Journal of Corporate Finance 82 (2023) 102429

Contents lists available at ScienceDirect

Journal of Corporate Finance

journal homepage: www.elsevier.com/locate/jcorpfin

Pricing of project finance bonds: A comparative analysis of primary market spreads

Sebastião S. Guedes [a], João M. Pinto [b,*]

[a] Universidade Católica Portuguesa, Católica Porto Business School, Portugal
[b] Universidade Católica Portuguesa, Católica Porto Business School and CEGE, Portugal

ARTICLE INFO

Editor: S Kedia

JEL classification:
G12
G15
G21
G32

Keywords:
Bond pricing
Project finance
Corporate bonds
Cost of borrowing
Debt choice

ABSTRACT

This paper provides a comparative analysis of project finance (PF) and traditional corporate finance (CF) bond spreads and pricing. Using a cross-section of 47,196 bonds issued worldwide in the 1993–2020 period, we show that PF and CF bonds are differently priced, PF bonds have higher spreads than comparable CF bonds, and although ratings are the most important pricing determinant for PF and CF bonds at issuance, investors rely on other contractual, macroeconomic, and firms' characteristics beyond these ratings. Our results do not support the hypothesis of PF transactions as mechanisms of reducing sponsoring firms' funding costs: the cost of borrowing affects financing choices and PF transactions' weighted average spread is higher than that of comparable CF bond deals. We also find that economies of scale, risk management, and information asymmetry arguments affect sponsoring firms' choice between PF and CF transactions.

1. Introduction

A sustained wave of innovation in asset-backed financing led to the emergence of new contractual designs, among others, of non-recourse, or limited recourse, project finance (PF) structures (John and John, 1991; Leland, 2007).[1] This milestone has led to the origination, since the 1990s, of a nascent PF bond market segment, as a funding alternative for the significant infrastructure gap needs around the world (Dailami and Hauswald, 2003). In Europe, the European Commission and the European Investment Bank launched the 'Europe 2020 Project Bond Initiative' in 2012, designed to (*i*) mobilize the necessary funding for the PF of infrastructure, which could exceed EUR 2 trillion between 2012 and 2020; and (*ii*) attract additional private finance from institutional investors such as insurance companies and pension funds.[2]

Furthermore, the 2008 global financial crisis has resulted in stricter regulations on banks and their lending requirements: one of the

* Corresponding author at: Católica Porto Business School, Rua Diogo Botelho, 1327, 4169-005 Porto, Portugal.
E-mail address: jpinto@ucp.pt (J.M. Pinto).

[1] For further discussion, see Brealey et al. (1996), Kleimeier and Megginson (2000), Esty (2003, 2004a, 2004b), Fabozzi et al. (2006), Dailami and Hauswald (2007), Gatti (2008), Pinto (2017), and references therein.

[2] In his 'State of the Union' speech in 2010, European Commission President José Manuel Barroso proposed the 'Europe 2020 Project Bond Initiative' to mobilize the necessary funding for the project financing of infrastructure: 'A European Union initiative to support project bonds, together with the European Investment Bank, would help address the needs for investment in large European Union infrastructure projects.' See Scannella (2012) for further analysis.

https://doi.org/10.1016/j.jcorpfin.2023.102429
Received 12 February 2023; Received in revised form 19 May 2023; Accepted 23 May 2023
Available online 1 June 2023

most conspicuous impacts of the implementation of Basel II (and the ongoing Basel III) capital adequacy standards on banks' PF business is an increase in capital requirements (Esty and Sesia, 2003; Buscaino et al., 2012). Under this framework, PF bonds emerged as an innovative way to mitigate regulatory constraints at the bank level, simultaneously allowing capital market financing, with longer maturities, for large-scale projects to be stimulated.

Despite the significant growth of PF bond issuance in the last decade, representing, in 2020, 15.3% of the Global PF market (PF bond issuance amounted to $50.2 billion in 2020; $58.6 billion in 2019),[3] we know very little about this new financial instrument and how it compares with conventional bonds. Therefore, our purpose is threefold. First, to compare spreads and pricing of PF *vis-à-vis* corporate finance (CF) bonds in a large sample of bonds (763 PF and 46,433 CF bonds, worth $282.7 billion and $16,935.3 billion, respectively), issued by nonfinancial firms worldwide between January 1, 1993, and December 31, 2020. Second, to examine whether spreads convey information beyond credit ratings across PF and CF bonds. And third, to examine, at a deal level, if public sponsoring firms use PF rather than internally organized investment projects funded via CF bonds to reduce the cost of borrowing, and what the firm-level characteristics that affect such a choice are.

This paper contributes to three strands of the literature. First, we extend the literature on the determinants of bond spreads. Despite the significant attention devoted by both academics and practitioners to the analysis of traditional corporate bond spreads,[4] research on PF bond spreads is relatively scant. A few exceptions are Dailami and Hauswald (2003, 2007) and Bonetti et al. (2010). To the best of our knowledge, our study is the first to examine how spreads and pricing compare between PF and CF bonds in addition to analyzing the impact of sponsoring (in PF deals) or issuing (in CF deals) firms' characteristics on the pricing, taking into consideration the potential self-selection by firms between choosing on- versus off-balance-sheet funding for a specific project.[5] This is of particular relevance, as extant literature documents that the choice of debt instruments influences the cost of borrowing in both private and public debt markets (Pinto and Santos, 2019; Marques and Pinto, 2020).

Second, the paper contributes to the literature that examines a potential mispricing phenomenon in bond markets. Prior research, mostly focused on the pricing of structured finance securities *vis-à-vis* traditional corporate bonds, show that similarly rated bonds issued by financial corporations have significantly different spreads (e.g., Coval et al., 2009a, 2009b; Wojtowicz, 2014; Cornaggia et al., 2017; Marques and Pinto, 2020). In this paper, we extend this literature by comparing PF and CF bond spreads across credit rating classes, controlling for macroeconomic factors, as well as contractual and firms' characteristics, which arguably affect spreads.

Third, the paper also contributes to the literature that studies the reasons why firms use PF. Brealey et al. (1996), Esty (2003, 2004a), and Corielli et al. (2010) argue that because PF can mitigate market frictions, it can reduce the sponsor's cost of funding. Empirically, only two papers examine this financial-economic issue and present contradictory results compared to what is predicted, providing evidence of equal or higher cost of debt for European PF syndicated loan deals (Klein et al., 1996; Pinto and Santos, 2019). However, these results might be driven by the fact that banks earn significantly higher spreads than those implied by the pricing of traditional CF bonds (Schwert, 2020). In addition, none of these works analyzed if the cost of borrowing affects sponsoring firms' choice between PF and corporate financing. This is of particular interest since, in our sample, 4,175 deals are issued by switchers, firms that choose both PF and CF bonds in the sampling period.

Our findings document that PF and CF bonds are differently priced and, despite credit ratings being a major pricing determinant at issuance, investors rely on other pricing factors. We find that factors important for CF pricing, such as time to maturity, transaction size, currency risk, number of banks involved and their reputation, market volatility and type of financial system in the host country are also relevant for determining spreads on PF bonds. Regarding the sponsoring/issuing firms' characteristics, we show that the pricing of PF bonds depends on a single characteristic of the sponsoring firm, the debt to total assets ratio. We also find evidence of sponsoring firms' choice between PF and CF bonds affecting bond pricing of such securities. Our results hold for sub-samples of PF and CF bonds used for the same purpose (i.e., mid-to-long-term financing of projects with the same characteristics).

We show that PF tranches have, on average, higher spreads than rating-matched alternatives, in line with the hypothesis that investors should demand larger spreads for holding securities that carry higher systematic risks (Brennan et al., 2009; Coval et al., 2009a, 2009b; Wojtowicz, 2014). Unlike traditional CF bonds, whose yields are primarily driven by firm-specific characteristics, the performance of PF bonds is strongly affected by projects' non-diversifiable risks, which are relatively neglected by credit ratings.[6] Therefore, ratings are not perfect measures of credit quality, and both PF and CF bond prices reflect information beyond credit ratings. Although we use virtually all PF bonds with primary market spread information issued since 1993 (the year the first PF bond was issued), our PF bond sample is about 2% of the total sample. In addition, the choice between PF and CF bonds may be endogenous to spreads. To mitigate these effects, we (*i*) build a bond-level matched sample of CF bonds following Flammer (2021) - for each PF bond, we match an otherwise similar CF bond by the same issuer -; and (*ii*) use an endogenous switching regression model (Lokshin and Sajaia, 2004) to study the pricing, taking into consideration the potential self-selection by firms between issuing PF versus CF bonds.

[3] According to Esty et al. (2014), in 2009, PF bonds represented 8% of the total PF market. Table 3, in the Online Appendix, reports the evolution of both PF and CF bonds over the years.

[4] See, among others, Collin-Dufresne et al. (2001), Elton et al. (2001), Campbell and Taksler (2003), Hull et al. (2004), Titman et al. (2004), Longstaff et al. (2005), Chen et al. (2007), Bao et al. (2011), and Flannery et al. (2012).

[5] Our analysis uses a dataset of worldwide PF and CF bonds, developed based on a hand-matching procedure between bonds extracted from DCM Analytics and firms' characteristics drawn from Datastream. Additionally, we use endogenous switching regression models to mitigate potential self-selection problems.

[6] Coval et al. (2009a, 2009b) argue that credit ratings are constructed to reflect physical default probabilities (S&P) or expected losses (Moody's), disregarding whether a security is likely to default in extreme economic conditions.

Additionally, we create sub-samples for PF and CF bonds used for the same purpose. Our results hold when we use these methodologies and sub-samples.

Our evidence is inconsistent with the cost of capital argument, according to which sponsoring firms would use PF to benefit from a cheaper source of borrowing. Findings at the deal level indicate that the cost of borrowing affects firms' financing choices and PF deals' *weighted average spread* (WAS) is higher than that of comparable CF bond deals. This difference in borrowing costs is even greater as financing costs of PF bonds are not adequately captured by spreads because they do not contain significant transaction costs (e.g., contractual design, structuring, and administrative fees) that issuers have to pay (Gatti et al., 2013). Under this framework, no sponsoring firms should choose PF bond deals to fund a large-scale project, and it is still necessary to address the question: what are the firm-level countervailing benefits other than borrowing costs that determine the choice between PF and CF transactions? Empirically, few papers investigate firm-level determinants of off-balance-sheet debt arrangements. A few exceptions are Mills and Newberry (2005), Lemmon et al. (2014), and Pinto and Santos (2019). We extend this literature by showing that public sponsoring firms choose PF when they are relatively smaller, less profitable and creditworthy, have higher asset tangibility, and seek long-term financing. Results are robust when subsamples of bonds issued by switchers or with the same purpose, and a deal-level matched sample of CF deals are used.

The remainder of the paper is organized as follows. Section 2 reviews the literature and describes the research hypotheses. Section 3 describes the data and variables we use in our tests. Section 4 examines the determinants of spreads for PF and CF bonds. It also analyzes if the market prices bonds differently across PF and CF bond classes, when controlling for credit ratings. Section 5 examines whether PF reduces sponsoring firms' cost of borrowing and whether it affects the choice between PF and CF. Section 6 provides additional robustness checks and section 7 concludes the paper.

2. Literature review and hypotheses

2.1. The financial economics of project finance bonds

Typically used for funding public and private capital-intensive facilities and utilities, PF has become an economically significant growing financial market segment in recent decades. Esty and Sesia (2007) report that a record $328 billion in PF funding was globally arranged in 2006, a 51.2% increase from the $217 billion reported for 2001. According to Refinitiv Deals Intelligence reviews, $328 billion was arranged worldwide in 2020, a drop of 11.2% from the $369 billion in 2019, the year the market hit a new global record.[7]

In our sample, the first PF bond was issued by Petronas Capital Ltd., an SPV of the Malaysian state-owned oil and gas company Petronas, in 1993, with a tranche size of $500 million and a 10-year maturity. The largest transaction, with a deal size of $4.0 billion in two tranches of $1 and $3 billion, with maturities of 10.6 and 29.9 years, respectively, was closed in 2017 by Mexico City Airport Trust (NAFIN), to finance a new international airport in Mexico City. Over the last 25 years, the bond market has financed a broad range of project types, tranche sizes, seniorities, and maturities. However, what are the main characteristics of these bonds that make them different from traditional CF bonds?

PF is a form of financing based on a legally-independent special purpose entity or vehicle (SPE/SPV), typically funded with larger amounts of non-recourse (or limited recourse) syndicated loans and bonds (Esty and Megginson, 2003; Dailami and Hauswald, 2003). Thus, a PF arrangement insulates its sponsors from project risk, which is fully allocated to SPE investors. To mitigate this exposure, investors may resort to two channels. The asset pledgeability channel, which is a contractual mechanism that allows the allocation of assets' control rights to debt financiers providing them with ‘insurance of first instance’ against project default risk (Bernhardt et al., 2020).[8] And the bankruptcy remoteness channel, which operates through contractual provisions aiming at lessening the risk of non-payment under a debt contract (Leland, 2007; Ayotte and Gaon, 2011). Both result in complex networks of contracts intended to disentangle the project's risk spectrum and allocate them individually to the party more suited to manage them (Corielli et al., 2010). These features provided by the instrumental SPE are not available concerning on-balance-sheet funding such as CF bonds (Caselli and Gatti, 2005; Gorton and Souleles, 2007; Ayotte and Gaon, 2011).[9]

Thus, PF bonds' credit risk largely depends on the assets and cash flows generated by the project and not on the reliability and creditworthiness of the sponsors (Esty, 2003; Fabozzi et al., 2006; Leland, 2007).[10] On the contrary, ‘corporate financing is based on being able to count on a much broader asset base than assets relating specifically to the individual initiative (if the latter fails, the financer can always count on the company's other assets)’ (Caselli and Gatti, 2005). Likewise, Dailami and Hauswald (2003) point out

[7] Global Project Finance Review, full year 2020; Global Debt Capital Markets Review, full year 2020. Source: Refinitiv (https://www.refinitiv.com/dealsintelligence).

[8] According to Bernhardt et al. (2020), ‘pledgeability increases investment efficiency and relaxes a firm's financing constraint.’

[9] Among the most important distinctive characteristics of PF transactions are (Esty, 2004a, 2004b; Pinto, 2017): (*i*) the debtor, a project company (an SPV or SPE) that is financially and legally independent from the sponsors; (*ii*) lenders that have only limited or no recourse to the sponsors; (*iii*) project risks that are allocated to those parties that are best able to manage them; (*iv*) that the project's cash flows must be sufficient to service the debt in terms of interest and debt repayment; and (*v*) collateral, which is given by sponsors to lenders as security for cash inflows and assets tied up in managing the project.

[10] Transactions are designed in terms of tranching, credit enhancement mechanisms, covenants, warrantees, corporate structures, and contracts to achieve credit risk segregation, which makes lenders, investors, and other stakeholders appraise the project strictly on its own economic merits (Shah and Thakor, 1987; John and John, 1991; Esty, 2004a, 2004b; Gatti, 2008).

that the main difference between PF and CF bonds is related to the guarantees provided to bondholders in case of default. This explains why PF bond investors are cash-flow oriented and demand a much more careful analysis of the factors that determine the underlying economics of the project, the covenants and guarantees that support the transaction, and the financing deal's economic and legal structures (Gatti, 2008). Moreover, in the context of PF, additional factors that affect idiosyncratic risk perceptions, like counter-party, price, and demand risk also affect the premium that bondholders demand in PF bonds (Dailami and Hauswald, 2007; Bonetti et al., 2010).

Therefore, due to the specific characteristics of PF transactions, PF bond spreads depend essentially on the project creditworthiness and not on the sponsors' accounting and financial characteristics. Under this framework, we raise the following hypothesis:

Hypothesis 1. (H1): PF and CF bonds are priced differently by common pricing factors and, as for CF bonds, investors rely on factors other than credit ratings when pricing PF tranches.

