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# EDHEC
# Research Insights

## EDHEC-RISK DAYS SPECIAL

EDHEC-RISK Institute

# Are infrastructure firms different from other firms? Evidence from 15 years of UK data

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In a new paper drawn from the work of the EDHEC*infra*/Meridiam/Campbell Lutyens research chair on the characteristics of privately-held infrastructure investments, we conduct the first large-scale empirical analysis of the characteristics of cash flows in private infrastructure firms from the perspective of equity owners.

The paper addresses two main questions: do infrastructure firms correspond to a different business model than the rest of the firms active in the economy? And do infrastructure firms exhibit different equity payout behaviour from other firms?

## Are infrastructure firms different?

Our motivation springs from what we have called the known "infrastructure investment narrative" (Blanc-Brude [2013]), according to which investors in infrastructure can look forward to low correlation of returns with the business cycle (hence potentially better diversification), as well as lower sensitivity to economic shocks (implying better drawdown protection).

Empirical evidence for or against such hypotheses has so far been very limited. This study is a first iteration in a series of research papers using a new, global database of infrastructure investment data, and that aims to measure the relative financial performance of such investments through the creation of fully-fledged benchmarks or reference portfolios. ►

◄ In this first article, we address the first dimension of this question with a study of the dynamics of cash flows to private equity holders in infrastructure investments.[1]

## A unique new database

We are interested in the volatility of revenues in infrastructure firms as well as their relative correlation with macro factors such as GDP growth, inflation or market factors. We are also interested in the equity payout behaviour of infrastructure firms, relative to the business cycle as well as to other private and public firms in the UK.

This study makes use of the EDHEC*infra* infrastructure database: a collection of infrastructure cash flows provided by infrastructure investors and creditors, as well as manually collected annual reports. To date, the database covers more than 500 individual sets of infrastructure assets over 10 different countries, making it the most comprehensive database of infrastructure cash flows currently available. For this study, we focus on firms situated solely in the UK.

Our infrastructure cash flow data correspond to a sample of UK firms identified as being either special purpose vehicles created in the context of the financing of a specific infrastructure project, or a firm conducting specific infrastructure-related activities (such as a port or an airport) or a regulated utility.

The detailed accounts for each firm were obtained from infrastructure investors, lenders and Companies House.[2] They were then analysed in order to classify each firm into one of three groups: contracted, merchant and regulated infrastructure (see Blanc-Brude [2013] for a detailed discussion of these different infrastructure business models).

Contracted infrastructure firms are not exposed to end-user demand. In the UK, the Private Finance Initiative (PFI) is the prime example of such projects. Under the PFI scheme, infrastructure investors have delivered a broad range of infrastructure, including schools, hospitals and prisons. Such projects generally spring from a long-term contract for the provision of an infrastructure asset or service between the public sector and private entity (the firm), by which the public sector commits to paying a regular income to the firm as long as the relevant infrastructure services are delivered according to a pre-agreed specification.

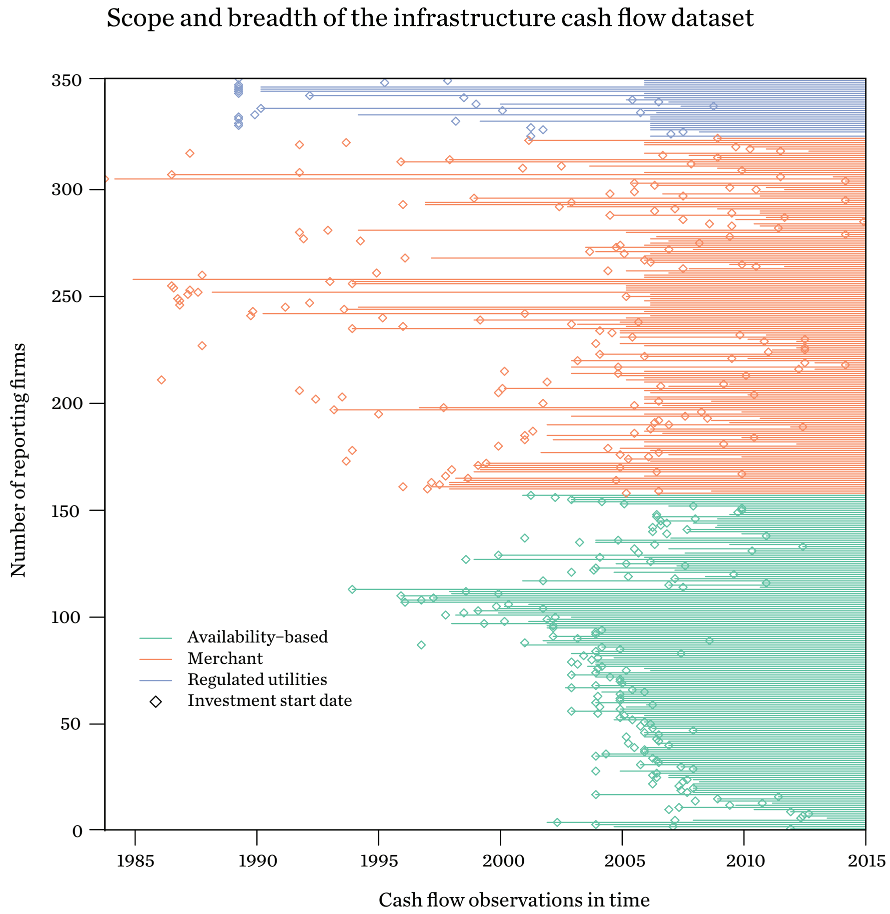
Merchant infrastructure firms in comparison are exposed to some degree of market risk. Such infrastructure projects can have long-term contracts supporting their revenue in the form of a power purchase agreement (PPA) or take-or-pay contract, but such contracts typically cover only part of the project's capacity or lifespan. Other merchant infrastructure firms are fully exposed to end user demand and market prices; these include airports or toll roads.

