. These styles differ widely in investment exposure, risk tolerance, or home bias. As we argue later, they also embody different levels of access to the market for private infrastructure equity investments.

EXHIBIT 39

2021 Risk–Return Profile of All Peer Groups



SOURCES: EDHEC*infra*, infraMetrics, 2022.

EXHIBIT 40

2021 Risk and Return Performance of Peer Groups within the Four Categories

Peer Group	Rank	1 y Total Return	3 y Total Return	Volatility	1 y Sharpe Ratio
Global Peer Groups					
Asset Owners	1	10.86%	10.53%	9.81%	1.10
Asset Managers	2	8.44%	10.67%	9.32%	0.90
Investors Home					
US investors	1	14.02%	13.84%	9.77%	1.43
North American investors	2	12.12%	12.13%	9.65%	1.25
Australia-New Zealand investors	3	12.85%	9.79%	10.36%	1.23
Rest of the World investors	4	12.04%	10.54%	10.25%	1.17
Canadian investors	5	9.50%	10.28%	9.49%	0.99
EU investors	6	8.50%	10.01%	9.58%	0.88
UK investors	7	7.34%	10.50%	9.22%	0.79
Asset Manager Styles					
Multi-Asset Managers	1	8.74%	11.00%	9.33%	0.93
Infrastructure Asset Managers	2	7.64%	10.56%	9.25%	0.82
Asset Owner Styles					
North American Pension Funds	1	14.36%	12.06%	9.93%	1.44
Sovereign Wealth Funds	2	12.33%	10.72%	9.81%	1.26
Superannuation Funds	3	12.61%	9.70%	10.31%	1.22
Global Insurers	4	9.80%	10.10%	9.84%	0.99
European Pension Funds	5	7.98%	10.28%	9.52%	0.84
All Investors		9.65%	10.60%	9.55%	1.01

SOURCES: EDHEC*infra*, infraMetrics, 2022.

Peer group styles fall into four broad categories: Global Peers, Home Peers, Manager Peers, and Asset Owner Peers. Peer groups are ranked within their category based on their 2021 risk-adjusted returns (Exhibit 44). The returns and risk of each peer group are computed using their style allocation and data on the financial performance of hundreds of unlisted infrastructure equity investments.[10]

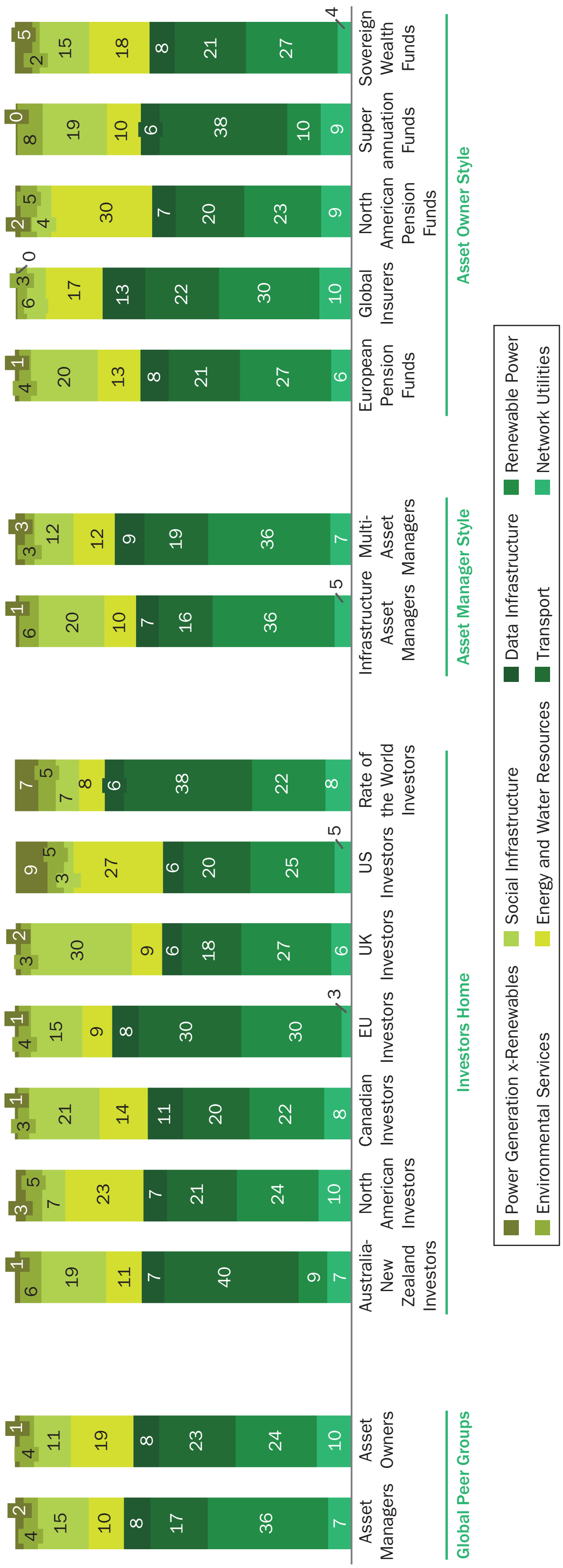
Peer group performance is presented gross of costs. In practice, investors face investment costs: Direct investment in infrastructure includes significant transaction costs, and indirect investment via managed funds requires paying management fees and carry. As a result, investors' realized returns would be different than the ones presented here for the purpose of benchmarking peer group styles. We use gross returns to provide a cost-agnostic view of performance across styles and a like-for-like measure of risk-adjusted returns to rank and measure relative performance across peer groups.

Exhibits 45 and 46 show the equivalent of the peer group styles expressed as Core, Core+ and Opportunistic risk buckets. (Unlike peer group rankings, these

[10] Starting with the allocation of the Infra300 index, which represents the overall infrastructure market, we rescale the weights of the underlying constituents with the constraints to match the TICCS style of each peer group. infraMetrics gross unlisted equity returns in local currency are then used to build each style benchmark. The style of each peer group is assumed constant for the past three years. To get a robust estimate of volatility, we use a 10-year (120 data points) standard deviation of returns measure, holding the style constant. Peer group styles are then ranked by category based on their 2021 risk-adjusted returns (Sharpe ratio, computed using the one-year excess return, subtracting the one-year risk-free rate in each market from total returns, and the standard deviation of monthly returns time series over 10 years).

EXHIBIT 41

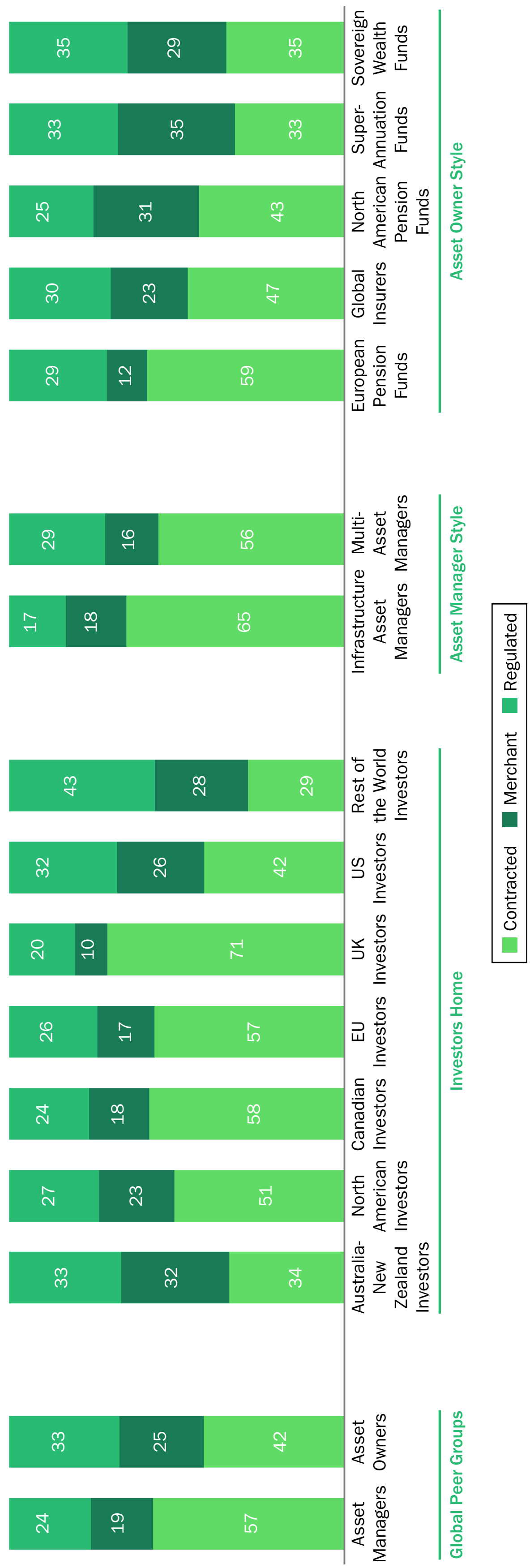
2021 Peer Group Investment Styles by TICCS Industrial Activity



SOURCES: EDHEC*infra*, infraMetrics, 2022.

EXHIBIT 42

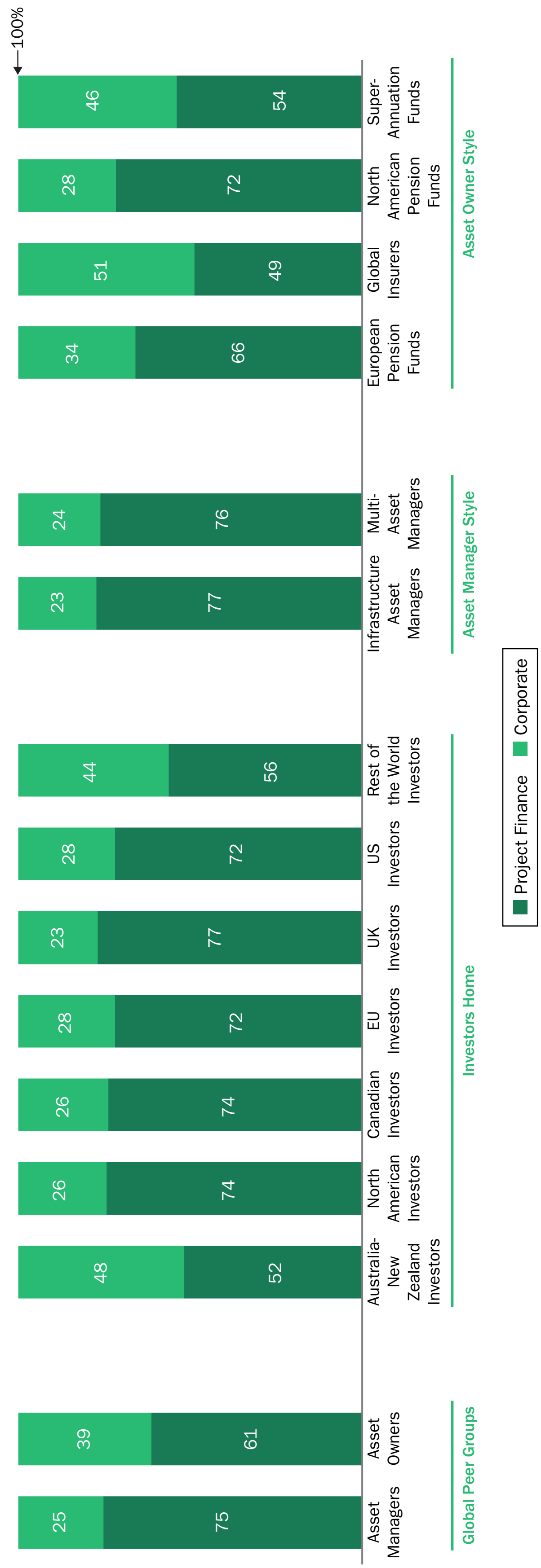
2021 Peer Group Investment Styles by TICCS Business Model



SOURCES: EDHEC*infra*, infraMetrics, 2022.