The first full-scale empirical study of PF, comparing the financial characteristics as well as the determinants of loan pricing for PF *vis-à-vis* non-PF syndicated loans, was presented by Kleimeier and Megginson (2000). Authors find that PF loans' financial characteristics differ significantly from non-PF credits, and that PF loan spreads are significantly affected by country risk, currency risk, and if a guarantee is provided by a third-party. Regarding the pricing determinants of PF bonds, Dailami and Hauswald (2003) examine the pricing of 105 emerging market PF bonds issued between January 1993 and March 2002 and find that legal and institutional frameworks of the host country have a relevant impact on spreads. Regarding contractual characteristics, authors show that maturity and credit rating are the most important determinants of PF bond pricing, while the spreads are industry-driven, which could be explained by asset-specificity, demand risk and any other specific risk involved. Dailami and Hauswald (2007) focus on the Ras Gas project and study the impact of three interlocking contracts - output sales and purchase agreements, bond covenants, and debt-service guarantee by Mobil Corporation - on bond spreads by means of a time-series analysis. They show that credibly managed - through the SPE's contractual structure - risk factors do not affect Ras Gas' spreads, and the most important explanatory variable is the off-taker's credit spread.[11] Bonetti et al. (2010) use the case of the Quezon Power Ltd. Co. to examine the effect of higher counterparty risk on Quezon's bond spread, and find that deterioration in the off-taker's credit rating causes an increase in the spread paid by Quezon Power. See section 1 of the online appendix for a detailed literature review on the determinants of spreads for PF loans and bonds issued by nonfinancial firms.

2.2. Spreads across PF and CF bonds

Extant empirical literature shows evidence of a mispricing phenomenon in bond markets. Lewis et al. (2021) provide evidence of Treasury securities trading at a premium relative to guaranteed U.S. corporate bonds with the same credit risk. Wojtowicz (2014) and Cornaggia et al. (2017) show that US structured bonds exhibit higher yields than similarly rated corporate bonds. On the contrary, Coval et al. (2009b) show evidence of senior collateralized debt obligation (CDO) tranches being significantly overpriced. For the European market, Marques and Pinto (2020) find that while European CDO tranches exhibit, on average, higher spreads, investment-grade asset-backed securities (ABS) and mortgage-backed securities (MBS) typically offer similar or lower compensation than rating-matched corporate bonds. In addition, Correia and Pinto (2022) show that asset securitization tranches have higher spreads than comparable and rating-matched covered bonds.

This mispricing effect can be explained by two different strands of the literature. The first argues that the information loss in the process of determining the credit rating may be a source of mispricing and securities more correlated with the market - e.g., asset securitization bonds - should offer higher spreads than securities with the same credit rating whose payoffs have a lower correlation with the market - e.g., corporate bonds (Coval et al., 2009b). According to Brennan et al. (2009) and Coval et al. (2009a, 2009b), structured finance bonds carry large systematic risks *vis-à-vis* comparable straight securities, which are relatively neglected by credit ratings - credit ratings are constructed to reflect only physical default probabilities (S&P) or expected losses (Moody's) (Shivdasani and Wang, 2011; Wojtowicz, 2014).[12] Therefore, structured finance bonds are expected to offer higher yields than similarly rated corporate bonds. On the other hand, the segmented financial markets hypothesis points out that the segmentation of financial markets creates the opportunity for the design of new securities to accomplish certain risk-return profiles desired by investors, who are available to pay a premium over comparable corporate bonds (Oldfield, 2000; Fender and Mitchell, 2005). According to Duffie and Rahi (1995) and Riddiough (1997), the segmentation of financial markets may lead to the appearance of arbitrage opportunities, which may be exploited by sponsors when designing structured finance securities (Lewis et al., 2021). DeMarzo (2005) offers market incompleteness and asymmetric information as major explanations for tranching in structured finance, namely when heterogeneous investors have different private information and different capabilities to screen investors. As PF bonds are a type of structured finance security, we raise the following hypothesis:

Hypothesis 2. (H2): Similarly rated PF and CF bonds have significantly different spreads.

[11] An off-taker is the party who buys the product being produced by the project. In the Ras Gas project, there is a 25-year output sales agreement in place with the Korea Electric Power Company, the dominant output buyer.

[12] Brennan et al. (2009) also show that the mispricing effect increases with the subordination level.

2.3. Why do firms use project finance?

Prior theoretical literature hypothesizes that PF contracting is designed aiming at (*i*) the reduction of asymmetric information problems; (*ii*) mitigating costly agency conflicts; (*iii*) maintaining the sponsors' financial flexibility; (*iv*) increasing interest tax shields; (*v*) and improving risk management (e.g., Shah and Thakor, 1987; Kensinger and Martin, 1988; John and John, 1991; Flannery et al., 1993; Brealey et al., 1996; Nevitt and Fabozzi, 2001; Esty, 2003, 2004a, 2004b; Gatti, 2008; An and Cheung, 2010).

One of the motivations presented by extant theoretical literature for firms using PF is the reduction of funding costs. According to Brealey et al. (1996), Kleimeier and Megginson (2000), Esty (2003, 2004a), Esty and Kane (2010), and Corielli et al. (2010), by mitigating deadweight costs of market imperfections and frictions and improving risk management, PF contractual structures reduce funding costs. In addition, PF can reduce the cost of debt by reducing the number of assets subject to costs related to financial distress and bankruptcy by separating some assets from their balance sheet (Corielli et al., 2010). We thus propose:

Hypothesis 3. (H3): PF bond deals have lower borrowing costs than comparable CF bond deals.

However, prior empirical literature focused on the syndicated loan market provides evidence that structuring a PF transaction is costlier than traditional CF alternatives (Klein et al., 1996; Pinto and Santos, 2019) due, at least partly, to: (*i*) legal, financial, insurance, accounting and fiscal, engineering and environmental advisory fees (Esty and Kane, 2010); (*ii*) structuring costs involved in a fairly extensive, detailed, highly restrictive, and complex nexus of contracts (Fabozzi et al., 2006; Gatti et al., 2013); (*iii*) higher credit and equity risk, in part due to greater leverage (Esty, 2004a, 2004b); and (*iv*) operational complexity (An and Cheung, 2010). These arguments would have the opposite effect to that expected in H3.

At the firm-level, Esty (2003, 2004a, 2004b) presents four primary reasons for why sponsors choose to use PF: (*i*) it can be used to mitigate costly agency/conflicts inside project companies and among capital providers - agency cost motivation; (*ii*) it allows companies with little spare debt capacity to avoid the opportunity cost of underinvestment in positive NPV projects - debt overhang motivation (Myers, 1977)[13]; (*iii*) it improves risk management - risk management motivation -, as PF arrangements are typically structured as extensive and detailed networks of contracts to transfer a variety of project risks to the parties that are best able to appraise and manage them (Brealey et al., 1996; Corielli et al., 2010); and (*iv*) it helps to reduce underinvestment due to asymmetric information problems - asymmetric information motivation (Shah and Thakor, 1987; Kensinger and Martin, 1988). Pinto and Santos (2019) show that informational frictions and issuance costs affect European nonfinancial firms' choice of structured finance transactions, namely asset securitization and PF. Hainz and Kleimeier (2012) find a negative relationship between the industry's leverage ratio and the use of PF. Subramanian and Tung (2016) point out that changes in investor protection have greater effects in industries with higher agency costs of free cash flow *vis-à-vis* tangible-asset-intensive industries.

3. Data and variable definition

3.1. Sample selection

Our sample consists of individual bond offers extracted from DCM Analytics and covers the 1993–2020 period. Although information is available on several types of bonds, we include only those with a deal-type code of 'corporate bond investment-grade' and 'corporate bond high-yield'. DCM Analytics does not have a deal type code of 'project finance bond', so we classified as PF bonds those bonds for which the use of proceeds (i.e., the bond's primary purpose code) is 'project finance'. The remaining bonds were classified as CF bonds. To have a more comparable sample and to avoid selection bias problems, we selected only CF bonds for which the issuer industry and country have at least one record of PF bond issuance. We also require that securities have available information on tranche and transaction size, and concentrate on PF bonds identified as having the purpose of financing new investments or projects. We therefore verified with DCM Analytics that our PF sample refers to deals made by a vehicle company, and exclude bonds made for refinancing existing SPEs. As PF is a method of financing tangible-asset-rich and capital intensive projects, using mid-to-long-term financing, we exclude securities with a maturity of less than 1 year. Finally, we exclude bonds with the following primary purpose: debtor-in-possession, working capital, and exit financing.

As the unit of observation is a single tranche, multiple tranches from the same PF transaction appear as separate observations in our database. Therefore, we aggregate tranche-level data (e.g., spread, maturity, and rating) in order to perform a deal-level analysis in section 5. To do this, we required that the primary purpose of each bond is the same for each specific deal, and that the sum of all bonds in the package equals the deal amount.

As we wish to analyze how spreads and pricing processes on PF bonds compare with those of similarly rated CF bonds, we select from our full sample those issues that have the necessary information to compute the spread. We include only bond tranches classified as fixed rate bonds with yield to maturity information. Perpetual bonds, bonds with additional features such as step-up, caps, or floors, and bonds classified as "fixed rate convertible to floating rate note", "fixed rate adjustable", and "fixed rate extendible" are excluded. To maximize the survival rate, we search in Datastream for yield to maturity information for those bonds with missing values. As DCM Analytics and Datastream do not have a common identification code, we hand-match borrowers' names. Finally, to take possible

[13] According to John and John (1991) and Nevitt and Fabozzi (2001), the off-balance-sheet treatment of the funding raised by the SPE is crucial for sponsors since it only has limited impact on sponsors' creditworthiness and does not impact sponsors' ability to access additional financing in the future.

Table 1
Industrial and geographic distribution, and top issuers and bookrunners.

Panel A: Industrial distribution

Industrial category of issuer	Project finance bonds			Corporate finance bonds		
	Number of Bonds	Total Value ($ Million)	Percent of total value	Number of Bonds	Total Value ($ Million)	Percent of total value
Commercial and Industrial						
Agriculture, Forestry and Fishing	2	525	0.19%	885	244,570	1.44%
Communications	33	11,239	3.97%	3,836	2,053,958	12.13%
Construction/Heavy Engineering	59	15,359	5.43%	4,162	1,053,221	6.22%
Manufacturing						
Chemicals, Plastic and Rubber	6	3,380	1.20%	1,641	554,985	3.28%
Food and Beverages	1	1,000	0.35%	1,946	748,540	4.42%
Machinery and Equipment	9	3,387	1.20%	4,408	1,955,066	11.54%
Steel, Aluminum and other Metals	1	175	0.06%	1,314	403,651	2.38%
Other	2	73	0.03%	1,602	579,175	3.42%
Mining and Natural Resources	17	3,238	1.15%	847	391,875	2.31%
Oil and Gas	118	68,447	24.21%	3,386	1,618,532	9.56%
Real Estate	39	12,845	4.54%	4,124	1,066,607	6.30%
Real Trade	5	738	0.26%	1,475	580,250	3.43%
Services	28	5,877	2.08%	4,591	1,851,508	10.93%
Utilities	330	118,662	41.97%	7,837	2,516,095	14.86%
Transportation	94	33,504	11.85%	3,629	1,078,324	6.37%
Public Administration/ Government	18	4,196	1.48%	21	5,114	0.03%
Other	1	100	0.04%	729	233,859	1.38%
Total	**763**	**282,745**	**100.00%**	**46,433**	**16,935,330**	**100.00%**

Panel B: Geographic distribution

Geographic location of issuer	**Project finance Bonds**			**Corporate finance Bonds**		
	Number of Bonds	**Total Value ($ Million)**	**Percent of total value**	**Number of Bonds**	**Total Value ($ Million)**	**Percent of total value**
North America	391	152,450	53.92%	22,117	8,845,470	52.23%
United States	244	108,729	38.45%	19,654	8,011,426	47.31%
Canada	99	25,967	9.18%	1,877	630,372	3.72%
United Kingdom	76	42,052	14.87%	5,463	3,219,262	19.01%
Western Europe	51	14,330	5.07%	2,337	1,109,361	6.55%
Eastern Europe	10	4,681	1.66%	337	176,738	1.04%
Northern Europe	9	2,826	1.00%	1,733	348,118	2.06%
Middle East	14	11,045	3.91%	292	161,359	0.95%
Qatar	7	5,630	1.99%	21	15,223	0.09%
South Africa	3	3,250	1.15%	94	31,218	0.18%
South East Asia	64	18,593	6.58%	7,602	1,676,338	9.90%
China	31	6,527	2.31%	6,174	1,340,691	7.92%
Malaysia	13	6,575	2.33%	112	26,245	0.15%
Australia	36	12,049	4.26%	677	218,146	1.29%
Latin America	99	17,552	6.21%	1,849	341,671	2.02%
Brazil	61	6,998	2.48%	1,359	235,825	1.39%
Chile	11	3,675	1.30%	165	61,709	0.36%
Other	10	3,917	1.39%	3,932	807,649	4.77%
Total	**763**	**282,745**	**100.00%**	**46,433**	**16,935,330**	**100.00%**

Panel C: Top 10 issuers

Project Finance Bonds			Corporate Finance bonds		
	By value of deals	By number of deals		By value of deals	By number of deals
Sabine Pass Liquefaction LLC	4.37%	1.18%	China Railway Corporation	0.69%	0.16%
Pemex Project Funding Trust	2.23%	0.92%	BP Capital Markets plc	0.60%	0.25%
North West Redwater Partnership	1.76%	1.70%	BMW Finance	0.40%	0.15%
Pemex Finance Ltd	1.72%	2.10%	IBM	0.39%	0.16%
Calpine Corporation	1.23%	1.05%	Telefonica Emisiones SAU	0.39%	0.12%
NGPL PipeCo LLC	1.06%	0.39%	John Deere Capital Corp.	0.37%	0.29%

(*continued on next page*)

Table 1 (*continued*)

Panel C: Top 10 issuers

Project Finance Bonds	By value of deals	By number of deals	Corporate Finance bonds	By value of deals	By number of deals
Iberdrola International BV	1.05%	0.39%	GE Capital	0.35%	0.09%
Mexico City Airport Trust	0.99%	0.26%	AT&T Inc.	0.35%	0.09%
Gatwick Funding Ltd	0.99%	0.79%	Électricité de France, SA	0.34%	0.12%
Cheniere Corpus Christi Holdings	0.97%	0.26%	Petróleos Mexicanos	0.32%	0.17%

Panel D: Top 10 bookrunners

Project Finance Bonds	**By value of deals**	**By number of deals**	**Corporate Finance bonds**	**By value of deals**	**By number of deals**
Citigroup Inc.	34.56%	34.86%	Citigroup Inc.	45.51%	38.72%
Bank of Tokyo Mitsubishi	17.83%	13.00%	Bank of America Merril Lynch	12.02%	12.15%
Bank of America Merril Lynch	10.40%	9.31%	Bank of Tokyo Mitsubishi	9.99%	9.58%
JP Morgan	9.51%	9.01%	JP Morgan	9.63%	9.75%
Crédit Agricole CIB	6.23%	4.28%	HSBC	3.83%	3.27%
HSBC	4.56%	5.91%	Crédit Agricole CIB	2.90%	1.92%
Barclays	2.89%	3.40%	BNP Paribas	2.73%	2.02%
Credit Suisse	2.86%	3.25%	Barclays	2.05%	2.19%
RBC Capital Markets	2.37%	4.28%	Credit Suisse	1.79%	4.56%
Deutsche Bank	1.93%	0.89%	Goldman Sachs	1.58%	2.08%

Panel E: Bonds classified by purpose

Category	**Number of bonds**	**Total value ($ Million)**	**Percentage of total value**
Project finance	763	466,016	1.66%
Corporate finance	46,433	27,531,764	98.34%
Corporate control	3,563	3,420,012	12.22%
Capital structure	9,501	4,697,166	16.78%
Fixed asset based	1,895	880,986	3.15%
General corporate purpose	31,474	18,533,600	66.20%

Panel A describes the industrial distribution of bonds, whereas Panel B details the bond allocation to issuers in a particular country. Panel C provides information on the biggest players and their relative importance in PF and CF bond markets, while Panel D ranks the top 10 bookrunners by value and number of deals. Finally, Panel E breaks down our sample per bond primary purpose, following the categorization strategy presented by Kleimeier and Megginson (2000). The category corporate control bonds includes bonds with the primary purpose of funding acquisitions, leveraged buyouts, management buyouts, or spin-offs. Capital structure bonds are issued for refinancing, recapitalizations, debt repayment, or securities purchase. Fixed asset based bonds are intended for general capital expenditures or to fund aircraft, property, or shipping purchases. General corporate purpose deals are those arranged for corporate purposes, investments, public finance, research and development, as well as bonds without a primary purpose description. Data are for bonds with spread and tranche/transaction amount available, closed by worldwide issuers during the 1993–2020 period.

outliers into account, we winsorize the data for transaction size, maturity, and spread at the 1% and the 99% levels.