Finally, regulated infrastructure firms are typically natural monopolies involved in the provision of essential services, such as sewage treatment, water distribution or power transmission. Such companies are regulated in the UK by independent agencies such as Ofwat or Ofgem.

The data span information from the early 1990s to 2015, as illustrated in figure 1.

We focus on UK data because they are

**1. Number and time frame of reporting firms in the EDHEC*infra* database**
Each line represents a time series of cash flow data



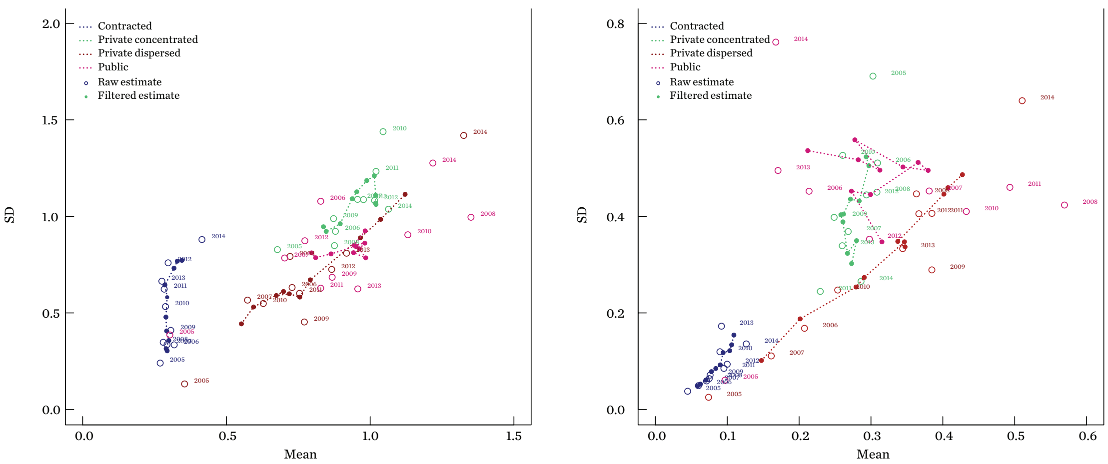

the largest, longest and most coherent set of infrastructure cash flow data available at this time, with the added advantage of corresponding to a single currency and regulatory environment, thus limiting the need to control for these dimensions in the analysis. Starting from UK infrastructure firms, we can also build robust control groups of non-infrastructure firms, with which to compare the data.

## Controlling for the different aspects of firm behaviour

Our sample of several hundred infrastructure firms is compared with a 'matched sample' of non-infrastructure UK firms, both private and listed.

Indeed, while public market data has sometimes been used as a proxy of private infrastructure firms, recent research has shown that private firms exhibit significant differences in terms of size, capital structure and dividend policy: private firms tend to be smaller than listed firms, they exhibit higher leverage, making their profits more sensitive to fluctuations in performance, they have different dividend payout policies than listed firms and are less inclined to smooth their dividends in the presence of profit shocks. Moreover, differences in ownership structure in private firms are also shown to explain how much they differ from public firms (see Brav [2009]; Michaely and Roberts [2012] for a detailed study).

**2. Estimates of the mean and variance parameters of the unit revenues and profits in calendar time for contracted infrastructure and matched control firms**




1 See Blanc-Brude and Hasan (2015) for a theoretical approach to discount rate estimation in private infrastructure assets.

2 The UK company register.

To control for the effect of ownership structure and corporate governance on the behaviour of infrastructure firms, we build three control groups for each of our infrastructure firm types: private firms with concentrated ownership, private firms with dispersed ownership and public (listed) firms.

Each of these three control groups is 'matched' to the infrastructure firm of a given type using a 'nearest neighbour' methodology for total asset size, leverage and profitability and an exact match for "investment year" – ie, the number of years since the creation of the firm.

Hence, we test the difference in revenue and profit volatility as well as in payout ratio level and volatility of infrastructure investment using nine different tests: three types of infrastructure firms (contracted, merchant and utilities) against three types of corporate governance (private concentrated, private dispersed, public), while controlling for individual firm characteristics (size, leverage, profitability).

Such tests go a long way in addressing the matter of the 'uniqueness' of infrastructure investments. Indeed, if firm characteristics and corporate governance can be expected to explain in large part the business model and dividend payout behaviour of the firm, then for infrastructure to be unique and not easily replicable by combining other types of investments, it must correspond to a unique combination of firm characteristics and corporate governance.

