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The Pricing of Private Infrastructure Debt

A Dynamic Approach and Comparison with Corporate Debt

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Executive Summary

Executive Summary

This paper examines the drivers and evolution of credit spreads in private infrastructure debt. We ask two main questions:

1. Which factors explain private infrastructure credit spreads (and discount rates) and how do they evolve over time?
2. Are infrastructure project finance spreads and infrastructure corporate spreads driven by common factors?

We show that **common risk factors partly explain both infrastructure and corporate debt spreads**. However, the pricing of these factors differs, sometimes considerably, between the two types of private-debt instruments.

We also find that **private infrastructure debt has been 'fairly' priced even after the 2008 credit crisis**. That is because spread levels are well-explained by the evolution of systematic risk factor premia and, taking these into account, current spreads are only about 29bps above their pre-2008 level. In other words, taking into account the level of risk (factor loadings) in the investible universe and the price of risk (risk factor premia) over the past 20 years, we only find a small 'unexplained' increase in the average level of credit spreads, whereas absolute spread levels are twice as high today as they were before 2008.

A Better Approach to Estimating Market Credit Spreads

The main difficulty facing econometric research on the pricing of infrastructure debt is the paucity and biases of observable data. Secondary transactions are very rare and usually not instrument-level sales. Still, a large number of primary transactions (at the time of origination) can be observed.

Nevertheless, this data is biased: origination follows procurement and industrial trends, that is, it tends to cluster in time and space when and where governments procure new infrastructure using a privately financed model. The simple observation of credit spreads over time does not take into account the underlying market for private infrastructure debt to which investors are exposed.

Primary spread data is also autocorrelated, that is, what best explains the spread for a given infrastructure borrower is not its characteristics but the spread of the previous transaction.

To address these issues and estimate the effect of individual risk factors on spreads, we proceed in two steps:

1. We estimate the evolution over time of the risk-factor premia and determine their unbiased effects on spreads over time.
2. We use the EDHEC*infra* universe, a representative sample of existing infrastructure borrowers – as opposed to the biased sample of new borrowers in the primary market – to apply the risk premia estimated in the first step to the "factor loadings" (the characteristics) of this better sample, thus computing a current market spread for each one, at each point in time.

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Using a *factor model* in combination with a representative sample of investable assets can correct the bias and paucity of available data: as long as such factors can be documented in a robust and *unbiased* manner, they can be used to assess the fair value of private-debt investments over time, whether they are traded or not.

What Factors Explain Infrastructure Credit Spreads?

Our results show how the aftermath of the 2008 crisis changed and sometimes removed well-established relationships between certain factors and the cost of corporate and infrastructure debt: the impact of base rates on loan pricing disappeared, structural differences between markets vanished, and certain sectors, like roads, experienced a continued increase in the price of long-term private financing.

Our results are statistically robust and explain the data well. We show that infrastructure and corporate credit spreads are determined by a combination of common factors that can be grouped into four categories:

- **Market Trend**: the largest effect driving credit spreads in both infrastructure and corporate debt is a time-varying trend factor which captures the state of the credit market over time. This effect is not explained by loan or borrower characteristics. In the case of infrastructure debt, this effect is roughly constant but exhibits "regime shifts", especially 2008 (up) and 2014 (down). In the case of corporate debt, it is an upward trend also exhibiting jumps in 2008 and 2012. We find a 29bps increase of infrastructure spreads compared to pre-crisis levels, down from 75bps at the height of the credit crisis, indicating a degree of mean-reversion.
- **Credit Risk** only explains part of the level of credit spreads.
  - We find that infrastructure borrowers that are exposed to *Merchant risk* are required to pay a time-varying premium from 20 to 40% above the market average at the time.
  - *Size* has no effect on average corporate spreads but is a driver of <u>lower</u> risk premium in infrastructure debt. In effect, larger loans can be interpreted as a signal of lower credit risk in infrastructure finance.
  - *Industrial groups* can be considered a partial proxy for credit risk but are mostly not significant, except for social infrastructure and, amongst corporate borrowers, infrastructure corporates, which have come to benefit from a substantial discount relative to average market spreads in recent years.
- **Liquidity**: Other drivers of spreads are proxies of the cost of liquidity for creditors.
  - Maturity: While it is difficult to capture in static models, maturity is found to be a significant and time-varying driver of spreads for corporate debt, with higher premium charged during periods of lower bank liquidity (2008-2016), whereas infrastructure debt has a constant maturity premium.
  - While the effect of size is primarily a matter of credit risk, we note that

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in periods of limited creditor liquidity (2008), even infrastructure debt becomes more expensive as a function of size. However, this effect is not strong enough to create a size premium.
  - Refinancings, which are not a significant driver of spreads in normal times, are shown to be more expensive in times of credit-market stress, especially for infrastructure debt.

- **Cost of funds**: The benchmark against which floating-rate debt is priced has been a factor explaining the level of credit spreads.
  - Base rates are inversely related to spread i.e. higher rates imply lower spreads, but this effect is shown to have all but vanished since 2008. Since then, the level of credit spreads and that of base interest rates has become completely uncorrelated.
  - Market Segments: taking base rates into account, some markets are cheaper than others as a result of the well-known segmentation of credit markets. This is the case when comparing Libor- vs Euribor-priced loans but also the different geographic areas in which different lenders operate. Again, since 2008, these differences have tended to disappear.

Toward Fair Value in Private Infrastructure Debt

Our assessment of the impact of certain risk factors in the formation of aggregate credit spreads is relevant for at least three reasons:

- While observable spreads are biased due to the segmentation and low liquidity of the private credit market, *unbiased* factor prices (premia) can be estimated from observable spreads and used to determine the factor-implied spreads for any instrument at any time;
- The time-varying nature of individual risk premia implies that repricing individual instruments over time can be material and is required if such investments are to be evaluated on a *fair-value* basis;
- A multifactor model of spreads, that is, discount rates, allows more robust valuation taking into account the effect of systematic risk factors.

One of the most important requirements of the IFRS 13 framework is to *calibrate valuations to observable market prices*, thus ensuring that estimated spreads represent current investor preferences at the measurement time. While fair value is not always required for debt instruments, which are booked at their face value unless they become impaired, the requirement to evaluate assets on a like-for-like basis will only grow as the private debt asset class becomes a more significant part of investors' portfolios.

1. Introduction

1. Introduction

Private debt has become a significant theme in the private debt investment strategies of large institutional investors in recent years. Private infrastructure debt is a segment of this market that has increasingly attracted investors' attention. It is expected to have an attractive risk-return profile and to create diversification benefits in a debt portfolio because infrastructure are understood to be credit-worthy borrowers with a low correlation with the business cycle.

Most privately invested infrastructure is both unlisted and privately financed. The long-term nature and size of infrastructure investments also imply that debt is the main source of financing for private infrastructure companies. As a result, the determinants of credit spreads in private infrastructure debt are some of the main drivers of the cost of capital in privately financed infrastructure, and they also condition the affordability of such schemes for the public sector and end users.

In this paper, we consider a financial instrument to be "infrastructure debt" as long as the main borrower qualifies under The Infrastructure Companies Classification Standard (TICCS).

Private infrastructure debt can be split into two main groups of instruments: project finance debt and corporate infrastructure debt. With project financing, the borrower is a Special Purpose Vehicle (SPV) and creditors lend on a limited- or non-recourse basis i.e. they can only rely on the value of the project as collateral. As a result, creditors also have extensive control rights, in particular after certain credit events.

Conversely, corporate infrastructure debt borrowers have a standard corporate structure and creditor control rights are not different than with other corporate debt instruments.

EDHEC*infra* market research shows that the majority of investable private infrastructure companies (by number) are infrastructure project finance entities, whereas infrastructure corporates tend to be much larger corporations.[1]

1 - See EDHEC*infra* Index Methodology Documentation.

In what follows, we examine the determinants of private infrastructure debt credit spreads and compare them with those of equivalent corporate debt. We aim to answer two empirical questions:

1. Which factors explain private infrastructure credit spreads (and discount rates) and how do they evolve over time?
2. Are infrastructure project finance spreads and infrastructure corporate spreads driven by common factors?

Like other illiquid private assets, private infrastructure project debt is not easily valued. Secondary market transactions are very rare (even more so than for unlisted infrastructure equity), and new origination follows the public procurement cycle in certain parts of the world and moments in time.

For instance, *merchant* toll roads and power plants were extensively financed with project

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finance debt in the mid-2000s, but these transactions, which were not always long-lived, have gradually been replaced by a deal flow of *contracted* renewable energy and social infrastructure projects over the last decade.

The simple observation of origination credit spreads over time does not take into account the underlying market for private infrastructure debt to which investors are exposed.

Moreover, observable spreads over that period are impacted by the evolution of creditors' preferences, including their appetite for credit risk and maturity, as well as the evolution of the type of creditors. For instance, the increasing role of institutional investors in the private infrastructure debt market implies a potential evolution of risk preferences away from those of banks which have been the dominant actor in this segment of the credit market.

Empirically, biases in observable spreads are inescapable: any data set of credit spreads observed at the time of origination, even large in size, is unlikely to be representative of the investable market and thus be directly suited for the calibration of asset-valuation models.

The use of a *factor model* of spreads offers a solution to correcting the bias and paucity of available data: as long as such factors can be documented in a statistically robust and *unbiased* manner, they can also be used to assess the fair value of private infrastructure debt investments over time, whether they are traded or not.

One of the most important requirements of the IFRS 13 framework is to *calibrate valuations to observable market prices*, thus ensuring that estimated spreads represent current investor preferences at the time of measurement. While fair value is not always required for debt instruments, which are booked at their face value unless they become impaired, the requirement to evaluate private debt on a like-for-like basis with other asset classes will only grow as the private-debt asset class becomes a more significant part of investors' portfolios.

In this paper, we first use a large sample of loan spreads observed at the time of origination over the past two decades to estimate the effect of a number of risk factors on aggregate spreads. The choice of these factors is rooted in existing research and academic literature on the determinants of credit spreads. We use a dynamic method to estimate time-varying effects in a multifactor model of private infrastructure and corporate debt spreads.

While the sample of observable transactions is found to be serially correlated and biased in terms of industries and geographies, estimated coefficients are shown to be robust and unbiased.

Finally, we apply this factor model to the EDHEC*infra* universe, a sample of private infrastructure borrowers that is designed to be representative of the investable market in the most active (or principal) markets in the world. This allows us to compute thousands of "shadow spreads" for those private infras-

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tructure loans that were not traded over the past 20 years.

Our assessment of the impact of certain risk factors in the formation of aggregate credit spreads is relevant for at least three reasons:

- While observable spreads are biased due to the segmentation and low liquidity of the private credit market, *unbiased* factor prices (premia) can be estimated from observable spreads and used to determine the factor-implied spreads for any instrument at any time;
- The time-varying nature of individual risk premia implies that repricing individual instruments over time can be material and is required if such investments are to be evaluated on a *fair-value* basis;
- A multifactor model of spreads, that is, discount rates, allows more robust valuation taking into account the effect of systematic risk factors.

We focus on private loans extended to infrastructure projects and corporates, as well as a control group of noninfrastructure corporate borrowers. Private loans represent the largest pool of credit instruments extended to well-identified infrastructure companies and are therefore the most relevant market for investors targeting private, illiquid infrastructure debt. [2]

2 - In a follow-up paper, we investigate similar questions with respect to infrastructure and corporate bonds using a different data set.

The rest of this paper is structured thus: chapter 2 reviews existing academic work on credit spread modeling for both corporate and project finance debt and discusses its limitations.

Chapter 3 describes our approach and data set.

Chapter 4 puts forward a dynamic approach to estimate the time-varying effects of multiple factors on credit spreads as new debt is being originated.

Chapter 5 describes our estimation results and compares the impact of various factors on the credit spreads of infrastructure project and corporates.

Next, chapter 6 discusses the findings derived from applying the factor model estimated at the previous step to the EDHEC*infra* universe of investable infrastructure debt.

Chapter 7 discusses our findings and concludes.

2. Credit Spreads in Corporate and Infrastructure Loans

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Despite project finance being a subset of corporate debt, existing research suggests that the drivers of corporate debt spreads do not necessarily impact project finance credit spreads in the same ways, and vice versa.

Below, we summarise some of the key findings of the existing academic literature on the determinants of credit spreads in corporate and infrastructure debt. We also discuss the key economic mechanisms justifying a difference in risk pricing between the corporate and infrastructure debt.

2.1 What Drives Credit Spreads?

The literature on corporate finance acknowledges that credit spreads should have multiple determinants. Churm and Panigirtzoglou (2005) identify three components of credit spreads: expected default, credit risk (uncertainty about probability of default), and noncredit risk, which is highly correlated to swap spreads [3] for investment-grade debt.

3 - Swap spreads refer to the difference between interest rate swaps and comparable Treasury yields

The noncredit-risk component, attributed to liquidity, tax, or regulatory effects, increases as the credit-risk component increases, consistent with the empirical evidence that lower-quality credits have higher credit default swap bid-ask spreads and that a small proportion of swap spreads is due to credit risk.

The differences between infrastructure and corporate spread determinants can be attributed to differences of corporate governance and structure, especially the role and control rights given to lenders. Following Brealey et al. (1996), project debt financing differs from corporate financing for three important reasons: separate incorporation, comprehensive contractual agreements, and higher leverage.

1. Project finance debt is undertaken by a special-purpose vehicle for the sole purpose of delivering a project and repaying debt and equity investors (Yescombe, 2002). Repayment of senior debt is funded by project cash flows only.

2. The extensive "network of contracts" required in project finance results in a form of corporate governance that reduces the information and agency problems found in corporate finance (Dailami and Hauswald, 2007; Corielli et al., 2010; Khan and Parra, 2003; EPEC, 2011; Sorge, 2004; Blanc-Brude and Ismail, 2013; Brealey et al., 1996; John and John, 1991; Sorge and Gadanecz, 2008).

   Thus, most of the exogenous determinants of credit risk in traditional corporate finance become endogenous variables in project finance (Blanc-Brude and Ismail, 2013; Blanc-Brude and Strange, 2007).

3. As a direct consequence, project financing typically involves higher leverage than corporate finance. Esty (1999) and Blanc-Brude and Ismail (2013) report average debt to total capitalisation ratios of 70-90% in project finance while similar size corporates have an average leverage ratio of one third.

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The willingness of lenders to finance most of a project's capital costs upfront can be interpreted as a signal of its creditworthiness (Blanc-Brude and Ismail, 2013).

Also as a result of the above, project finance debt also tends to have longer tenors (Sorge and Gadanecz, 2008; Kleimeier and Megginson, 2000).

2.2 Empirical Analyses of Corporate Debt Credit Spreads

However, according to existing empirical studies, a large portion of the corporate bond credit spread cannot be explained by previous dynamics in the spread or by reasonable proxies for risk captured in stock market variables.

Instead, variations in the credit spreads of individual bonds is explained by an aggregate factor common to all corporate bonds (Collin-Dufresne et al., 2001; Krainer, 2004). Guo (2013) also finds that traditional bond-pricing models ignore information risk premia and an "ambiguity" (or compensation to investors for ill-documented risks) that may be embedded in credit spreads.

Key findings of existing research on the determinants of corporate debt credit spreads include:

- **Maturity**: Corporate loan spreads are found to increase with maturity (Sorge and Gadanecz, 2008; Kleimeier and Megginson, 2000; Sorge, 2004),[4] since a lender's longer exposure to risk should warrant higher remuneration.
- **Leverage**: In Collin-Dufresne et al. (2001),[5] leverage does not have a statistically significant relationship with corporate bond credit spreads.
- **Size**: Larger loans are typically found to have lower spreads, although higher exposure at default should warrant higher credit spreads (Eichengreen and Mody, 1998; Kleimeier and Megginson, 2000; Sorge and Gadanecz, 2008; Gatti et al., 2013).[6] This is consistent with the fact that larger issues have greater liquidity on the secondary market (Eichengreen and Mody, 1998).
- **Syndicate size**: Loan pricing and syndicate size have a positive relationship (Esty and Megginson, 2000), aligned with Adamuz and Cortés (2015)'s argument that syndication helps limit competition among lenders, resulting in higher interest rates.
- **Ratings**: Sorge and Gadanecz (2008) found that for bonds, ratings did not provide significant explanatory value beyond that already accounted for by micro- and macroeconomic risk variables.

However, Burietz et al. (2017) found that for syndicated loans, controlling for region-specific[7] credit ratings explains the difference in interest rates charged to borrowers in Europe and the US, providing an explanation for the "syndicated loan pricing puzzle" of Carey and Nini (2007).[8]

4 - In Sorge and Gadanecz (2008), the sample covered international loans and bonds between 1993 and 2001 in both industrialised and emerging economies. Nonproject finance loans and bonds were used as benchmarks for comparison. A baseline specification was used

2. Credit Spreads in Corporate and Infrastructure Loans

The authors suggest that the puzzle results from the lack of uniformity of credit ratings across regions, such as variation in accounting standards across jurisdictions, which affect accounting ratios that ratings are based on.

- **Currency risk**: Currency risk (or mismatch) and spreads have a significantly negative relationship for all forms of debt. But Gatti et al. (2013) observe that spreads of loans with currency risk are about 37 BPS lower than the average, indicating that only the most creditworthy projects with such risk will be funded. Kleimeier and Megginson (2000) found that the negative relationship was stronger for general corporate purpose loans than project finance loans.

- **Macro factors**: Collin-Dufresne et al. (2001) also test for the significance of macrofactors such as the VIX index or the term structure of interest rates. While these factors are found to be significant for publicly traded bonds, recent tests using private syndicated loans and longer time series finds no statistical significance for such factors (see Coelho, 2016).

2.3 Empirical Analyses of Project Finance Credit Spreads

Existing research about the determinants of infrastructure project finance debt credit spreads suggests a range of potential factors; the effects of some differ from the effects in corporate debt pricing. Potential factors include:

- **Maturity**: Unlike in traditional corporate finance, a longer tenor may not equate to greater risk and larger spreads for lenders (Blanc-Brude and Ismail, 2013; Kleimeier and Megginson, 2000; Sorge and Gadanecz, 2008). Consistent with Esty's (2003) inference that high leverage signals low asset risk in project finance, longer maturities can signal greater lender confidence. Sorge (2004); Sorge and Gadanecz (2008) finds that the credit spread term structure in project finance, unlike other types of debt, is *hump-shaped* – beyond a certain maturity, longer-term projects are cheaper than short-term ones. The authors attribute this to the dependence of project finance debt repayments on project cash flows, which makes longer tenors beneficial. Additionally, time-idiosyncratic risks like construction risk dissipate with longer maturities (Blanc-Brude and Ismail, 2013).[9]

However, Blanc-Brude and Strange (2007), suggest that this may be a dynamic effect due to changing market conditions rather than evidence of a nonlinear term structure. In a panel regression of spreads, year and country effects were found to be much stronger drivers of the spreads in project loans. Similarly, Gatti et al. (2013) do not find a statistically significant relationship between maturity and spread.

- **Leverage**: Leverage can also be expected to have a nonlinear effect on spreads. Spreads can have a positive relationship with leverage, signaling a trade-off between cheaper credit and reduced equity

9 - A large sample of infrastructure project finance loans and bonds spanning 1994 to 2012 was studied – as well as a large sample of "plain vanilla" corporate loans over the same period, which was used as a control group – to determine the role of loan characteristics, project-level risk factors, and macrolevel risk factors on average credit spreads. Additionally, the role of fees during the life of each loan was also studied.