These screens yield a sample of 47,196 bonds (36,551 transactions) worth $17,218.1 billion, of which 763 tranches (516 transactions) worth €282.7 billion are classified as PF bonds and 46,433 tranches (36,035 transactions) worth €16,935.3 billion as CF bonds. Panel A of Table 1 presents the industrial distribution of the full sample of bonds, while Panel B details the bond allocation to an SPE (for PF bonds) or issuers (for CF bonds) in a particular country. Panel A reveals striking differences between PF and CF bond issuance, showing that PF bonds are concentrated in four key industries; i.e., utilities (41.97%), oil and gas (24.21%), transportation (11.85%), and construction/heavy engineering (5.43%) account for 83.5% of all PF bond issuance by volume. CF bond issuance reveals a far less concentrated industrial pattern, with issuers in utilities (14.86%), communications (12.13%), machinery and equipment (11.54%), and services (10.93%) industries receiving the higher percentages. Panel B reveals striking similarities between PF and CF issuance. PF and CF bonds are concentrated in two regions, with issuers located in North America and Europe accounting for 76.5% and 80.9% of all PF and CF issuance by volume, respectively. Perhaps the most remarkable difference is how frequently PF deals are extended to projects in Latin America, the Middle East, and Australia *vis-à-vis* CF deals. On the contrary, while Chinese corporations issue 7.92% of CF bonds, SPEs account for a mere 2.31% of PF issuance. Panel C provides information in relation to identifying the biggest players and their relative importance in PF and CF bond markets (see Table 2 in the Online Appendix for more details on the top 10 PF deals by transaction size), while Panel D ranks the top 10 bookrunners by value and number of deals. The top 10 PF and CF bond issuers contributed to a different weight, by value of deals: while the top 10 SPEs issue 16.4% of all tranches in our sample, the top 10 CF bond issuers are responsible for only 4.2% of bond issuance. Panel D shows that the top 10 PF and CF bond bookrunners contribute to a weight of 93.1% and 92.0% of all issuance by volume, respectively. It is interesting to note that only 2 banks (RBC Capital Markets and

Deutsche Bank) are in the top 10 for PF but not for CF bond issuance.

CF bonds were classified into 4 categories according to their primary purpose, following Kleimeier and Megginson (2000).[14] Panel E of Table 1 shows that a large portion of CF bonds is classified as general corporate purpose bonds (62%), followed by capital structure (16%) and corporate control (12%) categories, with relatively similar percentages. Finally, with a smaller size is the fixed asset based category, the category that most closely resembles project finance in that both are used to finance large-scale assets.

3.2. Dependent and independent variables

Table 2 provides detailed definitions and sources for all the variables used, as well as the expected impact of explanatory variables on bond spreads. A discussion of extant empirical literature on the determinants of PF loan and corporate bond spreads and summary descriptive statistics are presented in sections 1 and 3 of the Online Appendix, respectively.

3.2.1. Spread

Spread corresponds to the price for the risk associated with the bond at issuance, defined as the margin yielded by the security at issue above a corresponding currency treasury benchmark with a comparable maturity – the option adjusted spread (OAS). We use the OAS as it is the most common measure used by financial intermediaries to correct the normal yield spread for embedded options.

3.2.2. Rating

Credit ratings are a central determinant of CF bond spreads (e.g., Collin-Dufresne et al., 2001; Elton et al., 2001; Hull et al., 2004; Titman et al., 2004; Longstaff et al., 2005). Bond tranches in our study have at least one credit rating assigned by S&P or Moody's, which is converted as follows: AAA = Aaa = 1, AA+ = Aa1 = 2, and so on until D = 21 (Gabbi and Sironi, 2005; Cornaggia et al., 2017). If a tranche has two credit ratings, we computed the average. Rating scales are inverse scales, so we expect spreads to increase as rating decreases. As some bonds are not rated, we include the dummy variable *rated*, equal to 1 if the bond has a credit rating from S&P and/ or Moody's, and 0 otherwise. To examine whether a different rating assigned by S&P and Moody's has any statistically significant impact on credit spreads, we use, as in Gabbi and Sironi (2005) and Marques and Pinto (2020), a dummy variable - *rating discordance* - equal to one if the two ratings have a different numeric equivalent value, and zero otherwise. We expect rating agencies' discordance leads to a higher spread, reflecting a higher degree of uncertainty concerning the transaction's default risk.

3.2.3. Contractual characteristics

It is widely agreed that bonds with longer maturities tend to be riskier than bonds with shorter maturities. Therefore, investors usually demand higher premiums for longer-term securities. Dailami and Hauswald (2003) find a positive relationship between spread and maturity for PF bonds issued to fund large-scale projects in developing countries. For structured finance debt, the reported results suggest that the impact of maturity on spreads is non-linear (Sorge and Gadanecz, 2008; Marques and Pinto, 2020). Therefore, in addition to controlling for *maturity*, we specified the logarithm of maturity in our baseline multiple regressions, as a surrogate for any non-linear relationships between credit spread and maturity.

The issue size of a CB is, ceteris paribus, positively related to lower uncertainty and higher liquidity than smaller offerings (Gabbi and Sironi, 2005; Chen et al., 2007; Sorge and Gadanecz, 2008). Similarly, Buscaino et al. (2012) find *transaction size* has a negative impact on the spread of securitization bonds. We thus expect larger issues to exhibit lower spreads. We use two variables to control for differences in risk existing among different tranches of a deal. First, the *subordinated* dummy variable, which is equal to one for tranches that are subordinated. We expect subordinated bonds to have higher spreads than senior bonds. Second, as in Cumming et al. (2019), we use the *number of tranches*. We expect this ratio to have a positive impact on spread for CF bonds, but a negative relationship for PF bonds.

We expect tranches exposed to *currency risk* to have higher spreads than those that are not. Bank involvement is measured by the *number of banks* supporting the transaction, and we expect a negative relationship for both PF and CF bond spreads (Sufi, 2007). To capture additional differences in bank syndicates, we also control for *bank reputation*, computed according to the yearly Thomson Reuters EMEA bookrunner ranks. As the involvement of banks with a higher reputation may reduce information asymmetries, we expect a negative relationship between bank reputation and spreads (Kara et al., 2016). Finally, we include the *callable* dummy variable and expect that the introduction of a call option on both PF and CF bonds will increase the spread.

3.2.4. Macroeconomic factors

Extant literature argues that laws and institutions of different countries affect financial intermediary development, financial contracting, and the cost of borrowing (La Porta et al., 1997, 1998; Esty and Megginson, 2003; Boubakri and Ghouma, 2010; Gatti et al., 2013). Hainz and Kleimeier (2012) and Subramanian and Tung (2016) show that political risk and creditor rights correlate positively with the use of PF. As stronger investor protection and enhanced and transparent disclosure rules mitigate asymmetric information and agency costs, we expect *creditor rights* and *enforcement* level to have a negative impact on PF and CF bond spreads.

[14] The category corporate control bonds includes bonds with the primary purpose of funding acquisitions, leveraged buyouts, management buyouts, or spin-offs. Capital structure bonds are issued for refinancing, recapitalizations, debt repayment, or securities purchase. Fixed asset based bonds are intended for general capital expenditures or to fund purchases of aircraft, property, or shipping. General corporate purpose deals are those arranged for corporate purposes, investments, public finance, research and development, as well as bonds without a primary purpose description.

Table 2
Definition of variables, sources, and the expected impact on credit spread.

Variable Name	Variable definition	Source	Expected impact on spread	
			PF bonds	CF bonds
Dependent Variables:				
Spread	Margin yielded by the security at issuance above a corresponding currency treasury benchmark with a comparable maturity (OAS). We include only bond tranches classified as fixed rate bonds with yield to maturity information.	DCM Analytics		
Choice of debt	Dummy equal to 1 if the firm closes a PF deal and 0 if it, instead, closes a CF deal.	Authors'		
Independent variables:				
Contractual characteristics				
Rated	Dummy equal to 1 if the bond has a credit rating from S&P or Moody's, and 0 otherwise.	DCM Analytics	–	–
Rating	Bond rating based on the S&P and Moody's rating at the time of bond issuance. The rating is converted as follows: AAA = Aaa = 1, AA+ = Aa1 = 2, and so on until D = 22.	DCM Analytics	+	+
Rating discordance	Dummy equal to 1 if S&P and Moody's assign a different credit rating for the same tranche, and 0 otherwise.	DCM Analytics	+	+
Maturity	Maturity of bonds, in years.	DCM Analytics	**NL/** +	+
Transaction size	Bond transaction size, computed as the sum of all tranches per deal/transaction. Transaction size is converted into $ millions when necessary.	DCM Analytics	–	–
Subordinated	Dummy equal to 1 for tranches that are subordinated, and 0 otherwise.	DCM Analytics	+	+
Number of tranches	The number of tranches per transaction.	DCM Analytics	–	+
Currency risk	Dummy equal to 1 for bonds that are denominated in a currency different from the currency in the deal's nationality, and 0 otherwise.	DCM Analytics	+	+
Number of banks	The number of financial institutions participating in bond issuance, as bookrunners, underwriters or servicers.	DCM Analytics	–	–
Bank reputation	Bookrunners rank according to Thomson Reuters League Tables. Ranks range from 1 (worst) to 25 (best).	Thomson Reuters DMI	–	–
Collateralized	Dummy equal to 1 if a bond is collateralized, and 0 otherwise.	DCM Analytics	+	+
Management fee	Fees (in bps) that are periodically paid to the bank syndicates.	DCM Analytics	+	+
Gross spread	Gross spread (in bps) per tranche as given by bookrunner.	DCM Analytics	+	+
Callable	Dummy equal to 1 if the bond has a call option, and 0 otherwise.	DCM Analytics	+	+
Firm characteristics				
Log total assets	Natural logarithm of firm total assets measured in $ million.	Datastream	–	–
Debt to total assets	The ratio of total debt to total assets.	Datastream	+	+
Fixed assets to total assets	The ratio of fixed assets to total assets. Fixed assets includes property, plant and equipment.	Datastream	–	–
Market to Book	The sum of book value of liabilities and market value of equity divided by the book value of assets.	Datastream	–	–
Return on Assets	The net income before preferred dividends minus preferred dividend requirement, divided by total assets.	Datastream	–	–
Log Z-score	Logarithm of Altman's (1993) Z-score. Altman's Z-score is calculated as Z = 1.2 (Working Capital/Total Assets) + 1.4 (Retained Earnings/Total Assets) + 3.3 (Earnings Before Interest and Taxes/Total Assets) + 0.6 (Market Value of Equity/ Book Value of Liabilities) + 0.999 (Net Sales/Total Assets).	Datastream	–	–
FCF to total assets	The ratio of Free Cash Flow to total assets.	Datastream	–	–
Macroeconomic factors				
Market-Based	Dummy equal to 1 if the loan is extended to a borrower located in a country with a market-based financial system, and 0 otherwise.	Demirgüç-Kunt and Maksimovic (2002)	+	+
Creditor rights	Measured using La Porta et al. (1998) indices. We use four creditor rights variables (no automatic stay on assets; secured creditors first paid; restrictions for going into reorganization; management does not stay in reorganization) and added up the scores to create an index as in Esty and Megginson (2003).	La Porta et al. (1998)	–	–
Enforcement	Measured using La Porta et al. (1998) indices. We use five enforcement variables (efficiency of judicial system; rule of law; corruption; risk of expropriation; risk of contract repudiation) and added up the scores to create an index.	La Porta et al. (1998)	–	–
Country risk	Moody's country credit rating at close. The rating is converted as follows: Aaa = 1, Aa1 = 2, and so on until C = 22.	Moody's Global Rating	+	+
Volatility	The Chicago Board Options Exchange Volatility Index (VIX). VIX reflects a market estimate of future volatility.	Datastream	+	+
USTB5y-USTB3m	The slope of the U.S. Treasury swap curve. Obtained as the difference between the five-year U.S. Treasury Bond yield and the 3-month U.S. Treasury bill yield.	Datastream	–	–
Financial crisis	Dummy equal to 1 if the closing date falls within the 2007–2008 financial crisis period (September 15, 2008 – December 31, 2014) and 0, otherwise.	Authors'	+	+

(*continued on next page*)

Table 2 (*continued*)

Variable Name	Variable definition	Source	Expected impact on spread	
			PF bonds	CF bonds
Sovereign crisis	Dummy equal to 1 if the closing date falls within the sovereign debt crisis period (April 24, 2010 – December 31, 2016) and 0, otherwise.	Authors'	+	+

Characters meaning: – = negative impact on the credit spread | + = positive impact on the credit spread | NL = Not linear |.

To study whether the type of financial system affects pricing and the cost of borrowing, we use an indicator variable that takes the value 1 for bonds issued by borrowers in *market-based* financial systems. Since access to debt financing is a central issue in PF, we expect the type of financial system to influence the pricing of bonds extended to such transactions. In addition, as banks have comparative advantages in mitigating asymmetric information problems by monitoring borrowers more closely and can enforce contracts without judicial assistance by exercising contractual covenants (Alves et al., 2021), we expect borrowers in countries with market-based financial systems to face higher bond spreads.

We collected Moody's country rating to control for *country risk*. Dailami and Hauswald (2007) and Bonetti et al. (2010) report that investors charge higher corporate bond yields to firms that are in countries with higher sovereign risk. To examine the impact of additional macroeconomic factors on spreads, we use *USTB5y-USTB3m*, estimated as the difference between the five-year U.S. Treasury Bond yield and the 3-month U.S. Treasury bill yield, and *market volatility*, measured by the Chicago Board Options Exchange Volatility Index. We expect, for both PF and CF bonds, that increases in the slope of the yield curve should have a negative impact on spreads, while a contrary effect is expected for market volatility. Finally, to examine the impact of the supply side conditions of the corporate debt market on credit spreads, we include dummies for *financial crisis* and *sovereign crisis*. We also use industry dummy variables to control for unobserved macro trends and possible industry-specific variations.

3.2.5. Sponsoring/issuing firms' characteristics

Although PF deals employ bankruptcy remote SPVs, the financial strength of the sponsor, namely for the sponsor holding a controlling position in the vehicle company and in cases of limited-recourse debt, may matter in pricing the debt issued by the SPV (Gorton and Souleles, 2007). Considering asset securitization securities, Longstaff and Rajan (2008), He et al. (2011), and Marques and Pinto (2020) show that originating firms' characteristics affect bond yields. In line with other studies (Chen et al., 2007; Flannery et al., 2012; Lemmon et al., 2014), we include proxies for sponsoring/issuing firms' size (log *total assets*), financial leverage (*debt to total assets*), asset tangibility (*fixed assets to total assets*), profitability (*return on assets*), and growth opportunities (*market to book*). We expect total assets, fixed assets-to-total assets, ROA, and market-to-book to have a negative impact on spreads. On the contrary, we expect total debt-to-total assets ratio to have a positive impact.

Regarding the choice between PF and CF deals, we also use the previously referred variables as proxies for sponsoring firms' motivations for using PF. First, based on debt choice literature (Denis and Mihov, 2003; Altunbas et al., 2010), we use firm size to capture incentive problems related to information asymmetries and expect it to negatively influence the probability of a sponsoring firm choosing a PF deal rather than a CF deal. As in Pinto and Santos (2019), we use the deal's weighted average maturity (*WAM*), computed as the weighted average between the loan maturity, in years, and its weight in the deal size, to capture informational costs associated with liquidity risk induced by debt refinancing. We expect a positive relationship between *WAM* and the probability of a firm choosing a PF deal. Second, to investigate if firms with high agency costs of debt and with more growth opportunities are more likely to choose PF rather than CF, we use debt to total assets and market-to-book ratios (Denis and Mihov, 2003; Altunbas et al., 2010). We expect that firms with higher deadweight costs resulting from the debt overhang problem, those with higher leverage and investor expectations about future cash flow potential, to prefer PF *vis-à-vis* CF bond deals. Third, we use the free cash flow to assets ratio to examine if firms with higher agency costs of free cash flow increase the likelihood of PF over CF bond deals. Fourth, as in Pinto and Santos (2019), we use Altman's (1993) *Z-score* as a proxy for a firm's credit risk and expect that sponsoring firms with higher credit risk prefer PF over CF. We also use the bond deals' weighted average spread (*WAS*), computed as the weighted average between the bond tranche spread and its weight in the deal size, as a proxy for firms' borrowing costs. Fifth, we use the return on assets ratio as our surrogate for profitability and expect a negative impact on the probability of PF borrowing. Finally, considering that firms in capital-intensive industries most commonly use PF, we expect asset tangibility to have a positive impact on the likelihood of firms choosing PF.