Likewise, the revenues of infrastructure firms can only create a unique form of exposure to economic factors if their business model is not an easily replicable combination of the business models of other firms.

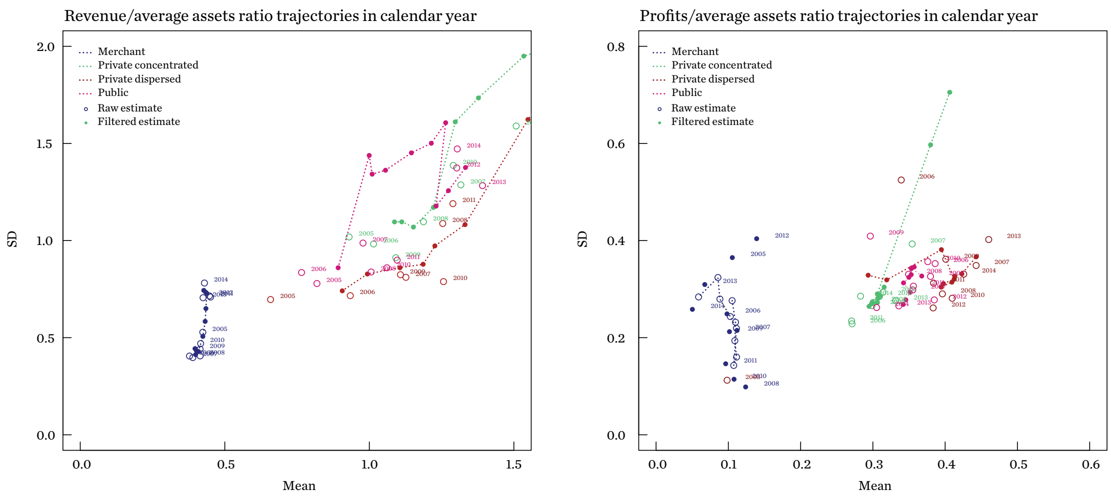
## Infrastructure is unique

We find that, as far as UK data show over the past 15 years, infrastructure firms are indeed truly unique: that is, after controlling for size, leverage and profitability, as well as the impact of the investment 'lifecycle', infrastructure firms exhibit lower revenue volatility and higher payout ratios (dividends to revenue) than any other group of private or public firms:

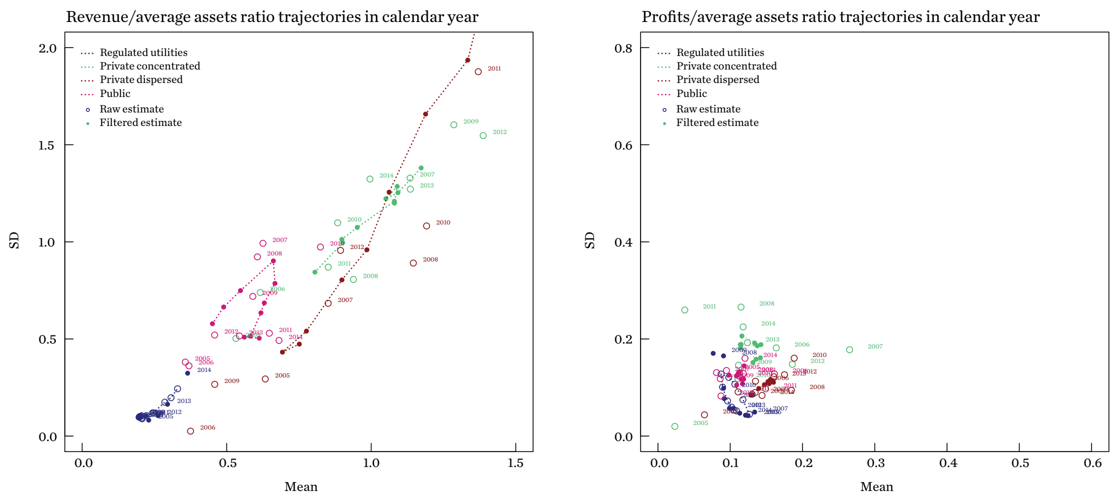
- Compared to their control groups, infrastructure firms have lower revenues and profits per dollar invested, highlighting the capital-intensive and long-term nature of their business.
- They are also characterised by significantly lower volatility of revenues and profits compared to their matched control groups, both at the aggregate level (all periods) and at each point in investment and calendar time.
- Infrastructure firms exhibit a very dynamic lifecycle compared to control groups, with unit revenues and profits evolving by an order of magnitude over the investment cycle.
- Regression analysis shows that infrastructure firms in general tend to be less sensitive to changes in revenues, profits, leverage or size:
  - More profitable firms tend to have higher revenues but this effect tends to be much smaller for infrastructure firms;
  - Firms with higher revenues tend to have higher profits; this effect tends to be much smaller than for control groups for contracted and merchant infrastructure firms, but it is much larger than for control groups in the case of regulated infrastructure firms;
  - Firms with higher leverage tend to have relatively lower revenues, but again this effect impacts infrastructure firms less and is not statistically significant for merchant infrastructure; such firms also tend to have relatively lower profits, but this effect is smaller for contracted infrastructure firms. However, the same effect is greater in merchant infrastructure than in the control groups and it is not significant in regulated utilities.
  - Larger firms tend to have lower revenues, but only in the case of infrastructure and private firms with concentrated ownership, and the effect is much larger for non-infrastructure firms. Larger firms, including infrastructure firms, also tend to have lower profits, but the effect is again much more muted than for control groups and it is not significant for merchant infrastructure.
- Regression analyses also show that different proxies of the 'business cycle' have a strong statistical effect on profits and revenues in non-infrastructure firms, but that this effect is absent in the different infrastructure firm test groups – ie, infrastructure firm revenues and profits are not correlated with the business cycle. Instead, the effect of the investment lifecycle is what explains the change in unit revenues and profits of infrastructure firms.
- The probability of positive equity payouts in infrastructure firms is significantly higher than in any of the control groups, reaching as high as 80% after investment year 10 in contracted infrastructure and the 60–70% range in merchant and regulated infrastructure. Control groups never reach a (conditional) probability of payout higher than 40%.
- Equity payout ratios in infrastructure firms are considerably higher than in control groups, reaching expected values of more than 10% of revenues when matched controls never pay out more than 5% of revenues.