2. Credit Spreads in Corporate and Infrastructure Loans

contribution (Corielli et al., 2010)[10], but high leverage can also be a signal of credit quality in project finance (Esty and Megginson, 2003).

- **Size**: Loan size and project finance credit spreads have a negative relationship in Sorge (2004). However, the effect in project loans is three to four times smaller than in the corporate debt control groups (Blanc-Brude and Ismail, 2013). Kleimeier and Megginson (2000); Blanc-Brude and Strange (2007) found the relationship to be statistically insignificant.[11]

- **Syndicate size**: The hypothesis that the number of creditors has an impact on spreads is not overwhelmingly supported by empirical evidence. While Esty and Megginson (2000) found that loan pricing is positively related to the number of arranging banks and the shares held by them, Blanc-Brude and Strange (2007) did not find a significant relationship between syndicate size and spreads.

- **Ratings**: Likewise, the impact of credit ratings is not very clear. Gatti et al. (2013) finds that rated project debt has higher spreads (by about 25 BPS) and argues the very decision to rate project debt signals higher *ex ante* project risk. Most project finance debt is, however, unrated.

- **Debt seniority**: In general mezzanine or subordinated debt is found to have higher spreads, reflecting a higher degree of risk for creditors who are not senior in the cash-flow waterfall (Blanc-Brude and Strange, 2007).

- **Guarantees**: Guarantees extended by multilateral banks are generally found to reduce average spreads by about 23 BPS in Gatti et al. (2013). Kleimeier and Megginson (2000) also find that among all forms of corporate debt, project finance loans display the greatest sensitivity to third-party guarantees, with a reduction in average spreads of more than 43 BPS. The same effect is found in Sorge (2004).

- **Business risk**: The uncertainty inherent in the business model of the borrower is another proxy for credit risk. Infrastructure projects that have a long-term, contracted revenue stream can raise debt that is systematically cheaper than those whose revenues are exposed to demand risk (Blanc-Brude and Ismail, 2013).

- **Refinancing**: Blanc-Brude and Strange (2007) find that refinanced loans tend to have lower spreads by 20 to 50 BPS. In a number of cases, credit spreads are planned to increase postconstruction to encourage debt refinancings (Blanc-Brude and Ismail, 2013).

In a recent study, (Coelho, 2016) considers and recomputes the results of most of the studies above and confirms these findings with a more recent dataset.

2.4 Limitations of Existing Studies

Key findings in the literature suggest that project finance debt is priced quite differently

10 - In Corielli et al. (2010), the sample studied includes 1,093 project loans with a total value of approximately 195 billion USD

11 - In Blanc-Brude and Strange (2007), floating-rate project finance loans from 125 EU roads and 177 UK PFIs covering a 12-year period from 1994 to 2005 were analysed. The relationship between weighted-average spread and variables expected to have an impact on spreads was tested using an OLS regression.

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than corporate debt in general, while being a subset of it.

However, these studies suffer from a number of limitations.

For the purpose of explaining the determinants of credit spreads, existing studies all use linear regression techniques, implying that the determinants of credit spreads do not fundamentally change over time but instead that risk pricing tends to revert to a long-term mean.

Most studies use data sets that generally predate the 2008 credit crisis, which resulted in a step change in the level of credit spreads in private debt as a result of a shock to creditors' cost of funds, followed by the evolution of the average creditor's risk preferences, partly due to new regulation of the banking sector and partly to the entry of new types of creditors in the private debt sector.

Even though more recent papers (Blanc-Brude and Ismail, 2013; Coelho, 2016) do take into account the 2008-2009 credit market dislocation event, they fail to capture the evolution of individual risk premia over time. Instead they fit a static linear model through a time series with highly nonlinear, nonstationary characteristics.

As a result, the results reported in previous studies are not always very robust and can be contradictory.

For the purpose of providing discount rates for the ongoing fair valuation of private assets, existing studies solely relying on observable spreads over time. Hence, if certain types of private infrastructure debt become less likely to be originated over a period, though such assets are still held on the balance sheet of an investor at that time, they may not be adequately valued using current market spreads.

As a result, at least two methodological improvements are possible:

- Estimating the impact of individual risk factors on aggregate credit spreads as they change through time.
- Applying the resulting time series of risk premia to a population of underlying investable loans that represents either the market or an investable segment of the market.

In this paper, we implement both. In the next chapter, we discuss our approach and the available data.

3. Approach & Data

3. Approach & Data

3.1 A Hedonic Approach

As suggested in the introduction, the main difficulty facing econometric research on the price formation of private infrastructure debt is the paucity and biases of observable spread data and the relevant explanatory variables.

Unlike unlisted infrastructure equity, for which a limited but significant number of secondary market transactions can be observed, private infrastructure debt is seldom the object of secondary transactions at all. It is however, possible to observe a large number of primary transactions, that is, spreads at the time of origination.

Nevertheless, private loan origination, even on a large scale, can be expected to exhibit significant biases: different types of infrastructure projects and companies raise financing in certain places at different points in time, and observable primary spreads are not likely to form a representative set of prices of the investable universe.

Instead, origination follows procurement and industrial trends, for example, it tends to cluster in time and space when and where governments procure new infrastructure using a privately financed model.

Reported spread data is also biased at the source: it is primarily obtained from the loan-syndication market and therefore does not cover transactions executed in "clubs" or markets where large syndications by international banks are less common. It is also likely to disproportionately cover larger transactions.

Furthermore, information about the borrowers of newly originated private infrastructure debt is typically limited.

While it is possible to observe the size and maturity of new loans, as well as some of the creditors' characteristics, proxies of credit risk are typically missing from such data sets: private debt is seldom rated, and the borrowers' financial structure or leverage also not reported.

As a result, we proceed in two steps:

- First, using a reasonably large sample of primary spreads and a number of control variables, we estimate an *unbiased* set of time-varying factors (coefficients) that explains the variance of observable spreads (chapter 5). We find that these factors explain spread movements well and are statistically robust.[12]
- Next, we apply the factor effects estimated from actual transaction prices to the EDHEC*infra* universe of infrastructure borrowers and derive a "shadow" spread for each of the companies at each point in time (chapter 6). The EDHEC*infra* universe is designed to be representative of the investable private infrastructure debt universe over time and allows reporting predicted spreads in relation to direct measures of credit risk such as leverage or debt service and interest cover ratios.

This *hedonic* approach allows documenting the dynamics of private infrastructure debt spreads over the past 15 years for the under-

12 - Residuals are uncorrelated and Gaussian, i.e., white noise.

3. Approach & Data

lying investable population and not just for available transaction data.

Next, we discuss our choice of factor model.

3.2 Model Specification

The potential risk factors identified in chapter 2 fall into three groups: macrovariables that do not depend on the choices made by lenders, such as interest rates; microvariables that are determined individually for each loan, such as size and maturity; and control variables that encapsulate both macro effects and the decision to lend, such as country or industry.

We aim for the most parsimonious model that takes the findings of existing research into account while maximising observable data (both the spreads and all the control variables need to be observable).

Since private debt is mostly unrated, we do try to use credit ratings as an explanatory variable. Likewise, we ignore variables that have proven irrelevant in previous specifications (e.g., VIX) or are only available for a very limited number of observations (e.g., mezzanine debt spreads).

Finally, to maximise comparability we aim to have as many common factors as possible in the infrastructure and corporate debt spread models.

We thus use the following factors:

- Microlevel: size, maturity, refinancing dummy, acquisition dummy
- Macrolevel: loan benchmark rate at the time of origination (LIBOR or Euribor), Euribor dummy
- Controls: geography and industry
- Infrastructure only: merchant business risk (dummy)

The size, maturity and benchmark rate independent variables are continuous variables. They use a log-transformation.

Control variables are "dummies," that is, they take a value of one or zero depending on the type of effect being controlled for. If a loan is originated in a given region, sector, etc., the relevant control variables take the value of one; otherwise they are zero. [13]

In the next section, we describe the data used in this study.

3.3 Data

3.3.1 Infrastructure Debt Spreads

The input data used in this study consists of credit spreads collected from multiple commercial databases [14] and aggregated manually to ensure that only unique observations are used.

This yields an initial sample of 3,969 project finance instruments for which complete information on initial spread at origination, size, financial close and maturity dates, and

13 - To avoid overspecifying the models (a problem known as the dummy trap) we remove one dummy from each set of controls, the joint effects of which will be captured by the intercept of the model.

14 - Thomson ONE Banker, Dealogic ProjectWare, and IJGlobal.

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geographic and industrial control variables can be obtained.[15]

Only *floating-rate term loans* benchmarked against LIBOR or Euribor are kept to ensure the coherence of the data and because LIBOR- and Euribor-based spreads make up the immense majority of observable credit spreads.

Geographic variables are mapped to the standard divisions of global credit markets used by commercial lenders: Europe, Middle East and Africa (EMEA), Asia Pacific (APAC), Latin America (LATAM), and North America (NORAM).

Sector classifications are mapped to The Infrastructure Company Classification Standard (TICCS), as shown on figure 1. Project finance loans that could not be mapped to TICCS are excluded from the sample.

Finally, we reduce this sample by taking average values for instruments that were originated on the same date. Indeed, obtaining unbiased estimators requires observing consecutive observations over time. Once the data is averaged over time, we obtain a time series of 1,980 infrastructure debt spreads and their explanatory variables.

3.3.2 Corporate Debt Spreads

We build an equivalent data set of floating -rate, corporate term loans using data from a commercial database.[16] Only transactions with complete information on initial spread, loan size, financial close, and maturity dates are included.

This yields a control group of 7,459 private corporate loans extended to corporations. This includes private loans extended to "infrastructure corporates" – companies that qualify as "infrastructure" under TICCS but are not set up as project SPVs. Instead, they are "normal" corporations and borrowers.

The control group includes most other sectors of the economy including retail, mining, manufacturing etc. Financials are excluded from the control group for the usual reasons. We also constrain the control group to include only those countries that are already present in the infrastructure debt sample.

Geographic classifications are similar to the infrastructure project loan data set. Sector classifications bundle all corporate borrowers that qualify under TICCS under a common "infrastructure" sector, while other borrowers are categorised according to standard industrial groupings as shown in table 4 and figure 2

As above, we also take the average of observations that are reported on the same date, yielding a time series of 3,357 unique observations of corporate spreads.

15 - We used only floating-rate loans. All transactions with negative or zero spreads were removed as they are likely to be erroneous or represent missing data. Additionally, debts with such spreads are not representative of a typical commercial lending transaction and so should not be included in our analysis. Extreme spreads (more than 1500 BPS or less than 50 BPS) were identified and checked. There were 421 such observations. To determine the validity of these basis point levels, we evaluated whether the extreme spread could be explained by the state of the economy in the borrower country during the year of the financial close. If a high spread matched a period of recession, or a low spread matched a period of recovery, the observation was kept.

16 - Thomson ONE Banker

3. Approach & Data

Figure 1: Country and Sector Distribution of the Infrastructure Debt Spread Data Set

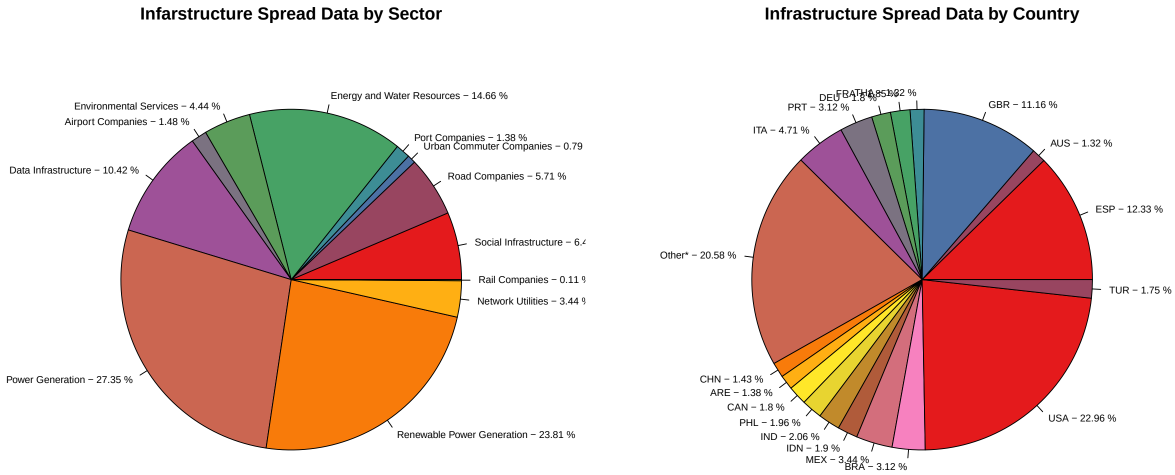
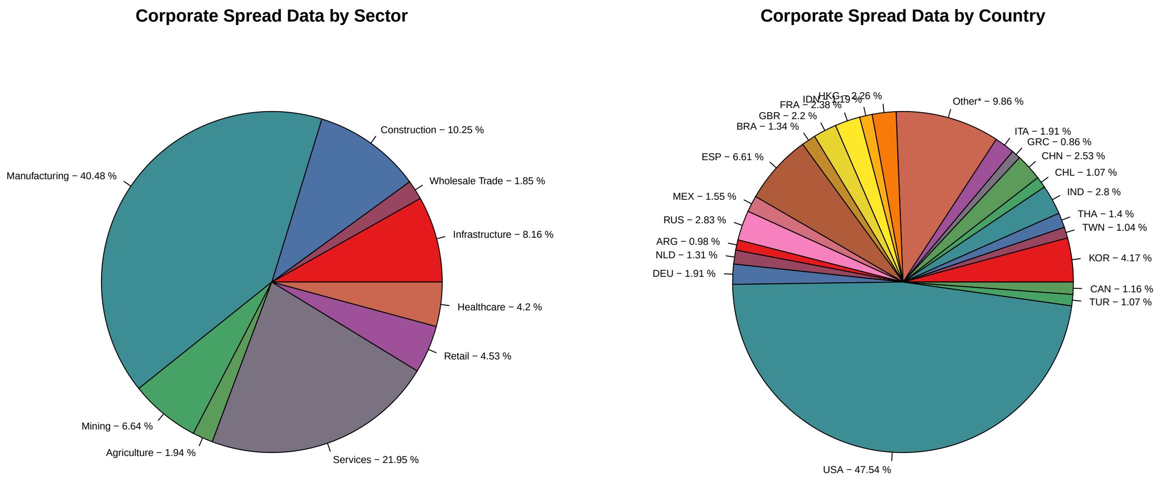


Figure 2: Country and Sector Distribution of the Corporate Debt Spread Data Set



3. Approach & Data

3.3.3 Input Spread Data sets

3.4 Descriptive Statistics

Figure 3 shows quarterly averages for observable infrastructure and corporate spreads. Clearly the two samples have common dynamics but also varying spread levels. Overall, observed infrastructure project spreads are lower than corporates spreads.

Tables 1 and 2 describe the range of spreads over the period by national markets for infrastructure and corporate debt, while tables 3 and 4 break down the same data by sector. Both tables are sorted by median spread.

We see that infrastructure debt spreads vary less between countries than they do for corporate debt with a maximum range in median spreads of 125bps between Spain and Turkey, whereas median corporate spreads range from 60bps in South Korea to 325bps in Canada. Within countries, the minimum and maximum range of observed spreads is also larger for corporates, with US corporate spreads going from 15 top 850bps, whereas US infrastructure project spreads range from 45 to 647bps.

Looking at sectors, spreads to infrastructure corporates are in the same range as average infrastructure spreads, with a mean (median) of approximately 200 BPS (180 BPS). However, spreads vary considerably within infrastructure sectors, with lower median spreads (below 120 BPS) in long-term contracted projects like social infrastructure and higher median spreads in sectors like renewable energy or network utilities (which are set up as SPVs). However, these median levels hide the evolution of the sector over time. For example, renewable energy projects have mostly been financed after the 2008 credit crisis, in a lower-rate, higher-spreads environment. This justifies the dynamic modeling undertaken in the rest of this paper.

Next, tables 5 to 8 show average infrastructure and corporate spreads broken down by size and maturity deciles. A first observation is that corporate-debt-size buckets are much larger than infrastructure-debt-size buckets, while corporate-debt-maturity buckets are much smaller. The top size bucket for corporate debt has a median size of USD 3.6 billion, compared to USD 900 million for infrastructure debt. Conversely, the top corporate-debt-maturity bucket is for an average of seven years, while the longest infrastructure loans have median maturity of 24 years.

These tables also suggest that size and maturity are independent factors since loans in almost every size bucket exhibit roughly the same median maturity and vice versa. This is confirmed by the correlation plots in the appendix: correlation coefficients between size and maturity, albeit significant at the 1% confidence level, are very small.

Finally, table 9 shows the infrastructure-spread data broken down according to the TICCS "business risk" pillar. As expected, contracted projects exhibit lower spreads, longer maturities, and lower median sizes. Regulated and merchant spreads are harder to distinguish. In effect, "regulated" SPVs, mostly telecom and data infrastructure, as well as a few airports, can be close to merchant projects

3. Approach & Data

Table 1: Descriptive Statistics for Infrastructure Loan Spreads by Country

CountryName	Mean	Median	Min	Max	Obs
ESP	171.67	130.00	27.50	500.00	233
AUS	182.82	132.50	87.50	537.50	25
GBR	170.71	138.00	27.50	600.00	211
THA	163.10	138.75	40.00	600.00	25
FRA	169.27	142.50	35.00	450.00	35
DEU	158.23	143.75	27.50	375.00	34
PRT	200.80	150.00	58.00	500.00	59
ITA	191.89	155.00	34.25	550.00	89
Other*	198.48	160.62	25.00	650.00	389
CHN	183.24	165.00	50.00	415.00	27
ARE	178.58	170.62	41.00	550.00	26
CAN	220.56	200.00	83.00	600.00	34
PHL	207.80	200.00	40.00	503.75	37
IND	242.30	225.00	50.00	485.00	39
IDN	263.70	232.50	50.00	600.00	36
MEX	224.07	237.50	35.00	475.00	65
BRA	246.88	250.00	55.00	600.00	59
USA	257.22	250.00	45.00	687.50	434
TUR	278.87	255.50	30.00	500.00	33
All	209.41	180.80	25.00	687.50	1890

* "Others" aggregates markets with fewer than 25 individual observations.

Table 2: Descriptive Statistics for Corporate Loan Spreads by Country

CountryName	Mean	Median	Min	Max	Obs
KOR	78.33	60.00	22.50	317.22	140
TWN	85.85	70.00	25.00	286.00	35
THA	88.67	72.00	30.00	241.00	47
IND	118.96	95.00	18.50	507.00	94
CHL	127.82	100.42	30.00	347.00	36
CHN	146.41	125.00	20.00	480.67	85
GRC	164.19	150.00	30.00	570.00	29
ITA	156.95	150.00	20.00	515.00	64
Other*	181.04	150.00	15.00	600.00	331
HKG	178.91	162.50	33.50	527.50	76
IDN	184.70	166.25	47.00	550.00	40
FRA	192.15	177.92	14.00	495.00	80
GBR	204.11	187.50	25.00	800.00	74
BRA	228.52	200.00	33.00	600.00	45
ESP	212.18	200.00	15.00	800.00	222
MEX	235.41	220.00	37.50	600.00	52
RUS	243.98	220.00	40.00	650.00	95
ARG	284.86	225.00	66.25	750.00	33
NLD	218.82	236.67	15.00	475.00	44
DEU	238.56	250.00	20.00	475.00	64
USA	287.84	269.58	15.00	850.00	1596
TUR	257.11	273.75	57.00	715.00	36
CAN	316.88	325.00	70.00	650.00	39
All	232.55	215.00	14.00	850.00	3357

* "Others" aggregates markets with fewer than 25 individual observations.