We collect public firm-specific accounting and market data in the fiscal year ending just prior to bond issuance from Datastream. As DCM Analytics does not provide an identification code, we hand-matched the sponsor with the highest equity ownership (if higher than 50%) to the separate PF firm in Datastream by using the sponsor's name. For CF bond deals, data from Datastream are merged with transaction information from DCM Analytics by hand-matching issuers' names. This method allows the deals to be matched with the ultimate party responsible for the financing choice decision.

3.3. Financial characteristics of PF versus CF bonds

We describe the sample, by asset class, in Table 3. This section constitutes the most exhaustive such comparison in the literature. Table 3 also presents Wilcoxon's z-tests and Fisher's exact tests comparing the values of each variable in the PF bond sample with the corresponding values in the CF bond sample. Almost all of the pair-wise comparisons indicate statistically significant differences between the common pricing variables associated with PF *vis-à-vis* CF bonds.

Regarding the relative pricing of PF versus CF bonds, Panel A of Table 3 shows that the average spread is economically and statistically higher for PF (241.0 bps) than it is for CF (206.8 bps) bonds. This holds when we break down spreads by credit rating class (Table 1 in section 2 of the Online Appendix): mean and median spreads are higher in PF *vis-à-vis* CF bonds for investment-grade classes. We also compare the evolution of spreads by considering a pre-crisis period from January 1, 2000, through to September 14, 2008, and a crisis and post-crisis period from September 15, 2008 (the first trading day after the Lehman Brothers' bankruptcy filing

Table 3
Univariate statistics - pricing features associated with bonds compared.

Variable of interest	Project finance bonds	Corporate finance bonds		Variable of interest	Project finance bonds	Corporate finance bonds	
Panel A | Univariate analysis - continuous variables | Contractual characteristics							
Spread (bps)				**Transaction size ($ Million)**			
Number	763	46,433		Number	763	46,433	
Mean	241.0	206.8	***	Mean	611.0	593.0	***
Median	195.0	145.7		Median	450.0	321.0	
Rating [1–22 weak]				**Tranche size ($ Million)**			
Number	592	45,603		Number	763	46,433	
Mean	8.5	6.7	***	Mean	371.0	365.0	
Median	9.0	7.0		Median	282.0	250.0	
Maturity (years)				**Number of banks**			
Number	763	46,433		Number	763	46,433	
Mean	13.7	9.6	***	Mean	5.0	5.9	***
Median	10.0	7.1		Median	4.0	4.0	
Number of tranches				**Country risk [1–22 weak]**			
Number	763	46,433		Number	763	46,433	
Mean	2.0	1.6	***	Mean	4.2	2.7	***
Median	1.0	1.0		Median	1.0	1.0	
Creditor rights [0–4 strong]				**Enforcement [32–85 strong]**			
Number	763	46,433		Number	763	46,433	
Mean	1.5	1.6	***	Mean	66.6	70.2	***
Median	1.0	1.0		Median	68.7	72.0	
Panel B | Univariate analysis - continuous variables | Firm characteristics							
Total assets ($ million)				**Return on assets**			
Number	364	22,499		Number	364	22,499	
Mean	97,794.5	45,116.6	***	Mean	3.7%	5.5%	***
Median	26,165.6	17,779.7		Median	3.7%	5.0%	
Fixed assets to total assets				**Market to book**			
Number	364	22,499		Number	364	22,499	
Mean	46.3%	44.7%		Mean	383.5%	245.8%	***
Median	57.4%	43.9%		Median	212.1%	181.1%	
Debt to total assets				***Z*-score**			
Number	364	22,499		Number	281	20,068	
Mean	34.0%	36.4%	***	Mean	1.5	2.0	***
Median	34.3%	35.4%		Median	0.8	1.1	
Panel C | Univariate analysis - dummy variables | Contractual charcteristics							
Callable				**Currency risk**			
Nr. of tranches	763	46,433		Nr. of tranches	763	46,433	
Nr. of tranches with d = 1	395	22,659	***	Nr. of tranches with d = 1	244	9,806	***
% of total	51.8%	48.8%		% of total	32.0%	21.1%	
Market-based				**Subordinated**			
Nr. of tranches	763	46,433		Nr. of tranches	763	46,433	
Nr. of tranches with d = 1	593	29,109	***	Nr. of tranches with d = 1	8	1,633	***
% of total	77.7%	62.7%		% of total	1.0%	3.5%	
Rated				**Rating discordance**			
Nr. of tranches	763	46,433		Nr. of tranches	763	46,433	
Nr. of tranches with d = 1	592	34,074	***	Nr. of tranches with d = 1	186	13,435	***
% of total	77.6%	73.4%		% of total	24.4%	28.9%	

This table reports summary statistics for a sample of PF and CF bonds issued during the 1993–2020 period. Information on the characteristics of bond issuances was obtained from DCM Analytics and Datastream. We test for similar distributions using Wilcoxon's rank-sum test for continuous variables and Fisher's exact test for discrete ones. ***, **, and * indicate significant difference at the 1%, 5%, and 10% levels, respectively, between the sample of PF bonds and the sample of CF bonds. Bond rating is based on the S&P and Moody's rating at the time of bond issuance. The rating is converted as follows: AAA = Aaa = 1, AA+ = Aa1 = 2, and so on until D = 22. For a definition of the variables, see Table 2.

the day before) through to December 31, 2020 (Table 5, section 3, of the Online Appendix). As expected, the evidence strongly supports the assumption that the average spread is significantly higher for both PF (281.7 bps versus 232.2 bps) and CF bonds (241.4 bps versus 162.4 bps) during the crisis and post-crisis period.

A CF bond of average size matures in 9.6 years, which is a short period if we compare it with the average of 13.7 for PF bonds. Average credit ratings for PF (8.5 | BBB) are significantly worse than for CF (6.2 | A-) bonds. This may suggest that PF tranches are riskier than CF lending. However, this can reflect the country rating, since PF issuers are, on average, located in far riskier countries than CF issuers. The average country risk for PF (4.2) SPEs is significantly higher than the corresponding value for CF (2.7), which is in line with the fact that PF deals are more likely to be implemented in riskier than average countries. Similarly, PF bonds are more commonly issued by firms located in countries with lower creditor rights and enforcement levels, when compared with CF.

The average tranche size does not differ significantly between the two asset classes. On the contrary, the average transaction size exhibited by CF bond issues is lower than the average transaction size exhibited by PF bond transactions. A significantly larger number of tranches per transaction is issued in a PF transaction: in a typical CF transaction, the average number of tranches per transaction is 1.6, which is smaller than the average of 2.0 for PF. In addition, the average number of banks participating in CF bond issues is 5.9 and is significantly larger than the average of 5.0 for PF. This finding suggests that underwriting banks wish to increase the number of institutions participating in a CF bond issuance of a given size in order to spread risks over a larger number of banks.

Panel B of Table 3 shows that, except for the fixed-assets-to-total-assets ratio, sponsoring firms' characteristics in PF transactions that use the bond market to raise debt differ significantly from those of CF bond issuers. On average, sponsors in PF bonds are typically larger, with an average (median) size of $97.8 billion ($26.2 billion) versus $45.1 billion ($17.8 billion) for CF bond issuers. As we expected, PF sponsors are less creditworthy - average *Z*-score of 1.5 versus 2.0 - and profitable - average ROA of 3.7% versus 5.5% - and have higher growth opportunities - average market-to-book ratio of 383.5% versus 245.8% -, than firms issuing on-balance-sheet CF bonds. The average debt-to-total-assets ratio is 36.4% for CF bond issuers, which is significantly higher than the 34.0% for PF bond sponsoring firms.

The dummy variables detailed in Panel C of Table 3 clearly suggest that PF and CF bonds are fundamentally different financial instruments. PF bonds are more frequently issued with a call option than CB issues (51.8% versus 48.8%). PF bonds are much more likely to be used by issuers located in countries with a market-based financial system (77.7% versus 62.3%) and be subject to currency risk (32.0% versus 21.1%) than corporate bonds. While about 3.5% of CF bonds are subordinated, these bonds are only 1.0% of PF bonds issued in the sampling period. Additionally, a significantly small fraction of CF is rated (73.4%) compared to the sub-samples of PF bonds. Finally, CF bonds verify a higher fraction of tranches with rating agencies' discordance, which can be explained by the fact that these bonds are rated *ex-ante* versus PF bonds, typically rated *ex-post*.

Our results indicate that the common pricing characteristics differ significantly in value between PF and CF bonds. Therefore, we would expect the impact on pricing to be bond-specific.

4. The pricing of PF versus CF bonds

4.1. Determinants of PF and CF bond spreads

To examine the common pricing determinants of individual PF and CF bonds, we use the model described in Eq. (1). The dependent variable is the *spread*, in basis points. We employ OLS regression techniques and adjust for heteroskedasticity. Due to time varying risk premia and cross-country differences, we estimate standard errors clustered by year and country.

$$\begin{aligned} Spread_{i,t} = \alpha_0 + \beta_1 Rated_{i,t} + \sum_{n=2}^{21} \beta_n Rating\ dummy_{n,i,t} + \beta_{22}\ rating\ discordance_{i,t} + \gamma\ Contractual\ characteristics_{i,t} \\ + \varphi\ Macroeconomic\ factors_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

A Chow test for a structural break is used to examine whether the spreads associated with PF and CF bonds are influenced differently by common pricing characteristics. In essence, we are testing whether the pricing characteristics used in eq. (1) are significant in both PF and CF tranches and, if so, whether they have the same coefficient values. We conclude that PF and CF tranches are distinct financial instruments and that they are financial instruments influenced differently by common pricing characteristics because of the Chow test statistic of 41.5 (69.1 if we include firms' characteristics as additional control variables), which is higher than the critical level.[15] Hence, we corroborate H1 and examine, in section 4.2., the determinants of spreads for each bond instrument separately.

We start our analysis by comparing spreads among securities. To do that we use eq. (1) and create one dummy variable set equal to 1 if the bond is a PF bond, and 0 if it is a CF bond – models [1] to [4] of Table 4. Results presented in columns 1 and 2 of Table 4, for the samples discussed in section 3.3., suggest that PF bonds are, on average, associated with higher spreads than similarly rated CF bonds: 46.5 bps for the full sample and 28.0 bps when controlling for firms' characteristics. In previous models, the PF bond dummy may suffer from endogeneity, due to the lack of plausibly exogenous variation in the choice between PF and CF. Second, both PF and CF bond

[15] Similar results were obtained when the chow test is applied to the following subsamples (see Panel E of Table 1): PF bonds versus corporate control bonds; PF bonds versus capital structure bonds; PF bonds versus fixed asset based bonds, and PF bonds versus general corporate purpose bonds.

Table 4
Regression analyses of the determinants of credit spreads.

Dependent variable:	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Spread (bps)	PF and CF bonds	PF and CF bonds	PF and CF bonds | matched sample	PF and CF bonds | matched sample	PF bonds	CF bonds	PF bonds	CF bonds
Independent variables:								
Intercept	180.70 ***	−1.87	105.80	−61.53	477.40 ***	95.01	401.80 *	−287.50 ***
	(0.008)	(0.984)	(0.399)	(0.658)	(0.000)	(0.194)	(0.099)	(0.000)
PF bond	46.51 ***	28.01 ***	24.69 ***	22.91 ***				
	(0.001)	(0.001)	(0.006)	(0.005)				
Rated	−92.44 ***	−77.54 ***	−193.50 ***	−101.30 ***	−117.20 ***	−89.70 ***	−83.23 ***	−75.01 ***
	(0.000)	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.010)	(0.000)
AA+	36.16 ***	48.88 ***	28.84	−91.82	16.86	38.88 ***	−101.00	49.76 ***
	(0.000)	(0.000)	(0.408)	(0.125)	(0.729)	(0.000)	(0.112)	(0.000)
AA	29.40 ***	24.51 *	77.34 ***	60.18 **	39.04	32.99	27.05	26.42
	(0.007)	(0.053)	(0.006)	(0.029)	(0.244)	(0.232)	(0.498)	(0.372)
AA-	20.99 ***	−1.75	54.91 ***	43.24 *	117.10 ***	24.20 ***	−1.18	−3.63
	(0.003)	(0.83)	(0.009)	(0.056)	(0.000)	(0.001)	(0.981)	(0.67)
A+	−7.79	0.67	77.64 ***	60.85 ***	38.11	−10.92	−20.06	−1.44
	(0.261)	(0.92)	(0.000)	(0.001)	(0.264)	(0.115)	(0.559)	(0.837)
A	1.79	8.41	76.20 ***	73.13 ***	37.22	−1.56	16.48	6.17
	(0.794)	(0.225)	(0.000)	(0.000)	(0.17)	(0.819)	(0.65)	(0.389)
A-	15.46 **	22.54 ***	86.64 ***	78.68 ***	73.87 ***	12.12 *	18.08 **	20.15 **
	(0.03)	(0.002)	(0.000)	(0.000)	(0.001)	(0.089)	(0.049)	(0.01)
BBB+	43.83 ***	45.83 ***	125.10 ***	100.80 ***	112.40 ***	39.77 ***	4.07	43.09 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.904)	(0.000)
BBB	60.97 ***	64.76 ***	141.30 ***	138.90 ***	103.10 ***	57.81 ***	86.37 ***	61.77 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)
BBB-	102.80 ***	104.50 ***	193.20 ***	182.30 ***	165.70 ***	98.85 ***	137.20 ***	100.90 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BB+	178.90 ***	180.90 ***	252.80 ***	257.90 ***	178.00 ***	175.60 ***	231.00 ***	177.10 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BB	195.30 ***	203.40 ***	303.70 ***	289.30 ***	268.10 ***	191.10 ***	197.10 ***	200.80 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BB-	258.70 ***	250.40 ***	396.30 ***	362.20 ***	374.50 ***	254.70 ***	326.90 ***	247.00 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B+	314.20 ***	305.00 ***	424.80 ***	392.20 ***	342.80 ***	310.50 ***	172.10 ***	302.60 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

(*continued on next page*)

Table 4 (*continued*)

Dependent variable:	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Spread (bps)	PF and CF bonds	PF and CF bonds	PF and CF bonds | matched sample	PF and CF bonds | matched sample	PF bonds	CF bonds	PF bonds	CF bonds
B	364.50***	347.00***	389.30***	364.00***	367.70***	361.20***	494.10***	343.20***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
B-	401.20***	387.50***	513.60***	423.80***	473.40***	397.60***	165.00	385.20***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.158)	(0.000)
CCC+	488.60***	484.80***	636.80***	758.90***	547.20***	484.30***	540.20***	480.40***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CCC	538.00***	574.50***				534.40***		571.00***
	(0.000)	(0.000)				(0.000)		(0.000)
CCC-	500.10***	507.60***	811.20***		152.10***	535.70***		505.00***
	(0.000)	(0.000)	(0.000)		(0.008)	(0.000)		(0.000)
CC	499.20***				494.00***	551.80***		
	(0.000)				(0.000)	(0.000)		
C	334.40***	427.60***				332.70***		424.70***
	(0.001)	(0.000)				(0.001)		(0.000)
Rating discordance	26.06***	17.75***	16.23*	17.38**	20.26	26.00***	−4.76	17.60***
	(0.000)	(0.000)	(0.062)	(0.038)	(0.136)	(0.000)	(0.749)	(0.000)
Contractual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macro controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	Yes	No	Yes	No	No	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	47,196	22,863	672	672	763	46,433	364	22,499
Adjusted R^2	0.55	0.63	0.62	0.72	0.53	0.56	0.63	0.63
Rated and rating dummies as independent variables only								
Adjusted R^2	0.38	0.44	0.40	0.49	0.29	0.39	0.43	0.44
Differences in adjusted R^2	0.17	0.19	0.22	0.23	0.24	0.17	0.20	0.19

Table 4 presents the results of an OLS regression analysis of the determinants of bond spreads for: (*i*) a sample of 763 PF bonds and 46,433 CF bonds - models [1], [5] and [6]; (*ii*) a sub-sample of 364 PF bonds and 22,499 CF bonds for which there is available information on sponsoring (for PF bonds) and issuing (for CF bonds) firms' characteristics - models [2], [7] and [8]; and (*iii*) a sub-sample of PF bonds and a matched sample (control group) of CF bonds - models [3] and [4]. To create a matched sample of CF bonds, we employ a propensity score matching approach (bond-level PSM), by creating a 1 to 1 matching algorithm that captures the most identical CF bond issued by the same sponsoring firm in the same year, using the following characteristics: bond size, maturity, and rating. For each independent variable, the first row reports the estimated coefficient, and the second row reports the *p*-value. Standard errors are heteroskedasticity robust and clustered at the country-year level. ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. For a definition of the variables, see Table 2.

transaction sizes are determined endogenously. Since PF deals are larger, they might be riskier and have higher financing rates. Third, in the full sample, PF bonds are about 2% of the total sample. As suggested by Roberts and Whited (2013) and following a methodology similar to Flammer (2021), we re-estimated model [1] for a matched sample. We proceed as follows. First, out of the 763 PF bonds issued by public firms, we restrict the sample to bonds with no missing information on sponsoring firms' accounting and market data. A total of 364 bonds meet these criteria. We then match each PF bond to the most comparable CF bond by using a propensity score matching (PSM) approach (bond-level PSM), by creating a 1 to 1 matching algorithm that captures the most identical CF bond issued by the same sponsoring firm in the same year, using the following characteristics: bond size, maturity, and rating. After applying this procedure, we end with a sample of 336 PF bonds and a quasi-identical bond-level matched sample of 336 CF bonds (see the descriptive statistics for the matched sample in Table 6, section 3, of the Online Appendix). By design, this matching procedure provides for each PF bond a matched CF bond issued by the same sponsoring firm that is as similar as possible except for the fact that the PF bond is issued off-balance sheet through a legally independent SPE that is more than 50% owned by the sponsoring firm.