Thus, as illustrated in figures 2 to 4, we find that infrastructure firms exhibit a truly unique business model compared to a large control group of public and private firms. We also report that the 'contracted' type of infrastructure investments is so unique that it cannot ►

### 3. Estimates of the mean and variance parameters of the unit revenues and profits in calendar time for merchant infrastructure and matched control firms




### 4. Estimates of the mean and variance parameters of the unit revenues and profits in calendar time for regulated infrastructure and matched control firms




*"Infrastructure firms are indeed truly unique: that is, after controlling for size, leverage and profitability, as well as the impact of the investment 'lifecycle', infrastructure firms exhibit lower revenue volatility and higher payout ratios (dividends to revenue) than any other group of private or public firms"*

successfully be matched to private non-infrastructure firms.

We find that the equity payout behaviour of infrastructure firms is very different from that of other firms: infrastructure firms pay off more often and in significantly higher proportions of their revenues than other firms once the lifecycle of the firm is taken into account.

We conclude that infrastructure firms have significantly lower volatility of revenues and profits and pay a much higher proportion of their revenues much more frequently to their owners, independent of the business cycle.

Another significant result is that each of the three types of infrastructure firms that we define (according to a typology we first described in Blanc-Brude [2013]) corresponds to a unique business model as well – albeit more alike among themselves when compared to the rest of the corporate universe, contracted, merchant and regulated infrastructure firms have their own coherent cash flow dynamic.

*The research from which this article was drawn was produced as part of the Meridiam Infrastructure/Campbell Lutyens Infrastructure Equity Investment Management and Benchmarking research chair at EDHECinfra.*

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# The cash flow dynamics of private infrastructure project debt:
## New results using a new infrastructure cash flow database

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In a new paper drawn from the EDHEC*infra*/NATIXIS research chair on infrastructure private debt, we document the statistical characteristics of debt service cover ratios (DSCRs), which measure the amount of cash available to make the current period's debt service in private infrastructure debt.

Indeed, robust and well-calibrated models of DSCR dynamics are an important part of the objective to create investment benchmarks of private infrastructure debt, as described in the EDHEC*infra* roadmap (Blanc-Brude [2014]).

In a previous paper (Blanc-Brude, Hasan and Ismail [2014]), we showed that debt service cover ratios can play a pivotal role in the modelling of credit risk in fixed income infrastructure investments because DSCRs provide us with:

- An unambiguous definition of the point of hard default (default of payment) – ie, $DSCR = 1$, and
- An equally unambiguous definition of key technical default covenants – ie, $DSCR = 1.x$ – while both types of default events create significant embedded options for creditors following a credit event.
- Moreover, knowledge of DSCR dynamics is sufficient to estimate the firm's distance to default (DD), which is the workhorse of the so-called Merton or structural credit risk model.
- DSCR dynamics can also be combined with future debt service to compute the expected value and volatility of the firm's future free cash flow, which is instrumental in measuring enterprise value in the case of infrastructure projects, since they derive their value almost entirely from future operating cash flows.

For this purpose, we collect a large sample of realised DSCR observations across a range of infrastructure projects spanning more than 15 years, representing the largest such sample available for research to date, and conduct a series of statistical tests and analyses to establish the most adequate approach to modelling and predicting future DSCR levels and volatility.

Using these results, we build a model of the conditional probability distribution of DSCRs at each point in the life of infrastructure projects.

### A combination of empirical analysis and statistical modelling is necessary

DSCRs in infrastructure project finance are mostly undocumented both in industry and academic empirical literature. While DSCR information is routinely collected by the creditors of infrastructure projects, this type of data is typically confidential and not available in large datasets.

From such data paucity, especially in time series, it follows that empirical observations alone are not sufficient to document the expected behaviour of infrastructure project cash flows over their entire investment life, and a combination of ex ante modelling and empirical observations is necessary.