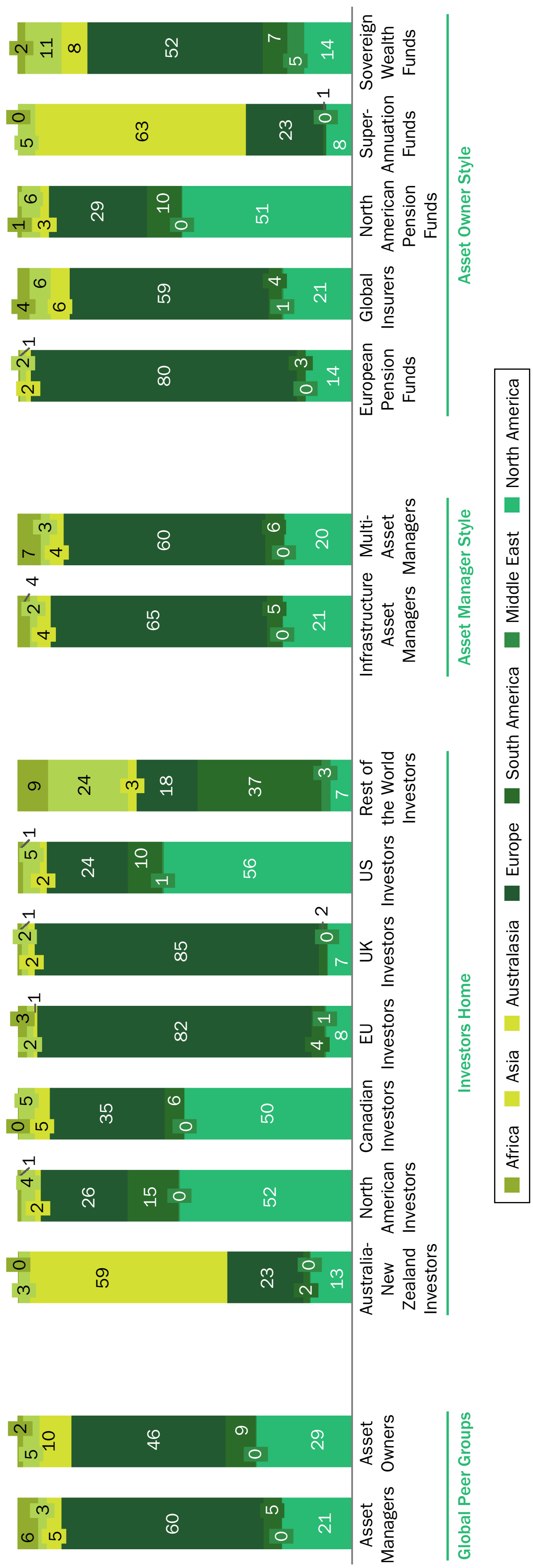
EXHIBIT 43

2021 Peer Group Investment Styles by TICCS Corporate Governance Model



SOURCES: EDHEC*infra*, infraMetrics, 2022.

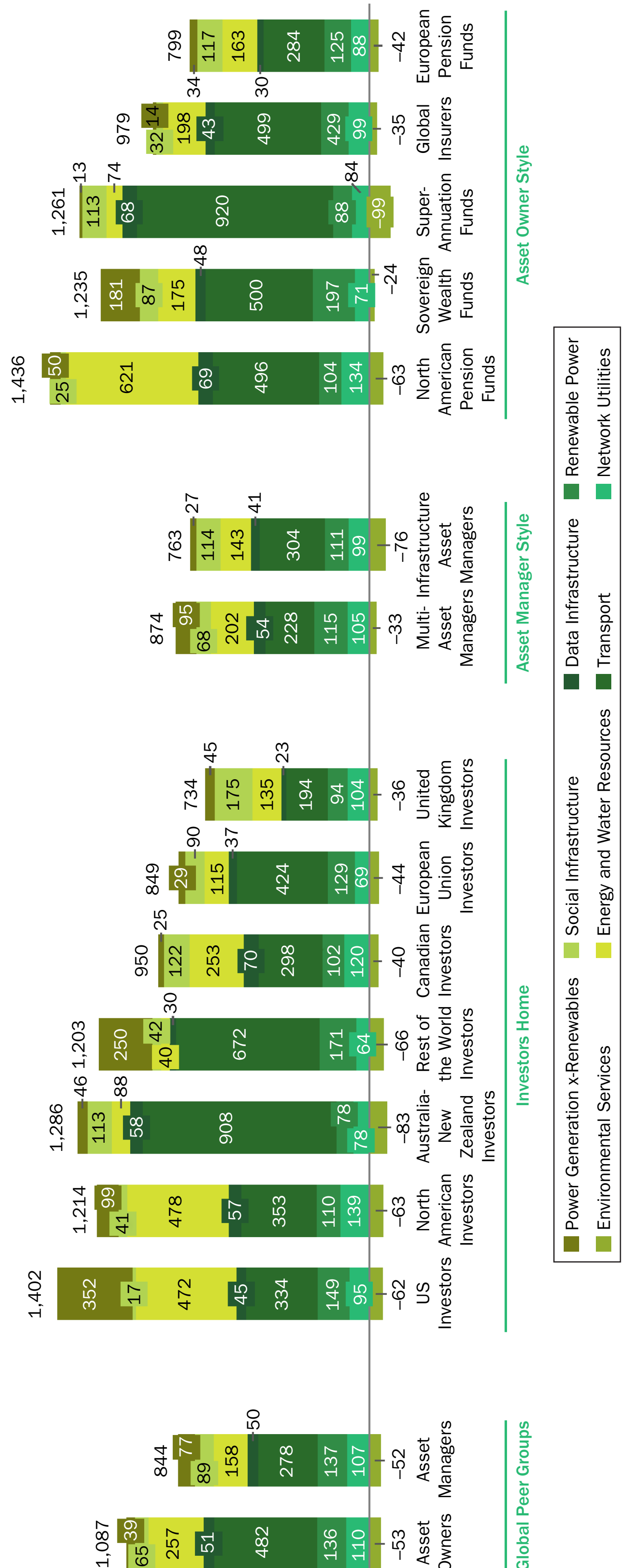
EXHIBIT 44
2021 Peer Group Investment Styles by Geography



SOURCES: EDHEC*infra*, infraMetrics, 2022.

EXHIBIT 45

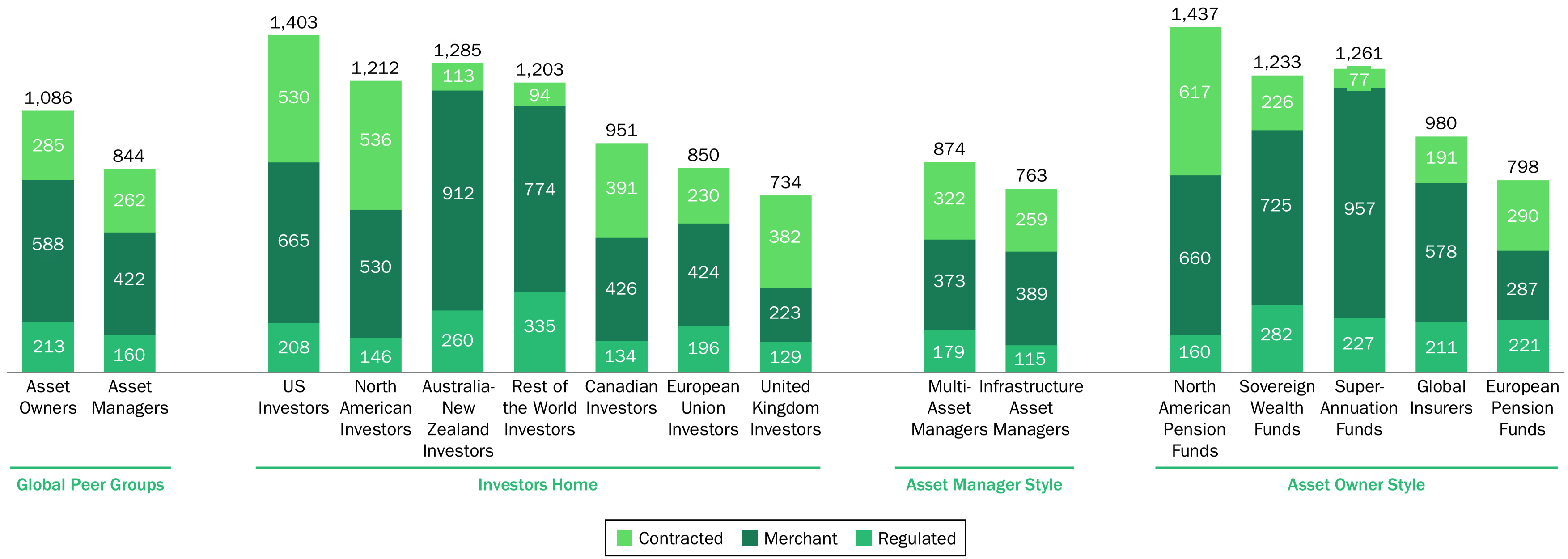
2021 Total Return Contributions by TICCS Industrial Activity



SOURCES: EDHEC*infra*, infraMetrics, 2022.

EXHIBIT 46

2021 Total Return Contributions by TICCS Business Model



SOURCES: EDHEC*infra*, infraMetrics, 2022.

categories represent investor styles by appetite for risk taking, from low to high). Finally, Exhibits 47–49 show contributions of the industry segments to the one-year total return. They are computed as the combination of the weight of the peer group in that segment and the performance of that segment. Each contribution is shown in basis points, and they add up to the 2021 total return of each peer group.

Global Peers

There are two global peer group styles: asset managers (also known as general partners, or GPs) and asset owners (limited partners, or LPs). In 2021, a group of 79 asset owners ranked first by gross risk-adjusted returns (Sharpe ratio of 1.1), ahead of 280 asset managers with an average risk-adjusted return of 0.9.