Results presented in column 3 of Table 4 show that the PF bond spread is 24.7 bps higher than that of matched CF bonds. Similar results are obtained in model [4] when re-estimating model [3] controlling for firms' characteristics. These results are contrary to the arguments of PF theoretical literature (John and John, 1991; Nevitt and Fabozzi, 2001; Esty, 2003, 2004a, 2004b), but in line with the empirical findings of Klein et al. (1996) and Pinto and Santos (2019). Therefore, thus far, we corroborate H2. We will analyze this further in the next section, when using endogenous switching regression models and computing average treatment effects.

Models [5] and [6] present pricing regression results for a sample of 763 PF bonds and 46,433 CF issues. Regarding the impact of credit risk on spread, Table 4 shows the exact results expected; rated bonds have lower spreads and the higher the credit risk, the higher the credit spread. For example, A- bonds have 73.9 bps and 12.1 bps higher spreads than AAA tranches for PF and CF bonds, respectively. However, it should be noted that the relationship between spread and rating is not linear; the impact of one unit increase in *rating* increases as the credit rating deteriorates. We also estimate models [5] and [6] considering only rated and rating dummies as independent variables and find that models yield adjusted R^2 values of 0.29 and 0.39, respectively. This confirms credit ratings as the most important determinant of spreads in both PF and CF issues. Furthermore, the adjusted R^2 value increases, on average, 0.24 for PF bonds and 0.17 for CF bonds with the inclusion of additional contractual and macroeconomic variables, which shows that credit rating is not the only determinant of spread. In fact, investors do not rely exclusively on ratings, and this effect is higher for PF *vis-à-vis* CF bonds: they consider other factors when pricing PF and CF bonds, and therefore do rely on information beyond the assigned credit rating, which corroborates H1. Additionally, we find that credit rating discordance between S&P and Moody's has a substantial positive impact (26.0 bps) on the spread for CF bonds only. This result shows that rating agencies' discordance is incorporated by investors in the pricing of CF bonds, requiring an additional risk premium to compensate for a greater degree of uncertainty concerning the issuer's default risk. Similar results were obtained in models [7] and [8] when controlling for firms' characteristics.

4.2. Bond pricing and borrowing choice

Results in Table 3 show that PF and CF bonds have significantly different characteristics (e.g., the average maturity of PF bonds is 13.7 years versus 9.6 years for CF bonds and the latter have A/A- average ratings versus BBB+/BBB average credit ratings for PF bonds). Therefore, the selection is important in this context. Additionally, in our sample sponsoring firms can choose between PF and CF. Table 5 shows that switchers, firms that use both PF and CF deals to fund their investment projects, are responsible for 4,175 deals worth $2,381.4 billion.

Table 5
Industrial distribution of deals closed by switchers.

Industrial distribution of deals closed by switchers				
Industrial category of issuer	Number of Deals	Number of switchers	Total Value ($ Million)	Percent of total value
Commercial and Industrial				
Agriculture, Forestry and Fishing	7	1	3250	0.14%
Communications	492	9	433,047	18.18%
Construction/Heavy Engineering	70	4	32,994	1.39%
Manufacturing				
Chemicals, Plastic and Rubber	51	2	33,063	1.39%
Food and Beverages	72	2	62,110	2.61%
Machinery and Equipment	41	1	31,356	1.32%
Other	30	1	5409	0.23%
Mining and Natural Resources	28	3	19,056	0.80%
Oil and Gas	485	27	348,342	14.63%
Real Estate	177	11	92,400	3.88%
Real Trade	46	1	29,202	1.23%
Services	126	6	90,440	3.80%
Utilities	2,341	60	1,048,324	44.02%
Transportation	190	12	130,318	5.47%
Public Administration/Government	5	1	895	0.04%
Other	14	1	21,209	0.89%
Total	**4,175**	**142**	**2,381,415**	**100.00%**

Table 5 displays the number of PF and CF bond deals closed by switchers - firms that use both deal types in our sampling period.

Table 6
Endogenous switching regression models.

Dependent variable:	[9]	
Spread (bps)	PF bonds | with firms' characteristics	CF bonds | with firms' characteristics
Independent variables:		
Intercept	396.81	−183.68***
	(0.168)	(0.000)
Rated	−171.28***	−276.46***
	(0.000)	(0.000)
Rating*rated	26.28***	32.14***
	(0.000)	(0.000)
Rating discordance	56.41***	18.59***
	(0.001)	(0.000)
Log transaction size	−23.50*	17.82***
	(0.074)	(0.000)
Maturity	−0.75	0.40***
	(0.465)	(0.000)
Log maturity	22.92*	−1.01
	(0.053)	(0.777)
Subordinated	172.89**	51.28***
	(0.029)	(0.000)
Currency risk	38.15*	30.40***
	(0.093)	(0.000)
Collateralized	−21.71	51.99***
	(0.766)	(0.000)
Callable	8.81	39.70***
	(0.475)	(0.000)
Number of Banks	−0.12*	−0.51***
	(0.092)	(0.002)
Bank reputation	3.96***	1.46***
	(0.008)	(0.000)
Number of Tranches	−1.57*	−13.93***
	(0.098)	(0.000)
Market-based	24.20**	21.76***
	(0.017)	(0.000)
Creditor Rights	3.13	−0.16*
	(0.653)	(0.086)
Financial crisis	−21.09	137.50***
	(0.630)	(0.000)
Sovereign crisis	40.72**	52.31***
	(0.029)	(0.000)
Volatility	3.43**	3.43***
	(0.035)	(0.000)
USTB5y-USTB3m	0.03	−0.12***
	(0.738)	(0.000)
Log total assets	0.05	−5.43***
	(0.996)	(0.000)
Fixed assets to total assets	1.77	−16.45***
	(0.949)	(0.000)
Debt to total assets	121.54***	20.69***
	(0.004)	(0.001)
Return on assets	0.77	−1.14***
	(0.608)	(0.000)
Market to book	−0.54	0.01
	(0.228)	(0.375)

Dependent variable:	
Probability of observing:	PF versus CF bonds
Independent variables:	
Intercept	0.15
	(0.866)
Rated	−0.58***
	(0.000)
Rating*rated	0.00
	(0.666)
Rating discordance	−0.34***
	(0.000)
Log transaction size	0.16***

(*continued on next page*)

Table 6 (*continued*)

Dependent variable:	
Probability of observing:	PF versus CF bonds
	(0.000)
Maturity	0.01***
	(0.000)
Log maturity	−0.77***
	(0.000)
Subordinated	−1.38***
	(0.000)
Currency risk	−0.13
	(0.126)
Collateralized	1.07***
	(0.000)
Callable	0.02
	(0.781)
Number of Banks	0.00
	(0.998)
Bank reputation	−0.01
	(0.037)
Number of Tranches	−0.07**
	(0.018)
Financial crisis	−0.72***
	(0.000)
Sovereign crisis	0.18***
	(0.002)
Volatility	−0.03***
	(0.001)
USTB5y-USTB3m	0.00***
	(0.000)
Market-based	0.13***
	(0.010)
Creditor Rights	0.03
	(0.311)
Log total assets	−0.14***
	(0.000)
Fixed assets to total assets	0.25**
	(0.042)
Debt to total assets	−0.38**
	(0.034)
Return on assets	−0.02***
	(0.000)
Market to book	0.01*
	(0.052)
Number of observations	22,863
Average treatment effect	24.82***
	(0.003)
Wald chi2	737.19***
Log pseudolikelihood	−142,434.23
Wald test of indep. equations	26.94***

Table 6 presents the results of estimating endogenous switching regression models on a sample of 364 PF bonds and 22,499 CF bonds for which there is available information on sponsoring (for PF bonds) and issuing (for CF bonds) firms' characteristics. We implement the full information maximum likelihood (FIML) method to simultaneously estimate binary and continuous parts of the model in order to yield consistent standard errors. For each independent variable, the first row reports the estimated coefficient, and the second row reports the *p*-value. Standard errors are heteroskedasticity robust and clustered at the country-year level. ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively. For a definition of the variables, see Table 2.

As the choice between PF and CF deals may be endogenous to spreads, we examine bond pricing by using an endogenous switching regression model (Lokshin and Sajaia, 2004) to study the pricing, taking into consideration the potential self-selection by firms between issuing PF versus CF bonds. We perform a full information maximum likelihood (FIML) method on the credit spread samples of our model specifications - models [7] and [8] of Table 4 - simultaneously with a probit selection equation, where the choice between PF and CF is a function of contractual and firms' characteristics, and macroeconomic factors.[16] The empirical model consists of the following three equations:

[16] We implement an FIML method to simultaneously estimate binary and continuous parts of the model to yield consistent standard errors. For further analysis, see Lokshin and Sajaia (2004).

Table 7
Regression analyses of credit spreads by rating category.

Dependent variable:	[10]	[10a]	[10b]	[10c]	[10d]	[10e]	[10f]	[10 g]	[10*h*]	[10i]	[10j]
Spread (bps)	All bonds	AAA / Aaa	AA+ / Aa1	AA / Aa2	AA- / Aa3	A+ / A1	A / A2	A- / A3	BBB+ / Baa1	BBB / Baa2	BBB- / Baa3
Panel A - PF versus CF *bonds* | full sample											
PF bond	46.51 ***	22.70 **	−0.90	44.35 ***	10.41 **	44.96 **	26.28 **	53.80 ***	72.06 *	43.66 ***	37.23 *
	(0.001)	(0.019)	(0.951)	(0.004)	(0.043)	(0.014)	(0.045)	(0.000)	(0.082)	(0.001)	(0.100)
[…]											
Number of observations	47,196	602	373	1,032	1,642	2,131	3,599	3,806	4,288	4,372	2,678
Adjusted R^2	0.55	0.41	0.40	0.37	0.51	0.46	0.42	0.41	0.45	0.39	0.39
Panel B - PF versus CF *bonds* | with firms' characteristics											
PF bond	24.69 ***	35.97 ***	49.62 **	57.55 **	−0.51	34.79 **	21.25	49.97 ***	25.58 *	47.99 ***	44.65 **
	(0.006)	(0.007)	(0.035)	(0.024)	(0.959)	(0.029)	(0.267)	(0.000)	(0.063)	(0.003)	(0.050)
[…]											
Number of observations	22,863	248	158	566	989	1,409	2,462	2,672	2,887	2,897	1,533
Adjusted R^2	0.63	0.47	0.65	0.47	0.54	0.55	0.50	0.49	0.47	0.43	0.41
Panel C - PF versus CF *bonds* | matched sample											
PF bond	24.69 ***						6.60 **	30.07 **	41.69 ***	14.62 **	22.71
	(0.006)						(0.035)	(0.033)	(0.004)	(0.024)	(0.467)
[…]											
Number of observations	940						78	119	136	140	109
Adjusted R^2	0.62						0.53	0.41	0.77	0.47	0.44
Panel D - PF versus CF *bonds* | CF = fixed asset based											
PF bond	72.74 ***	132.29 **	123.70 *	59.63 ***	29.68 *	−0.70	−0.61	29.20 *	78.43 ***	13.41 *	12.37 *
	(0.000)	(0.025)	(0.069)	(0.000)	(0.052)	(0.963)	(0.981)	(0.061)	(0.007)	(0.054)	(0.062)
[…]											
Number of observations	2,658	55	32	193	37	174	165	326	253	263	186
Adjusted R^2	0.58	0.94	0.98	0.93	0.60	0.84	0.64	0.66	0.60	0.41	0.52

Table 7 presents the results of an OLS regression analysis of the determinants of bond spreads for sub-samples of PF and CF bonds with available information on credit rating. Models [1], [2], and [3] of Table 4 are re-estimated for sub-samples by rating scales - models [10a] to [10j], Panels A, B, and C. In Panel D, we re-estimate our models restricting CF bonds to the fixed asset based category, following Kleimeier and Megginson (2000). PF bond is a dummy variable. For each independent variable, the first row reports the estimated coefficient, and the second row reports the *p*-value. Standard errors are heteroskedasticity robust and clustered at the country-year level. ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively.

$$Spread\ PF\ bond_{i,t} = \alpha_0 + \beta_1 Rated_{i,t} + \beta_2 Rated^*Rating_{i,t} + \beta_3\ Rating\ discordance_{i,t} + \gamma\ Contractual\ characteristics_{i,t} + \varphi\ Macroeconomic\ factors_t + \omega\ Firm\ characteristics_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

$$Spread\ CF\ bond_{i,t} = \alpha_0 + \beta_1 Rated_{i,t} + \beta_2 Rated^*Rating_{i,t} + \beta_3\ Rating\ discordance_{i,t} + \gamma\ Contractual\ characteristics_{i,t} + \varphi\ Macroeconomic\ factors_t + \omega\ Firm\ characteristics_{i,t-1} + \varepsilon_{i,t} \quad (3)$$

$$I^*_{i,t} = \delta_0\left(Spread\ PF\ bond_{i,t} - Spread\ CF\ bond_{i,t}\right) + \beta_1 Rated_{i,t} + \beta_2 Rated^*Rating_{i,t} + \beta_3\ Rating\ discordancei,t + \gamma\ Contractual\ characteristics_{i,t} + \varphi\ Macroeconomic\ factors_t + \omega\ Firm\ characteristics_{i,t-1} + u_{i,t} \quad (4)$$

where the third equation models bond selection: if $I^*_i > 0$, then firm i issues a PF bond; otherwise, it issues a CF bond. We adjust for heteroscedasticity and due to time varying risk premia and cross-country differences, we estimate standard errors clustered by year and country. Considering the Wald test statistics of independent equations presented in Table 6, we reject the hypothesis of equations being independent, meaning that the sponsoring firms' choice between on- versus off-balance-sheet funding, via the bond market, affects the pricing of such securities.

To examine further if characteristically similar bond tranches, which differ by bond type, have different spreads, we computed the average treatment effect (ATE) for spreads of PF versus CF. We used model [9] and obtained the correct standard errors (as we account for the errors in the selection equation) for the ATE through bootstrapping. We show, as presented in Table 4, that PF bonds are, on average, associated with 24.8 bps higher spreads than CF bonds. This result again corroborates H2. We can use two lines of research to explain why PF bonds have higher spreads than similarly rated CF bonds. The first, related to PF, is based on the specificities of PF transactions. As pointed out by Dailami and Hauswald (2003), in PF bonds there is no cross-insurance as in the case of CF bonds: the moment the single source of cash flows ceases to exist, the issuer experiences a liquidity crisis that might force it to default on its bonds. In addition, projects suffer from asset-specificity and, when used in developing countries, projects typically suffer from often ill-defined or ill-enforced property rights, and bilateral monopoly settings, leading to higher financial risk. The second studies a mispricing phenomenon in bond markets, namely asset securitization bonds versus corporate bonds. Brennan et al. (2009), Coval et al. (2009a, 2009b), and Cornaggia et al. (2017) argue that, as asset-backed securities carry large systematic risks relatively neglected by credit ratings, which are constructed to reflect only physical default probabilities (S&P) or expected losses (Moody's), structured bonds are

Table 8
Descriptive statistics for WAS and public firms' characteristics.