Finally, private infrastructure investment tends to be characterised by very large individual investments, almost necessarily leading to poorly diversified portfolios. This suggests that assuming the mean-reversion of investors' infrastructure debt portfolios may not be realistic and that idiosyncratic risk should be taken into account.

In particular, individual infrastructure investments can exhibit significant 'path dependency' and investors cannot necessarily take for granted the notion that they are exposed to the 'median infrastructure project'.

For both sets of reasons (data limitations and the importance of firm-specific risk), an adequate model of the DSCR should be able to capture conditional dynamics and explicitly integrate the different credit 'states' that an infrastructure project might go through.

This can help both to learn from the data as and when it becomes available, and to take into account the path-dependency of each instrument when estimating future cash flows, instead of assuming a reversion to the population mean.

Current academic and industry literature is static in nature and relies on 'reduced form' credit models, which are likely to be biased given the nature of empirical data available and, in the current state of empirical knowledge, can only address a limited number of dimensions of private infrastructure debt investment: the historical frequency of default events, and to some extent, average recovery rates.

For these reasons, in our research we endeavour to better document the dynamics of DSCRs in infrastructure project finance and build a model of DSCR dynamics using Bayesian inference to describe credit state transitions and to estimate the mean and variance of the DSCR in each state and at each point in an instrument's life. This allows better prediction of defaults, conditional on the actual trajectory of individual investments or groups of projects. The ability to predict cash flows and their volatility is then instrumental in the implementation of the private infrastructure debt valuation model defined in Blanc-Brude, Hasan and Ismail (2014).

## Dividing infrastructure investments into groups defined by their 'business model'

In Blanc-Brude, Hasan and Ismail (2014), we described two generic and intuitive types of infrastructure project companies and called them 'contracted' and 'merchant'.

This distinction was informed by the casual observation that the financial structure of infrastructure project finance vehicles is often such that it requires, at the onset, either a rising or a flat 'base case' DSCR profile.

A rising base case DSCR profile then implies increasing volatility of $DSCR_t$. That is, creditors would demand a higher DSCR in the future to protect themselves against rising expected volatility of the cash flows available for debt service (CFADS). Such projects would also have longer 'tails'[1] and exhibit between 70% and 80% of initial senior leverage. We argued that such structuring decisions signalled infrastructure projects that were exposed to commercial risks, such as a power plants selling electricity at market prices, and referred to these projects as merchant infrastructure.

Conversely, we argued that the decision to structure a project while requiring a lower and flatter base case DSCR profile implied the expectation of lower and constant conditional volatility of cash flows. We observed that projects with little to no market risk are financed with such a flat DSCR base case and also have shorter tails and a higher level of senior leverage, usually around 90%. Examples of these projects include social infrastructure projects, such as schools or hospitals that receive a fixed payment from the public sector, or energy projects that benefit from a long-term 'take-or-pay' purchase agreement. We called these projects contracted infrastructure.

In our research, we endeavour to determine statistically whether realised DSCR dynamics fall into categories determined by the distinctions made above between contracted and merchant infrastructure, as well as exogenous conditions at the time of financing and when the data is observed. We then use our results to design a model of DSCR dynamics.

## The largest sample of DSCR data available for research to date

Our dataset of realised DSCRs is built using data manually collected and verified from the audited statements of accounts of several hundred project companies, as well as DSCR data reported by private contributors.

We hand-collected 15 years of realised DSCR data for more than 200 projects in Europe and the US covering our two broad categories of projects (those receiving contracted income and those exposed to merchant or commercial risks), in seven sectors, from the early 1990s to 2015. Our initial analysis of the data reveals some important points that confirm our intuition: the average credit risk profile of infrastructure projects can be usefully captured by categorising instruments into broad groups or families of underlying 'business models'.

The two groups correspond to two distinctive DSCR processes, with statistically different mean and variance parameters and following different project time dynamics. We also find, as intuition predicts, that contracted infrastructure DSCRs in the cross section are much less affected by macro-variables or the business cycle than merchant projects.

We confirm our hypothesis that the DSCR profile of an infrastructure project is strongly related to the firm's total business risk, and show that more highly leveraged projects achieve lower levels of realised DSCR volatility – ie, in project finance high leverage signals low asset risk, as initially argued by Esty (2003).

That said, while descriptive statistics and linear regression models provide some insights about the determinants of the DSCRs, they fail to capture DSCR dynamics in full. Indeed, we find that the DSCR profiles of individual projects and families of projects are highly non-linear, auto-regressive and heteroskedastic (variance is not constant).

Hence, a more advanced model that can capture these dynamics is needed.

## Tracking the 'coordinates' of the DSCR distribution in the mean-variance state-space

If the $DSCR_t$ is serially correlated and can change profile during the investment lifecycle of infrastructure projects, the ex post trajectory of individual projects could in principle correspond to any combination of high/low expected value $E(DSCR_t)$ and high/low volatility $\sigma^2 DSCR_t$. The DSCR of populations of projects would equally reflect the weighted trajectory of their constituents in a $DSCR_t$ mean/variance 'plane'.

Numerous models exist that aim to determine the position of a dynamic system and, based on the latest round of observations, to predict where it will be positioned in future periods. Such systems are frequently used in robotics, aero-spatial and chemistry applications. In our research, we apply such approaches to estimate the position of a given infrastructure project in a mean/volatility DSCR plane at a given point in time, and to predict its position, its DSCR mean and variance 'coordinates' so to speak, in the following periods.