Asset manager portfolios are more heavily invested in the lowest risk, contracted business models, in which infrastructure providers have long-term revenue agreements with the public sector or private companies to deliver specific services. About one-third of their portfolios consists of renewable power projects. Asset managers also mostly invest in projects (as opposed to corporates). Their bias toward contracted renewables projects is indicative of the more specialized nature of many asset managers. The global asset manager peer group is also mostly exposed to European investments (60%), while a fifth of assets are found in North America.

By contrast, asset owners appear to be less risk averse, with about 60% of their investments in merchant and regulated corporates and a higher allocation in the riskier Energy Resources and Transport sectors. Global asset owners have less than 50% of their infrastructure assets invested in Europe and close to 30% in North America. As the so-called Canadian model exemplifies, part of an asset owner's portfolio consists of direct investments in infrastructure. These investors have tended to invest more in large corporates (utilities, airports, etc.) as shown in Exhibit 42. It is also possible that they have less access to project finance transactions, especially greenfield projects, which require winning a public tender. There is also anecdotal evidence of a preference for so-called trophy (i.e., large) assets, to deploy capital fast. As a result of this bias toward transportation and power in particular, the global asset owner peer group style benefited from the strong post-Covid performance of these sectors in 2021, as shown in Exhibit 46.

While global asset owners outranked global asset managers in 2021, we note that they would not have on a three-year (2019–2021) basis (Exhibit 44).

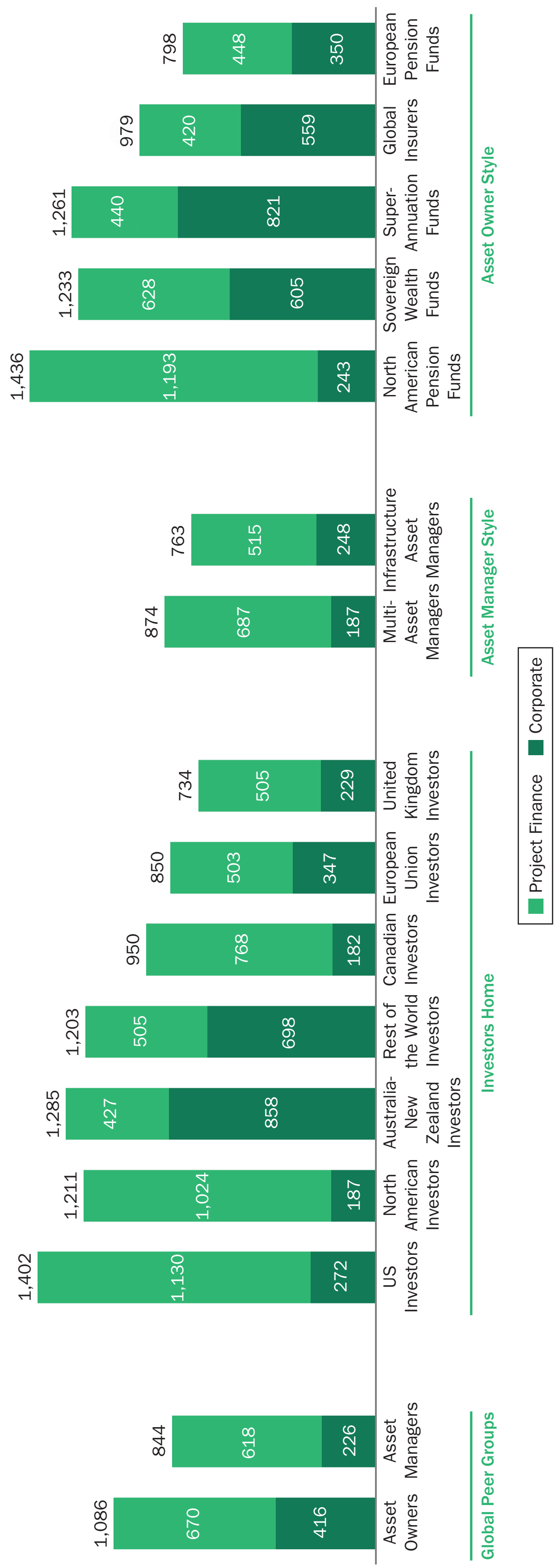
Home Peer Groups

There are seven home peer groups defined by the geographic origin of investors, such as North American, EU-based, or Canadian, and so on. Peer group styles and performance vary considerably by geography of origin: US investors rank first by realized risk-adjusted returns in 2021 (Sharpe ratio of 1.43, see Exhibit 44), followed by the broader group of North American investors (Sharpe ratio 1.25). This exceptional performance is driven by the much higher exposure to conventional merchant power (coal and gas) and energy resources (mostly gas pipelines) of these investors as shown on Exhibits 40 and 41. These investors also exhibit the strongest home bias with more than 50% of their assets located in North America.

However, still in North America, the Canadian investor peer group ranks fifth in the home peer groups, with a lower Sharpe ratio of 0.99. Compared with US investors, the Canadian peer group is exposed to almost zero conventional power and much more social infrastructure, which tends to have a more stable, contracted business profile. On a risk-adjusted basis, this stance did not pay off as well in 2021 as it did for the US neighbors.

EXHIBIT 47

2021 Total Return Contributions by TICCS Corporate Governance



SOURCES: EDHEC*infra*, infraMetrics, 2022.

EXHIBIT 48

2021 Peer Group Investments by Core/Core+/Opportunistic Styles

Peer Group	Core	Core+	Opportunistic
Global Peer Groups			
Asset Managers	52.9%	24.0%	23.1%
Asset Owners	43.2%	29.0%	27.8%
Investors Home			
Australia-New Zealand investors	44.1%	29.6%	26.3%
North American investors	43.6%	28.5%	27.9%
Canadian investors	46.7%	28.2%	25.1%
EU investors	55.1%	23.4%	21.5%
UK investors	55.5%	27.8%	16.7%
US investors	44.4%	25.4%	30.3%
Rest of the world investors	49.5%	23.7%	26.8%
Asset Manager Styles			
Infrastructure Asset managers	55.1%	24.6%	20.3%
Multi-asset Managers	53.5%	23.2%	23.4%
Asset Owner Styles			
European Pension Funds	53.4%	26.0%	20.5%
Global Insurers	43.4%	26.9%	29.8%
North American Pension Funds	38.2%	30.3%	31.5%
Superannuation Funds	42.9%	31.0%	26.1%
Sovererign Wealth Funds	45.9%	26.2%	27.9%

SOURCES: EDHEC*infra*, infraMetrics, 2022.

Third and fourth in the rankings of home peer groups are Australia and New Zealand investors and the Rest of the World investors group, which mostly includes investors from Asia and the Middle East. Similar to US investors, Australian investors have more merchant and regulated assets in their portfolio, however, they are much more exposed to transportation investments and less to conventional energy supply and generation. These investors also exhibit a significant home bias, with close to 60% of their investments located in the same region (Exhibit 43).

EU and UK investors rank last in the home peer group ranking due to lower returns that are not compensated by a commensurate reduction in risk. EU investors are as exposed to renewable energy projects as UK investors but much more to transport investments that tend to be merchant or regulated (Exhibits 40 and 41). These two peer groups invest almost exclusively in Europe, with less than with less than 8% of their investments in the rest of the world.

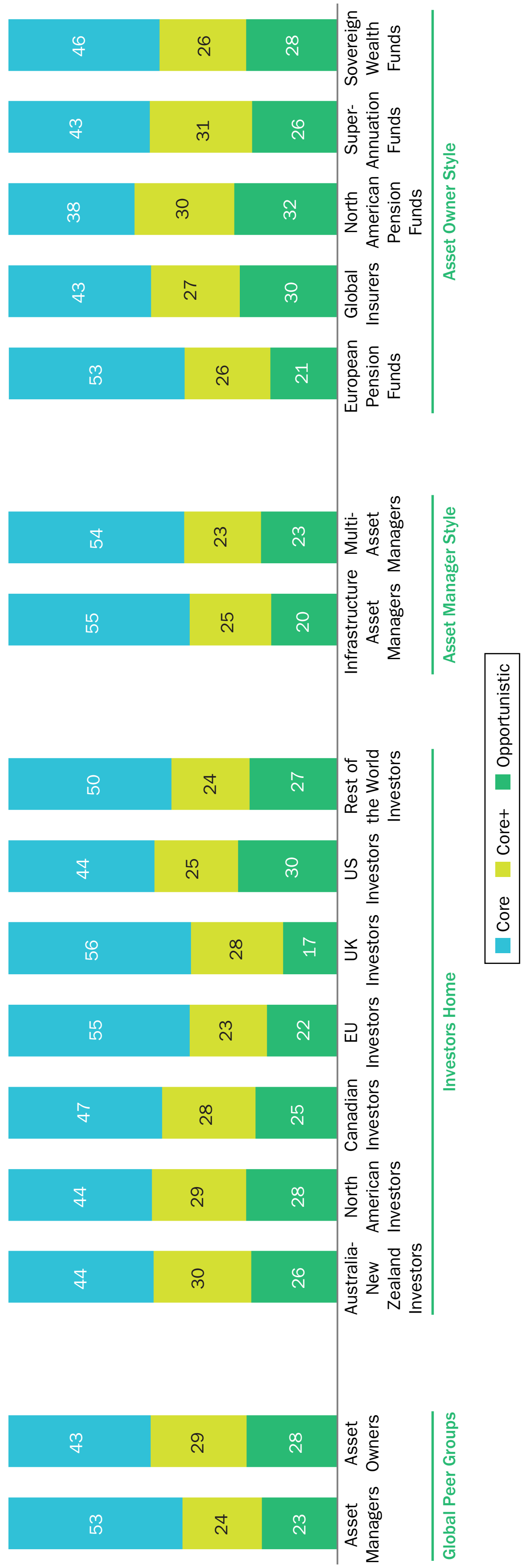
As before, the impact of the 2021 post Covid-19 recovery on asset prices explains this year's ranking to the extent that investors were more exposed to transport and energy, and merchant and regulated business models. Looking at the three-year performance (Exhibit 44) North American and US investors would still top the home peers ranking, but Australian investors would be at the bottom of the list due to their exposure to transportation, especially airports, and the impact of Covid-19 on air travel.

Asset Manager Peers

Asset manager peers include either specialist infrastructure managers or larger multi-asset managers. In 2021, the multi-asset manager peer group tops the ranking with a Sharpe ratio of 0.93, ahead of specialized fund managers with a Sharpe ratio of 0.82.

EXHIBIT 49

Graphical Representation of 2021 Peer Group Investments by Core, Core+, and Opportunistic Styles



SOURCES: EDHEC*infra*, infraMetrics, 2022.

The main style differences between pure play and multi-asset managers echoes that between global asset managers and asset owners: Specialist asset managers tend to invest more in contracted projects but also more in social infrastructure and utilities. Multi-asset managers invest more in merchant and regulated assets, more in power and energy resources, and more in transport.