Variable of interest		Firms categorized according to choice of deals					
		[I]		[II]		[III]	
		PF deals only		CF deals only		PF and CF deals (switchers)	
WAS (bps)	Number	53		13,136		3,599	
	Mean	217.65		202.24		172.84	
	Median	208.09	a,b	140.00	a,c	130.00	b,c
Total assets ($ million)	Number	53		13,136		3,599	
	Mean	129,000		33,000		68,800	
	Median	10,600	b	11,600	c	32,800	b,c
Fixed assets to total assets	Number	53		13,136		3,599	
	Mean	29.15%		43.62%		56.43%	
	Median	12.81%	a,b	40.33%	a,c	62.16%	b,c
Debt to total assets	Number	53		13,136		3,599	
	Mean	28.11%		37.77%		36.39%	
	Median	26.85%	a,b	36.58%	a,c	35.79%	b,c
Return on assets	Number	53		13,136		3,599	
	Mean	0.28%		0.38%		4.73%	
	Median	0.26%	a,b	0.36%	a,c	4.50%	b,c
Market to book	Number	53		13,136		3,599	
	Mean	489.79%		252.34%		183.28%	
	Median	251.90%	a	176.84%	a,c	210.23%	c
Z-score	Number	38		11,498		3,295	
	Mean	1.57		2.21		1.42	
	Median	1.14	b	1.18	c	0.76	b,c
FCF to total assets	Number	52		12,914		3,479	
	Mean	3.30%		13.34%		10.47%	
	Median	3.08%	a,b	7.52%	a,c	6.81%	b,c

Table 8 presents the descriptive statistics for weighted average spread (WAS) and public firms' characteristics by category. We test for similar distributions in public firms' characteristics across samples via Wilcoxon's rank-sum test. [a] denotes statistical difference at the 1% level between 'PF deals only' and 'CF deals only' subsamples; [b] denotes statistical difference at the 1% level between 'PF deals only' and 'PF and CF deals' subsamples; [c] denotes statistical difference at the 1% level between 'CF deals only' and 'PF and CF deals' subsamples. We use the WAS, computed as the weighted average between the bond tranche spread and its weight in the deal size, as a measure of the total cost of borrowing. For a definition of the variables, see Table 2.

Table 9
Regression analyses of the cost of borrowing: PF versus CF deals.

Dependent variable:	[11]	[11a]	[11b]	[11c]	[11d]	[12]	[13]
WAS	PF and CF deals	PF and CF deals | CF = corporate control	PF and CF deals | CF = capital structure	PF and CF deals | CF = fixed asset based	PF and CF deals | CF = general corporate purpose	PF and CF deals | switchers	PF and CF deals | matched sample
Independent variables:							
Intercept	339.40 ***	428.20 ***	166.80	82.61	470.50 ***	110.30	824.80 ***
	(0.001)	(0.004)	(0.102)	(0.579)	(0.000)	(0.18)	(0.004)
PF deal	48.54 ***	11.19 **	42.56 ***	62.94 ***	49.75 ***	59.92 ***	61.98 ***
	(0.000)	(0.049)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log deal size	−4.08 **	−17.84 ***	−6.03	−7.82	−7.11 **	−11.80 ***	−38.99 ***
	(0.013)	(0.01)	(0.159)	(0.242)	(0.011)	(0.000)	(0.005)
WAM	0.04	0.10	−0.13	−0.33	0.15	0.45 *	−0.99
	(0.873)	(0.803)	(0.798)	(0.508)	(0.584)	(0.081)	(0.275)
WAR	18.99 ***	27.17 ***	27.96 ***	14.57 ***	14.11 ***	21.78 ***	20.81 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of tranches	−15.52 ***	−12.60 ***	−19.92 ***	−15.90 ***	−12.07 ***	−1.44	1.51
	(0.000)	(0.006)	(0.000)	(0.002)	(0.000)	(0.638)	(0.807)
Currency risk	21.02 ***	0.70	32.06 ***	54.87 ***	16.03 ***	20.89 ***	25.56
	(0.000)	(0.965)	(0.006)	(0.001)	(0.004)	(0.008)	(0.229)
Number of banks	−0.95 **	−3.58 ***	−3.35 ***	−0.14	−0.19	0.02	0.32
	(0.048)	(0.001)	(0.000)	(0.914)	(0.72)	(0.967)	(0.887)
Bank reputation	1.90 ***	3.74 ***	1.50 **	1.67 ***	1.44 ***	1.08 **	3.90 ***
	(0.000)	(0.001)	(0.046)	(0.008)	(0.001)	(0.037)	(0.007)
Financial crisis	101.60 **	137.30 ***	15.03	37.30	118.90 ***	128.30 **	246.80 ***
	(0.041)	(0.001)	(0.886)	(0.613)	(0.004)	(0.010)	(0.000)
Sovereign crisis	83.05	129.00 **	−15.27	−6.44	98.52 **	112.00 **	201.80 ***
	(0.120)	(0.011)	(0.885)	(0.94)	(0.04)	(0.041)	(0.000)
Country risk	0.43	3.46	−0.26	−0.88	1.25	0.13	11.31 **
	(0.821)	(0.436)	(0.94)	(0.818)	(0.523)	(0.946)	(0.030)
Creditors rights	−5.52 **	3.91	10.70 *	−4.63	−6.47 **	7.95 **	−3.85
	(0.020)	(0.552)	(0.063)	(0.59)	(0.011)	(0.027)	(0.709)
Market-based	36.12 ***	26.08	37.86 **	83.25 ***	25.97 ***	14.70	−40.19
	(0.000)	(0.164)	(0.035)	(0.000)	(0.004)	(0.120)	(0.233)

(*continued on next page*)

Table 9 (*continued*)

Dependent variable:	[11]	[11a]	[11b]	[11c]	[11d]	[12]	[13]
WAS	PF and CF deals	PF and CF deals | CF = corporate control	PF and CF deals | CF = capital structure	PF and CF deals | CF = fixed asset based	PF and CF deals | CF = general corporate purpose	PF and CF deals | switchers	PF and CF deals | matched sample
Enforcement	0.26	−1.14	0.54	1.43	−0.34	−0.57	−0.09
	(0.544)	(0.329)	(0.468)	(0.115)	(0.427)	(0.232)	(0.926)
Volatility	2.34 ***	3.00 ***	3.51 ***	0.67	2.42 **	2.58 ***	2.50
	(0.009)	(0.007)	(0.007)	(0.46)	(0.016)	(0.006)	(0.257)
USTB5y-USTB3m	−0.06	−0.28 **	−0.14	−0.04	−0.01	−0.03	−0.10
	(0.262)	(0.028)	(0.264)	(0.61)	(0.901)	(0.662)	(0.495)
Log total assets	−22.63 ***	−8.06 **	−13.99 ***	−15.08 ***	−23.34 ***	1.01	−9.91
	(0.000)	(0.02)	(0.000)	(0.000)	(0.000)	(0.659)	(0.122)
Debt to total asset	37.51 ***	13.78	47.60 ***	51.94 *	42.06 ***	69.31 ***	18.06
	(0.001)	(0.649)	(0.004)	(0.075)	(0.003)	(0.004)	(0.75)
Fixed assets to total assets	−44.20 ***	−36.13 *	−27.83	−58.64 **	−38.06 ***	−3.36	14.03
	(0.000)	(0.061)	(0.111)	(0.024)	(0.000)	(0.855)	(0.745)
Market to book	−0.01	0.08	0.01	0.23	−0.01	−0.07	−0.25
	(0.799)	(0.674)	(0.988)	(0.619)	(0.807)	(0.265)	(0.566)
Return on assets	−2.28 ***	−1.28 ***	−2.57 ***	0.43	−2.52 ***	−4.13 ***	−1.97
	(0.000)	(0.007)	(0.000)	(0.526)	(0.000)	(0.000)	(0.334)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	16,788	1,578	3,185	1,159	11,622	3,599	332
Adjusted R^2	0.51	0.60	0.63	0.55	0.45	0.49	0.44

This table presents the results of OLS analyses of the determinants of deals' weighted average spread (WAS). *PF deal* is a dummy variable. The WAS is calculated as the weighted average between the bond tranche spread and its weight in the deal size. Similarly, we computed both the weighted average maturity (WAM) and the weighted average rating (WAR). CF deals were classified into 4 categories according to their primary purpose, following Kleimeier and Megginson (2000). To create a matched sample of CF deals - model [13] -, we employ a propensity score matching (PSM) approach, by creating a 1 to 1 matching algorithm that captures the most identical CF deal in the same year and industry, using the following characteristics: deal size, WAM, and WAR. For a definition of the remaining variables, see Table 2. For each independent variable, the first row reports the estimated coefficient, and the second row reports the *p*-value. Standard errors are heteroskedasticity robust and clustered at the firm-year level. ***, ** and * indicate that the reported coefficients are significantly different from zero at the 1%, 5% and 10% levels, respectively.

Table 10
Determinants of firms' debt choice between PF and CF.

Dependent variable:	[14]	[15]	[16]	[17]	[18]	[19]
Choice of debt	PF and CF deals	PF and CF deals	PF and CF deals	PF and CF deals | switchers	PF and CF deals | CF = fixed asset based	PF and CF deals | matched sample
Independent variables:						
Intercept	−0.349	−7.064**	−0.015	−3.324	6.562	5.600
	(0.9)	(0.016)	(0.996)	(0.206)	(0.166)	(0.294)
WAS	0.003***	0.003***	0.003***	0.004***	0.006***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log transaction size	0.391***	0.475***	0.395***	0.445***	0.890***	−0.177
	(0.002)	(0.001)	(0.002)	(0.000)	(0.000)	(0.559)
WAM	0.018***	0.019***	0.018***	0.006	0.002**	0.008
	(0.005)	(0.006)	(0.005)	(0.348)	(0.086)	(0.639)
WAR	−0.112***	−0.119***	−0.113***	−0.138***	−0.073*	−0.215
	(0.001)	(0.001)	(0.001)	(0.000)	(0.073)	(0.435)
Number of tranches	−0.060	−0.111	−0.075	0.000	−0.419	−0.267
	(0.656)	(0.503)	(0.596)	(0.999)	(0.169)	(0.230)
Currency risk	−0.211	−0.175	−0.173	−0.146	0.151	−0.066
	(0.340)	(0.473)	(0.455)	(0.527)	(0.706)	(0.883)
Number of banks	−0.017	−0.031	−0.012	−0.018	−0.041	−0.034
	(0.307)	(0.155)	(0.493)	(0.296)	(0.271)	(0.273)
Bank reputation	−0.020	−0.026	−0.017	−0.037*	−0.010	−0.112***
	(0.181)	(0.129)	(0.277)	(0.060)	(0.621)	(0.001)
Market-based	0.634**	0.478**	0.683**	0.132*	0.103*	0.736
	(0.030)	(0.017)	(0.023)	(0.068)	(0.085)	(0.148)
Country risk	0.059	0.059	0.060	0.053	0.044	0.194**
	(0.120)	(0.149)	(0.122)	(0.236)	(0.649)	(0.039)
Creditor rights	0.326***	0.336***	0.321***	0.305***	0.530**	0.265
	(0.001)	(0.009)	(0.002)	(0.009)	(0.015)	(0.124)
Enforcement	−0.047***	−0.052***	−0.052***	−0.034*	−0.096***	−0.026
	(0.002)	(0.003)	(0.001)	(0.051)	(0.000)	(0.279)
Financial crisis	−1.655***	−1.775***	−1.576**	−2.832***	−1.338	0.224
	(0.008)	(0.008)	(0.013)	(0.000)	(0.119)	(0.616)
Sovereign crisis	−0.328	−0.239	−0.311	−0.252	−0.278	−0.323
	(0.162)	(0.341)	(0.181)	(0.309)	(0.449)	(0.342)
Volatility	−0.033**	−0.028*	−0.035**	−0.036**	−0.073***	−0.054
	(0.033)	(0.078)	(0.018)	(0.044)	(0.001)	(0.101)
USTB5y-USTB3m	−0.001	−0.002*	−0.001	−0.003**	−0.004*	0.002
	(0.181)	(0.081)	(0.193)	(0.014)	(0.084)	(0.211)
Log total assets	−0.187***	−0.300***	−0.191**	−0.282***	−0.174*	−0.053
	(0.009)	(0.000)	(0.01)	(0.000)	(0.081)	(0.689)
Debt to total asset	0.403	0.121	0.419	0.770	−0.670	1.562
	(0.507)	(0.846)	(0.497)	(0.321)	(0.462)	(0.207)
Fixed assets to total assets	−1.655***	−1.047**	−1.592***	−0.126	−2.679***	−1.828***
	(0.000)	(0.018)	(0.000)	(0.785)	(0.000)	(0.002)
Market to book	0.000	−0.001	0.000	0.001	−0.001	0.000
	(0.481)	(0.550)	(0.635)	(0.670)	(0.938)	(0.985)
Return on assets	−0.033***	−0.002*	−0.030**	−0.051**	−0.030**	−0.062
	(0.001)	(0.092)	(0.014)	(0.016)	(0.012)	(0.240)
Switcher	2.845***	3.112***	2.885***		3.237***	2.731***
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)
Log *Z*-score		−0.566**				
		(0.012)				
FCF to total assets			−1.191			
			(0.612)			
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	16,788	14,831	16,445	3599	1159	332
Wald statistic	758.83***	911.22***	758.99***	162.73***	93.44***	56.88***
Correct predictions	98.49%	98.58%	98.52%	94.44%	90.09%	77.71%
Pseudo-R^2	0.265	0.276	0.272	0.103	0.488	0.305

Table 10 presents the results of logistic regressions which predict firms' choice between PF and CF. The dependent variable equals 1 when a firm selects a PF deal and 0 when it chooses a CF deal. WAS is the bond deals' weighted average spread; WAS is the bond deals' weighted average maturity; and WAR is the bond deals' weighted average rating. To create a matched sample of CF deals - model [18] -, we employ a propensity score matching (PSM) approach, by creating a 1 to 1 matching algorithm that captures the most identical CF deal in the same year and industry, using the following characteristics: deal size, WAM, and WAR. For each independent variable, the first row reports the estimated coefficient, and the second row reports the *p*-value. Standard errors are heteroskedasticity robust and clustered at the firm-year level. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

expected to offer higher yields than similarly rated corporate bonds.

Model [9] presents pricing regression results for a sample of 364 PF and 22,499 CF bonds, respectively. Regarding the impact of credit risk on spread, Table 6 shows that rated bonds have lower spreads, and the higher the credit risk, the higher the spread. Additionally, we find that credit rating discordance between S&P and Moody's has a substantial positive impact on the spread for both PF and CF bonds (56.4 bps and 18.6 bps, respectively). This result shows that rating agencies' discordance is incorporated by investors in the pricing process, requiring an additional risk premium to compensate for a greater degree of uncertainty concerning the issuer's default risk. These results are in line with what was expected (see Table 2).

The influence of *transaction size* on spread is negative and significant for PF bonds, suggesting that increasing the transaction size of a PF bond by €100 million will reduce the required spread by 46.9 bps. Therefore, our results indicate a positive price liquidity effect related to the size of the PF bond deal. On the contrary, CF bonds have higher spreads, which can be explained by the fact that larger issues might mean higher financial risk for investors. As we expected, a positive relationship between spread and maturity appears strongly significant for CF bonds in model [9]. Contrary to what is presented by extant literature on the term structure of spreads in PF syndicated loans, which finds a hump-shaped relationship between spreads and maturity, the relationship between spreads and maturity is significant and positive for PF bonds. This result is in line with Dailami and Hauswald (2003) findings for a sample of PF bonds in developing countries.

Creditor rights index and the yield curve slope (*USTB5y-USTB3m*), as well as collateralized, callable, and financial crisis dummy variables, behave differently for PF bonds than for CF bonds. As expected, the financial crisis significantly increases the rate charged by 137.5 bps, while callable CF bonds are associated with 39.7 bps higher spreads. Contrary to what we expected, collateralized CF bonds have higher spreads. This can be explained by the fact that CF bond issues that require collateralization are, ceteris paribus, riskier than those that do not require such structuring devices; i.e., the issuer's credit risk is higher in collateralized CF bonds. The impact of the creditor rights index is, as expected, negative and significant for CF bonds. Similarly, a steeper yield curve is associated with lower spreads on CF bonds. However, all these variables have an insignificant impact on PF bond spreads.