In the descriptive part of our analysis of the data, we show that realised DSCRs can be fitted to a lognormal process up to their 90th and 85th quantiles for contracted and merchant projects, respectively, at each point in their lifecycle, which allows us to develop an easily tractable model of parameter inference.

Hence, we propose a two-step modelling strategy combining a three-state model corresponding to break up points in the otherwise lognormal dynamics of the DSCR, with a filtering model to infer the values of the lognormal process parameters (its 'coordinates') in the state in which the DSCR is indeed lognormal.

## Three-state transition probabilities

The DSCR process is assumed to occur in any one of three states at time $t$: a risky state (R) in which it is indeed an autoregressive lognormal process, a default state (D) defined by a threshold corresponding to $DSCR_t = 1$ in which the DSCR process stops until it emerges from default; and a safe state (S), corresponding to high realised values above the 'good-lognormal-fit' quantile, in which case, as long as the DSCR stays in that state, the project debt is considered risk-free.

Hence, once a project's DSCR breaches the hard default threshold represented by $DSCR_t = 1$, it enters the default state, which it may or may not leave after a number of periods. In this state, creditors can take over the firm and optimise the value of exercising this option depending on the size of their exit costs and of restructuring costs. They may decide to waive the event of default or engage in negotiations with the project sponsor in order to restructure the firm and its debt, or indeed take over the firm and seek another sponsor (see Blanc-Brude, Hasan and Ismail [2014]).

Hence, the firm may transit out of the default state (into the risky state) with some probability (say, $\pi_{dr}$) at the next period, or stay in this state and again transit out of default at the next period, etc.

In this state, the DSCR process effectively stops (in most cases, there is no debt service), hence estimating its mean and variance is irrelevant since the project is already in default.

In the safe state, on the contrary, the realised DSCR is so high that no matter how volatile the process might be, from a senior creditor perspective, the probability of default is not significantly different from zero. The debt is (conditionally) risk-free. As before, in expectation at time $t$, an infrastructure project may transit in and out of the safe state at each point in the future, with some probability (say, $\pi_{sr}$).

In this state, estimating the parameters of the DSCR distribution, in particular estimating its variance, is also irrelevant.

Finally, in between the default and safe states, a project's DSCR may take values between 1 and some higher threshold $\overline{DSCR}$. From this state, it may either stay in the risky state at the next period, or transit out of it into the state of default 'D' or the safe state 'S', both described above.

In this state, we know from our empirical results that if the upper threshold is set at the 85th/90th quantile of our DSCR sample, the data follows a lognormal process, the parameters of which (position and scale) have to be estimated.

Formally, this set-up amounts to a relatively simple model of conditional state transition probabilities, which can be set in terms of a series of binomial draws and calibrated using Bayesian inference given some prior knowledge (eg, we know from credit rating studies that projects tend to stay in default for 2.3 years) and counting the number of projects crossing the different state thresholds, conditional on which state they are in at the previous period.

The combination of the conditional probabilities of switching state at each point in time is then combined into the probability of being in any given state at time .

For contracted projects the probability of being in the risky state is much higher compared to the probability of being in the other two states – ie, contracted projects are more likely to stay in the 'normal' risky state.

For merchant projects, the probability of being in the risky state is lower, while the probabilities of being in the default and safe states are higher compared to the corresponding probabilities for contracted projects. Thus, merchant projects are found to have more diverse DSCR trajectories in state space, and each state is less persistent (stable).

This result confirms that path dependency can be an important dimension of infrastructure investment insofar as assets are more or less heterogeneous and it can be difficult to fully diversify very large and bulky assets. For instance, our results suggest that contracted infrastructure is more homogenous than ►

1 The amount of time between the original loan maturity and the end of the project's life, thus allowing higher recovery rates in the event of restructuring.

◄ merchant projects, which are more likely to follow paths that diverge strongly from the mean of the population.

## Group and individual DSCR trajectories

To determine the value of the lognormal process parameters in the 'risky' state discussed above, we propose to use a straightforward implementation of so-called particle filtering models to infer the parameter values of the DSCR's lognormal process in the risky state – ie, the state in which documenting and tracking the volatility of the DSCR really matters, because it is a direct measure of credit risk.

Filtering models are a form of signal processing and aim to arrive at some best estimate of the value of a system, given some limited and possibly noisy measurements of that system's behaviour. Given our modelling objectives to accommodate small samples, and to avoid assuming static values for the distribution parameters, we must be able to revise any existing parameter estimates once new data becomes available. This process is best estimated iteratively using Bayesian inference techniques described in detail in our paper.

We show that such a framework allows the dynamics of DSCR to be derived in well defined groups of projects as well as individual projects, including tracking the individual DSCR 'path' followed by investments that do not necessarily correspond to the median infrastructure project.

The estimated dynamics of the DSCR process in contracted and merchant projects is shown in figure 1, which describes the change in density of the DSCR process in investment time, and figure 2, which describes the trajectory of the DSCR state in the mean/standard deviation plane.