Again, the higher exposure of multi-asset managers to sectors and business models that benefited from the post-Covid recovery led to a better 2021 performance. In general, however, both asset manager peer groups show total returns in 2021 that are below the all-investor average of 9.65% and Sharpe ratio of 1.

Asset Owner Peers

The asset owner peer category includes five peer groups: US pension funds are the best ranked peer group for reasons like the ones highlighted previously for the North American peer group. They tend to be underfunded and to allocate more to the performance-seeking portfolio, hence a greater exposure to merchant assets.

Sovereign wealth funds (SWFs) rank second with a gross Sharpe ratio of 1.26. One of the most geographically diversified peer groups, it is also the most exposed to regulated assets in this category. SWFs also have a greater exposure to power, second only to US investors.

Superannuation funds ranked third in this category with a Sharpe ratio of 1.22. They generated most of their returns from transport investments and invest considerably less in renewable power than other peer groups, but this is not compensated by a greater exposure to conventional power. In line with the Australian and NZ peer group, Australian superfunds are exposed to more transport risk and more merchant risk and corporates than most other peer groups.

Global insurers come in fourth, with a gross Sharpe ratio of 0.99. Unlike other groups, they invest truly globally with a focus on Europe and the United States, and they have an unusual 50/50 exposure to projects and corporates, which they share only with the Australia/NZ peer group. Like other investors, insurers benefited from the rebound of transport and gas in 2021. Note that global insurers almost completely shun conventional power but still adopt a yield-seeking style when it comes to infrastructure as opposed to a lower-risk, liability-hedging style.

Finally, European pension funds ranked last in this category with the lowest Sharpe ratio but also the lowest portfolio volatility. They have the lowest allocation to merchant assets of all the peer groups in this category and invest instead in contracted transport, social, and renewable projects, adopting a distinctively more risk-averse style.

Core and Core+ Styles by Peer Group

We use definitions of Core, Core+, and Opportunistic infrastructure investments based on the five-year average expected returns of individual assets. Using a risk-based approach, investments in the first two quartiles of expected returns are considered Core, those in the third quartile as Core+, and the companies in the top quartile of expected returns as Opportunistic.

Exhibits 45 and 46 show that all peer group styles include some exposure to all three segments, but in line with earlier findings, UK investors are the least exposed to the opportunistic style, while North American pension funds are the most exposed. Note that EU investors and multi-asset managers are also the most exposed to Core strategies.

Peer Group Investment Style Facts

Several investment style facts emerge from our findings.

- The 2021 post-Covid recovery was strong, leading to high returns and a bull market average Sharpe ratio of 1. This recovery benefited some peer groups more than others, and transport and energy investors were able to par some of the losses they had incurred in previous years.
- Renewable energy is everywhere in investors' portfolios. With the notable exception of superannuation investors, who have put significantly less weight on renewable power investments, all infrastructure investor styles now include a quarter to a third of renewable energy projects.
- Power and gas still pay. After transport, the main beneficiaries of the 2021 recovery, especially because wind levels were lower than usual, was gas and conventional power generation. Those peer groups that stayed more exposed to these sectors benefited, while peer groups that have already mostly divested conventional power generation from their portfolios did not.
- While infrastructure investment used to be equated with airport and utilities acquisitions, the contracted infrastructure projects are now the basic building block of almost every infrastructure investor's portfolio and represent between 50% and 70% of infrastructure AUM across all peer groups. Still, infrastructure corporates remain part of the infrastructure mix, and all peer groups are also exposed to them, albeit in varying amounts.
- Like renewables, data infrastructure is the infrastructure of the future. Unlike wind and solar projects, however, it has yet to grow into a significant part of the style of the various peer groups.

FUND BENCHMARKING AND MANAGER SELECTION

In 2022, 80% of institutional investors exposed to unlisted infrastructure equity are invested via managed private investment funds. As a result, fund manager selection and performance monitoring are key aspects of the investment process in infrastructure. Indeed, most individual infrastructure portfolios are concentrated in a limited number of investments reflecting active manager choices.

To select skilled managers, investors and fund of funds managers typically rely on rankings by quartiles of net IRR and multiples and aim to work with asset managers that are consistently in the top quartiles. Likewise, to monitor performance, investors need to compare the reported performance of the funds they are invested in with that of comparable funds and, again, hope to achieve top quartile results.

However, this process is hindered by the limited availability of infrastructure fund performance data. There are at least five reasons why such data are sufficiently scarce and biased to make both manager selection and monitoring very challenging. Indeed, it is more akin to a lottery than a rigorous, criteria-based selection process.

1. Available sample sizes are small (usually less than 30 data points), and as we demonstrate later, estimating quartile boundaries reliably is impossible with so little data.
2. The data contributed by managers can suffer from several biases (reporting, selection, and survivorship biases), making the estimation of quartiles of manager and fund performance unreliable.

3. In the case of some strategies and geographies, too few funds may exist in the first place to achieve any robust estimate of the quartiles of returns and multiples, even if all the available data could be collected.
4. Because this information is contributed and processed by humans, it is sometimes wrong: Either the exact investment year or the performance data itself can sometimes be inaccurate. Such human errors are compounded by the limited number of data points available; with 30 data points per vintage or fewer to rely on, there is no law of large numbers to “wash out” human errors, and a single inaccurate data point can create large deviation in reported quartiles.
5. The same is true of outliers: If reported data include one or two very high or very low IRRs, with a small sample, estimated quartile boundaries are not robust. As far as we know, there is no outlier treatment in existing commercial datasets used to rank funds and managers.

Finally, contributed fund data are also typically stale, that is, available with a lag of one to three years, depending on the age of the fund. New funds usually do not report any performance data for the first two or three years, and more mature funds tend to report with a lag of up to four quarters.

Moreover, because most funds also arbitrarily set a fixed hurdle rate at 7% or 8%, in the absence of robust performance quartile data, there typically is no relative benchmark against which infrastructure funds and managers can be assessed.

Such a paucity of performance data for infrastructure funds means that asset managers (GPs) can struggle to demonstrate whether they are performing adequately or not, while investors (LPs) are left none the wiser about the skills or performance persistence of their asset managers.

Hence, fund quartile ranking can be a lottery as we show in the following; top quartile funds can be ranked in lower, even the lowest quartile, and vice-versa. This is of course problematic for LPs who wish to select good managers but also for these same good managers who may not be able to showcase their skills if they cannot be benchmarked fairly. We show such examples using real-world fund data in the following discussion.

Unless investors have large datasets, they cannot rely on quartile ranking and that creating such datasets is possible for infrastructure funds thanks to the infraMetrics technology.

Using the contributed infrastructure fund performance datasets typically available to investors to estimate performance quartiles leads to random and even misleading results. We show that a much larger amount of data is needed to achieve reliable quartile estimates of the relative performance of funds and fund managers and that much better results can be achieved by simulating “typical” funds, given access to enough data for the funds’ underlying assets, their valuations, and cash flows.

In what follows, we first demonstrate the lack of robustness of quartile rankings based on small samples then discuss the greater robustness of simulated fund performance. We also provide back-testing results confirming the superiority of simulated results compared with contributed data, especially when it comes to evaluating individual vintages or strategies.

Step 1: Fund Quartiles Estimated with Contributed Data Are Not Reliable

Quartiles of net IRRs and multiples have been used to select and assess private investment funds for decades, and unlisted infrastructure funds are no exception. Ranking and selecting managers based on quartiles is not just a matter of sorting funds by IRR and picking the top of the list. The notion of quartiles implies an underlying statistical distribution of returns and a relative ranking; that is, ranking funds or managers by quartile is a basic form of performance benchmarking.

Using quartiles to rank observations requires either knowing what the underlying distribution of returns is or observing a sufficiently large number of realized performance metrics to estimate the quartiles of that distribution empirically with reasonable accuracy.

Unfortunately, the distribution of private infrastructure fund returns in any given year is unknown and unobservable. Also, as we show, using contributed performance data to estimate quartiles boundaries leads to unreliable results due to the paucity of available data.

For example, looking at the Preqin dataset of unlisted infrastructure fund performance metrics (see www.preqin.com), recent vintage years typically Exhibits 47–57 contributors for net IRRs and 15–35 contributors for net multiples.

As of Q3 2021, the full Preqin dataset includes 228 observations of infrastructure fund IRRs going back to 1993 (one observation) and includes at least 10 observations per vintage from 2006 onward. Thereafter, the number of unique fund observations per vintage ranges between 8 in 2009 to 24 in 2016 with an average of 15 observations per vintage year.

What are the consequences of using such small samples to describe the empirical quartiles of the underlying distribution of returns?

In a given vintage year, the true distribution of returns includes all the possible outcomes that a large number of hypothetical funds could have experienced. Assume for simplicity that the underlying distribution of infrastructure fund returns follows a normal law that does not change from one vintage year to another. Each data point in a manager-contributed dataset would correspond to an individual draw from this distribution, which is used to estimate the quartile boundaries of fund performance in that vintage year.

Exhibit 50 shows the empirical quartiles for five rounds of drawing 10 observations from a well-defined normal law, that is, observing 10 IRR data points for five consecutive vintage years when we already know what the quartiles are. In their paper, Blanc-Brude and Gupta (2021) also show the same results for five consecutive rounds of making 20, 50, 100, 1000, and 10,000 observations. We see that obtaining 10 or 20 data points per year from the same well-defined distribution leads to completely different estimates of the quartiles boundaries from one year to the next.

With 10 observations per year, quarter estimates are off by several hundred basis points relative to their true value and their 95% confidence interval has a range of 1,000–3,000 basis points. With 20 or 50 observations of net IRR per year, the estimation error and the size of the confidence intervals are still so large that fund rankings can be considered random. For example, with 20 observations, the typical sample size available in the Preqin dataset, a fund with a 12% IRR, which should be ranked in the second-best quartile (because the true median is 10%), could still be considered bottom quartile because available observations can lead to a 300–400 basis point error in the estimation of the median IRR. Likewise, a fund with a 15% IRR could be considered a top-quartile fund when the true top-quartile boundary is 18%, but with too few observations, the estimation error is easily large enough to miscategorize such funds.

Increasing the number of observations can lead to considerably higher confidence in the estimation of quartile boundaries of net IRR. With 10,000 observations estimation errors are in the 0–30 basis point range and 95% confidence intervals have a range about 60 basis points. At this level of precision and robustness, ranking and comparing funds by quartile based on reported net IRRs becomes feasible and meaningful.