As expected, subordinated bonds have higher spreads, after adjusting for the other factors included in the regression. Similarly, the influence of currency risk is positive and significant for both PF and CF bonds: a mismatch in the currency of the deal's nationality and the currency of the bond issue significantly increases the rate charged by 38.2 bps and 30.4 bps, respectively. Both the *number of banks* and the *number of tranches* have a significant and negative relationship with spreads for the two security types. Contrary to what we expected, *bank reputation* has a significant and positive impact on spreads. This result can be explained by the fact that most reputable banks might extract rents from the borrower and charge higher borrowing costs, as they provide a superior guarantee for the success of the bond issuance and a greater capacity to hold those bonds on-balance sheet if demand does not outstrip supply.

As expected, the type of financial system affects bond pricing: the *market-based* dummy variable has a significant and positive impact on spreads for both PF and CF bonds. Our results show that after controlling for contractual and firms' characteristics as well as macroeconomic factors, spreads for bonds extended to borrowers in market-based financial systems have higher spreads than those in bank-based financial systems. These results corroborate Dailami and Hauswald (2003) findings that institutional frameworks affect PF bond pricing. Finally, spread and market volatility are significantly positively related for both PF and CF bonds.

Results in Table 6 show that the impact of sponsoring (for PF bonds) and issuing (for CF bonds) firms' characteristics on bond spreads is significantly different for PF *vis-à-vis* CF bonds. Regarding CF bonds, results show, as expected, that larger issuing firms and those with higher asset tangibility and profitability face lower bond spreads. For PF bonds, our proxies for size, asset tangibility, profitability, and growth opportunities do not affect spreads. Interestingly, the spreads of both bonds are positively affected by the debt-to-total-assets ratio. If this result is expected for CF bonds, meaning that more levered issuing firms pay higher spreads, it is surprising for PF bonds. This can be explained by two reasons. First, some PF transactions are financed through limited-recourse debt; i.e., debt upon which a financier can claim certain, but not all, assets of the sponsor if the SPE defaults. Second, there are projects in which sponsors are also constructors or operators, and off-takers. In this case, a sponsoring firm's higher leverage level increases the overall risk of the project, leading to a higher PF bond spread. This result is in line with extant structured finance literature, showing that although asset securitization deals employ bankruptcy remote SPVs, the financial strength of the originator may matter in pricing the debt issued by the SPV (Gorton and Souleles, 2007; Landsman et al., 2008).

Overall, our results are in line with H1 by showing that PF and CF issues are priced differently by common pricing factors; and that investors do consider factors other than credit ratings, some of which are already considered by rating agencies, in assessing spreads.

Although a thorough analysis of the determinants of sponsoring firms' choice between PF and CF is implemented in section 5 on a deal-level analysis, Table 6 presents some interesting results. Findings suggest that PF deals mitigate the deadweight costs of asymmetric information frictions. Public firms that choose project financing over corporate financing are relatively smaller and seek long-term financing. We also find that more profitable firms are less likely to use PF bonds. Results seem to be consistent with the prediction that firms choose PF bonds for larger debt borrowings because of the potential economies of scale in relation to issuance costs: the transaction size increases the likelihood of observing a PF bond over a CF bond. Our results also suggest that firms that resort to project financing rather than to public placed CF bonds, have higher asset tangibility and a larger growth opportunity set. Finally, contrary to what we expected, we find that there is a negative relationship between the debt to total assets ratio and the probability of observing a PF bond.

4.3. Project finance versus corporate finance bond spreads by rating scales

Previous results show that, when controlling for credit rating and other contractual and macroeconomic factors (Table 4), as well as for the firms' choice between issuing the two bond types (Table 6), PF bonds have higher yields than comparable corporate bonds and bond prices reflect information beyond credit ratings, which corroborate both H1 and H2. In this section, we examine this further by focusing on investment grade rating scales. Panels A, B, and C of Table 7 presents the results of re-estimating models [1], [2], and [3] of Table 4, respectively, for sub-samples of PF and CF bonds by rating classes. Models [10a] to [10j] indicate, for the full sample, that PF bonds are issued with significantly higher spreads than CF bonds with identical credit ratings for all rating classes, except for AA+. Results hold when controlling for firms' characteristics (with the exception of model [10d] for AA-, PF bonds have higher spreads than similarly rated CF bonds for the remaining rating classes), and considering a matched sample of CF bonds (the PF dummy variable does not affect bond spreads for BBB- rating class only). Kleimeier and Megginson (2000) point out that 'PF loans are often similar to fixed asset based loans'. Hence, we re-estimate our models restricting CF bonds to the fixed asset based category - Panel D of Table 7. Results show, again, that PF bonds have a higher spread than CF bonds with identical credit ratings.

Overall, our results corroborate H2, that characteristically similar PF and CF bond tranches have different spreads, with PF bonds being issued, on average, with significantly higher spreads than CF bonds with identical credit ratings; and H1, that credit spreads reflect information beyond credit ratings. Therefore, our results are in line with those of Cornaggia et al. (2017) and Marques and Pinto (2020). In fact, bond prices reflect additional information other than credit ratings across asset classes, which can be explained by the fact that rating methodologies are based on physical default probabilities (or expected losses) that do not capture risk premia. We thus show that systematic risk is relatively more important for PF bonds than for traditional corporate bonds. Therefore, in line with Wojtowicz (2014) and Coval et al. (2009b), we show that ratings are not perfect measures of credit quality in pricing PF bonds.

5. Bond issuance and firms' cost of borrowing: a deal-level analysis

In this section, we focus on the sponsoring firms' cost of borrowing and their accounting and market characteristics. Our goal is to examine if nonfinancial firms use PF to manage their cost of borrowing; i.e., examine (*i*) which financing structure, if any, allows firms to raise debt with a lower cost of borrowing, and (*ii*) if the cost of borrowing affects the choice process between PF and CF. Our sample comprises deals that are divided into smaller bond tranches. Therefore, in this section, our descriptive and econometric analyses are based on the deals.

5.1. *Firms' characteristics*

After applying the procedures mentioned in section 3.2.5., we identified 516 and 36,035 firms that were sponsors and issuers of PF and CF bond deals, respectively. Of these firms, 53 were sponsors of PF bond deals only - category [I] -, 13,136 were issuers of CF bond deals only - category [II] -, and 3599 were classified as switchers - category [III]. Table 8 reports the cost of borrowing and the characteristics of firms segmented into three categories according to their issuance record. As we have more than one bond tranche per deal, the cost of borrowing is determined by the combination of the different tranches' credit spreads. We use the weighted average spread (WAS), calculated as the sum of the product of the weight of each tranche in the transaction size and the tranche's credit spread, as a measure of the total cost of borrowing. We find that the average WAS for PF deals is higher than that of CF deals. Similar results are obtained when comparing firms using PF and CF deals only. Interestingly, switchers face, on average, lower borrowing costs *vis-à-vis* those firms that belong to categories [I] and [II] in Table 8, which may reflect a diversification effect of funding sources.

Results also show that, on average, firms that used only PF deals are typically less levered and have lower profitability and lower fixed-assets-to-total-assets and FCF-to-total-assets ratios, than those accessing CF bond markets, exclusively. While firms' size and creditworthiness do not differ at the 1% significance levels for the two subsets of firms, firms that only used CF deals have a lower market-to-book ratio than firms that only used PF. Firms utilizing both markets are larger than those reliant on PF or CF only. They have relatively higher asset tangibility and profitability, but lower *Z*-scores than firms in categories [I] and [II] do. Firms that used PF and CF simultaneously are more levered and have a higher FCF-to-total-assets ratio when compared with firms that issued PF only, but these ratios are lower than those belonging to firms in category [II]. Finally, the market-to-book ratio is significantly higher for firms that use both debt types than for those that use CF deals only.

5.2. *Firms' cost of borrowing: PF versus CF deals*

We examine which one of the two financing transactions has the lowest borrowing cost by using the model specified in eq. (5). The dependent variable is the WAS, in basis points, and we create a dummy variable set equal to one if the deal is a PF versus a CF deal. We employ OLS regression techniques and adjust for heteroskedasticity. Standard errors are clustered by year and firm.

$$WAS_{i,t} = \alpha_0 + \beta_1 PF\ deal_{i,t} + \gamma\ Contractual\ characteristics_{i,t} + \varphi\ Macroeconomic\ factors_t + \omega\ Firm\ characteristics_{i,t-1} + \varepsilon_{i,t} \tag{5}$$

Models [11] and [12] in Table 9 report estimates of this equation, using the samples presented in Table 8. The results suggest that, holding other factors constant, the WAS is significantly higher for PF deals *vis-à-vis* CF deals. As CF deals are closed for different purposes, which might significantly affect their cost of borrowing, we re-estimate model [11] for different subsamples based on the categories presented in Panel E of Table 1. The results in models [11a] to [11d] show that the WAS for PF deals is significantly higher than that for any of the 4 categories of CF deals used. In previous models, the PF deal dummy may suffer from sample selection bias because we only observe borrowing costs for the deal type that firms choose; we do not observe counterfactual borrowing costs. In addition, the choice between PF and CF deals may be endogenous. Ideally, we would address this endogeneity concern by using an instrument for the choice of PF deals. Unfortunately, it is difficult to find such an instrument - the closing of a PF deal is not random, and it is hard to find an empirical setting in which sponsoring firms (quasi-) randomly close a PF deal *vis-à-vis* standard on-balance sheet funding. Instead, as in section 4.1., we use a deal-level matched sample. Specifically, for each of the PF deals for which we have information on firms' characteristics, we match a "control" CF deal that is as similar as possible to the treated PF deal *ex ante*. We employ a PSM approach (deal-level PSM), by creating a 1 to 1 matching algorithm that captures the most identical deal in the same year and industry, using the following characteristics: deal size, weighted average maturity (WAM), and weighted average rating (WAR). Results in model [13] show, again, that PF deals are associated with higher WAS than a matched sample of CF deals. Consequently, PF bond deals have higher borrowing costs than comparable CF bond deals and we do not corroborate H3. As mentioned in the bond-level analysis, the difference in WAS between samples should be even greater, as the spread for a PF bond does not include a set of additional fees (legal, financial, insurance, accounting, and fiscal advisory fees) that a PF transaction has.

5.3. Do borrowing costs affect firms' choice between PF and CF?

To examine if the WAS affects the choice between off-balance-sheet financing, via PF, and on-balance-sheet financing, via CF, we utilize a logistic regression model. Our dependent variable, choice of debt, is a binary variable equal to 1 if the firm closes a PF deal and 0 if it closes a CF deal.

$$Choice\ of\ debt_{i,t} = \alpha_0 + \beta_1 WAS_{i,t} + \gamma\ Contractual\ characteristics_{i,t} + \varphi\ Macroeconomic\ factors_t + \omega\ Firm\ characteristics_{i,t-1} + \varepsilon_{i,t} \tag{6}$$

where the subscripts refer to deal *i* at time *t*. Coefficients were estimated based on heteroskedasticity-consistent standard errors clustered by year and firm. Furthermore, in Table 10, we report coefficients, rather than odds ratios (exponential coefficients) because our main interest is in the direction of the effects, instead of their magnitude.

Table 10 reports the results of the logistic regression (6). Estimations were developed following a stepwise approach, focusing firstly, on deals for which we have no loss of observations due to lack of information on firms' characteristics - model [14]. Second, we introduce the *Z-score* and *FCF to total assets* variables one at a time to assess the impacts of firms' creditworthiness and cash flow generation capacity on the choice process - models [15] and [16]. Third, the same estimation method was extended to also include firms that used both instruments during the period of study, the switchers, to guarantee that our results are unbiased and that firms can in fact choose between PF and CF - model [17]. Fourth, as PF deals, in terms of financing purposes, are more similar to the fixed asset based category of CF deals (Kleimeier and Megginson, 2000), we re-estimate model [14], restricting the CF deals' sample to deals intended for general capital expenditures or to fund aircraft, property, or shipping purchases - model [18]. Finally, in model [19] we focus on a sub-sample of PF deals and a matched sample of CF deals: the deal-level PSM sub-sample discussed in section 5.2.[17] Results reported in all models of Table 10 show that the cost of borrowing, proxied by WAS, significantly affects firms' choice between PF and CF deals: the WAS variable has a significant and positive impact on the likelihood of observing a PF deal. This can be partly explained by the negative relationship between *WAR* variable and the likelihood of observing PF deals for all models (with the exception, as expected, of model [19]). These results are in line with those presented in section 5.2. and, again, show that the cost of borrowing is, ceteris paribus, higher in PF deals.

Considering that PF is more expensive than CF, other contractual, macroeconomic, and firm-level countervailing benefits than borrowing costs should play a key role in the sponsors' decision of choosing PF *vis-à-vis* CF. Table 10 presents some interesting results. Contrary to Pinto and Santos (2019), who compare a sample of PF syndicated loans with a sample of standard corporate bonds, we find that sponsoring firms choose PF over CF when issuing large amounts of debt due to issuance costs; i.e., PF is used for relatively large amounts of debt to economize on scale. Findings suggest that firms use PF to reduce underinvestment due to asymmetric information problems. Firms with potential asymmetric information problems, relatively smaller ones, prefer project financing. Moreover, our findings document that coefficients of the *WAM* variable are significant and positive, which support the security design and PF literature (Flannery, 1986; Diamond, 1991, 1993; John and John, 1991; Gatti et al., 2013; Pinto and Santos, 2019). Concerning macroeconomic variables, we find that the market-based dummy variable has a significant and positive impact on the choice process: sponsors are more likely to use PF bond deals in projects located in countries with a market-based financial system. While the *creditor rights* variable significantly and positively affects the sponsors' choice of PF over CF deals, the impact of the enforcement level is significant and negative, which is in line with Subramanian and Tung (2016) findings.

We do not find evidence that the debt choice is related to the agency cost motivation: results do not corroborate that firms with higher deadweight costs resulting from the debt overhang problem, and those with higher agency costs of free cash flow, are more likely to choose PF. In line with Pinto and Santos (2019), we show that firms with lower profitability use PF rather than CF. Results also show that firms that employ both PF and CF lending within our sample period - switchers - are more likely to choose PF deals when issuing new debt. We find evidence supporting the risk management motivation of using PF, as these SF deals are more relevant for sponsors with higher expected costs of distress, either from a higher probability of distress or higher costs given distress (negative impact of the *Z-score* variable in model [15]). Finally, as we expected, sponsoring firms with more asset tangibility frequently use PF deals to implement large-scale, relatively more risky projects.

Overall, we show that PF bond deals have higher borrowing costs than comparable CF bond deals. Therefore, we do not corroborate extant PF theoretical literature arguing that by mitigating deadweight costs of market imperfections and frictions and improving risk

[17] In unreported estimations, we examine whether results presented in Table 10 are robust by considering firm fixed effects to address possible time invariant firm-level issues. We also re-estimate our models by using year times industry and country times industry fixed effects. Results are qualitatively the same and are available if required.

management, PF contractual structures reduce funding costs (Brealey et al., 1996; Esty, 2003, 2004a; and Corielli et al., 2010). On the contrary, our results are in line with those of Klein et al. (1996) and Pinto and Santos (2019): due to larger advisory fees, significant structuring costs, higher leverage, and greater operational complexity, PF transactions are costlier than traditional CF alternatives.

6. Robustness checks

We perform a number of additional robustness checks that further control for the bond's primary purpose, adjustments to our rating variable, and the industry to which the CF bond issuer belongs. First, in section 4.1 we show that PF bonds are, on average, associated with higher spreads than similarly rated CF bonds. As firms issue CF bonds for different purposes, we re-estimate model [1] of Table 4 for the subsamples presented in Panel E of Table 1. Results presented in Table 7 of the Online Appendix show, again, that PF bond spreads are higher than that of corporate control, capital structure, fixed asset based, and general corporate purpose bond spreads. Second, we use a linear downward scale from AAA = 1 to D = 22 in our bond-level models. We test the sensitivity of the results reported in Tables 4, 6, and 7 by reclassifying the credit ratings into five categories ranging from best to default, like the ones proposed by Corielli et al. (2010), and results remain qualitatively the same. Finally, we estimate models [11] and [14] restricting the sample to deals closed by firms belonging to capital-intensive industries only. According to Panel A of Table 1, more than 80% of PF deals by volume are concentrated in four industries (utilities, oil and gas, transportation, and construction/heavy engineering), all capital-intensive. Our goal is to ensure that we are comparing deals that finance the same type of investment projects. We find that PF transactions' WAS is higher than that of CF bond deals and it positively and significantly affects the choice between PF and CF deals. Overall, these additional sensitivity tests further confirm the robustness of our results.