From such results, certain credit risk conclusions are immediately available, such as the expected default frequency for hard defaults, but also any level of technical default ($DSCR_t$ = 1.*x*) as shown in figure 3.

These results allow us to characterise the behaviour of groups of infrastructure projects which exhibit reasonably homogeneous dynamics; however, we know that highly idiosyncratic trajectories and path dependency should be a point of interest in a context where diversification is difficult to achieve in full.

Hence, we also show that the ability to infer both the expected value and the volatility of the DSCR process allows us to take a much more informed view on the credit risk of projects that substantially deviate from their base case.

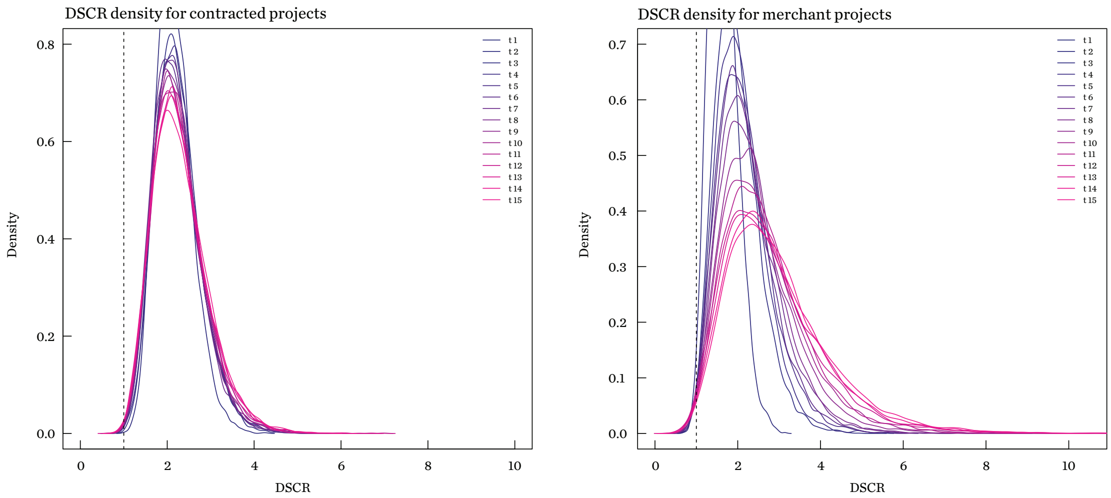
For instance, consider an infrastructure project that follows an oft-observed trajectory: while it remains in the risky state throughout its life, it starts off with a relatively high DSCR, implying a merchant-type structure with relatively high DSCR volatility, but later on undergoes a large downward shift in its realised DSCR level – eg, as the result of a negative demand shock, while its DSCR realised volatility from that point onwards also decreases markedly.

A concrete case of such a trajectory could be a toll road experiencing significant loss of traffic after an economic recession, but for which the residual 'baseload' traffic is much less volatile than before the shock, and still sufficiently high to keep the DSCR out of the default state.

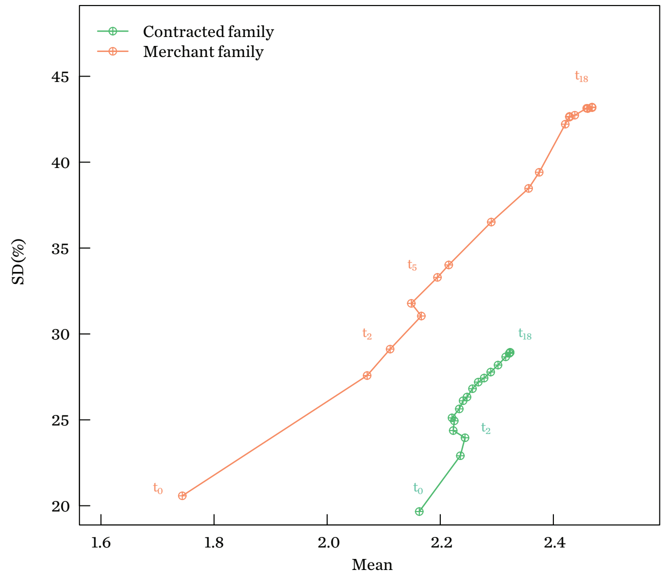
Such a project would not be adequately captured by the mean DSCR process of its original family, even though this was the best available starting point to anticipate its behaviour at $t_0$.

In this illustration, we know the 'true' underlying DSCR process that is otherwise unobservable, and how it is impacted by the negative demand shock. The point of the example is to