EXHIBIT 50

Precision of IRR Quarter Estimates for Five Consecutive Rounds, 10 Observations

True Value of Bottom Quartile: 1.9%; 2nd Quartile: 10%; Top Quartile: 18.1%

Vintage	n	Quantile	Estimate	Error (bps)	Lower c.i.	Upper c.i.	95% Confidence Range (bps)
Bottom Quartile Boundary Estimates, Five Consecutive Vintage Years							
1	10	25%	9.6%	770	–6.5%	18.5%	2,500
2	10	25%	–1.1%	–300	–2.6%	6.3%	890
3	10	25%	7.6%	570	–5%	19.7%	2,480
4	10	25%	5.1%	320	2.7%	15.8%	1,310
5	10	25%	3.9%	200	–10%	13.5%	2,360
3rd/2nd Quartile Boundary Estimates, Five Consecutive Vintage Years							
1	10	50%	16.9%	690	–3.1%	25.6%	2,870
2	10	50%	15.7%	570	6.8%	20.4%	1,360
3	10	50%	12.7%	270	9.3%	29.6%	2,030
4	10	50%	6.1%	–390	–1.5%	28.5%	3,000
5	10	50%	14.5%	450	–1%	34.5%	3,560
Top Quartile Boundary Estimates, Five Consecutive Vintage Years							
1	10	75%	11.8%	–630	7.4%	21%	1,360
2	10	75%	20.8%	270	12.9%	28.2%	1,530
3	10	75%	17.8%	–30	10.2%	24.6%	1,440
4	10	75%	21.9%	380	13.2%	34.4%	2,120
5	10	75%	17.6%	–50	6.6%	24%	1,740

In other words, *when only 10 to 30 observations of IRRs or multiples are available in any given vintage year, the confidence with which investors can estimate quartile boundaries is so low that the resulting rankings of managers and funds are meaningless.* The same fund may find itself switching from the top quartiles to the bottom quartiles simply because of a difference in contributed performance data in two consecutive years.

Exhibit 51 shows this result graphically: For a given return distribution, the three horizontal red lines indicate the true value of IRR quartile boundaries. The chart shows empirically derived quartile boundaries and their 95% confidence intervals for sample sizes ranging from 10 to 1,000.

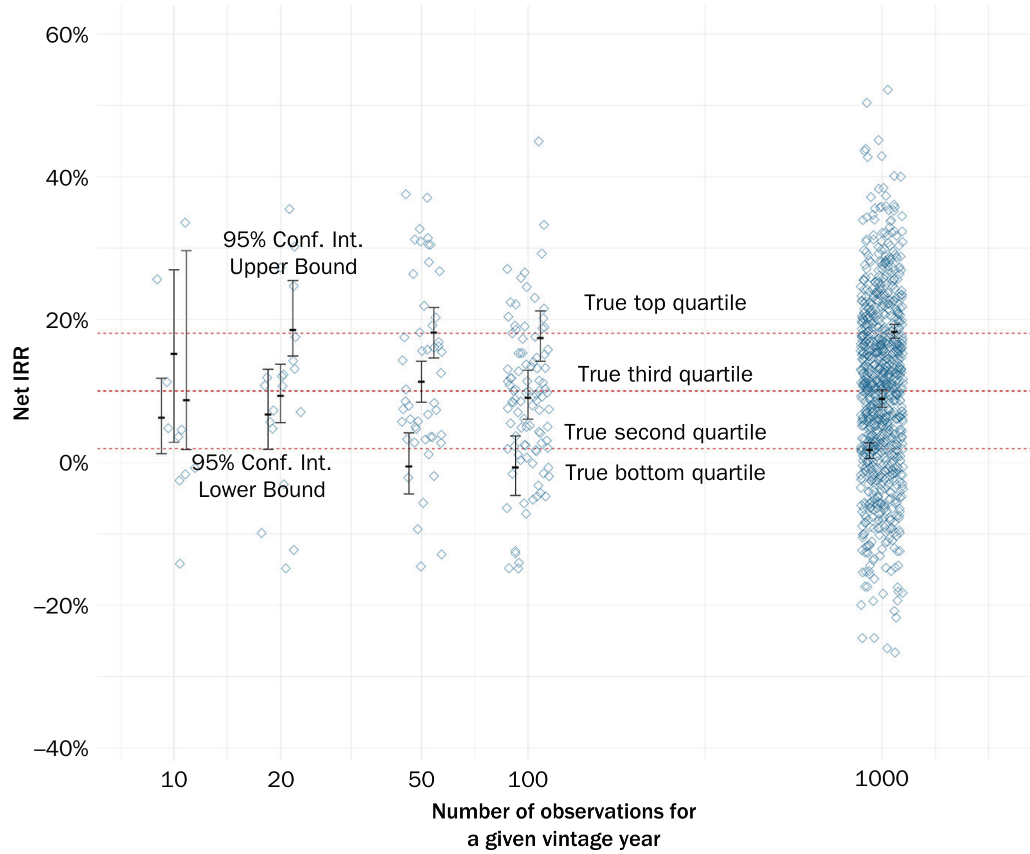
Exhibit 51 shows that up to 50 observations, the estimation of the true quartile boundaries is still so imprecise that it is not possible to distinguish between quartiles with a reasonable level of confidence as the 95% confidence intervals of the quartile boundaries frequently overlap. From 100 observations, it is possible to distinguish between the quartile boundaries confidence intervals, but estimation errors remain large. With 1,000 observations, on the right-hand side of the chart, the true quartiles are approximated sufficiently closely and precisely to serve as a point of reference to rank investment funds.

Thus, using IRR and multiple quartiles to rank and select private fund managers is practically impossible until at least 1,000 (ideally 10,000) observations are available to investors or consultants.

Clearly, there are not enough infrastructure funds in the world to report that much performance data, let alone in the same vintage year. Moreover, the true distribution of infrastructure fund returns is unlikely to follow a time-invariant normal law as in our example. With nonnormal and dynamic return distributions, even more observations may be needed to achieve robust estimates of IRR quartile boundaries.

EXHIBIT 51

Illustrative Example of Estimating IRR Quartile Boundaries and 95% Confidence Intervals with Small and Large Datasets Given a Known Underlying Distribution of Returns



SOURCE: infraMetrics.

We also see that aggregating contributed data over several consecutive years, as is sometimes done, can only improve precision so much: With five years of data (about 100 observations), the 95% confidence interval of the quartiles boundaries is still very large for the purpose of ranking annual rates of returns (between 700 and 1,200 basis points).

Aggregating all the data available in the Preqin dataset since 1993 yields more than 200 observations. This is more precise but also backward-looking and not helpful for investors to rank funds today. Indeed, the underlying distribution of returns is unlikely to be static over time. This a well-known phenomenon for investors who have experienced the yield compression of infrastructure of the past two decades. The type of infrastructure funds available and their strategies have also changed over the past 20 years, and so has the variance (the risk) of their return distribution. Hence, using a rolling average (or even all previously reported returns) creates a backward-looking (in this case, upward) bias in quartile boundary estimates.

Finally, beyond the central issue of sample size for quartile boundary estimation and robustness, individual outliers can have a significant impact when samples are very small, as is the case for contributed infrastructure fund performance data. If even 1 of the 10 or 20 reported IRR data points in a given vintage year is a significant outlier, adding or removing this single observation completely changes quantile estimation results as shown in Exhibit 52. As far as we are aware, quarter rankings

EXHIBIT 52

Differences between Empirical Net IRR Quartiles of Contributed Data before and after Removing a Single Positive Outlier, Vintage Years 2009 and 2018

	Vintage Year	Obs.	Bottom Quartile (25% quantile)	2nd Quartile (Median)	Top Quartile (75% quantile)	Max Value
Raw data	2009	9	0.075%	7.10%	10.11%	448%
…without outlier		8	–4.05%	5.20%	9.04%	13.2%
Difference		1	–412.5 bps	–190 bps	–107 bps	–4340 bps
Raw data	2018	19	7.25%	9.80%	16.40%	55.2%
…without outlier		18	7.02%	7.44%	13.40%	23%
Difference		1	–22.5 bps	–36 bps	–300 bps	–322 bps

NOTE: "Without outlier" data are obtained by removing values above 50% net IRR.

SOURCES: Preqin, EDHEC*infra*.

currently produced using contributed data do not include any systematic outlier treatment. In fact, with so little data, it is not possible to estimate the parameters of the distribution of returns, thus it is not very clear how to define outliers either. In Exhibit 52, we remove a single data point in two vintages that exhibit one IRR above 50%. As the table shows, the presence of this single data point completely changes the estimates of IRR quartiles.

In conclusion, with sparse contributed fund performance data, investors cannot know with a reasonable degree of confidence what the quartile of the net IRR or net multiple distributions really are. Because quartile rankings are an important part of the private fund investment decision and monitoring process, in the case of infrastructure funds, investors (LPs) and managers (GPs) do not have any usable point of reference to evaluate performance.

Moreover, data paucity gets worse as one tries to drill down to the subsegments of the infrastructure universe, making any comparisons or assessments between styles and fund risk profiles also impossible.

Step 2: Simulating Private Funds Achieves Superior Quartile Estimation Results

Exhibit 51 shows that with a large number of observations of fund performance, reliable estimates of the quartile boundaries can be obtained. In the absence of enough observable data, such a high number of observations can only be achieved through simulation. The solution to the issue described is to bootstrap the estimation of returns and multiples quartile boundaries by creating a large sample of possible investment outcomes with at least 1,000 data points per vintage or segment.

Simulating private fund returns has been suggested before in industry research as an approach that can palliate for the lack of observable data described here (see, for example, Cornel 2017 for BlackRock's approach to private equity funds).

For these results to be relevant to investors, two important conditions must be met:

1. The valuations of the assets purchased and sold by the simulated funds need to represent the market values of the underlying assets at the time, as well as the distributions made by each invested company in any given year.
2. The simulated behavior of the funds should correspond to the typical path followed by such investment vehicles.

We build our approach using the market value of hundreds of infrastructure investments and their dividend cash flows obtained from the infraMetrics database. This information presents a number of advantages that make it the best available input for a simulation exercise:

- The infraMetrics database of 700+ tracked unlisted infrastructure firms is designed to track a broader investible universe of 7,000+ firms in 25 countries in a representative manner. Hence, it does not suffer from reporting and survivorship biases.
- infraMetrics valuations are recalibrated each quarter to match the most current level of expected returns, including the unlisted infrastructure equity risk premia and the relevant yield curve (see Blanc-Brude and Gupta 2021 for a summary).

Next, our fund simulations rely on a number of assumptions about the investment pace and size of private infrastructure funds, fee levels, ability to deploy capital, and so on. We develop these assumptions through a combination of desk-based research and semi-structured interviews with investment managers. Market participants were also involved in the validation and "reality check" of the simulation results.

We simulate the path of thousands of potential funds using this data, in each vintage and in each segment of the market. It should be noted that such simulations aim to represent all the standard or typical outcomes of the activity of private investment funds; some extreme cases will, by definition, fall outside the scope of the simulations. For example, a fund manager may have a legal dispute with its LPs and terminate the fund. Another fund may use financial engineering to achieve extremely high returns, or just be very lucky. Such scenarios produce outliers in the distribution of fund returns and are outside the scope of the simulation. They are also irrelevant because our objective is to estimate accurate and robust quartile boundaries; outliers should not make any difference to the results. As opposed to the small contributed datasets, with a large number of observations, outliers do not have any significant impact on quartile boundary estimation.