3. Approach & Data

Figure 3: Input Infrastructure and Corporate Debt Spreads over Time (Quarterly Averages)

Table 3: Descriptive Statistics for ***Infrastructure Loan Spreads by Sector***

Sector	Mean	Median	Min	Max	Obs
Social Infrastructure	169.59	117.50	27.50	573.50	121
Road Companies	167.25	125.00	32.50	600.00	108
Urban Commuter Companies	181.53	140.00	30.00	485.00	15
Port Companies	208.24	151.25	55.00	490.00	26
Energy and Water Resources	200.49	167.50	35.00	687.50	277
Environmental Services	187.36	174.38	41.00	465.00	84
Airport Companies	193.64	175.30	30.00	385.00	28
Data Infrastructure	221.29	200.00	27.50	600.00	197
Power Generation	222.70	200.00	25.00	650.00	517
Renewable Power Generation	218.25	200.00	35.00	650.00	450
Network Utilities	226.68	231.33	50.00	450.00	65
Rail Companies	350.00	350.00	350.00	350.00	2
All	209.41	180.80	25.00	687.50	1890

3. Approach & Data

Table 4: Descriptive Statistics for Corporate Loan Spreads by Sector

Sector	Mean	Median	Min	Max	Obs
Infrastructure	201.43	178.12	15.00	750.00	274
Wholesale Trade	199.30	193.75	22.50	495.00	62
Construction	211.05	200.00	14.00	550.00	344
Manufacturing	221.58	200.00	15.00	850.00	1359
Mining	250.06	207.50	17.50	850.00	223
Agriculture	240.86	212.50	40.00	617.50	65
Services	251.66	237.50	15.00	825.00	737
Retail	257.04	250.00	22.50	600.00	152
Healthcare	308.05	306.25	40.00	825.00	141
All	232.55	215.00	14.00	850.00	3357

in terms of their overall business-risk profile, which is why they are structured as SPVs in the first place. The immense majority of regulated infrastructure businesses fall in the corporate category and are not project financed.

3.5 Explanatory Variables

As suggested above, factors used in this paper to explain the variance of spreads are:

1. Loan size, expressed in USD converted at the prevailing three-month moving-average exchange rate at the time of origination;
2. Loan maturity, expressed in years and computed as the difference between maturity date and origination date;
3. Euribor control variable: casual observation suggests that Euribor-based spreads tend to have different levels than LIBOR-based spreads; theoretically, the well-documented segmentation of credit markets (Gaspar et al., 2004) also justifies fitting a different intercept for Euribor spreads;
4. Specific use of funds, such as refinancings or acquisitions, flagged using dummy variables;
5. Geographic areas and industrial sectors, also used as control variables, following the classifications described above;
6. A "merchant" business-model dummy, built for infrastructure debt and based on an analysis of the types of projects and markets in which the financing took place. This variable is expected to proxy higher credit risk since the projects being financed have to rely on commercial revenues (as opposed to contracted or regulated income) to service their debt.

Figures 4 and 5 describe the evolution of average maturities and sizes over time in the two samples used.

The effect of the 2008/2009 financial crisis on average corporate-debt maturities and sizes is visible but has also clearly passed.

Infrastructure debt, with smaller average sizes and longer maturities, has responded differently to the credit and regulatory cycle, with a slower decrease in maturities after 2008 only bottoming out in 2013, while average loan size has been increasing since 2002 from USD 100 million to USD 250 million today, on average. In comparison, average corporate loan size

3. Approach & Data

Table 5: Descriptive Statistics for Infrastructure Loan Spreads by Size

Median Size (m)	Median Spread	Mean Spread	Median Maturity	Obs
17.30	170.00	199.48	12.51	189
39.44	177.92	215.00	12.05	189
64.54	190.00	207.71	11.01	189
88.05	200.00	216.84	10.67	189
121.93	187.50	213.65	11.51	189
167.18	175.00	213.00	10.01	189
225.28	193.33	208.90	10.16	189
307.09	203.90	222.32	8.51	189
450.00	175.00	207.08	8.70	189
900.00	165.00	190.15	10.01	189

Table 6: Descriptive Statistics for Corporate Loan Spreads by Size

Median Size (m)	Median Spread	Mean Spread	Median Maturity	Obs
153.68	175.00	212.39	4.00	336
545.38	225.00	239.09	4.00	336
863.55	210.00	230.35	4.60	336
1270.00	222.50	225.96	4.53	335
1527.47	232.75	243.82	4.34	336
1807.78	210.83	234.02	4.65	336
2134.74	241.25	250.71	4.37	335
2509.00	204.90	226.72	4.24	336
2894.50	218.75	234.44	4.61	336
3630.00	200.00	228.03	4.67	335

Table 7: Descriptive Statistics for Infrastructure Loan Spreads by Maturity

Median Maturity (yrs)	Median Spread	Mean Spread	Median Size (m)	Obs
2.38	181.50	212.59	164.81	189
5.01	225.00	244.93	160.13	189
7.00	275.00	273.80	246.00	189
8.01	225.00	236.37	182.28	189
10.01	180.00	203.97	125.00	189
11.76	175.00	204.99	105.40	189
14.01	150.00	184.62	120.50	189
15.63	157.50	187.38	135.28	189
18.01	160.00	188.23	98.69	189
24.02	125.00	157.26	139.58	189

Table 8: Descriptive Statistics for Corporate Loan Spreads by Maturity

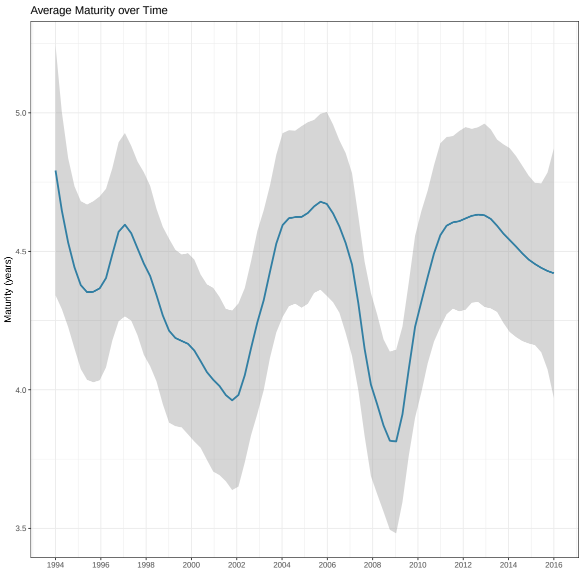
Median Maturity (yrs)	Median Spread	Mean Spread	Median Size (m)	Obs
1.00	154.17	187.64	1643.65	336
2.59	208.33	225.04	1675.02	336
3.00	200.00	223.53	1856.16	336
3.59	243.75	246.46	1422.94	335
4.01	248.44	264.06	1658.49	336
4.73	250.00	242.47	1629.97	336
5.00	156.25	201.03	1791.59	335
5.30	292.08	279.45	1648.11	336
6.01	232.12	260.43	1674.03	336
7.34	175.00	195.23	1846.49	335

Table 9: Descriptive Statistics for Infrastructure Loan Spreads by Business Model

Business Risk	Median Spread	Mean Spread	Median Maturity	Median Size (USDm)	Obs
Contracted	169.64	196.93	13.51	122.47	1033
Merchant	203.33	228.97	7.94	200.00	446
Regulated	200.00	217.27	8.50	125.00	193

3. Approach & Data

Figure 4: Evolution of Average Maturities in the Corporate (left) and Infrastructure (right) Data Sets (Gray Ribbon = 1 Std. Dev.)



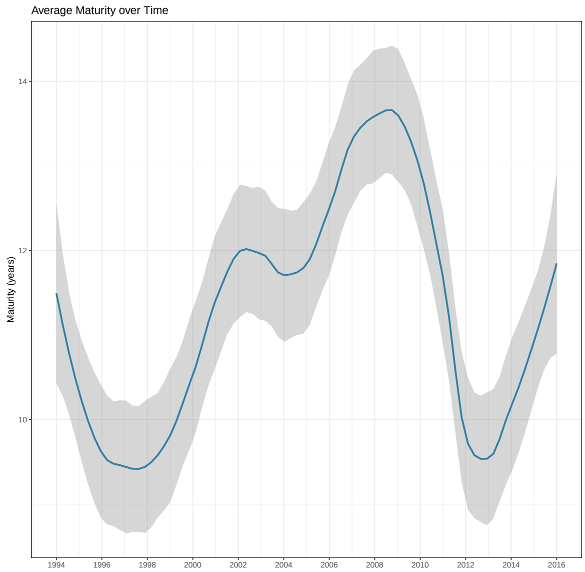
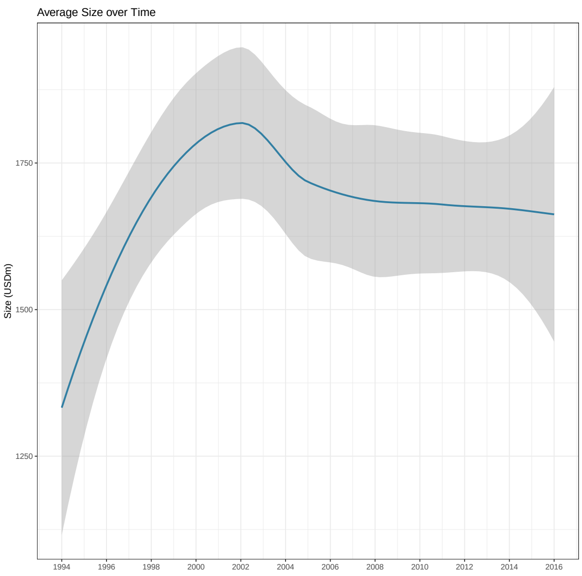
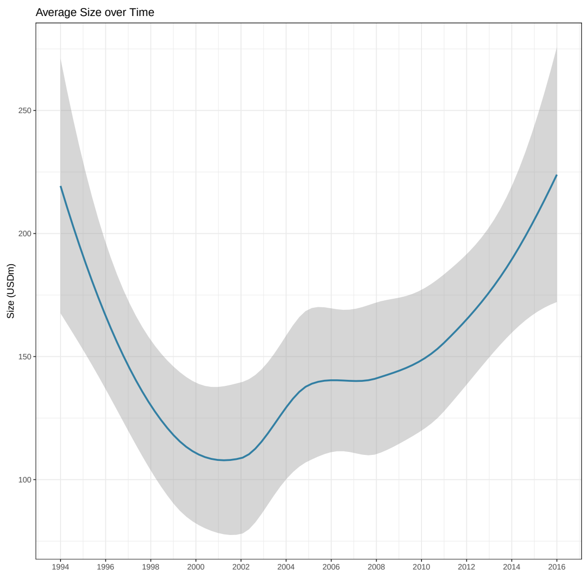


Figure 5: Evolution of Average Sizes in the the Corporate (left) and Infrastructure (right) Data Sets (Gray Ribbon = 1 Std. Dev.)





3. Approach & Data

peaked in 2002 at USD 1.3 billion and has since return to and exceeded this level.

In the next chapter, we describe a dynamic model to estimate the impact of time-varying factors on credit spreads, thus capturing variations in the risk premia that explain aggregate spreads.

4. Dynamic Modeling

4. Dynamic Modeling

As discussed in chapter 1, the objective of this paper is to identify relevant explanatory factors of the spreads of private infrastructure and corporate debt. The empirical challenge is to estimate the price of the various risk factors discussed in chapter 2 using the observable credit spread data described in chapter 3, t.

Factor models typically represent the relationship between the quantity of interest (here, credit spreads) and various explanatory variables as a *linear* function. In this setting, each factor or coefficient represents an independent component of the aggregate credit spreads. Moreover, the level of these coefficients can be expected to vary over time: for example, the impact on credit spreads of loan maturity depends on creditor preferences for extending long-term credit. Over time, each of these coefficients may evolve as creditors' willingness to lend for longer maturities evolves or prices change as the economic and credit cycles unfold.

In what follows, we describe a dynamic linear model specifically suited to estimating the value of time-varying risk premia that explain aggregate credit spreads in private infrastructure and corporate debt.

4.1 Model Setup

At its simplest, the relationship between observable spreads and their explanatory factors is described using a linear model such as:

$$Y_t = \beta_1 + \sum_{k=2}^{K} \beta_k x_{k,t} + \varepsilon_t, \text{with } \varepsilon_t \overset{iid}{\sim} \mathcal{N}(0, \sigma^2) \tag{4.1}$$

where Y_t is the price process at time t; $x_{k,t}$ is a vector of K explanatory variables such as instrument maturity, size, etc. at the time of measurement; and β_k are the corresponding $k = 1 \ldots K$ coefficients or risk premia.

However, the assumption of independently distributed errors $\varepsilon_t \overset{iid}{\sim} \mathcal{N}(0, \sigma^2)$ is unlikely to be realistic if measurements (recorded spreads) are taken over time.

For instance, the impact of maturity, size, or certain geographic and sector effects on spreads, even if they can be assumed to be independent from one another, are likely to be *autocorrelated*, that is, not independent from one decision to originate or lend to the next.

Moreover, these factors are likely to be *nonstationary*, that is, to evolve over time as investor preferences and market conditions evolve.

Hence, we introduce a temporal dependence between Y and x_k by considering that coefficients may evolve over time. That is,

$$Y_t = \beta_{1,t} + \sum_{k=2}^{K} \beta_{k,t} x_{k,t} + \varepsilon_t, \text{with } \varepsilon_t \overset{iid}{\sim} \mathcal{N}(0, \sigma^2) \tag{4.2}$$

The evolution of the coefficients is modeled as

$$\beta_{k,t} = \beta_{k,t-1} + w_{k,t}$$

, with $k = 1 \ldots K$ and $w_{k,t}$ independent.

With time-varying and explicitly autocorrelated coefficients $\beta_{k,t}$, equation 4.2 can be rewritten as a system of two equations.

4. Dynamic Modeling

Defining $\theta_t = [\beta_{1,t} \ldots \beta_{K,t}]'$ and $F_t = x_t'$, the linear relationship between spreads and their factors is:

$$\begin{aligned} Y_t &= F_t\theta_t + v_t, \text{with } v_t \overset{iid}{\sim} \mathcal{N}(0, V_t) \qquad (4.3) \\ \theta_t &= G_t\theta_{t-1} + w_t, \text{with } w_t \overset{iid}{\sim} \mathcal{N}_k(0, W_t) \end{aligned}$$

with $V_t = \sigma_t^2$, the variance or noise of the pricing equation and W_t the (co)variance (matrix) of the model's K coefficients.

Equation 4.3 is a state-space or hidden Markov chain model [17] consisting of an *observation* equation $Y_t = F_t\theta_t + v_t$ – here, the relationship between observable spreads and their explanatory variables – and a *system* or state equation capturing the autoregressive and time-varying nature of a vector of the model's coefficients, θ_t.

Note that with $G_t = I$, the identity matrix, and W_t diagonal, the regression coefficients are represented as independent random walks. In other words, each factor's impact on prices is serially correlated, but its evolution is independent from that of other risk premia.

Also note that if $W_t = 0$, that is, if there is no innovation over time in the regression coefficients, equation 4.3 is equivalent to equation 4.1, the static model.

To summarise, the standard linear relationship between spreads and risk factors described in equation 4.1, which describes the average effect of K factors on aggregate credit spreads, can be generalised using a state-space model to represent the evolution of each factor on prices over time. In this dynamic setting, an observable process Y_t (loan spreads at origination) is driven by a latent (unobservable) process θ_t up to (independent) Gaussian errors. This latent process has autoregressive dynamics of order 1, that is, it only depends on its own previous realisation up to some innovation over time.

Next, we discuss how Bayesian techniques can be used to estimate the K coefficient estimates each time new observations – here new credit spreads – become observable, thus tracking the time-varying impact of each factor on the average level of spreads.

4.2 Model Estimation

State-space models, such as the one described above in equation 4.3, present several advantages: their dynamics follow a so-called Markov process [18], and observations are assumed to be *conditionally independent*, that is, conditioning on the state θ, any price y_t is independent of previous realisations $y_{1:t-1}$. As a result, state-space models can be computed recursively starting from an initial or prior density of the state vector.

We return below to how the initial prior of the state vector might be set. Here, we describe the recursive process by which the *posterior* state of the system can be estimated using the Kalman filter.

First, before the next transaction can be observed, a prior of the state vector is given by

$$\theta_{t-1}|y_{1:t-1} \sim \mathcal{N}_k(m_{t-1}, C_{t-1})$$

.

17 - State-space models represent a time series (here, the prices or price ratios corresponding to individual transactions) as the result of a dynamic system that can be made of multiple components including trend, regressive, or cyclical components. Such models can be used to capture nonstationary effects, structural breaks, and other patterns affecting the process over time (see Petris et al., 2009, for a detailed discussion).

18 - Any process by which $\pi(y_t|y_{1:t-1} = \pi(y_t|y_{t-1})$, i.e., a so-called memory-less process by which all relevant information up until $t-1$ is encapsulated in y_{t-1}.

4. Dynamic Modeling

Using this prior estimate of θ_{t-1}, the system equation is used to predict the state of the system (the K coefficients of the model) for the next transaction, given the information available up until that transaction $y_{1:t-1}$.

Using equation 4.3, it can be shown that the *predictive distribution* of θ_t given $y_{1:t-1}$ follows a Gaussian process with parameters

$$a_t = E(\theta_{t-1}|y_{1:t-1}) = G_t m_{t-1}, \qquad (4.4)$$
$$R_t = Var(\theta_{t-1}|y_{1:t-1}) = G_t C_{t-1} G'_t + W_t$$

If $G_t = I$, as suggested above, the predictive state vectors at time t simply are the $\beta_{k,t-1}$ coefficients estimated for the previous transaction.

Next, the predictive distribution of the new transaction price is derived using the relevant variables x_t at the time of the new transaction.

The one-step-ahead (predictive) distribution of Y_t given $y_{1:t-1}$ also follows a Gaussian process with parameters:

$$f_t = E(Y_t|y_{1:t-1}) = F_t a_t, \qquad (4.5)$$
$$Q_t = Var(Y_t|y_{1:t-1}) = F_t R_t F'_t + V_t$$

Finally, in the last step of the Kalman filter, the *posterior* or filtering distribution of the state vector $\pi(\theta|y_{1:t})$ is computed using the law of conditional probability.

The *filtering* distribution of θ_t given $y_{1:t}$ is a Gaussian process with the parameters

$$m_t = E(\theta_t|y_{1:t}) = a_t + R_t F'_t Q_t^{-1} e_t \qquad (4.6)$$
$$C_t = Var(\theta_t|y_{1:t} = R_t - R_t F'_t Q_t^{-1} F_t R_t$$

where $e_t = Y_t - f_t$, the so-called forecast error, is the difference between the predicted price in the second step (before observing the transaction) and the realised value of Y_t.