7. Summary and conclusions

This paper compares spreads and the pricing of project finance (PF) to that of corporate finance (CF) bonds, using a cross-section of worldwide bonds closed in the 1993–2020 period. We also examine if comparable PF and CF bonds have significantly different spreads, and whether spreads convey information beyond credit ratings across PF and CF. At the deal level, we study whether sponsoring firms use PF to reduce borrowing costs and what the determinants of firms' bond deal choices are.

Our results are relevant for investors and market supervisors. We find that PF and CF bonds are securities influenced differently by common pricing characteristics. We show that PF bonds have higher spreads than comparable CF bonds and spreads convey information beyond credit ratings. A detailed analysis of how sponsoring firms' characteristics affect bond spreads reveals that the debt to total assets ratio is the unique determinant of PF bond spreads, while sponsoring firms' choice between PF and CF bonds affects the pricing of such securities. When implementing a deal-level analysis, we find that PF deals are not used as a mechanism for reducing sponsoring firms' cost of borrowing. Rather, the choice between these two financing solutions may depend on exogenous factors like creditor protection, debt enforcement and financial market development levels of the borrower's country; in relation to sponsoring firms' characteristics - size, asset tangibility, profitability, and creditworthiness -; and objectives to be achieved by firms, particularly with regard to obtaining higher volumes of financing with longer maturities, maintaining sponsors financial flexibility, and improving risk management.

Considering the increasing role of PF in a post-Basel III scenario, where syndicated long-term lending is more and more restrained by capital requirements, we believe that this study is also important for policymakers. Taking into consideration the important role of PF in promoting public investment and as a driver of economic growth (Kleimeier and Versteeg, 2010), we believe that policymakers should have better knowledge of PF bond instruments, allowing for more precise and efficient regulatory interventions.

In addition, our findings indicate that credit ratings may be limited for the purpose of pricing bonds correctly: investors do not rely exclusively on ratings when pricing bonds, and this effect is higher for PF *vis-à-vis* CF bonds. Given the contracting complexity of PF transactions and the frequent unavailability of detailed information about the nexus of contracts used and the underlying cash flows, many investors do not have the expertise, or the incentive, to price these bonds correctly and have to rely on credit ratings, or incur free riding. We argue that improving transparency and disclosure standards in PF bond markets, mainly through rating agencies (e.g., methodological information, key assumptions, underlying data used, and fees), may improve market informational efficiency and make it possible for non-institutional investors to access these markets as well. In addition, the 'rating inflation' observed in structured finance products, mainly for CDO, during the 2008 financial crisis (Griffin et al., 2013), led legislators and regulators to propose that credit ratings should be applied consistently across asset classes. We show that a standardized credit rating approach for PF and CF classes can be dangerous since we document significant differences in spreads and pricing of PF versus CF bonds.

Declaration of Competing Interest

None.

Data availability

The authors do not have permission to share data.

Acknowledgments

The authors thank the editor (Simi Kedia), an anonymous referee, Carol Alexander, Paulo Alves, Miguel Ferreira, Kim Kaivanto, Ricardo Ribeiro, William Megginson, Danielle Santos, Mário Santos, Anthony Saunders, and Tiago Teixeira for their helpful suggestions. We would also like to thank participants in the 11th Accounting and Finance Conference of the Catholic University of Portugal - Porto, the European Financial Management Association 2023 Annual Conference, and the 2023 Portuguese Finance Network International Conference for helpful comments on earlier drafts. Financial support from Fundação para a Ciência e Tecnologia (through project UIDB/00731/2020) is gratefully acknowledged.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcorpfin.2023.102429.

References

Altman, E., 1993. Corporate Financial Distress and Bankruptcy. John Wiley & Sons, New York.
Altunbas, Y., Alper, K., Marqués-Ibáñez, D., 2010. Large debt financing: syndicated loans versus corporate bonds. Eur. J. Financ. 16, 437–458.
Alves, P., Cunha, R., Pacheco, L., Pinto, J., 2021. How banks price loans for LBOs: an empirical analysis of spread determinants. J. Financ. Serv. Res. 62, 163–200.
An, Y., Cheung, K., 2010. Project financing: deal or no deal. Rev. Financ. Econ. 19, 72–77.
Ayotte, K., Gaon, S., 2011. Asset backed securities: costs and benefits of bankruptcy remoteness. Rev. Financ. Stud. 24, 1299–1336.
Bao, J., Pan, J., Wang, J., 2011. The illiquidity of corporate bonds. J. Financ. 66, 911–946.
Bernhardt, D., Koufopoulos, K., Trigilia, G., 2020. Is there a paradox of pledgeability? J. Financ. Econ. 137, 606–611.
Bonetti, V., Caselli, S., Gatti, S., 2010. Offtaking agreements and how they impact the cost of funding for project finance deals: a clinical case study of the Quezon Power Ltd Co. Rev. Financ. Econ. 19, 60–71.
Boubakri, N., Ghouma, H., 2010. Control/ownership structure, creditor rights protection, and the cost of debt financing: international evidence. J. Bank. Financ. 34, 2481–2499.
Brealey, R., Cooper, I., Habib, M., 1996. Using project finance to fund infrastructure investments. J. Appl. Corp. Financ. 9, 25–38.
Brennan, M., Hein, J., Poon, S., 2009. Tranching and rating. Eur. Financ. Manag. 15, 891–922.
Buscaino, V., Caselli, S., Corielli, F., Gatti, S., 2012. Project finance collateralised debt obligations: an empirical analysis of spread determinants. Eur. Financ. Manag. 18, 950–969.
Campbell, J., Taksler, G., 2003. Equity volatility and corporate bond yields. J. Financ. 58, 2321–2349.
Caselli, S., Gatti, S., 2005. Structured Finance: Techniques, Products and Market. Springer Berlin.
Chen, L., Lesmond, D., Wei, J., 2007. Corporate yield spreads and bond liquidity. J. Financ. 62, 119–149.
Collin-Dufresne, P., Goldstein, R., Martin, J., 2001. The determinants of credit spread changes. J. Financ. 56, 2177–2207.
Corielli, F., Gatti, S., Steffanoni, A., 2010. Risk shifting through nonfinancial contracts: effects on loan spreads and capital structure of project finance deals. J. Money Credit Bank. 42, 1295–1320.
Cornaggia, J., Cornaggia, K., Hund, J., 2017. Credit ratings across asset classes: a long-term perspective. Rev. Financ. 21, 465-210.
Correia, M., Pinto, J., 2022. Are covered bonds different from securitization bonds? A comparative analysis of credit spreads. Eur. Financ. Manag. 1–60.
Coval, J., Jurek, J., Stafford, E., 2009a. The economics of structured finance. J. Econ. Perspect. 23, 3–25.
Coval, J., Jurek, J., Stafford, E., 2009b. Economic catastrophe bonds. Am. Econ. Rev. 99, 628–666.
Cumming, D., Lopez-de-Silanes, F., McCahery, J., Schwienbacher, A., 2019. Tranching in the syndicated loan market around the world. J. Int. Bus. Stud. 50, 1–26.
Dailami, M., Hauswald, R., 2003. The Emerging Project Bond Market: Covenant Provisions and Credit Spreads. World Bank Policy Research Working Paper No. 3095.
Dailami, M., Hauswald, R., 2007. Credit-spread determinants and interlocking contracts: a study of the Ras Gas project. J. Financ. Econ. 86, 248–278.
DeMarzo, P., 2005. The pooling and tranching of securities: a model of informed intermediation. Rev. Financ. Stud. 18, 1–35.
Demirgüç-Kunt, A., Maksimovic, V., 2002. Funding growth in bank-based and market-based financial systems: evidence from firm-level data. J. Financ. Econ. 65, 337–363.
Denis, D., Mihov, V., 2003. The choice among bank debt, nonbank private debt, and public debt: evidence from new corporate borrowings. J. Financ. Econ. 70, 3–28.
Diamond, D.W., 1991. Debt maturity structure and liquidity risk. Q. J. Econ. 106, 709–737.
Diamond, D., 1993. Seniority and maturity of debt contracts. J. Financ. Econ. 33, 341–368.
Duffie, D., Rahi, R., 1995. Financial market innovation and security design: an introduction. J. Econ. Theory 65, 1–42.
Elton, E., Gruber, M., Agrawal, D., Mann, C., 2001. Explaining the rate spread on corporate bonds. J. Financ. 56, 247–277.
Esty, B., 2003. The Economic Motivations for Using Project Finance. Harvard Business School publishing, Boston.
Esty, B., 2004a. Modern Project Finance – A Casebook. Wiley, New Jersey.
Esty, B., 2004b. Why study large projects? An introduction to research on project finance. Eur. Financ. Manag. 10, 213–224.
Esty, B., Kane, M., 2010. BP Amoco (A): Policy Statement on the Use of Project Finance. Harvard Business School case study No. 9-201-054.
Esty, B., Megginson, W., 2003. Creditor rights, enforcement, and debt ownership structure: evidence from the global syndicated loan market. J. Financ. Quant. Anal. 38, 37–59.
Esty, B., Sesia, A., 2003. Basel II: Assessing the Default and Loss Characteristics of Project Finance Loans. Harvard Business School Publishing case# 9-203-035.
Esty, B., Sesia, A., 2007. An Overview of Project Finance & Infrastructure Finance – 2006 Update. Harvard Business School publishing, Boston.
Esty, B., Chavich, C., Sesia, A., 2014. An Overview of Project Finance and Infrastructure Finance - 2014 Update. Harvard Business School.
Fabozzi, F., Davis, H., Choudhry, M., 2006. Introduction to Structured Finance. Wiley Finance.
Fender, I., Mitchell, J., 2005. Structured finance: complexity, risk and the use of ratings. BIS Q. Rev. 67–79. June.
Flammer, C., 2021. Corporate green bonds. J. Financ. Econ. 142, 499–516.
Flannery, M., 1986. Asymmetric information and risky debt maturity choice. J. Financ. 41, 19–37.
Flannery, M., Houston, J., Venkataraman, S., 1993. Financing multiple investment projects. Financ. Manag. 22, 161–172.
Flannery, M., Nikolova, S., Öztekin, Ö., 2012. Leverage expectations and bond credit spreads. J. Financ. Quant. Anal. 47, 689–714.
Gabbi, G., Sironi, A., 2005. Which factors affect corporate bonds pricing? Empirical evidence from Eurobonds primary market spreads. Eur. J. Financ. 11, 59–74.
Gatti, S., 2008. Project Finance in Theory and Practice – Designing, Structuring, and Financing Private and Public Projects. Academic Press, San Diego.
Gatti, S., Kleimeier, S., Megginson, W., Steffanoni, A., 2013. Arranger certification in project finance. Financ. Manag. 42, 1–40.
Gorton, G., Souleles, N., 2007. Special purpose vehicles and securitization. In: Carey, M., Stulz, R. (Eds.), The Risks of Financial Institutions. University of Chicago Press, Chicago.

Griffin, J., Nickerson, J., Tang, D., 2013. Rating shopping or catering? An examination of the response to competitive pressure for CDO credit ratings. Rev. Financ. Stud. 26, 2270–2310.
Hainz, C., Kleimeier, S., 2012. Political risk, project finance, and the participation of development banks in syndicated lending. J. Financ. Intermed. 21, 287–314.
He, J., Qian, J., Strahan, P., 2011. Credit ratings and the evolution of the mortgage-backed securities market. Am. Econ. Rev. 101, 131–135.
Hull, J., Predescu, M., White, A., 2004. The relationship between credit default swap spreads, bond yields, and credit rating announcements. J. Bank. Financ. 28, 2789–2811.
John, T., John, K., 1991. Optimality of project financing: theory and empirical implications in finance and accounting. Rev. Quant. Finan. Acc. 1, 51–74.
Kara, A., Marques-Ibanez, D., Ongena, S., 2016. Securitization and lending standards: evidence from the European wholesale loan market. J. Financ. Stab. 26, 107–127.
Kensinger, J., Martin, J., 1988. Project finance: raising money the old-fashioned way. J. Appl. Corp. Financ. 1, 69–81.
Kleimeier, S., Megginson, W., 2000. Are project finance loans different from other syndicated credits? J. Appl. Corp. Financ. 13, 75–87.
Kleimeier, S., Versteeg, R., 2010. Project finance as a driver of economic growth in low-income countries. Rev. Financ. Econ. 19, 49–59.
Klein, M., So, J., Shin, B., 1996. Transaction Costs in Private Infrastructure Projects-Are They Too High?, Viewpoint, Note No. 95. The World Bank Group. October.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1997. Legal determinants of external finance. J. Financ. 52, 1131–1150.
La Porta, R., Lopez-de-Silanes, F., Shleifer, A., Vishny, R., 1998. Law and finance. J. Polit. Econ. 106, 1113–1155.
Landsman, W., Peasnell, K., Shakespeare, C., 2008. Are asset securitizations sales or loans? Account. Rev. 83, 1251–1272.
Leland, H., 2007. Financial synergies and the optimal scope of the firm: implications for mergers, spinoffs, and structured finance. J. Financ. 62, 765–807.
Lemmon, M., Liu, L., Mao, M., Nini, G., 2014. Securitization and capital structure in nonfinancial firms: an empirical investigation. J. Financ. 69, 1787–1825.
Lewis, K., Longstaff, F., Petrasek, L., 2021. Asset mispricing. J. Financ. Econ. 141, 981–1006.
Lokshin, M., Sajaia, Z., 2004. Maximum likelihood estimation of endogenous switching regression models. Stata J. 4, 282–289.
Longstaff, F., Rajan, A., 2008. An empirical analysis of the pricing of collateralized debt obligations. J. Financ. 63, 529–563.
Longstaff, F., Mithal, S., Neis, E., 2005. Corporate yield spreads default risk or liquidity? New evidence from the credit default swap market. J. Financ. 60, 2213–2253.
Marques, M., Pinto, J., 2020. A comparative analysis of EX ante credit spreads: structured finance versus straight debt finance. J. Corp. Finan. 62, 101580.
Mills, L., Newberry, K., 2005. Firms' off-balance sheet and hybrid debt financing: evidence from their book-tax reporting differences. J. Account. Res. 43, 251–282.
Myers, S., 1977. Determinants of corporate borrowing. J. Financ. Econ. 5, 147–175.
Nevitt, P., Fabozzi, F., 2001. Project Financing. Euromoney, London.
Oldfield, G., 2000. Making markets for structured mortgage derivatives. J. Financ. Econ. 57, 445–471.
Pinto, J., 2017. What is project finance? Invest. Manag. Financ. Innov. 14, 200–210.
Pinto, J., Santos, M., 2019. The choice between corporate and structured financing: evidence from new corporate borrowings. Eur. J. Financ. 26, 1271–1300.
Riddiough, T., 1997. Optimal design and governance of asset-backed securities. J. Financ. Intermed. 6, 121–152.
Roberts, M., Whited, T., 2013. Endogeneity in empirical corporate finance. In: Constantinides, G., Harris, M., Stulz, R. (Eds.), Handbook of the Economics of Finance, 2A. Elsevier, Amsterdam, pp. 493–572.
Scannella, E., 2012. Project finance in the energy industry: new debt-based financing models. Int. Bus. Res. 5, 83–93.
Schwert, M., 2020. Does borrowing from banks cost more than borrowing from the market? J. Financ. 75, 905–947.
Shah, S., Thakor, A., 1987. Optimal capital structure and project financing. J. Econ. Theory 42, 209–243.
Shivdasani, A., Wang, Y., 2011. Did structured credit fuel the LBO boom? J. Financ. 66, 1291–1328.
Sorge, M., Gadanecz, B., 2008. The term structure of credit spreads in project finance. Int. J. Financ. Econ. 13, 68–81.
Subramanian, K., Tung, F., 2016. Law and project finance. J. Financ. Intermed. 25, 154–177.
Sufi, A., 2007. Information asymmetry and financing arrangements: evidence from syndicated loans. J. Financ. 62, 629–668.
Titman, S., Tompaidis, S., Tsyplakov, S., 2004. Market imperfections, investment flexibility, and default spreads. J. Financ. 59, 165–205.
Wojtowicz, M., 2014. CDOs and the financial crisis: credit ratings and fair premia. J. Bank. Financ. 39, 1–13.