In summary, simulations allow us to produce much more robust results than simply observing contributed data.

- *No selection bias*. By covering a large number of possible simulated paths across the entire universe of infrastructure, this technique ensures that the fund benchmarks are free from the selection biases that are typically seen in those contributed benchmarks that rely on the reported track records of a subset of GPs and LPs;
- *No survivorship bias*. With contributed data, poor-performing GPs may stop contributing, thus making the benchmarks biased toward survivors. With infraMetrics Fund Strategy Analyser (iFSA), by design some of the simulated paths result in funds investing in poorly performing assets and/or failing to deploy capital, especially in periods of market stress. Such zombie funds remain in the iFSA dataset making the results free of survivorship bias;
- *Robust quantile estimates*. Contributed datasets are found to be very limited in individual vintages or subsegments but a bootstrapping (resampling) approach enables as much data as needed to be generated to ensure the robustness of the results;
- *Granularity of fund strategies*. As a result, data are available for granular strategies, such as core funds or renewable energy funds, across the entire fund lifecycle (J-curve) and in multiple geographies;

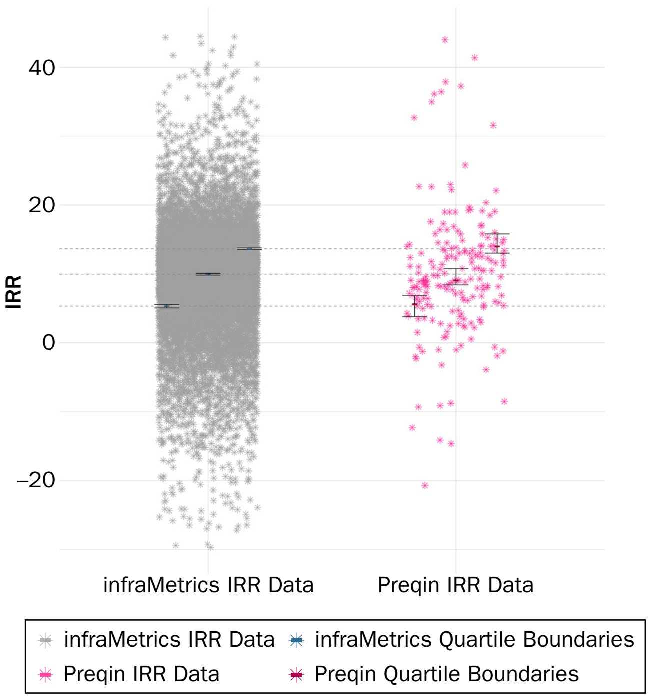
EXHIBIT 53

Descriptive Statistics of the InfraMetrics and Preqin Datasets of Net Infrastructure Fund IRR, 2005–2018 Vintages

	Mean	Min	Q1	Q3	Max	Obs.
infraMetrics Net IRR	8.84	–50.2	5.2	13.5	134.5	13,993
Preqin Net IRR	12.33	–39.5	5.6	14.0	448.0	206

EXHIBIT 54

Scatterplot of InfraMetrics and Preqin Net IRR Datasets, Quartile Boundaries and Confidence Intervals, Aggregates for 2005–2018 Vintages



SOURCES: Preqin, EDHEC*infra*.

- *Up-to-date data*. Contributed benchmarks exhibit reporting lags and the timing of reporting may differ between contributors as well, resulting in blended data that are not strictly comparable. infraMetrics produces results at T + 10 from the end of every quarter end, thus, ensuring that investors have access to up-to-date information.

Step 3: Back-Testing

Comparing aggregate datasets. We first compare the infraMetrics net IRR fund simulation results and the Preqin dataset on an aggregate basis, for the period 2005–2018 (Preqin data are not available beyond the 2018 vintage).

As discussed earlier, this creates a backward-looking bias that precludes using such results for the purpose of benchmarking funds today, but this bias is common to both datasets and with 200+ data points the Preqin quartile boundaries are now more accurate, albeit still biased, as shown earlier.

Exhibit 53 shows descriptive statistics for the two datasets, and Exhibit 54 shows a scatterplot of the data and the estimates and confidence intervals of the quartile boundaries. We see that while contributed data tend to have higher mean and quartile boundaries, the two datasets correspond to the same range of IRR values, with the exception of one large outlier in the contributed dataset. However, simulated quartile boundaries are much more precise due to the number of data points available, as shown in Exhibit 54, where the confidence interval whiskers are very small for the simulated data.

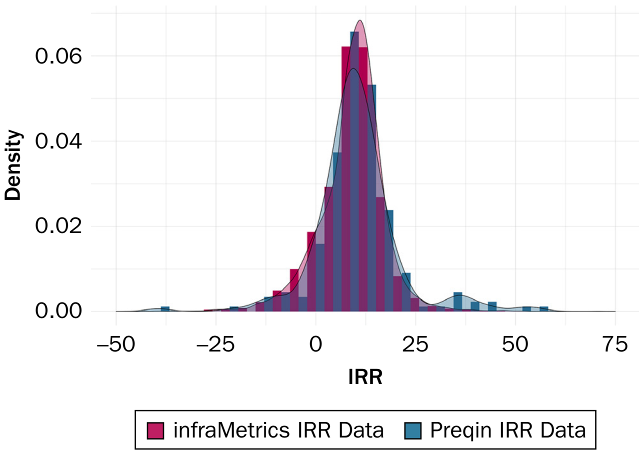
It is worth noting that simulated results also fall within the confidence interval of contributed data points, as shows by the horizontal dashed lines in Exhibit 54. Thus, the largest available sample of contributed data agrees with the simulation results about the overall distribution of the data taken in aggregate over 13 vintage years. This is a first validation of the ability of simulation to generate market-like results.

This is also evident looking at Exhibit 55, which shows how, in aggregate and over many years, both contributed and simulated datasets tend to tell the same story.

We see that in a few cases, contributed datapoints exhibit very high returns compared with simulated ones. This can be the result of managers using strategies that are riskier than what is implied by the simulation, such as investing in private equity-style assets or using fund-level or holding company–level leverage to boosts

EXHIBIT 55

Probability Density Plots of InfraMetrics and Preqin Net IRR Datasets, Aggregates for 2005–2018 Vintages



NOTE: The data on the plot have been rescaled to compare densities directly because the infraMetrics dataset includes 38 times more data, making a regular histogram difficult to read.

SOURCES: Preqin, EDHEC*infra*.

returns. Such manager-specific decisions are not meant to be captured by the simulation, which only reflects the path of thousands of "standard" funds, but does not, for example, include assumptions about the use of additional leverage, style drift, or any other reason why individual funds might not fall within the distribution of returns of infrastructure funds.

Hence, while the aggregate distribution of net IRRs in the contributed and simulated cases are different, they are still close enough to suggest that the simulation is capable of producing market-like results.

Comparing individual vintage years. This comparison is, however, only valid at the aggregate level. When comparing contributed and simulated data in individual vintage years, which is what investors and asset managers really need to do, the two datasets are very different.

Exhibits 57 and 58 show scatterplots and quartile boundary estimates for simulated versus contributed data in individual fund vintage years. As before in our example, the very limited number of contributed data points within individual vintages leads to highly uncertain quartile estimates that often overlap between quartiles.

In other words, the true quartiles are unknown when using only contributed data. The same conclusion applies when looking at contributed data by strategy or sector within vintage years or even across multiple vintage years: Contributed data are too scarce, and quartiles are unknowns or random. Conversely, simulated quartiles continue to be robust and precise within vintages as well as within strategies or sectors.

Exhibit 58 also shows examples of biases in the contributed data of more recent vintage years: Simulated results include data for funds in their early development, which often exhibit negative returns because of the so-called J-curve. These funds do not contribute data to the Preqin database, which only reports positive net IRRs for the 2015 or 2018 vintages, leading to quartile boundary estimates that are biased upward because only funds that are able to generate positive returns in these vintages report their data.

Investors have to wait for a number of years for the performance of more funds to be reported as shown in Exhibit 57 for older vintages such as 2010 and 2011. Still, even in these older vintages we see that limited data availability leads to very imprecise quartile boundary estimation and meaningless fund or manager quartile rankings.

In conclusion, simulated results are both congruent with contributed data at the aggregate level over a long period, and more robust and precise at the vintage year or subsegment level. Alignment of the results with market data is simply due to the use of market valuations and realized asset-level cash flows as the inputs of a bottom-up simulation.

Next, we describe the simulation methodology used to obtain these results.

EXHIBIT 56

Fee scenarios used in the iFSA Simulations

Management Fees	Performance Fees	Hurdle Rate
2.00%	20%	8%
1.50%	20%	8%
1.50%	20%	6%
1.50%	15%	8%
1.25%	15%	8%
1.00%	10%	6%

EXHIBIT 57

Scatterplot of InfraMetrics (1,000 obs.) and Preqin Net IRR Datasets, Quartile Boundaries and Confidence Intervals ("Whiskers") for the 2010 and 2011 Vintages

SOURCES: Preqin, EDHEC*infra*.

BENCHMARK DESIGN METHODOLOGY

The methodology relies on a Monte Carlo simulation of bottom-up data on infrastructure companies along with some assumptions on the investing behavior of a fund. Each simulation run can then be broadly divided into four sections: defining the fund characteristics, selecting the underlying investments, computing the fund cash flows, and calculating the fund metrics such as IRR and TVPI. This process is explained in Exhibit 59.

Fund Characteristics

This step lays the foundation of the approach. Based on the data from actual fund prospectus and other industry consultations, we define the following characteristics of a fund:

- *Fund size*. With ever-growing investor interest in the unlisted infrastructure asset class, average fund size has ballooned from USD200 million in 2000 to USD1 billion in 2019. In this simulation, we have assumed fund size to be distributed between USD100 million and USD2 billion, with some custom probabilities, such that the average tracks this historical evolution.