This provides a correction of the initial estimate of the K coefficients, which is a function of how much the new spread differs from what the prior estimate of θ suggested. The weight given to this correction to the estimate of θ is called the *Kalman Gain* and is written

$$K = R_t F'_t Q_t^{-1}$$

that is, the uncertainty (or variance) of the measurement (V_t, which determines Q_t) and the variance of the state itself (W_t, which determines R_t).

The ratio W/V is known as the signal-to-noise ratio and reflects the ability of the model to learn from new data. If the system/state variance is very low (i.e., its precision is very high) then new observations affect the estimate of θ less than if the state is considered as highly undetermined.

In effect, the posterior expected value of θ_t is

$$m_t = K_t y_y + (1 - K_t) m'_{t-1} x_t$$

which is a weighted average of the new spread's observation y_t and its predicted expected value before observing the new data.

This *posterior* estimate of the state vector (of model coefficients) combines the difference between actual and predicted spread with the relative uncertainty of the state and observation to *optimally* learn about the evolution of model coefficients in each transaction without discarding too much of the information captured by the prior distribution.

4. Dynamic Modeling

4.3 Recursion and Initial Prior

4.3.1 Prior Values of m_{t-1} and C_{t-1}

Note that the recursive nature of the estimation is made possible by the assumption of conditional independence of Y_t given θ_t. That is, at time t, before new information arrives, all information available about the process Y is encapsulated in the latest estimate of the distribution of θ_{t-1}.

Each such estimate can thus become the prior distribution of θ_t in the next iteration without loss of information, that is,

$$\pi(y_n|\theta_{t-1}, y_{1:t-1}) = \pi(y_t|\theta_{t-1})$$

Initiating the recursive estimation of the vector of $\beta_{k,t}$ coefficients does require an initial prior θ_0.

In this case, setting prior values for the state vector of model coefficients θ_t is straightforward: with the evolution of each coefficient $\beta_{k,t}$ modeled as a random walk with independent noise, the prior value of each coefficient is simply set to zero.

This prior mirrors the null hypothesis of the t-test applied to the coefficients of static linear models, that is, until proven otherwise by observable inputs, the effect of each factor is assumed not to exist.

Likewise, we start from the premise that the initial values of the state vector are unknown and set the variance of each coefficient to be a high value such as 10^7.

Hence, $\theta_{y_0} \overset{iid}{\sim} \mathcal{N}_k(m_0, W_0)$ with $W_0 = diag(10^7_1 \ldots 10^7_K)$.

This can be described as an "agnostic" prior: we do not make any economically meaningful assumptions about the density of the coefficients in equation 4.3 until we observe some spread data.

4.3.2 Meaning of V_t

Finally, we will need to set an estimate for V_t, the "noise" level of the price observations. While the notion of noisy observations typically refers to physical measurements (e.g., distance or speed), the notion of noisy spread observations also makes sense from the standpoint of asset-pricing theory. Indeed, while actual aggregate spread encapsulates the market prices of risk required by the average creditor (i.e., the effect of systematic risk factors on spreads), they also include idiosyncratic "noise" created by individual creditor preferences. This is especially relevant in private, relatively illiquid, and *incomplete* markets where the law of one price cannot be expected to hold at all points in time.

In effect, the multifactor model of prices represented by equation 4.2, which the filtering process above aims to estimate, represents the combination of each factor's effect on average spreads only, and it treats the idiosyncratic component of transaction prices as white noise V_t.

Whether the model's residuals are indeed white noise (zero-mean, Gaussian) is an important test of the robustness of the coeffi-

4. Dynamic Modeling

cient estimates (we report these results in chapter 5).

4.4 Smoothed Coefficient Estimators

Kalman filtering, as outlined above, aims to estimate the value of the state vector up until the most recent observation and update the posterior density of the state accordingly. This is useful for an understanding of the present state of system given available information at time t.

However, since we aim to document the evolution of the factors impacting unlisted infrastructure prices over the entire sample period, we can also use each filtered estimate of the K coefficients to derive "smoothed" coefficient estimates that take all realised information, up until the last observation time T, into account.

Hence, a retrospective time sequence of state vectors can be be estimated for each origination date in the past given the data available up until now, $y_1 \ldots y_T$. This allows for the complete study of the system underlying the realised observations and is solved by recursively computing the conditional distribution of $\theta_t | t_{1:T}$ for any $t < T$ and estimating backward previous states. With Gaussian priors, the computations are straightforward, and, using the notation for equation 4.3, it can be shown (Petris et al., 2009) that if the latest state estimate is

$$\theta_{t+1} | y_{1:T} \sim \mathcal{N}(s_{t+1}, S_{t+1})$$

then,

$$\theta_t | y_{1:T} \sim \mathcal{N}(s_t, S_t)$$

with the parameters

$$\begin{aligned} s_t &= m_t, C_t G'_{t+1} R^{-1}_{t+1}(s_{t+1} - a_{t+1}) \qquad (4.7) \\ S_t &= C_t - C_t G'_{t+1} R^{-1}_{t+1} \left(R_{t+1} - S_{t+1}\right) R^{-1}_{t+1} G_{t+1} C_t \end{aligned}$$

Typically, the smoothed state estimates have lower variance (S_t) than filtered estimates (C_t) due to the fact that smoothed estimates are conditioned on the entire data up until time T. Hence, in an historical analysis such as the one conducted in this paper, smoothed estimates provide the best possible signal content and optimal estimates of the model's coefficients. They are reported in the next chapter for our model of the determinants of spreads in private infrastructure and corporate debt.

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In this chapter, we discuss the estimation of the coefficients or factors that impact private infrastructure debt spreads using the data and dynamic multifactor approach described in chapters 3 and 4.

5.1 Estimating the K Factor Effects

Linear models assume independence between draws from the stochastic process, as well as between explanatory variables. However, examination of the raw data reveals several issues in this respect.

First, debt spreads are not independent over time but show clear signs of serial correlation. Figure 22 in the appendix shows the autocorrelation and partial autocorellation [19] test plots for the infrastructure and corporate debt spread samples. [20]

Second, correlations between spreads and candidate explanatory variables are found to be time varying. Tables 17 and 18 in the appendix show the Pearson correlation coefficients [21] of observed spreads with some of the main expected factors in 10 consecutive time brackets.

Clearly, correlations between the dependent variable (the spreads) and some of the potential explanatory variables change in magnitude and sign over time. This can be the result of a time-varying relationship between these variables ($\beta_{k,t}$ changes over time) or the result of noise in the data due to the observation biases discussed earlier (e.g., different types of loans are originated at different times in different markets).

For instance, the correlation between observed spreads and size changes sign and magnitude over time. In the case of infrastructure debt it tends to be negative but becomes positive in 2001-2003, 2007-2009 (periods of credit market stress).

In the case of corporate debt, the relationship with maturity evolves over time as well. While the correlation is negative or close to zero until 2008, it then becomes positive after 2008.

The idea that individual spread observations "explain each other" in sequence (autocorrelation) makes sense from a financial point of view since loans are originated one after the other as the credit and economic cycle unfolds. Each decision to lend is not taken in isolation, solely taking the borrower's characteristics into account, but also with reference to the most recent transactions in credit markets.

Likewise, it is intuitive that loan size and maturity should impact spreads more or less and even change sign at different times in the credit cycle, depending on creditors' appetites for risk, the evolution of creditor regulatory constraints, and the business cycle.

However, such serial correlation and time-varying correlations violate the premises of the standard linear factor models used in the literature described earlier, by which spreads should be independent draws from some distribution and explanatory variables or factors should have a constant, persistent effect on average spreads across the data set.

19 - Autocorrelation refers to linear correlation of a signal with itself at two different points in time. Partial autocorrelation is the autocorrelation of a signal with itself at different points in time, with linear dependency with that signal at shorter lags removed.

20 - The Ljung-Box test, which identifies whether any of a group of autocorrelations of a time series are different from zero, is also used, and we can reject the null hypothesis that autocorrelation in the transaction-price data is zero with a very high degree of confidence.

21 - The Pearson correlation coefficient between two variables x and y is written $\rho_{x,y} = \frac{COV(x,y)}{\sigma_x \sigma_y}$, hence it is a direct proxy of regression coefficients or βs, which are written $\beta = \rho_{x,y} \frac{\sigma_x}{\sigma_y}$.

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Next, we report the results for both the static and dynamic linear models described in chapter 4.

5.2 Static-Model Results

We begin by estimating the coefficients of the standard ordinary least square (OLS) regression model described in equation 4.1 and used throughout the literature described in chapter 2.

Table 10 and 11 show the estimated OLS coefficients and their t-statistics for the infrastructure project and corporate spreads, respectively.

By design the OLS model is static and ignores any time variation of the coefficients. It pools all spread data together; considers the relationship between each spread and each of the corresponding, contemporaneous explanatory variables; and estimates an average effect for each factor across the whole sample.[22]

22 - These effects are those that minimise the sum of squared differences between observed spreads and those predicted by the model.

While the static linear model achieves an adjusted R-squared of approximately 34% for infrastructure spreads and 44% for corporate spreads, tables 10 and 11 also report no significance for maturity, in the case of infrastructure spreads, or size, in the case of corporate spread. This is in line with previous papers, which often report such insignificant effects, especially for infrastructure credit spreads.

As discussed above, if the relationship between spreads and these factors has evolved over time, fitting a static linear model can capture the average value of spreads over the entire period but does not address the two issues described above: spreads are not independent in time, and their covariance with explanatory variables is time varying, partly because of the heterogeneity of observable spreads over the period and partly because creditor preferences evolve over time.

The relevant statistical tests confirm that the residuals of the static model are serially correlated and not "white noise" (see below, section 5.3.1). In other words, the estimated coefficients are at least biased. As we will show, next, they also fail to represent the dynamic effect of factors like maturity or size.

Next, we examine the relationship between loan spreads and each factor by estimating iteratively the dynamic model described in chapter 4.

5.3 Dynamic-Model Results

Using the dynamic model in equation 4.3, we estimate each of the K coefficients $\beta_{k,t}$ on each transaction date and report their effect on prices, ceteris paribus.

By design, Kalman filters aim to separate the signal (systematic effects) from the observation noise (the idiosyncratic component of prices), which is treated as Gaussian white noise (we return to this below).

Tables 12 and 14 show the descriptive statistics for each coefficient estimated over

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*Table 10: Coefficient Estimates for the Static Model of **Infrastructure Debt** Spreads*

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	5.5164	0.0785	70.31	0.0000
Benchmark Rate*	-0.2449	0.0103	-23.87	0.0000
Euribor	-0.1250	0.0337	-3.71	0.0002
Size*	-0.0608	0.0101	-6.00	0.0000
Maturity*	0.0119	0.0161	0.74	0.4595
Refi	0.0359	0.0325	1.10	0.2701
Acquisition	0.1083	0.0780	1.39	0.1653
Merchant	0.0329	0.0363	0.91	0.3642
North America	0.3535	0.0369	9.57	0.0000
Latin America	0.4321	0.0432	9.99	0.0000
APAC	0.1199	0.0514	2.33	0.0198
Power Generation	0.0282	0.0494	0.57	0.5689
Renewable Power Generation	-0.0194	0.0512	-0.38	0.7053
Energy and Water Resources	-0.1135	0.0571	-1.99	0.0470
Network Utilities	0.0175	0.0832	0.21	0.8333
Social Infrastructure	-0.1957	0.0628	-3.12	0.0019
Data Infrastructure	0.2909	0.0580	5.01	0.0000
Road Companies	-0.0756	0.0608	-1.24	0.2139

Adj-R2:34.17pct, 1890 obs. 1872 deg. of freedom.

*Table 11: Coefficient Estimates for the Static Model of **Corporate Debt** Spreads*

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	4.8136	0.0946	50.89	0.0000
Benchmark Rate*	-0.2698	0.0093	-28.99	0.0000
Euribor	-0.1250	0.0498	-2.51	0.0121
Size*	0.0175	0.0093	1.87	0.0611
Maturity*	0.0281	0.0176	1.59	0.1109
Refi	0.1664	0.0293	5.67	0.0000
Acquisition	0.1051	0.0512	2.05	0.0402
NorthAmerica	0.5836	0.0367	15.92	0.0000
LatinAmerica	0.4653	0.0557	8.35	0.0000
APAC	-0.1654	0.0399	-4.14	0.0000
Infrastructure	-0.1238	0.0689	-1.80	0.0723
Manufacturing	0.0612	0.0592	1.03	0.3015
Construction	0.0577	0.0718	0.80	0.4217
Healthcare	0.0689	0.0998	0.69	0.4903
Mining	0.1765	0.0700	2.52	0.0118
Retail	0.1276	0.0729	1.75	0.0800
Services	0.1007	0.0597	1.69	0.0917

Adj-R2:43.72pct, 3357 obs. 3340 deg. of freedom.

time as well as the median standard error for that coefficient (for the entire time period) for infrastructure and corporate spreads estimated iteratively as each new loan is originated. Tables 13 and 15 show the median of estimated coefficients within consecutive five-year time buckets since 2000.

We note that both approaches achieve higher adjusted R-squared than static models (39% and 48% respectively for the infrastructure and corporate debt).

Since the spread variable is log-transformed, coefficient estimates can be interpreted as semielasticities (percent change in spreads for one unit change in raw variables) for untransformed explanatory variables, or elasticities (percent change in spreads for 1% change in the logged variable) for log-transformed variables.

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*Table 12: Coefficient Estimates for the Dynamic Model of **Infrastructure Debt** Spreads*

	Min	Max	Median	Mean	StdDev	SE
Intercept*	5.16	5.58	5.28	5.33	0.13	0.10
Benchmark Rate*	-0.15	-0.00	-0.10	-0.10	0.04	0.04
Euribor	-0.31	0.10	-0.14	-0.12	0.14	0.07
Size*	-0.08	-0.00	-0.06	-0.05	0.02	0.02
Maturity*	0.03	0.03	0.03	0.03	0.00	0.01
Refi	-0.21	0.32	0.07	0.07	0.12	0.08
Acquisition	-0.07	0.25	0.20	0.15	0.11	0.11
Merchant	-0.31	0.34	0.09	0.08	0.19	0.08
North America	0.05	0.58	0.42	0.34	0.17	0.07
Latin America	-0.24	0.80	0.33	0.35	0.29	0.11
APAC	-0.10	0.24	0.14	0.11	0.09	0.10
Power Generation	-0.02	0.08	0.03	0.03	0.03	0.06
Renewable Power Generation	-0.05	0.07	-0.00	0.00	0.04	0.05
Energy and Water Resources	-0.44	0.23	-0.13	-0.11	0.14	0.12
Network Utilities	0.08	0.08	0.08	0.08	0.00	0.07
Social Infrastructure	-0.47	0.27	-0.16	-0.15	0.19	0.13
Data Infrastructure	0.01	0.54	0.30	0.29	0.13	0.10
Road Companies	-0.23	0.18	-0.06	-0.05	0.12	0.09

Adjusted-R2: 39.29 pct

*Table 13: Coefficient Estimates by Time Bucket – Dynamic Model of **Infrastructure Debt** Spreads*

	2000-2005	2005-2010	2010-2015	Since 2015
Intercept*	5.25	5.26	5.51	5.39
Benchmark Rate*	-0.11	-0.14	-0.06	-0.01
Euribor	-0.16	-0.20	0.07	0.04
Size*	-0.07	-0.05	-0.03	-0.04
Maturity*	0.03	0.03	0.03	0.03
Refi	0.01	0.16	0.09	0.04
Acquisition	0.25	0.23	0.08	-0.06
Merchant	0.06	0.14	0.19	0.33
North America	0.47	0.39	0.10	0.18
Latin America	0.62	0.25	0.22	0.06
APAC	-0.02	0.17	0.14	0.11
Power Generation	0.06	0.05	0.01	-0.02
Renewable Power Generation	-0.05	0.01	0.06	0.06
Energy and Water Resources	-0.18	-0.12	-0.01	0.14
Network Utilities	0.08	0.08	0.08	0.08
Social Infrastructure	-0.17	-0.33	0.04	0.18
Data Infrastructure	0.46	0.31	0.17	0.15
Road Companies	-0.20	-0.14	0.04	0.12

Median coefficient estimates are reported.∗ log-transformation.

As discussed at the end of chapter 4, we report smoothed coefficient estimates, that is, estimated backward from the values filtered at each point in time, thus using all available information. Despite the fact that smoothed coefficients are much less volatile that values estimated at time *t*, we report significant dynamics among the factors that explain credit spreads in both infrastructure and corporate debt.

Importantly, certain factors that did not have statistically significant effects in a static setting, such as maturity for infrastructure loans, are found to play a significant role in a dynamic setting.

Thus, controlling for size and other effects, loan maturity has an effect on infrastructure spreads that is positive and constant in time. Looking at figure 6 (first column, second row), the 99.5% confidence interval of the coeffi-

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Table 14: *Coefficient Estimates for the Dynamic Model of* Corporate Debt *Spreads*

	Min	Max	Median	Mean	StdDev	SE
Intercept*	4.44	5.39	5.05	5.03	0.29	0.12
Benchmark Rate*	-0.44	0.03	-0.19	-0.19	0.13	0.07
Euribor	-0.92	0.15	-0.32	-0.26	0.26	0.14
Size*	0.01	0.01	0.01	0.01	0.00	0.01
Maturity*	-0.04	0.18	0.06	0.07	0.06	0.04
Refi	-0.07	0.07	-0.03	-0.00	0.05	0.05
Acquisition	0.04	0.04	0.04	0.04	0.00	0.05
North America	-0.03	1.07	0.51	0.43	0.33	0.09
Latin America	-0.48	1.44	-0.02	0.15	0.50	0.16
APAC	-0.47	0.47	-0.22	-0.15	0.26	0.11
Infrastructure	-0.46	0.07	-0.05	-0.12	0.15	0.10
Manufacturing	0.03	0.11	0.08	0.07	0.03	0.06
Construction	-0.03	-0.03	-0.03	-0.03	0.00	0.07
Healthcare	-0.09	0.32	0.07	0.08	0.10	0.13
Mining	-0.21	0.34	0.13	0.10	0.15	0.11
Retail	0.12	0.12	0.12	0.12	0.00	0.07
Services	0.09	0.09	0.09	0.09	0.00	0.05

Adjusted-R2: 47.97 pct

Table 15: *Coefficient Estimates by Time Bucket – Dynamic Model of* Corporate Debt *Spreads*

	2000-2005	2005-2010	2010-2015	Since 2015
Intercept*	4.99	5.07	5.31	5.38
Benchmark Rate*	-0.20	-0.25	-0.03	0.01
Euribor	-0.45	-0.35	0.01	-0.00
Size*	0.01	0.01	0.01	0.01
Maturity*	0.03	0.08	0.15	0.06
Refi	-0.04	-0.02	0.05	0.04
Acquisition	0.04	0.04	0.04	0.04
North America	0.62	0.48	0.03	0.04
Latin America	0.28	0.04	-0.24	-0.41
APAC	-0.37	-0.34	-0.25	-0.22
Infrastructure	-0.05	-0.04	-0.27	-0.45
Manufacturing	0.06	0.08	0.10	0.11
Construction	-0.03	-0.03	-0.03	-0.03
Healthcare	0.04	-0.04	0.10	0.29
Mining	0.10	0.03	0.25	0.29
Retail	0.12	0.12	0.12	0.12
Services	0.09	0.09	0.09	0.09

Median coefficient estimates are reported. ⋆ log-transformation.

cient estimate is above zero (i.e., statistically different from zero) at all points in time. Conversely, the size factor is not significant for corporate debt spreads in both static and dynamic models.