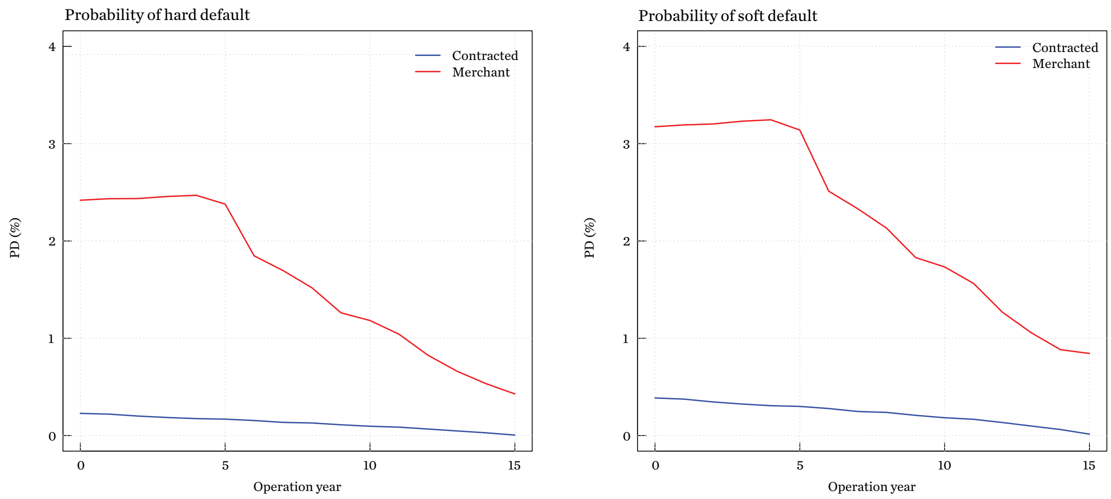
### 1. DSCR densities for contracted and merchant families




### 2. DSCR trajectories in the state ($m$, $\sigma$) plane, for both families




### 3. Probabilities of hard and soft defaults for contracted and merchant families, computed as the probabilities of $DSCR_t$ falling below 1.0 and 1.5 respectively



show that as we observe realised information for individual investments, our estimates of the true process can quickly converge to the true value and then track it as it evolves during the life of the investment.

Figure 4 shows the filtered DSCR mean and standard deviation along with the realised DSCR values and the true standard deviation of the project. As soon as the DSCR diverges from its original trajectory the model takes this new information into account, and if the divergence persists, future estimates of the expected value of $DSCR_t$ are updated accordingly. Likewise, initial estimates of the volatility of $DSCR_t$ on the right panel of figure 4 are corrected as information about the lower realised volatility becomes integrated into each posterior value.

In our example, the ability to revise the DSCR dynamics of individual projects directly leads to the revision of their risk metrics, of the probabilities of dividend lockup, soft default, and hard default, respectively, and suggests that the negative jump in the DSCR, combined with lower realised volatility of DSCR, has no noticeable effect on the project's probability of hard default, a negligible impact on probability of soft default, but a noticeable impact on the probability of a dividend lockup.

## Towards large samples of DSCR data

Our research shows that a powerful statistical model of credit ratio dynamics can be developed, which can provide important insights for the valuation of private credit instruments in infrastructure project finance.

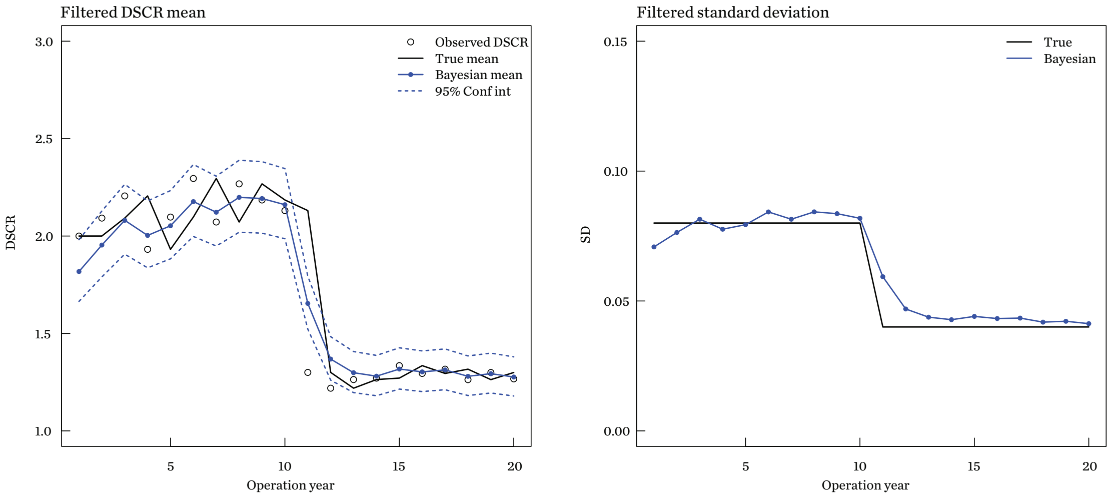
It also militates for standardising the data collection and computation of items such as the debt service cover ratio in infrastructure project finance, and for pooling this information in central repositories where it can be used to create the investment metrics that investors need (and regulators require) to be able to invest in large, illiquid assets such as private infrastructure project debt.

Such analyses will be further developed as new data is collected and standardised to improve our ability to track the DSCR path of individual and groups of infrastructure projects, and increase the number of control variables and the robustness of parameter estimates.

EDHEC is committed to the continued development of this research agenda, both in terms of data collection and technological development.

*The research from which this article was drawn was produced as part of the Natixis Investment and Governance Characteristics of Infrastructure Debt Instruments research chair at EDHECinfra.*

### 4. Filtered DSCR quantiles and standard deviation for a single project experiencing a negative shock

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