EXHIBIT 58

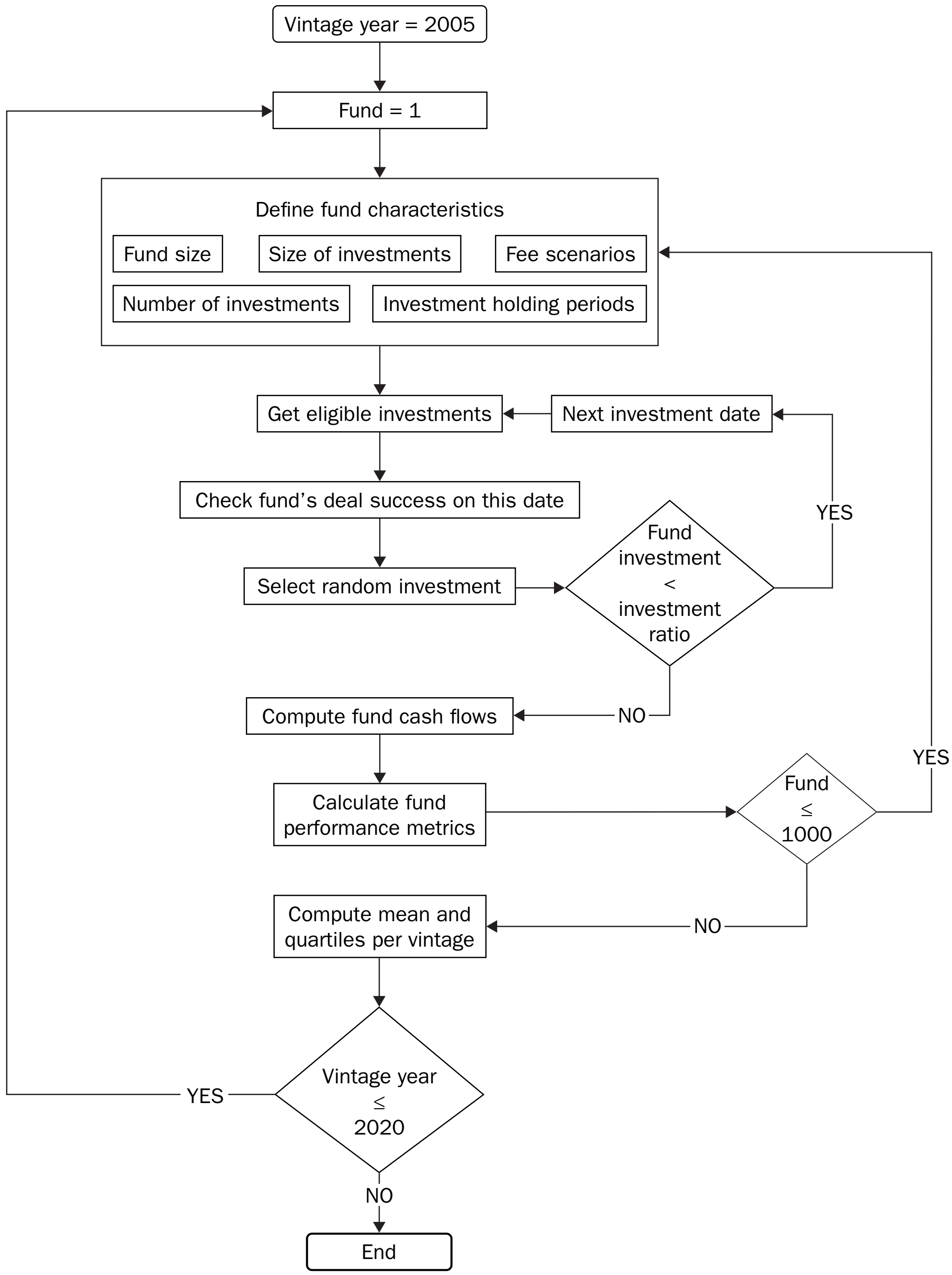
Scatterplot of InfraMetrics (1,000 obs.) and Preqin Net IRR Datasets, Quartile Boundaries, and Confidence Intervals ("whiskers") for the 2015 and 2018 Vintages

SOURCES: Preqin, EDHEC*infra*.

- *Number of investments in a fund*. A closed-end infrastructure fund typically invests in 5–20 deals, so we make an ex-ante assumption of a uniform distribution over this range. The final number of deals is also impacted by the market activity in any given investment year.
- *Holding period of an investment*. Holding periods typically depend on the market conditions, investment performance, and so on. However, after several rounds of consultations with industry participants, we have assumed a uniform distribution between four and eight years.
- *Deal success rate*. For any given investment year, we assume a deal success probability depending on market activity. This determines which funds are eligible to make an investment at any given time. These data are calibrated based on the historical number of deals/number of funds ratio. It can be seen that in crisis periods, there is less opportunity to make new deals, which leads to an increase in dry powder in some funds, for example, the deal activity had dropped by about 90% in the 2008–09 period.
- *Investment size*. We assume that capital is equally deployed (at the price given by prevailing NAV) to all the randomly selected companies in the fund.

EXHIBIT 59

Fund Simulation Algorithm (e.g., Vintage Year 2005)



SOURCE: infraMetrics.

- *Fees*. In closed-end fund structures, fees have several components and also various computation methods. In this solution, we pre-compute the net-of-fees performance metrics of all the funds using six different scenarios and allow our users to choose as per their needs. Performance fees are computed at the fund level and include a 100% catch-up provision for GPs. There is no second close, but this will be included in a future version of the tool.

Selection of Underlying Investments

EDHEC*infra* has collected the financial accounts of more than 700 companies since 2000. These includes the crucial information of dividends paid by an operating company to its equity investors. Furthermore, our asset pricing models allow us to value each of these companies in our universe on a quarterly or monthly basis. Translating these data points into fund terminology, we have historical information of NAV and distributions of hundreds of unlisted infrastructure companies in the 25 most active markets in the world, going back 20 years.

With this dataset, we shortlist the companies eligible for investment given the fund's strategy, vintage, and other characteristics. We also check whether the fund is eligible to make a deal on that investment date based on a deal success rate assumption. Out of the possible options, we then randomly invest in one company, which becomes unavailable for investment for the rest of the investment period. This process is followed until the fund has invested up to the investment ratio or the fund is abandoned.

Computing Fund Cash Flows

Every time a fund makes an investment, we draw down capital from the fund corresponding to the NAV of the underlying company multiplied by the investing funds stake. We also rescale any distributions paid back from the company and the NAV by the fund's stake. This gives us the cash-flows and NAV data for the fund's investment in any selected company.

Finally, we pool all the cash flows and NAV data at the investment level, to obtain quarterly fund cash flows and NAV gross of any fees.

$$\mathrm{DD}_t = \sum_n dd_t$$

$$D_t = \sum_n d_t$$

$$\mathrm{NAV}_t = \sum_n nav_t$$

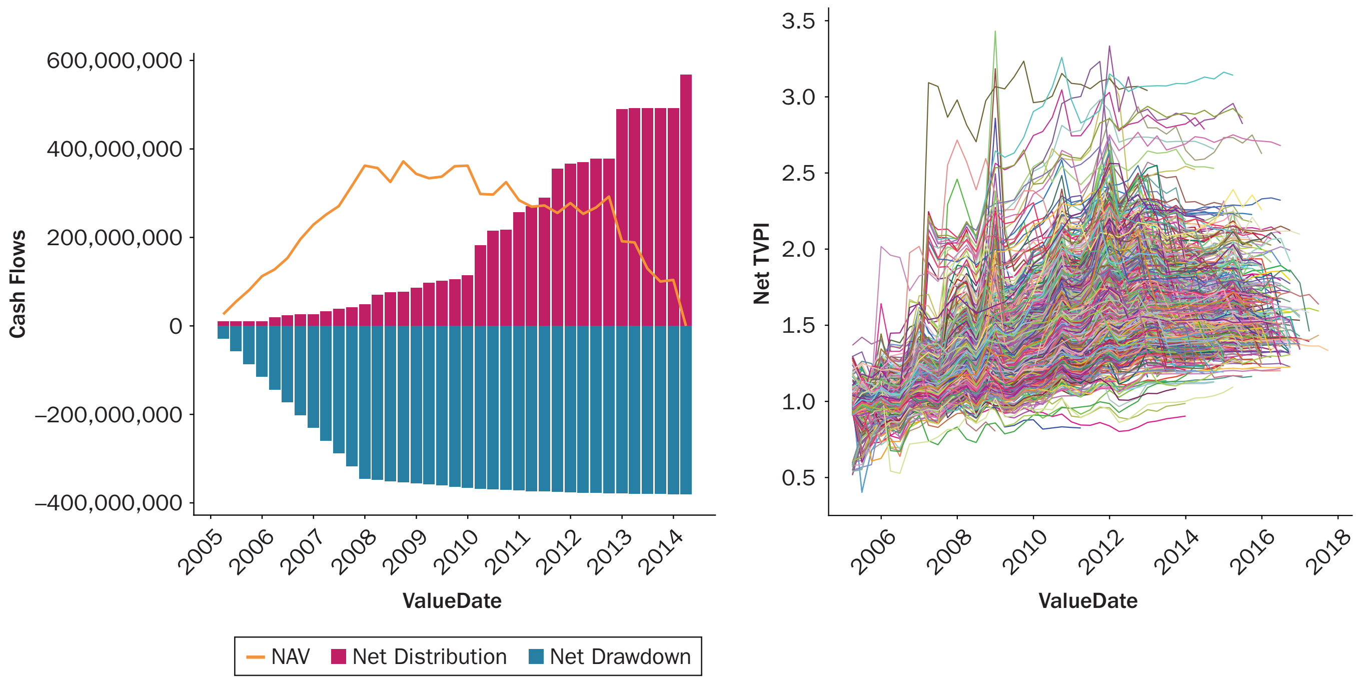
where dd_t, d_t, and nav_t are the drawdown, distribution, and net asset value at the investment level, respectively, at time t; n is the number of investments in the fund; DD_t, D_t, and NAV_t are the drawdown, distribution; and net asset value at the fund level; respectively; at time t.

We then apply multiple fee scenarios, as described earlier, to compute the fund level cash flows net of all fees. $\widehat{\mathrm{DD}}_t$ is the net drawdown from investors that includes the quarterly payment of management fees in addition to the capital drawn by underlying investments, and $\hat{\mathrm{D}}_t$ is the net distribution to the investors after the payment of performance fees to the manager.

Exhibit 60 shows the net-of-fees cash flows of a sample fund from the 2005 simulations. For the first few years of investment, the fund draws down capital as it continues to invest in underlying assets. During this period, NAV grows and there are limited distributions paid back to investors. Following this period, the fund starts to exit the investments resulting in increased distributions and gradual decrease in NAV, before it is fully liquidated. Exhibit 60 also shows all the possible paths that different 2005 vintage funds take in the simulation. There is a wide range of final total value paid in (TVPI) ranging anywhere from less than 1× to more than 2.5×. There are also some funds that invest in poor-performing assets and suffer up to 50% write-downs in the initial period.

EXHIBIT 60

Cash Flows of Sample Funds from All the Vintage 2005 Simulations



SOURCE: infraMetrics.

BENCHMARKING INFRASTRUCTURE FUND STRATEGIES

Private market funds often have unique characteristics, such as irregular timing of cash flows, size of those cash flows, and so on. Due to these, return calculations and benchmarking methodologies often differ from those used in public markets. Consequently, a number of fund-style metrics have been implemented in the Fund Strategy Analyser to give infrastructure investors an intuitive understanding of the performance reported for various infrastructure strategies and segments and enable them to use these results directly against the data reported by infrastructure investment fund managers.