Next we summarise the main findings for each factor. These are also illustrated in figures 6 to 11. We first look at the traditional spread drivers found in the literature:

1. The **intercept** of the regression captures a significant part of the predicted level of spreads. This can be equated with the "global" factor described in Collin-Dufresne et al. (2001) and Krainer (2004). Average infrastructure spreads fluctuate over the period (before taking into account the impact of other factors). The trend is mostly flat until 2008. It then shifts to a higher level until 2013, when it decreases again in a stable trend. Using this baseline, ceteris paribus, average infrastructure

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spreads are only about 29 BPS higher from 2015 than they were in 2000-2005.[23]

Conversely, the intercept for corporate debt spreads increases continuously over the period, albeit more slowly after 2015. Likewise, taking all the effects into account, corporate spreads are about 70 BPS higher after 2015 than they were a decade earlier.[24]

2. **Base interest rates** have an increasingly negative effect on spreads in the case of infrastructure debt until 2008: an increase in base rates by 10% lowered credit spreads by 1% until the credit crisis.[25] The impact of base rates on corporate spreads is stronger (closer to 2%) but follows the same trend. After 2008, this effect gradually disappears as the coefficient estimates converge toward zero. In other words, spreads and interest rates eventually become completely disconnected.

3. **Euribor** spreads, as noted earlier, could be different from LIBOR spreads, which are the majority of those observed. Our Euribor control variable shows that this effect has also dissipated over time. Euribor-priced corporate debt could be up to 5% lower than equivalent LIBOR-priced loans until 2010, when this effect disappears. Likewise, infrastructure debt spreads tend to be lower when financed against the Euribor benchmark, up to 2% cheaper until 2008, after which this effect ceases to be a persistent driver of debt prices.

4. **Size** is not a significant driver of corporate credit spreads since it can take a value of zero, which is within its 95% confidence interval, at any time during the period as shown in figure 9. On the contrary, size is a significant factor in the determination of infrastructure credit spreads: until 2008, a 10% larger loan size tends have a 0.8% lower spread. However, from 2009, this effect, while still statistically significant, has been reduced to 0.4%. The cost of liquidity (proxied by size) has thus increased for lenders to infrastructure projects.

5. The effect of **maturity**, again, differs between corporate and infrastructure debt. The latter exhibit a constant positive but small cost of greater maturities, with loans with 10% longer tenors requiring 0.3% higher spreads. Corporate loans essentially did not price maturity until 2006 when it became a source of higher spreads with, at its 2012 peak, 10% longer loans requiring a 1% additional spread premia. In other words, raising 15-year instead of 10-year debt would increase the cost of debt by 5%, ceteris paribus. However, by 2016, this effect all but vanished again.

6. **Re-financings**: In previous research re-financings had been found to lower the cost of debt. Here, controlling for pother effects dynamically, this is not the case effect is also time-varying. Corporate debt re-financings were priced essentially like equivalent loans until 2008 i.e. the effect is not different from zero. Afterwards,

23 - Because the spreads are logged in the regression, it is necessary to take the exponential of the coefficients to get a value in basis points. Here, using the results in table 13, $e^{5.39} - e^{5.25} = 28.63$

24 - $e^{5.38} - e^{4.99} = 70.08$

25 - The exact effect is, taking the 2000/2010<OK or 2000-2010?> median coefficient, $exp(\beta_k) - 1 = exp(-0.125) - 1 = -0.1175$.

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they become more expensive than the average loan by a small margin, but this effect disappears after 2013/14. For infrastructure loans, this effect is even more dynamic. Re-fis were more expensive around 2002 (a year of high project finance default rate (Moody's, 2013)) and even more between 2008/13. Since then, project loan re-financing has ceased being more expensive than equivalent loans.

7. **Acquisition debt financing** has also evolved over time in the case of infrastructure debt. While it used to be roughly 20% more expensive than traditional project loans, the pricing of such transactions has decreased gradually since 2008 to reach average levels by 2014. For corporate debt, the effect is hard to distinguish from zero, that is, on average, acquisition financing is not more or less expensive than other forms of corporate debt.

Next, we look at two factors that are specific to infrastructure debt pricing:

1. **Merchant project** (infrastructure debt model only): Merchant risk in infrastructure debt financing is a good discriminant of the level of credit risk. Merchant projects are exposed to commercial risk and the business cycle. From 2002 onward (just after the US merchant-power collapse of 2001), merchant infrastructure project loans exhibit clearly positive premia, higher than 20% above the average spread until 2007. Between 2007 and 2009, merchant project spreads decrease and converge with the market mean. This is the result of two effects: first, the mean market spread captured by the model intercept is now much higher; and, second, there is selection bias created by the credit crisis, that is, only the best, least-risky merchant projects can raise debt at that time. From 2010, normal lending conditions resume in most markets, and merchant spreads begin to increase again until they reach a 35% premium by the end of 2016.

2. **Infrastructure corporates** (corporate debt model only): The infrastructure control variable shows the level of credit spreads for corporates that qualify as infrastructure under TICCS. Average infrastructure corporate spreads could not be distinguished from the average until 2008 (mean premium is zero). However, since that period they have decreased continuously, to 45% below average in 2016. We note that the mix of infrastructure corporates evolves over the period, with the earlier period dominated by power-generation and energy-resources companies while a more diverse group of infrastructure corporate borrowers taps the private loan market after 2008, including network-utilities and data-infrastructure companies.

The dynamics of geographic control variables also differ between infrastructure and corporate loans. The effect of the reference region (EMEA) is captured by the intercept discussed above.

1. **North American** spreads follow a decreasing trend over the period. However the dynamics differ between corporate and infrastructure loans. Corporate

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Figure 6: Infrastructure Project Debt Spread Factors – Time-Varying Factor Effects

⋆ log-transformation

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Figure 7: Infrastructure Project Debt Spreads Factors – Time-Varying Factor Effects (Continued)

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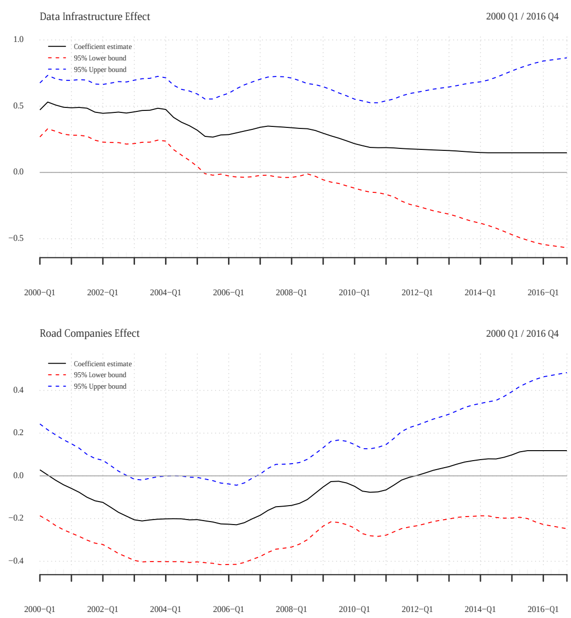
Figure 8: Infrastructure Project Debt Spread Factors - Time-Varying Factor Effects (Continued)



debt is significantly more expensive in North America in 2000 but this premium decreases until 2004 and again sharply after 2007. By 2012, it has all but disappeared, and the "syndicated loan pricing puzzle" of Carey and Nini (2007) no longer exists. In the case of infrastructure debt, the North American premium only begins to recede from its 60% peak after 2006 and today still exists at approximately 20% above comparable loans, as it does during the rest of the period.

2. In **Latin America**, corporate spreads are not particularly higher or lower than the global average, ceteris paribus, after 2004 and even tend to be below it from 2011. This effect is not systematic however. Private infrastructure project loans go from a high premium until 2005 to a negative premium in 2007 (cheaper than the market average). This period is short-lived however, and infrastructure project spreads have returned to positive levels since then.

3. Corporate debt in **Asia Pacific** is usually cheaper then global averages, and corporate loans are no exception, with average spreads consistently below the global average by at least 20%, except in 2008, when the effect disappears briefly. In the case of commercial infrastructure debt, the pattern is different: after a decrease in the cost of debt until 2007, infrastructure debt spreads trended up after the credit crisis and remain, tendentially, above global averages even though the effect is not systematic, since the 95% confidence interval indicates that some loans do not have a positive premium.

Finally, once the variables above are taken into account, industrial-sector control variables

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are mostly not significant, that is, we do not find evidence that loans in certain sectors always receive a premium (positive or negative) that is different from zero.

Corporate-industrial groupings reveal that manufacturing debt spreads are on a constant upward trajectory during the period (despite monetary policies designed to reduce the cost of capital in such sectors). By 2016, this effect is close to being systematic.

Health care and mining also see average spreads increase but more sharply and only after the credit crisis. The construction sector mostly exhibits average spreads that are very close to the global average over the period. Borrowers in the retail and services sectors have to pay a premium of 12 and 9% above the average, respectively, unchanged during the period. These last two effects are the only systematic ones.

Infrastructure industrial groupings are mostly not systematic. There is a downward trend in **power-generation** spreads, which have been converging toward the market average since 2005. This can be a reflection of the changing nature of the business model of power-generation companies over the period (more long-term contracted projects) but also of the rise of the average level of market spreads.

There is an upward trend in **renewable power generation** and **energy and water resources** but no systematic effect on prices. Likewise, **network utilities** are not priced differently than the sample mean.

Loans extended to **data-infrastructure** companies over the period have seen their credit spreads decrease relative to the market average from a systematic premium of 50% to a point where, after 2011, they are indistinguishable from the average. This is mostly due to the evolution of business models and industrial operations in this sector, from telcos exposed to market risk to contracted data centres and other 3G-telecommunication assets.

Road companies were able to systematically raise infrastructure debt up to 20% below the market on average until 2006-2007. Since then, road credit spreads have increased steadily and are now in line with market averages. Over this period, numerous merchant toll roads experienced difficulties (e.g., in Spain and Australia), and the creditors have required additional premia to take credit risk in this sector.

Finally, **social-infrastructure** debt was cheaper than other infrastructure loans until 2013, which is consistent with the long-term contracted nature of revenues in such projects. Thus, since 2013, size and maturity are sufficient factors to explain credit spreads in public-private partnerships (PPPs).

5.3.1 Robustness

The multifactor model in equation 4.2 represents the combination of each factor's individual and independent effect on *average* transaction prices and treats the idiosyncratic component of transaction prices as **white noise**, that is, uncorrelated, zero-

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Figure 9: Corporate Debt Spread Factors – Time-Varying Factor Effects

⋆ log-transformation

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Figure 10: Corporate Debt Spread Factors – Time-Varying Factor Effects (Continued)

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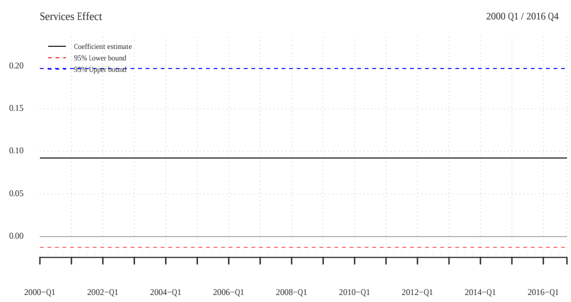
Figure 11: Corporate Debt Spread Factors – Time-Varying Factor Effects (Continued)



mean, and symmetrically distributed random disturbances in the observed spreads.

Our primary robustness check is to test whether the model's residuals, that is, the difference between predicted and observed spreads, are indeed white noise.

Overall, the residuals can indeed be considered to be distributed according to a Gaussian process, as shown in figure 13.

Tables 19 and 20 in the appendix show that for both the static and dynamic models, residuals can be considered to have zero mean and present limited skewness and kurtosis, that is, the model residuals have zero-mean and symmetrical distributions.

However, as indicated before, the static-model residuals show clear evidence of serial correlations and fail the Ljung-Box test, which asks whether any of a group of autocorrelations in a time series are different from zero, as well as the white-noise test using different lags.

The residuals of the dynamic model, on the contrary, are uncorrelated and pass the Ljung-Box test.

The absence of correlation in the residuals validates the hypothesis of conditional independence of the price observations made in chapter 4: conditional on the state $\theta_{1:t} = [\beta_{1,1:t} \ldots \beta_{K,1:t}]$, spreads $Y_{1:t}$ are independent in time. We also report variance-inflated factors (VIF) of less than 1.5, signaling the absence of significant multicollinearity in the model's variables, that is, the model's explanatory variables are reasonably uncorrelated. Correlation plots can be seen in the appendix in figures 24 and 25.

5. Findings

With reasonably Gaussian and uncorrelated residuals, our coefficient estimates can be considered unbiased and robust.

A final robustness test consists of comparing the filtered spreads in the last step of the Kalman filter at each point in time with the actual observed transaction price at that time. Table 16 reports mean and median error as well as mean and median absolute errors for infrastructure and corporate spread models.

*Table 16: Goodness of Fit: **Infrastructure Debt** (left) and **Corporate Debt** (right) Spread Models*

	Metric
MSE	0.21
ME	0.01
MedE	0.00
MAD	0.33
MedAD	0.24
MAPE	0.07
MedAPE	0.05

	Metric
MSE	0.31
ME	0.01
MedE	0.02
MAD	0.42
MedAD	0.32
MAPE	0.09
MedAPE	0.06

ME: mean error, MedE: median error, MSE: median squared error, MAD: mean absolute deviation, MedAd: median absolute deviation, MAPE: mean absolute percentage error, MedAPE: median absolute percentage error

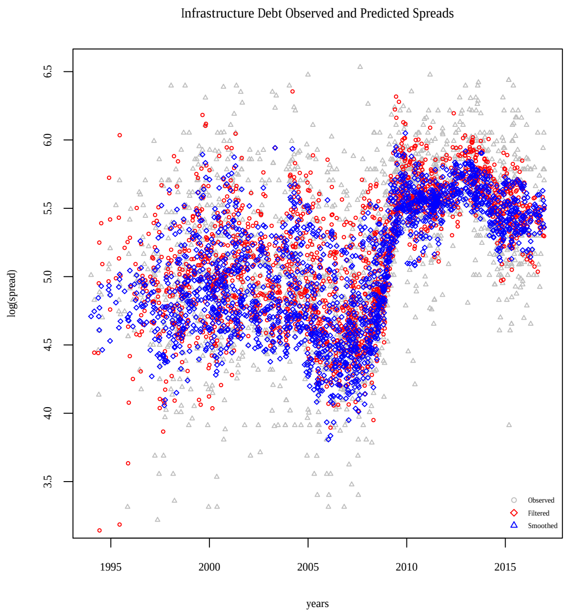
The mean and median absolute percentage errors (MAPE) of the models are between 5 and 7% for infrastructure spreads and between 6 and 9% for corporate spreads. This is reasonable, considering that the model predicts the systematic part of spreads, which should also exhibit an idiosyncratic component. As shown above, this idiosyncratic component – the residuals of the model – is found to be equivalent to white noise. Nevertheless, the model cannot predict spreads with 100% accuracy, which would require no pricing noise at all.

Figure 12 also shows the observed (gray dots), filtered at time *t* (red dots), and backward smoothed (blue dots) estimates of credit spreads for infrastructure (left) and corporate (right) spreads.

Clearly, the two models are capable of predicting a wide range of spreads, in line with observable data. Systematic effects also capture credit-crisis dynamics, especially around the 2008/9 credit crisis.

5. Findings

Figure 12: Observed, Filtered, and Smoothed Spreads Using the Dynamic Linear Model



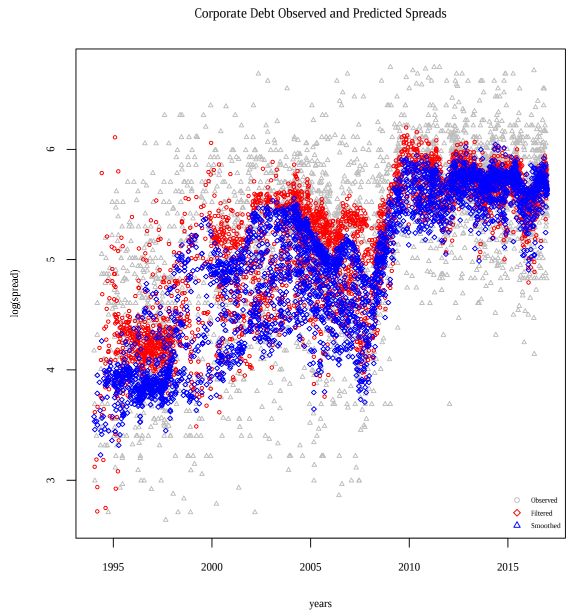
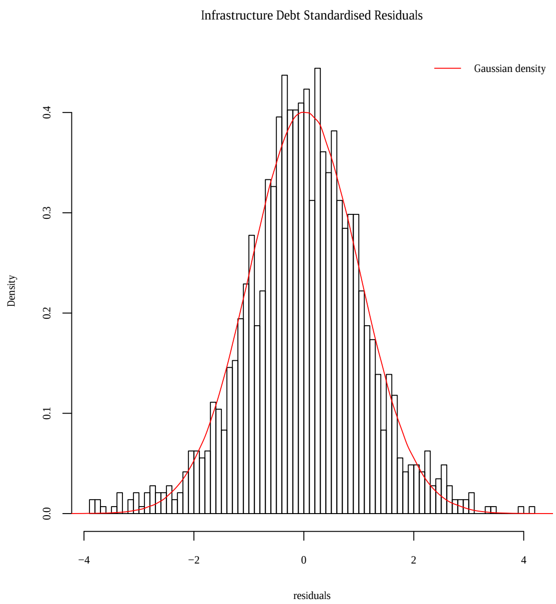
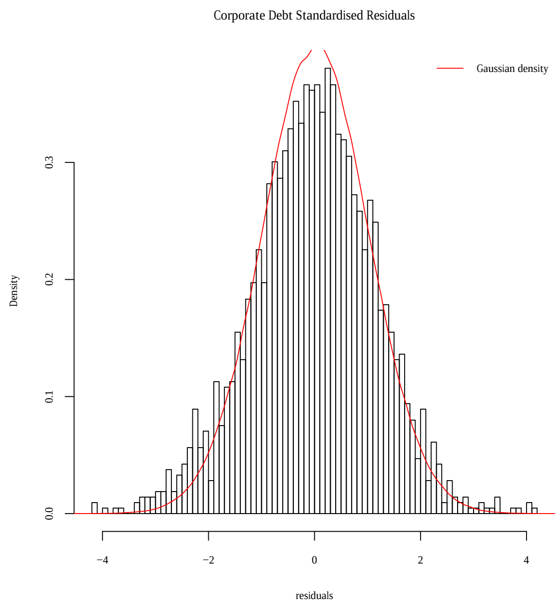


Figure 13: Residuals Distribution of Project Finance and Corporate Debt Spread Models





6. Market Trends

6. Market Trends

6.1 Application to the EDHEC*infra* Universe of Infrastructure Loans

In this chapter, we apply the spread premia estimated in the previous chapter to the instruments of the EDHEC*infra* universe.

The EDHEC*infra* universe is designed to cover a representative set of investable infrastructure companies in major markets globally. It covers 50% of these markets by book value in each year and aims to capture the same share of sectors and business models available to investors in each year since 2000.

As of 2018, a sample of 637 companies represents an underlying population of 4,400 companies in 25 different countries. [26]

26 - See EDHEC*infra* Index Computation Methodology for more details.

Among these, 554 have senior private debt that can be priced according to factors identified earlier. There are 159 infrastructure corporates, and the remainder are infrastructure projects, as defined earlier and under the fourth TICCS pillar on corporate governance.

We use this data set to create the necessary factor loadings ($X_{k,t}$ in equation 4.3) to compute a shadow spread for each senior debt instrument on the balance sheet of each borrower in the universe.

This yields 14,770 factor-implied or "shadow" credit spreads for 2,569 senior debt instruments between 1987 Q4 and 2018 Q2.

Figure 14 shows the median level of infrastructure credit spreads over the period for infrastructure projects (left) and infrastructure corporates (right), free from any of the reporting biases found in the original input data set described in chapter 3. We see that on this basis infrastructure project debt creditors benefit from a 50 BPS uplift in 2018 compared to lenders to infrastructure corporates.

6.2 Market Trends

We note that the average market price of credit risk for private infrastructure debt bottomed out at the end of 2006, when signs of credit stress were beginning to appear in the banking sector, but well before the 2008 credit crisis had fully developed. Spreads then peak in late 2009 but also in 2011, at the height of the European debt crisis.

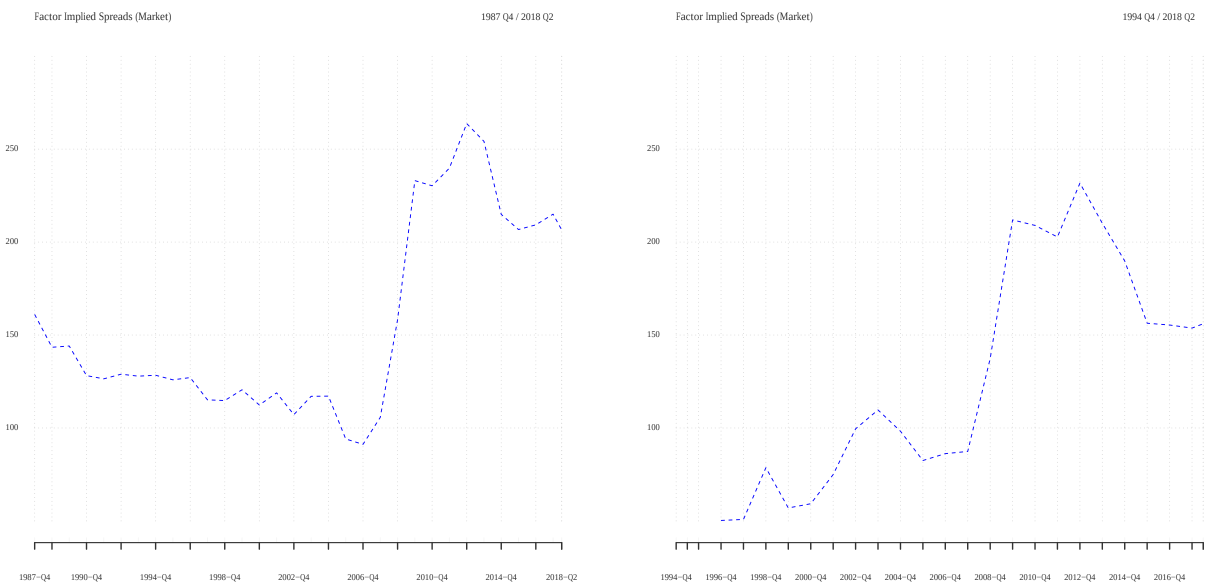
Since then, average market spreads for infrastructure projects have remained slightly over 200 basis points despite the accommodating funding conditions created by central banks. In comparison, infrastructure corporate spreads have decreased further to slightly above 150 BPS.

As we saw in chapter 5, the impact of short-term interest rates on credit spreads has gradually disappeared since 2008. Small changes in base rates now leave credit spreads unaffected.

However, as discussed in the previous chapter, the level of infrastructure credit spreads that is not driven by priced systematic risk factors (the model intercept) has only increased by about 20 BPS for infrastructure projects compared to precrisis levels.

6. Market Trends

Figure 14: *Market Factor-Implied Debt Spreads for Infrastructure Projects (Left) and Infrastructure Corporates (Right)*



This level of spreads also persists despite constant or decreasing aggregate credit risk in the underlying population of instruments, as shown in figure 15, which includes the average size, maturity, leverage, or debt service cover ratio levels in the EDHEC*infra* universe.

Hence, the evolution of credit spreads shown in figure 14 has not been driven by changes in risk-factor exposures but by a significant shift in the pricing of these risk factors by creditors.

In other words, it can be argued that the pricing is "fair" in the sense of IFRS: spread levels today can be explained by the systematic effects of risk factors that are found in market prices at the time of evaluation.

6.3 Analytics

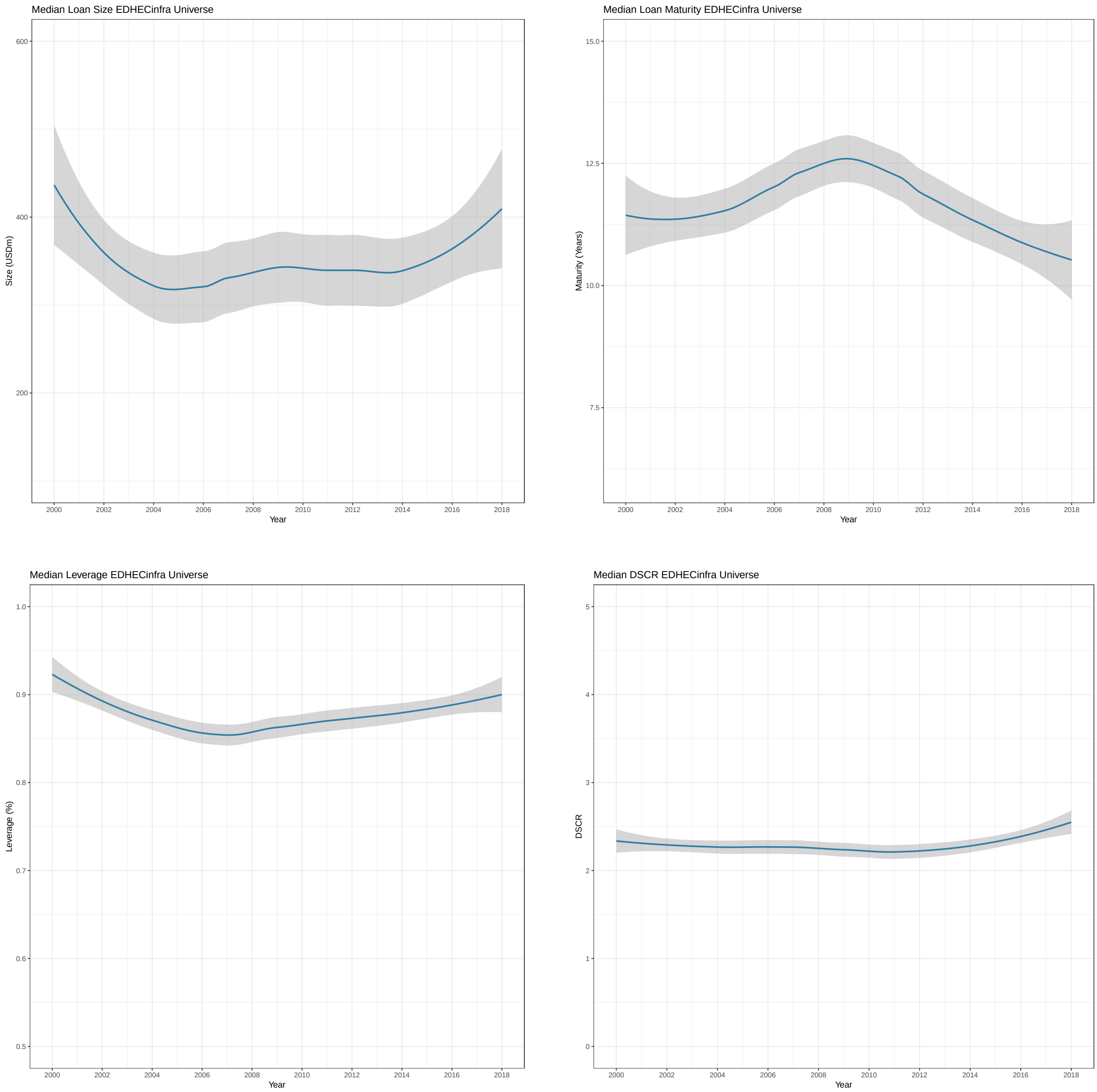
Next, using these results, we can compare the dynamics of credit spreads for infrastructure projects and for infrastructure corporates in more detail. We look at the estimated spreads by slicing and dicing the results along a number of dimensions of the firms' financials.

It should be noted that, contrary to the regression coefficients reported in chapter 5, these results are not stand-alone effects reported ceteris paribus, but they incorporate all the factor effects described earlier.

Hence, these results are more akin to "stylised facts" about infrastructure and corporate credit spreads, while the individual relationships between spreads and factors are documented in the chapter 5.

6. Market Trends

*Figure 15: Size, Maturity, Leverage, DSCR Trends in the EDHEC*infra *Universe*



The gray ribbon equals one standard deviation.

6. Market Trends

6.3.1 Maturity, Size, and Spreads

Figure 16 compares the level of spreads for loans at various stages of maturity, from very short maturities to 33 years (12,000 days). The gray band around the average values represents one standard deviation.

We see that with the combined effect of different factors on spreads, longer infrastructure loans tend to have lower spreads, as is often reported, but only because they also also larger in size.

Indeed, we see in figure 17 that larger infrastructure loans tend to have lower spreads beyond a certain size (USD 150 million, i.e., e^5).

For infrastructure corporates, the picture is reversed: longer maturities and larger sizes both coincide with higher spreads.

Here, we find evidence of the usual "puzzles" found in infrastructure debt since larger, longer loans tend to be cheaper, but explained from a factor perspective. Applying the factor effects documented in chapter 5, we can explain how spreads, size, and maturity relate to each other.

6.3.2 Credit Risk and Spreads

Looking at credit-risk metrics for the companies in the EDHEC*infra* universe, figure 18 shows average spreads relative to the level of the debt service cover ratio (DSCR), that is, the ratio of (senior) debt service to cash flow available for debt service. The level of the DSCR is a standard measure of credit risk.

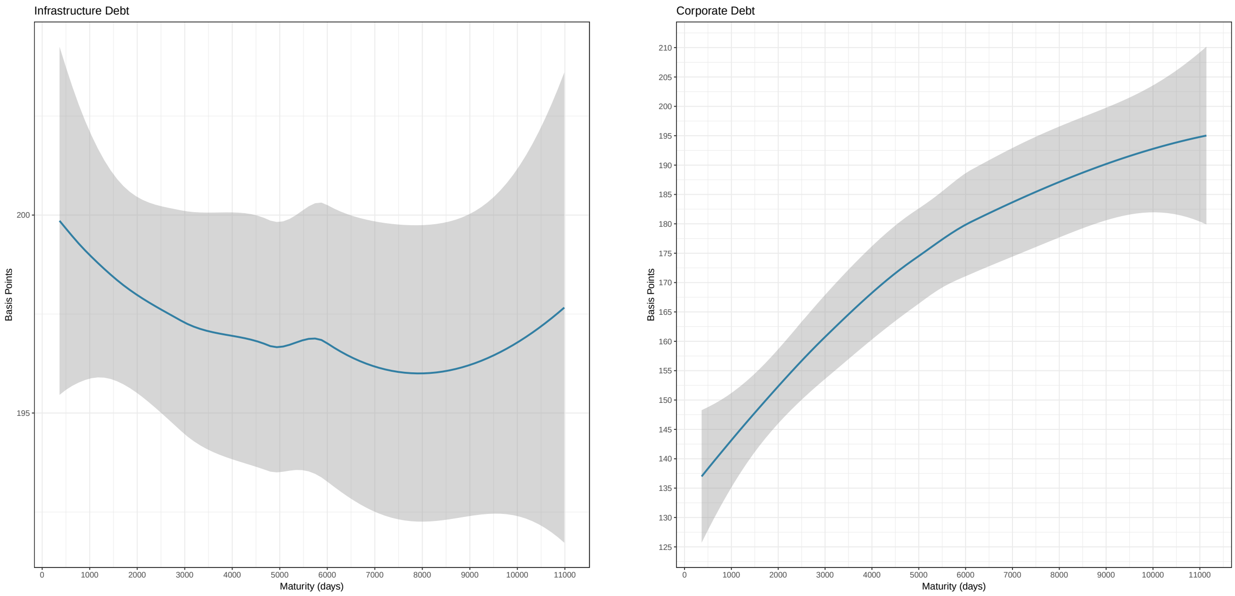
We see that infrastructure project spreads are higher for companies that have a higher DSCR up until about two, beyond which there is no clear trend. Indeed, borrowers with low credit risk tend to be required to keep a lower DSCR level and are charged lower spreads as well. This is typically the case with social-infrastructure projects. If project companies exhibit a higher DSCR (implying a higher minimum required DSCR), they tend to represent higher credit risk hence also exhibit higher spreads. However, beyond a threshold of two, this effect disappears and credit spreads are not explained by the DSCR level.

Infrastructure corporates exhibit a clearer, inverted-U-shaped relationship between spreads and DSCRs. Likewise, higher DSCRs are related to higher spreads, which can seem surprising since the cash-flow covenants found in corporate infrastructure loans are typically less stringent than in project finance. Companies that have a DSCR higher than five, however, also have increasingly lower spreads.

Leverage is another indication of credit risk. Infrastructure debt exhibits roughly constant average spreads for any level of leverage up until 90%. Beyond that threshold, spreads are lower, confirming the notion that higher levels of leverage are an indication of lower asset risk, as discussed in chapter 2. These high-leverage, low-spreads project companies are the borrowers that exhibit a low DSCR in figure 18.

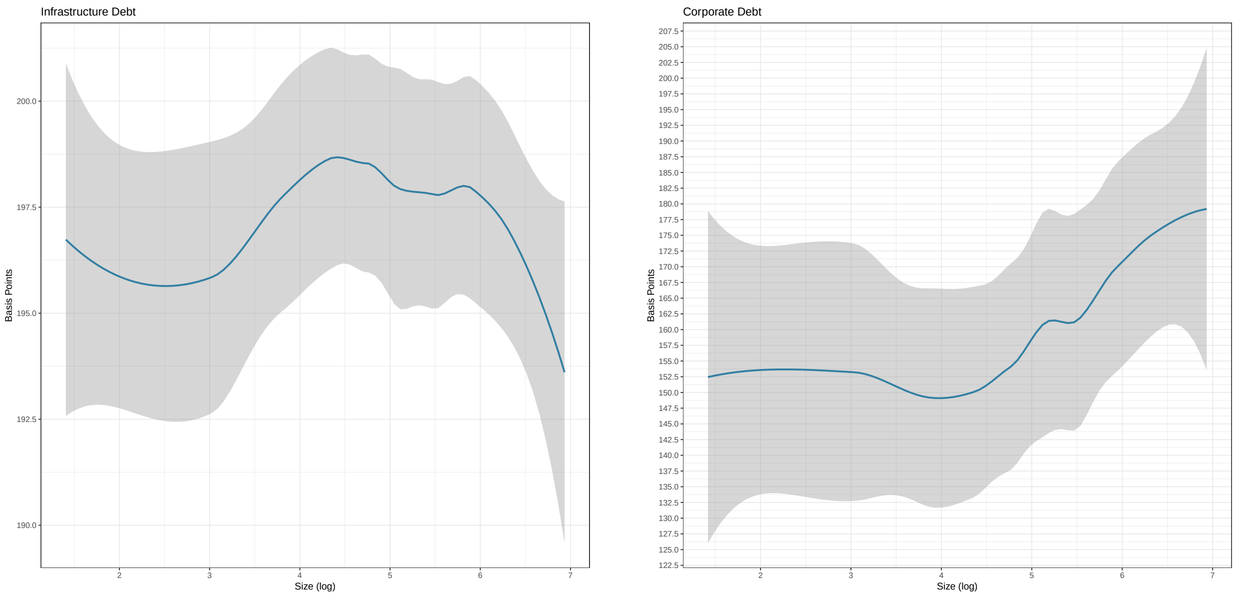
6. Market Trends

Figure 16: Spreads and Maturity – Infrastructure Projects and Infrastructure Corporate Debt



The gray ribbon equals one standard deviation.

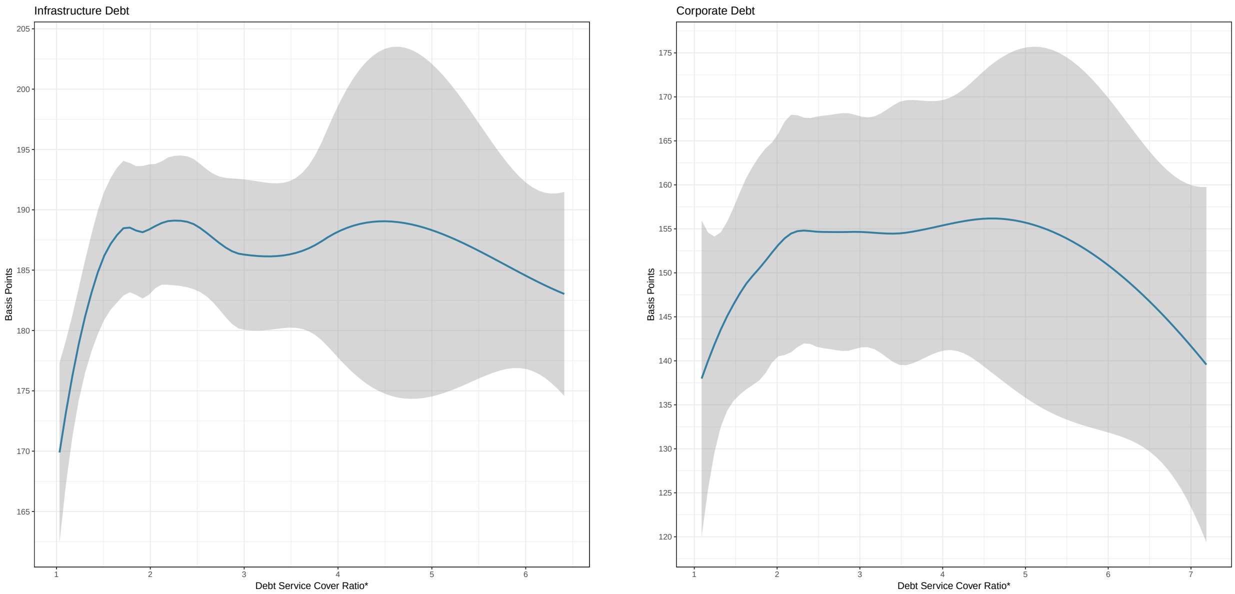
Figure 17: Spreads and Size – Infrastructure Projects and Infrastructure Corporate Debt



The gray ribbon equals one standard deviation.