Analyzing the performance of private funds from the point of view of LPs requires taking fees into account. iFSA returns metrics are both gross and net of fees. Indeed, fees can make a significant difference in the reported performance, particularly the fee drag of long holding periods or when portfolio distributes larger amount in earlier periods.

In this section, we cover the calculation methodology of various performance metrics and also describe some of the results for selected fund strategies.

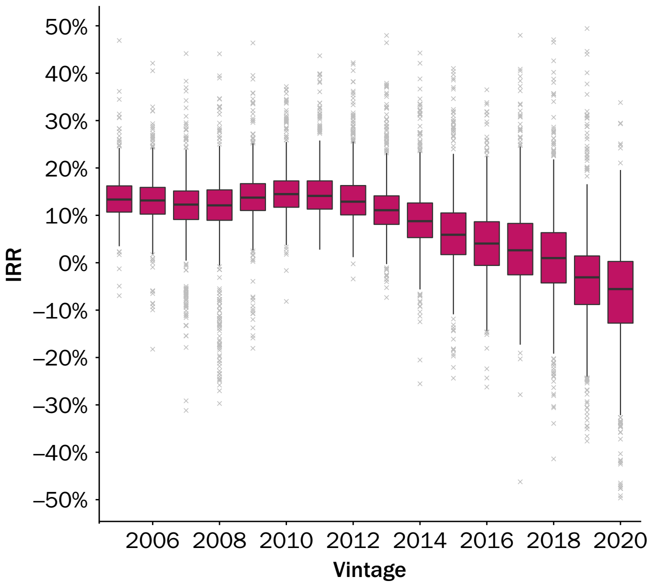
IRR

The internal rate of return is one of the most popular metrics used for closed-end funds. It is the rate at which the net present value of negative cash flow equals the net present value of positive cash flow.

$$NPV = \sum_{t=1}^{T} \frac{\left(\widehat{\mathrm{DD}}_t + \hat{D}_t\right)}{(1+IRR)^t} + \frac{\mathrm{NAV}_T}{(1+IRR)^T} = 0$$

EXHIBIT 61

Distribution of Fund IRR by Vintage Year for Global Infrastructure Strategy



SOURCE: infraMetrics.

It is a dollar-weighted calculation, which is considered most appropriate for assessing private closed-end fund managers because it holds the manager responsible for both the amount and timing of the investment, because the limited partners have no control over when the capital is called or distributed after the initial commitment.

The most direct way to benchmark a private fund is to compare its IRR against that of other funds in the same vintage year. Exhibit 61 shows the distribution of IRR by vintage years for global infrastructure funds using the following fee scenario: management fees of 1.5%, performance fees of 15%, and a hurdle rate of 8%.

Note that more mature vintages (2005–2012) generally have the higher returns (mean fund return is higher than 10%). There are also some very low return funds in the vintage years just preceding the financial crisis as a lot of managers could not deploy capital or invested in infrastructure assets that performed poorly either during or after the Global Financial Crisis. In more recent vintages (2017–2020), lower mean returns are due to the J-curve effect (the impact of fees is greater than that of the valuation uplift) as well as the impact of Covid-19 from 2020 onward.

We can also use quartile ranks to compare different segments of the infrastructure market. Exhibit 62 shows a comparison of IRR between Core and Core+ strategies by vintage year. We see that mature Core funds have an average net IRR of 10%, which is approximately 5% lower than the Core+ funds, a persistent trend throughout the vintage years.

TVPI

The total value to paid-in (TVPI) ratio reflects the valuation multiple (realized or expected) of an investment. It is calculated by dividing the fund's cumulative net distributions to the investors (after the performance fees) and residual value by the paid-in capital (includes drawdowns for investments and management fees).

$$\text{TVPI}_T = \frac{\left(\sum_{t=1}^{T} \hat{D}_t + \text{NAV}_T\right)}{\sum_{t=1}^{T} \widehat{\text{DD}}_t}$$

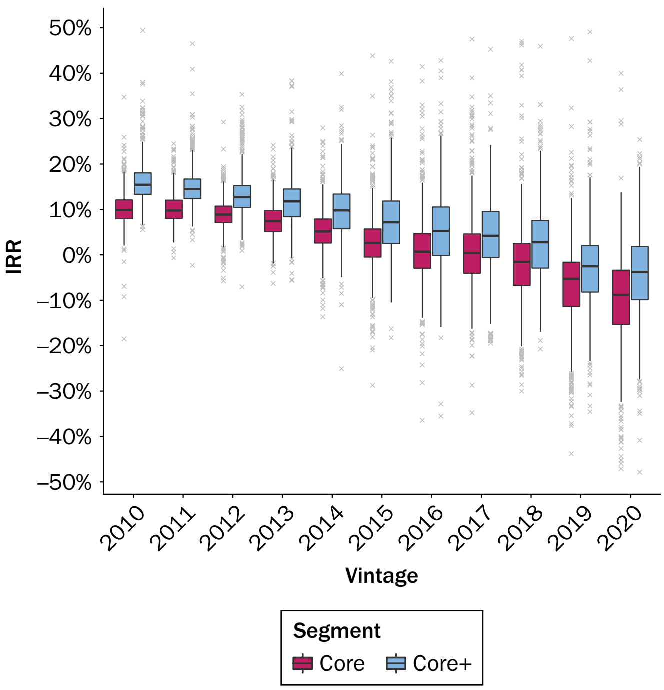
Multiples ignore the time value of money and offer a quick and readily digestible means of indicating the performance of a fund. Any multiple above 1× shows that the fund has returned (or would return) more than its initial investment to its investors.

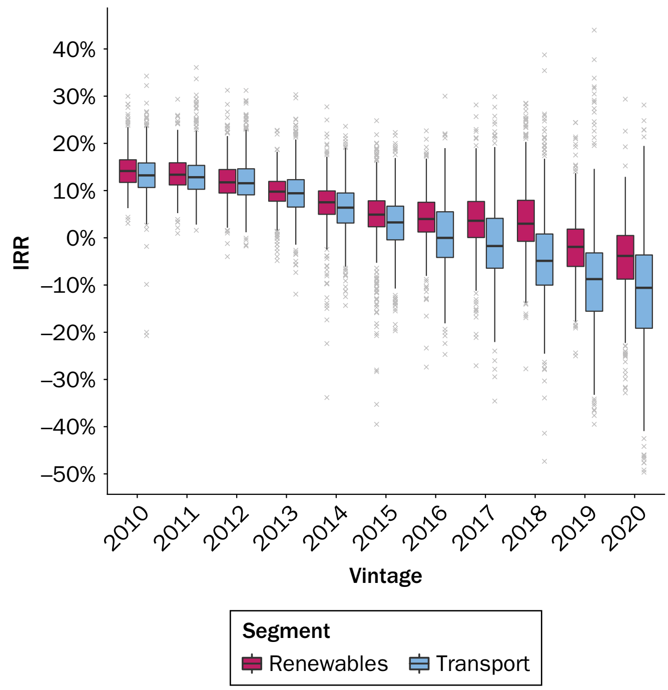
Exhibit 63 shows the distribution of TVPI by vintage year for global infrastructure funds. Note a similar trend as for fund IRRs, with the average TVPI of mature vintages at about 1.75×, implying that, in aggregate, funds returned 75% more than the initial investment over their full lifetime. The recent vintage year funds have an average net TVPI of a bit under 1×, indicating the effect of fees on the return and causing the J-curve effect.

The same approach also allows computing distributions to paid-in (DPI) ratios, residual value to paid-in (RVPI) ratios, K-S public market equivalents (Kaplan and Schoar 2005) and the funds' direct alpha (Gredil, Griffiths, and Stucke 2014).

EXHIBIT 62

Comparison of Fund IRR by Vintage Year in Core and Core+ Strategies and in the Renewables and Transport Sectors

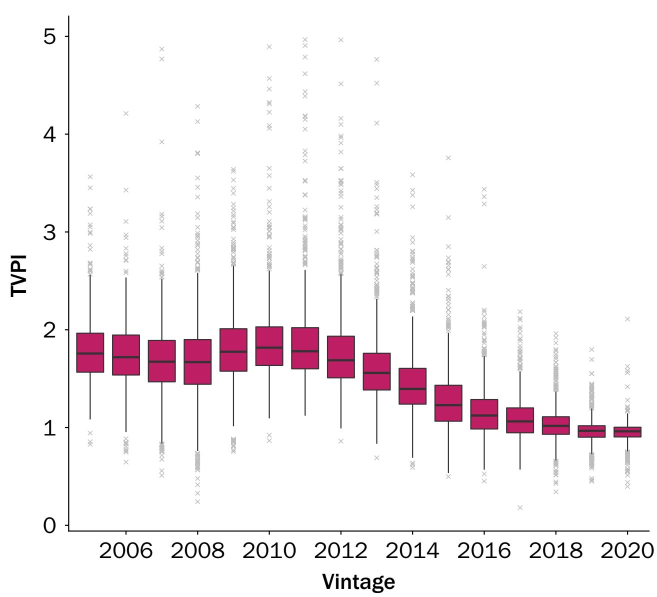




SOURCE: infraMetrics.

EXHIBIT 63

Distribution of Fund TVPI by Vintage Year for Global Infrastructure Strategy



SOURCE: infraMetrics.

APPENDIX

EXHIBIT A1

Test of the Autocorrelation (smoothing) of Total Returns in the Infra300 and Preqin Infrastructure Indices

	Infra300 Index	Preqin Unlisted Infrastructure Index
Autocorrelation	0.0201	0.39***
Ljung–Box test (p-value)	0.887	0.006

SOURCES: EDHEC*infra*, Preqin. The Ljung–Box test is a type of statistical test of whether any of a group of autocorrelations of a time series are different from zero. *** indicates statistical significance at the 1% confidence level.

EXHIBIT A2

Definition of Factor Exposure Buckets

Factor	Low	Medium	High
Leverage	≤70%	70%–90%	>90%
Size	≤200 million	200 million–1 billion	>1 billion
Profitability	≤6%	6%–12%	>12%
Investment	≤5%	5%–10%	>10%
Term spread	≤0.5%	0.5%–2%	>2%

EXHIBIT A3

Descriptive Statistics for the Factor Buckets

	Share of Universe	Mean Value	Median Value	Standard Deviation
High leverage	40%	97.5%	99.4%	3.2%
Low leverage	33%	48.7%	52.6%	17.1%
Mid leverage	28%	80.9%	82.2%	5.9%
High size (USD millions)	26%	4,447	2,394	5,425
Mid size (USD millions)	40%	476	443	206
Low size (USD millions)	35%	82	62	63
High profitability	29%	22.4%	17.7%	15.0%
Mid profitability	44%	8.6%	8.5%	1.6%
Low profitability	27%	2.2%	2.6%	4.4%
High investment	9%	19.0%	15.8%	8.0%
Mid investment	18%	6.9%	6.9%	1.2%
Low investment	74%	1.1%	0.4%	1.4%
Merchant	24%	NA	NA	NA
Not Merchant	76%	NA	NA	NA

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