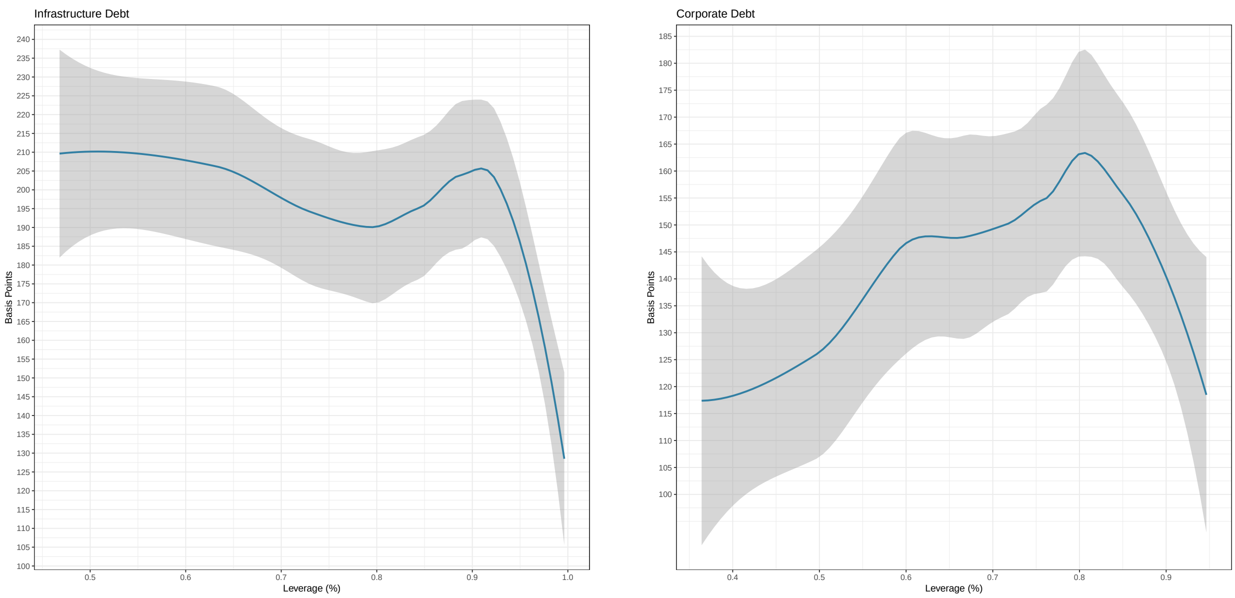
6. Market Trends

Figure 18: Spreads and Debt Service Cover Ratios – Infrastructure Projects and Infrastructure Corporate Debt



The gray ribbon equals one standard deviation.

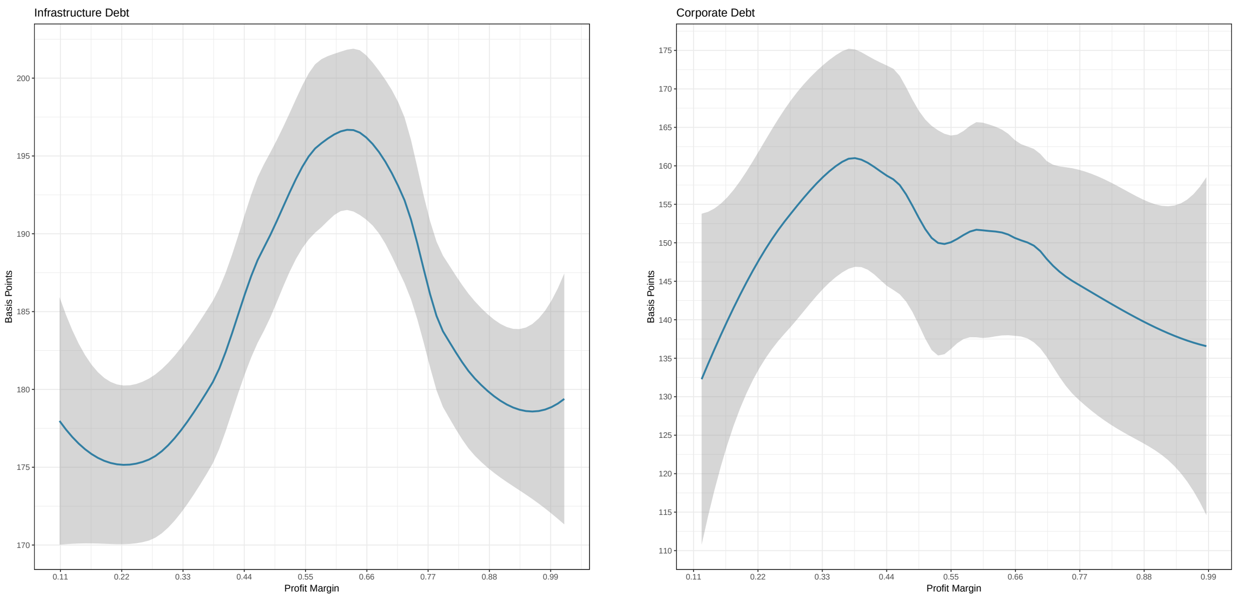
Figure 19: Spreads and Leverage – Infrastructure Projects and Infrastructure Corporate Debt



The gray ribbon equals one standard deviation.

6. Market Trends

Figure 20: Spreads and Profit Margins – Infrastructure Projects and Infrastructure Corporate Debt



The gray ribbon equals one standard deviation.

For infrastructure corporates, leverage and spreads are positively related, that is, higher leverage corresponds to higher spreads, but the same high-leverage/lower-spread effect also occurs beyond the 80% leverage threshold, indicating that creditors can recognise that low-risk borrowers may have higher leverage outside of project financing. This nonlinearity in the pricing of infrastructure corporate debt shows that common pricing mechanisms exist between project and corporate infrastructure debt.

6.3.3 Profitability and Spreads

Finally, looking at infrastructure profit margins (profits divided by revenues), we see a comparable inverted-U-shaped relationship: up to a certain level of profitability (60% for projects and 40% for infrastructure corporates), spreads increase with profitability, suggesting that firms that take time to achieve a certain level of profitability are understood to be higher credit risks.

Beyond these thresholds, spreads decline rapidly for both infrastructure projects and corporates.

7. Conclusions

7. Conclusions

In this paper, we examine the determinants of the credit spreads for private infrastructure project and corporate loans, which constitute the vast majority of the debt instruments used in privately financed infrastructure.

We significantly improve on the findings of previous studies by using a combination of dynamically estimated risk factors to explain observable aggregate spreads and hedonic factor pricing to represent the factor-implied spreads of a representative population of investable infrastructure.

7.1 What Factors Explain Infrastructure Credit Spreads?

Our results are statistically robust and explain the data well. We show that infrastructure and corporate credit spreads are determined by a combination of common factors that can be grouped into four categories:

- **Market trend / regime**: the largest effect driving credit spreads in both infrastructure and corporate debt is a time-varying trend or regime factor that captures the state of the credit market over time. This effect is not explained by loan or borrower characteristics.[27]

  In the case of infrastructure debt, this effect is roughly constant but exhibits "regime shifts" at certain points in time, especially 2008 (shift up) and 2014 (shift down). In the case of corporate debt, there is an upward trend also exhibiting upward shifts in 2008 and 2012.

  Overall, these shift have been limited. We find a 29bps increase of infrastructure spreads compared to pre-crisis levels, down from 75bps at the height of the credit crisis, and a 70bps increase for corporate debt over the same period.

- **Credit risk** only explains part of the level of credit spreads.

  - Business risk: We find that infrastructure borrowers that are exposed to commercial risks are required to pay a time-varying premium from 20% to 40% above the market average.
  - Size has no effect on average corporate spreads but is a driver of lower risk premium in infrastructure debt. In effect, larger loans can be interpreted as a signal of lower credit risk in infrastructure finance.
  - Industrial groups can considered to be a partial proxy for credit risk but are mostly not significant, except for social infrastructure and, among corporate borrowers, infrastructure corporates, which have come to benefit from a substantial discount relative to average market spreads in recent years.

- **Liquidity**: Other significant drivers of spreads are proxies of the cost of liquidity for creditors.

  - Maturity: While it is difficult to capture in static models, maturity is found to be a significant and time-varying driver of spreads for corporate debt, with higher premia charged during

27 - This is consistent with previous research, which has found a large "common factor" to all credit instruments – see chapter 2.

7. Conclusions

periods of lower bank liquidity (2008-2016), whereas infrastructure debt has a constant maturity premium.

- While the effect of size is primarily a matter of credit risk, we note that in periods of limited creditor liquidity (2008), even infrastructure debt becomes more expensive as a function of size. However, this effect is not strong enough to create a size premium.
- Refinancings, which are not a significant driver of spreads in normal times, are shown to be more expensive in times of credit-market stress, especially for infrastructure debt.

- **Cost of funds**: The benchmark against which floating-rate debt is priced has been a factor explaining the level of credit spreads.

  - Base rates are inversely related to spread, that is, higher rates imply lower spreads, but this effect is shown to have all but vanished since 2008. Since then, the level of credit spreads and that of base interest rates has become completely uncorrelated.
  - Market segments: Taking base rates into account, some markets are cheaper than others as a result of the well-known segmentation of credit markets. This is the case when comparing LIBOR- vs. Euribor-priced loans but also the different geographic areas in which different lenders operate. Again, since 2008, these differences have tended to disappear.

7.2 Is Infrastructure Project Debt Expensive?

By documenting the impact of various factors on credit spreads over time, these results highlight the fact that the 2008 credit-market dislocation changed and sometimes removed well-established relationships between certain factors and the cost of corporate and infrastructure debt.

The impact of base rates on loan pricing disappeared, structural differences between markets vanished, and certain sectors, like roads, experienced a continued increase in the price of long-term private financing.

The average level of spreads shifted to a new, higher average level and remained above 200 BPS even as interest rates decreased.

However, we show that this evolution can be explained primarily by the evolution of individual risk-factor prices and that, controlling for these factors' prices and the level of exposure to these factors in the population of relevant assets, average infrastructure spreads have increased by about 20 BPS.

We conclude that the pricing of infrastructure debt is "fair" in the IFRS sense, that is, it is driven by the prices of systematic risk factors that are revealed in market prices as and when they occur.

These results also show that infrastructure and corporate debt are exposed to a number of common risk factors, including liquidity, cost of funds, and credit risk. They also respond

7. Conclusions

to equivalent pricing signals or mechanisms: for instance, we find that, as is the case in project finance, infrastructure corporate debt and high leverage (above 80%) signals lower credit risk and spreads.

Still, infrastructure project and corporate debt retain fundamental differences, and common factors are priced differently. For instance, the relationship between spreads and maturity is convex for infrastructure project debt and concave for infrastructure corporates.

A. Appendix

A. Appendix

Figure 21: Distribution of the Log Spread of Corporate and Infrastructure Project Debt

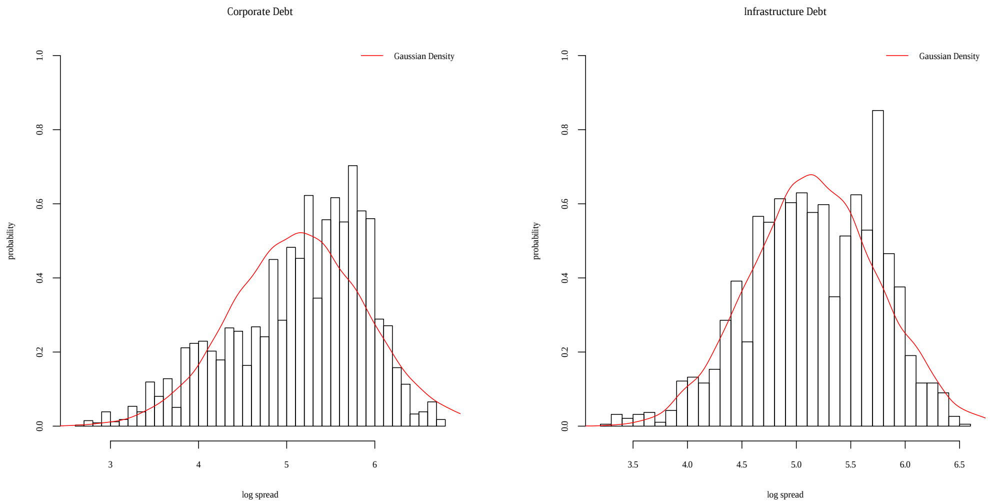


Table 17: Time-Varying Correlations of Infrastructure Loan Spreads and Key Explanatory Variables

Starting	Ending	Size	Maturity	Euribor	Refinancing	Sterling	Obs
1994	1999	-0.090	-0.139	-0.124	-0.149	-0.156	189
1999	2001	-0.177	-0.199	-0.205	0.124	-0.176	189
2001	2003	0.012	-0.282	-0.095	0.080	-0.228	189
2003	2005	-0.056	-0.241	-0.250	0.053	-0.203	189
2005	2007	-0.053	-0.330	-0.288	0.009	-0.033	189
2007	2008	0.022	-0.420	-0.408	0.239	-0.166	189
2008	2009	0.221	-0.227	-0.371	0.304	0.065	189
2009	2011	-0.027	-0.228	-0.026	0.076	-0.192	189
2011	2014	-0.158	-0.099	-0.063	0.091	-0.082	189
2014	2016	-0.045	0.022	0.078	0.077	-0.155	189

Table 18: Time-Varying Correlations of Corporate Loan Spreads and Key Explanatory Variables

Starting	Ending	Size	Maturity	Euribor	Refinancing	Sterling	Obs
1994	1996	0.046	0.093		-0.013	-0.016	336
1996	1999	-0.063	-0.126	-0.050	-0.073	-0.075	336
1999	2002	0.028	-0.103	-0.313	-0.066	-0.038	336
2002	2004	0.040	-0.146	-0.348	-0.005	-0.040	335
2004	2006	-0.044	-0.098	-0.280	-0.040	-0.115	336
2006	2008	0.045	-0.008	-0.286	-0.055	-0.116	336
2008	2011	0.060	0.126	-0.180	0.120	0.006	335
2011	2013	0.119	0.261	0.019	0.155	-0.023	336
2013	2015	0.111	0.093	0.025	-0.008	0.055	336
2015	2016	0.003	0.043	0.041	-0.060	-0.053	335

Table 19: Residuals Testing: Infrastructure Debt Spread Model

	T-Test	Skew	Kurt.	K-S Test	B-L test	WN Test (5)	WN Test (10)	WN Test (20)
Static Model	1.00	-0.26	0.67	0.00	0.00	0.00	0.00	0.00
Dynamic Model	0.63	-0.10	1.31	0.00	0.74	0.36	0.74	0.78

K-S: Kolmogorov-Smirnov Test, B-L: Box-Ljung Test, WN: White Noise Test (number of lags)

Table 20: Residuals Testing: Corporate Debt Spread Model

	T-Test	Skew	Kurt.	K-S Test	B-L test	WN Test (5)	WN Test (10)	WN Test (20)
Static Model	1.00	-0.36	0.47	0.00	0.00	0.00	0.00	0.00
Dynamic Model	0.35	-0.17	1.04	0.00	0.44	0.22	0.44	0.15

K-S: Kolmogorov-Smirnov Test, B-L: Box-Ljung Test, WN: White Noise Test (number of lags)

A. Appendix

Figure 22: Autocorrelation of the Project Finance and Corporate Debt Spreads

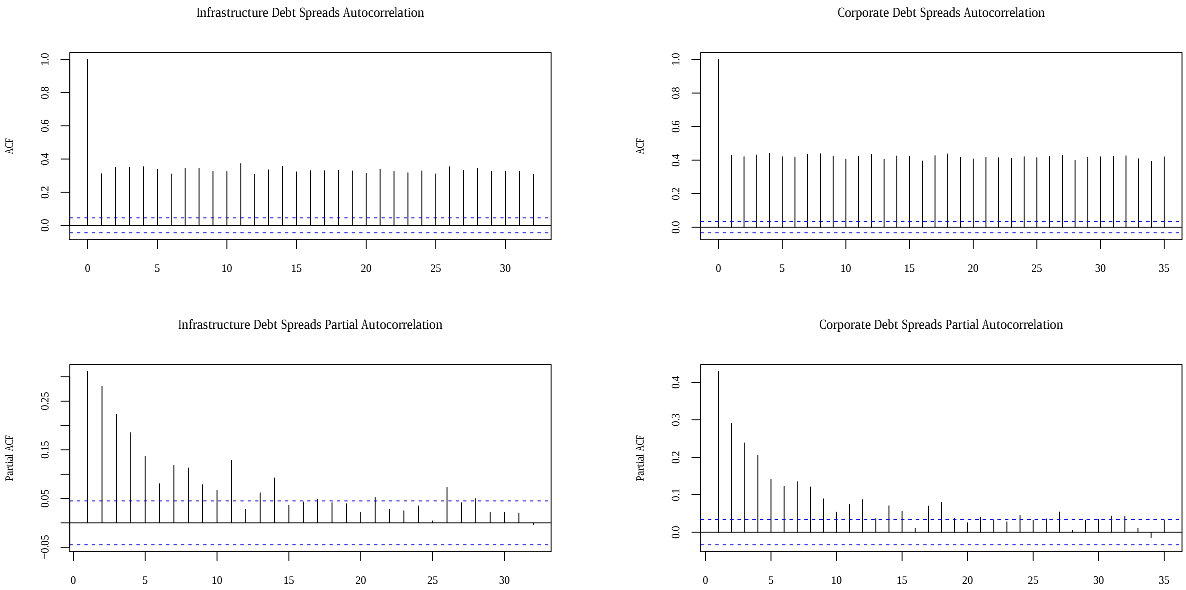
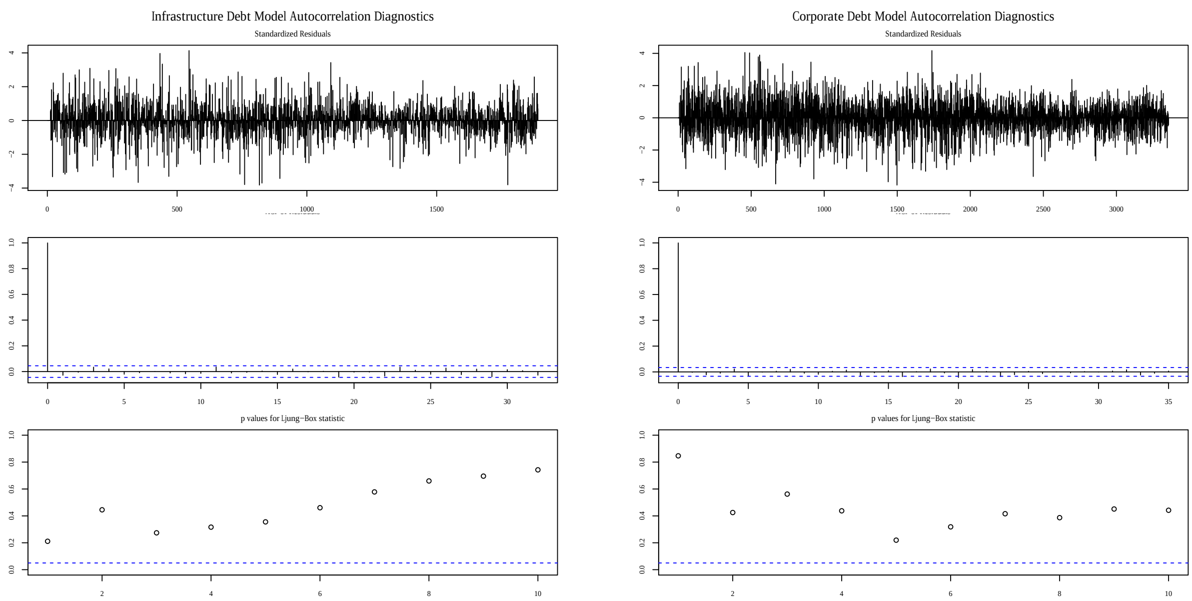
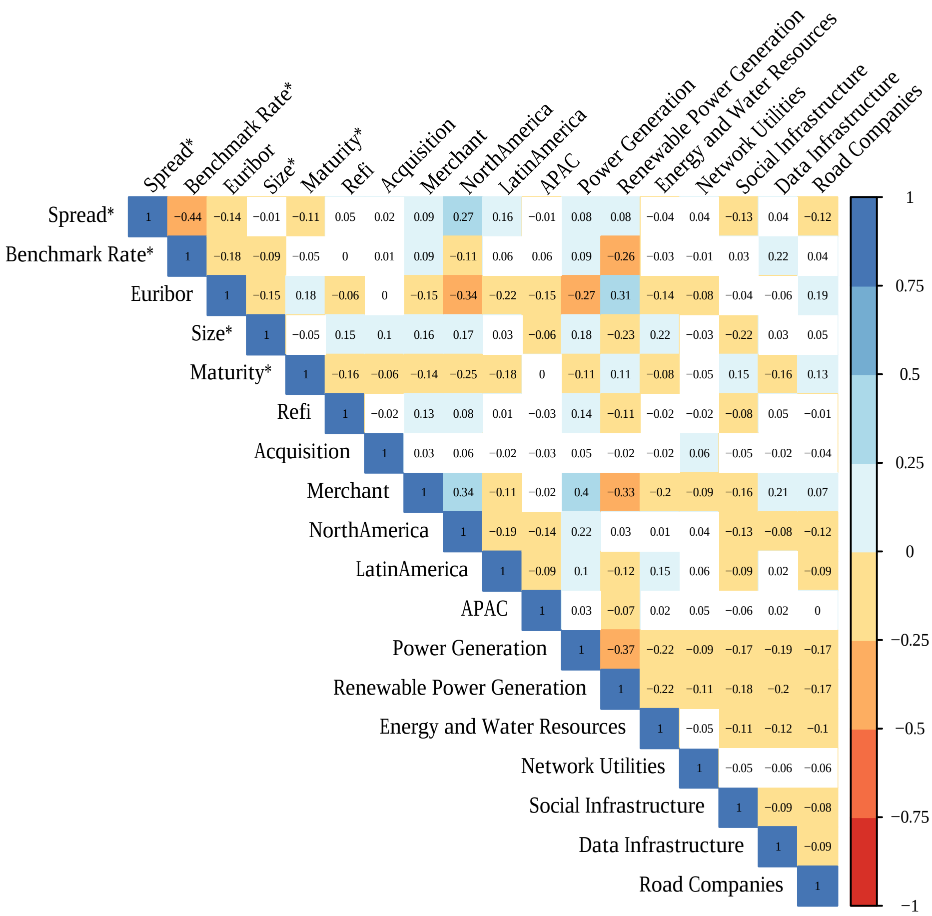


Figure 23: Residuals Distribution of the Project Finance and Corporate Debt Spread Models



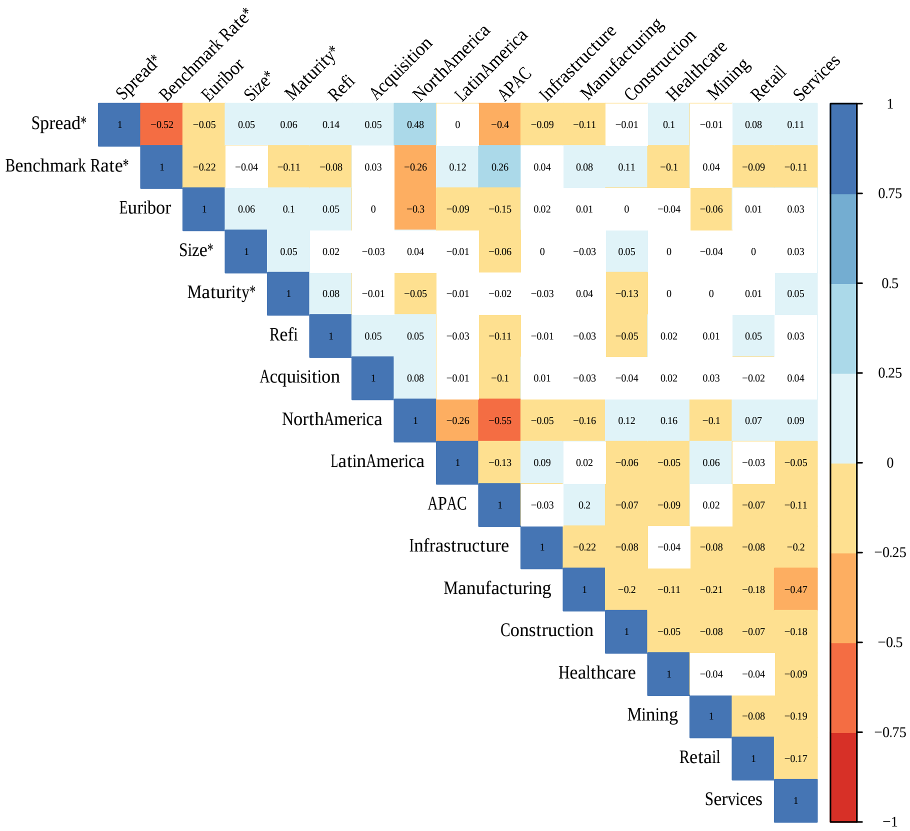
A. Appendix

Figure 24: Correlation Plot for the Project Finance Debt Spread Models (Colors Indicate Statistical Significance at the 1% Confidence Level)



A. Appendix

Figure 25: Correlation Plot for the Corporate Debt Spread Models (Colors Indicate Statistical Significance at the 1% Confidence Level)



References

References

- Adamuz, M. d. l. M. and J. H. Cortés (2015). Endogenous screening and the formation of loan syndicates. *International Review of Economics and Finance 37*, 290–307.
- Blanc-Brude, F. and O. R. H. Ismail (2013). Who is afraid of Construction Risk? Portfolio Construction with Infrastructure Debt. *EDHEC-Risk Institute Publications*, 128.
- Blanc-Brude, F. and R. Strange (2007). How Banks Price Loans to Public-Private Partnerships: Evidence from the European Markets. *Journal of Applied Corporate Finance 19*(4), 94–106.
- Brealey, R. A., I. A. Cooper, and M. A. Habib (1996). Using project finance to fund infrastructure investments. *Journal of Applied Corporate Finance 9*(3), 25–39.
- Burietz, A., K. Oosterlinck, and A. Szafarz (2017). Europe vs. the u.s.: A new look at the syndicated loan pricing puzzle. *Economics Letters 160*, 50–53.
- Carey, M. and G. Nini (2007). Is the corporate loan market globally integrated? a pricing puzzle. *The Journal of Finance 62*, 2969–3007.
- Churm, R. and N. Panigirtzoglou (2005). Decomposing credit spreads. Technical report, Bank of England.
- Coelho, J. P. F. (2016). *The term structure of credit spreads in syndicated loans: a comparative analysis between corporate control, capital structure and project finance loans*. Ph. D. thesis.
- Collin-Dufresne, P., R. S. Goldstein, and J. S. Martin (2001). The determinants of credit spread changes. *The Journal of Finance 56*(6), 2177–2177.
- Corielli, F., S. Gatti, and A. Steffanoni (2010). Risk shifting through nonfinancial contracts: effects on loan spreads and capital structure of project finance deals. *Journal of Money, Credit and Banking 42*(7), 1295–1320.
- Dailami, M. and R. Hauswald (2007). Credit-spread determinants and interlocking contracts: A study of the Ras Gas project. *Journal of Financial Economics 86*, 248–278.
- Eichengreen, B. and A. Mody (1998). What explains changing spreads on emerging-market debt: Fundamentals or market sentiment? Technical report, National Bureau of Economic Research.
- EPEC (2011). The Guide to Guidance - How to Prepare, Procure and Deliver PPP Projects. Technical report, European Investment Bank.

References

- Esty, B. C. (1999). Improved techniques for valuing large-scale projects. *The Journal of Structured Finance*.
- Esty, B. C. and W. L. Megginson (2000). Syndicate Structure as repsonse to political risk in the project finance loan market.
- Esty, B. C. and W. L. Megginson (2003). Creditor Rights, Enforcement, and Debt Ownership Structure: Evidence from the Global Syndicated Loan Market. *The Journal of Financial and Quantitative Analysis 38*(1), 37–59.
- Gaspar, V., G. Pérez-Quirós, and H. Rodríguez Mendizábal (2004). Interest rate determination in the interbank market.
- Gatti, S., S. Kleimeier, W. Megginson, and A. Steffanoni (2013). Arranger certification in project finance. *Financial Management 42*, 1–40.
- Guo, L. (2013). Determinants of credit spreads: The role of ambiguity and information uncertainty. *North American Journal of Economics and Finance 24*, 279–297.
- John, T. A. and K. John (1991). Optimality of project financing: Theory and empirical implications in finance and accounting. *Review of Quantitative Finance and Accounting 1*(1), 51–74.
- Khan, M. F. K. and R. J. Parra (2003). *Financing Large Projects: Using Project Finance Techniques and Practices*. Pearson/Prentice Hall.
- Kleimeier, S. and W. L. Megginson (2000). Are project finance loans different from other syndicated credits? *Journal of Applied Corporate Finance 13*(1), 75–87.
- Krainer, J. (2004). What determines the credit spread? Technical report, Federal Reserve Bank of San Francisco.
- Moody's (2013, February). Default and recovery rates for project finance bank loans 1983-2011. Technical report, Moody's Investor Service, London, UK.
- Petris, G., S. Petrone, and P. Campagnoli (2009). *Dynamic Linear Models with R*. Springer.
- Sorge, M. (2004). The nature of credit risk in project finance. *BIS quarterly review*.
- Sorge, M. and B. Gadanecz (2008). The term structure of credit spreads in project finance. *International Journal of Finance and Economics 13*, 68–81.
- Yescombe, E. R. (2002). *Principles of Project Finance*. Academic Press.

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About Natixis

Natixis is a French multinational financial services firm specialized in asset & wealth management, corporate & investment banking, insurance and payments.

A subsidiary of Groupe BPCE, the second-largest banking group in France through its two retail banking networks, Banque Populaire and Caisse d'Epargne, Natixis counts nearly 16,000 employees across 38 countries. Its clients include corporations, financial institutions, sovereign and supranational organizations, as well as the customers of Groupe BPCE's networks.

Listed on the Paris stock exchange, Natixis has a solid financial base with a CET1 capital under Basel 3(1) of EUR11.8 billion, a Basel 3 CET1 Ratio(1) of 10.8% and quality long-term ratings (Standard & Poor's: A+ / Moody's: A1 / Fitch Ratings: A+).

(1) Based on CRR-CRD4 rules as reported on June 26, 2013, including the Danish compromise - without phase-in. Figures as at 31 December 2018

About EDHEC Infrastructure Institute-Singapore

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EDHEC*infra* addresses the profound knowledge gap faced by infrastructure investors by collecting and standardising private investment and cash-flow data and running state-of-the-art asset pricing and risk models to create the performance benchmarks that are needed for asset allocation, prudential regulation, and the design of new infrastructure investment solutions.

Origins

In 2012, EDHEC-Risk Institute created a thematic research program on infrastructure investment and established two Research Chairs dedicated to long-term investment in infrastructure equity and debt, respectively, with the active support of the private sector.

Since then, infrastructure investment research at EDHEC has led to more than 20 academic publications and as many trade press articles, a book on infrastructure asset valuation, more than 30 industry and academic presentations, more than 200 mentions in the press, and the creation of an executive course on infrastructure investment and benchmarking.

A testament to the quality of its contributions to this debate, EDHEC*infra*'s research team has been regularly invited to contribute to high-level fora on the subject, including G20 meetings.

Likewise, active contributions were made to the regulatory debate, in particular directly supporting the adaptation of the Solvency-II framework to long-term investments in infrastructure.

This work has contributed to growing the limited stock of investment knowledge in the infrastructure space.

A Profound Knowledge Gap

Institutional investors have set their sights on private investment in infrastructure equity and debt as a potential avenue toward better diversification, improved liability-hedging, and reduced drawdown risk.

Capturing these benefits, however, requires answering some difficult questions:

1. **Risk-adjusted performance measures** are needed to inform strategic asset allocation decisions and monitor performance;
2. **Duration- and inflation-hedging properties** are required to understand the liability-friendliness of infrastructure assets;
3. **Extreme risk measures** are in demand from prudential regulators, among others.

Today none of these metrics is documented in a robust manner, if at all, for investors in privately held infrastructure equity or debt. This has left investors frustrated by an apparent lack of adequate investment solutions in infrastructure. At the same time, policy-makers have begun calling for a widespread effort to channel long-term savings into capital projects that could support long-term growth.

To fill this knowledge gap, EDHEC has launched a new research platform, EDHEC*infra*, to collect, standardise, and produce investment performance data for infrastructure equity and debt investors.

Mission Statement

Our objective is the creation of a global repository of financial knowledge and investment benchmarks about infrastructure equity and debt investment, with a focus on delivering useful applied research in finance for investors in infrastructure.

We aim to deliver the best available estimates of financial performance and risks of reference portfolios of privately held infrastructure investments and to provide

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investors with valuable insights about their strategic asset allocation choices in infrastructure, as well as to support the adequate calibration of the relevant prudential frameworks.

We are developing unparalleled access to the financial data of infrastructure projects and firms, especially private data that is either unavailable to market participants or cumbersome and difficult to collect and aggregate.

We also bring advanced asset pricing and risk-measurement technology designed to answer investors' information needs about long-term investment in privately held infrastructure, from asset allocation to prudential regulation and performance attribution and monitoring.

What We Do

The EDHEC*infra* team is focused on three key tasks:

1. **Data collection and analysis**: we collect, clean, and analyse the private infrastructure investment data of the project's data contributors as well as from other sources, and input it into EDHEC*infra*'s unique database of infrastructure equity and debt investments and cash flows. We also develop data collection and reporting standards that can be used to make data collection more efficient and more transparently reported. This database already covers 15 years of data and hundreds of investments and, as such, is already the largest dedicated database of infrastructure investment information available.

2. **Cash- flow and discount-rate models**: Using this extensive and growing database, we implement and continue to develop the technology developed at EDHEC-Risk Institute to model the cash flow and discount-rate dynamics of private infrastructure equity and debt investments and derive a series of risk and performance measures that can actually help answer the questions that matter for investors.

3. **Building reference portfolios of infrastructure investments**: Using the performance results from our asset pricing and risk models, we can report the portfolio-level performance of groups of infrastructure equity or debt investments using categorisations (e.g., greenfield vs. brownfield) that are most relevant for investment decisions.

Partners of EDHEC*infra*

Monetary Authority of Singapore

In October 2015, Deputy Prime Minister of Singapore Tharman Shanmugaratnam announced officially at the World Bank Infrastructure Summit that EDHEC would work in Singapore to create "usable benchmarks for infrastructure investors."

The Monetary Authority of Singapore is supporting the work of the EDHEC Singapore Infrastructure Investment Institute (EDHEC*infra*) with a five-year research development grant.

Sponsored Research Chairs

Since 2012, private-sector sponsors have been supporting research on infrastructure investment at EDHEC with several Research Chairs that are now under the EDHEC Infrastructure Investment Institute:

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1. The EDHEC/NATIXIS Research Chair on the Investment and Governance Characteristics of Infrastructure Debt Instruments, 2012-2015
2. The EDHEC/Meridiam/Campbell-Lutyens Research Chair on Infrastructure Equity Investment Management and Benchmarking, 2013-2016
3. The EDHEC/NATIXIS Research Chair on Infrastructure Debt Benchmarking, 2015-2018
4. The EDHEC / Long-Term Infrastructure Investor Association Research Chair on Infrastructure Equity Benchmarking, 2016-2019
5. The EDHEC/Global Infrastructure Hub Survey of Infrastructure Investors' Perceptions and Expectations, 2016

Partner Organisations

As well as our Research Chair Sponsors, numerous organisations have already recognised the value of this project and have joined or are committed to joining the data collection effort. They include:

- The Global Infrastructure Hub;
- The European Investment Bank;
- The World Bank Group;
- The European Bank for Reconstruction and Development;
- The members of the Long-Term Infrastructure Investor Association;
- Over 20 other North American, European, and Australasian investors and infrastructure managers.

EDHEC*infra* is also :

- A member of the Advisory Council of the World Bank's Global Infrastructure Facility
- An honorary member of the Long-term Infrastructure Investor Association

EDHEC Infrastructure Institute Publications

EDHEC Infrastructure Institute Publications

EDHEC Publications

- Blanc-Brude, F., A. Chreng, M. Hasan, Q. Wang, and T. Whittaker. "Private Infrastructure Equity Indices: Benchmarking European Private Infrastructure Equity 2000-2016" (June 2017).
- Blanc-Brude, F., A. Chreng, M. Hasan, Q. Wang, and T. Whittaker. "Private Infrastructure Debt Indices: Benchmarking European Private Infrastructure Debt 2000-2016" (June 2017).
- Blanc-Brude, F., G. Chen, and T. Whittaker. "Towards Better Infrastructure Investment Products: A Survey of Investors' Perceptions and Expectations from Investing in Infrastructure" (July 2016).
- Blanc-Brude, F., T. Whittaker, and S. Wilde. "Searching for a Listed Infrastructure Asset Class: Mean-Variance Spanning Tests of 22 Listed Infrastructure Proxies" (June 2016).
- Blanc-Brude, F., T. Whittaker, and M. Hasan. "Cash Flow Dynamics of Private Infrastructure Debt" (March 2016).
- Blanc-Brude, F., T. Whittaker, and M. Hasan. "Revenues and Dividend Payouts in Privately-Held Infrastructure Investments" (March 2016).
- Blanc-Brude, F., and M. Hasan. "The Valuation of Privately-Held Infrastructure Equity Investments" (January 2015).

Peer-Reviewed Publications

- Hasan, M., and F. Blanc-Brude. "You Can Work It Out! Valuation and Recovery of Private Debt with a Renegotiable Default Threshold." *Journal of Fixed Income*, 26(4), 2017, pp. 113-127.
- Blanc-Brude, F., S. Wilde, and T. Witthaker. "Looking for an Infrastructure Asset Class: Definition and Mean-Variance Spanning of Listed Infrastructure Equity Proxies." *Financial Market & Portfolio Management*, 31, 2017, pp. 137-179.
- Blanc-Brude, F., and M. Hasan. "A Structural Model of Credit Risk for Illiquid Debt." *Journal of Fixed Income*, 26(1), 2016, pp. 6-19
- Blanc-Brude, F., M. Hasan, and T. Witthaker. "Benchmarking Infrastructure Project Finance–Objectives, Roadmap and Recent Progress." *Journal of Alternative Investments*, 19(2), 2016, pp. 7-18
- Bianchi, R., M. Drew, E. Roca, and T. Whittaker. "Risk Factors in Australian Bond Returns," *Accounting & Finance*, 2015.

EDHEC Infrastructure Institute Publications

- Blanc-Brude, F. "Long-Term Investment in Infrastructure and the Demand for Benchmarks." *JASSA: The Finsia Journal of Applied Finance*, 3, pp. 57–65, 2014.

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