



Firms' Bond Market Access and Impact on Bank Borrowing Costs

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Abstract

This paper documents that companies with bond issuance are larger, are more leveraged, and have higher financing needs, but have lower observed syndicated loan spreads. Using endogenous treatment and outcome estimations, we find that companies would potentially face an average of 114 to 185 basis points (bps) higher loan spreads in counterfactual absence of bond market access, significantly larger than observational difference (57 bps) or existing estimates in the literature. This finding underscores the importance of bond markets for corporate financing and overcoming lending constraints or market power of banks, and also casts doubt on valued banking services as the explanation why loans are more costly to bonds. We also find bond issuance as information release a partial explanation only.

Keywords Syndicated loans · Bonds · Loan spreads · Corporate finance

JEL Classification E44 · G20 · G32 · G30

1 Introduction

The choice between loan or bond financing is one that most firms reaching a certain size would have to make. On the other side of the transaction, banks or financial institutions will need to decide whether to lend and at what spread. Should firms choose to raise bond financing, investors' demand will determine the costs of borrowing.

The data for this research has been deposited in Mendeley Data website (<https://data.mendeley.com/datasets/nrs7c8v4m2/1>). We are grateful for the industry insights from Thierry de Longuemar (former CFO), Erik Berglöf and comments from colleagues at the AIIB, as well as the suggestions from anonymous reviewer and editors of this journal.

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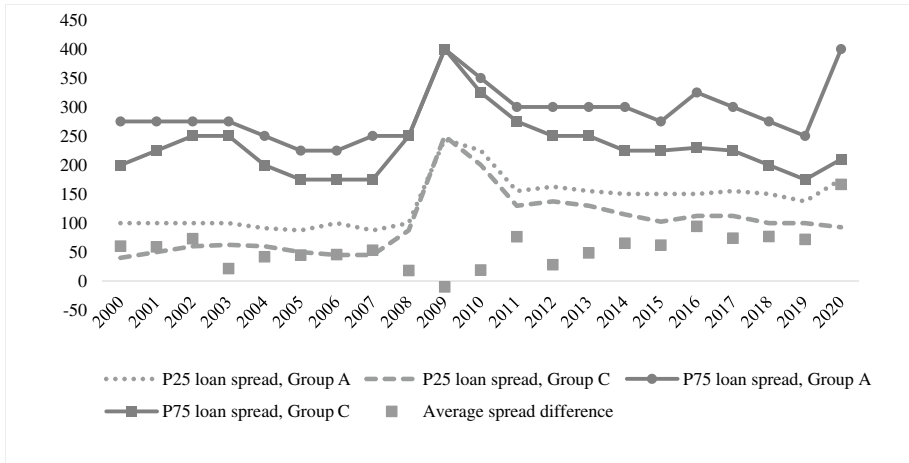


Fig. 1 P25 and P75 Loan Spreads of Group A vs. Group C (bps). The figure shows that Group A companies (those without bond issuance) have higher average cost of bank loans

Applying endogenous treatment and outcome models to a large dataset, this paper estimates the impact that bond market access has on syndicated loan spreads. This paper explains that endogenous treatment effect estimation can be more robust in the context of bond issuances. In doing so, this paper provides a more nuanced understanding of the effects of bond market access.

Our research is motivated by the following observational data, combining three datasets – one on syndicated loans, one on bond issuances, and one with firm-level characteristics. These public companies are categorized into three groups: (A) those that use syndicated loans only, (B) those that finance through bonds only, and (C) those that finance through both syndicated loans and bonds.¹ Taking the 25th percentile (P25) to 75th percentile (P75) loan spreads, it can be seen from observational data that Group C has lower loan spreads compared to Group A (Fig. 1). The average spreads are 239 bps and 183 basis points (bps) for Groups A and C, respectively, a difference of 57 bps on average. Bond market access appears to have led to lower loan spreads or borrowing costs. A primary objective of this research is to quantify more robustly the impact that bond market access has on loan pricing.

It is important to highlight why endogenous treatment is important in this context. Clearly, firms that go through a share IPO or issue bonds are not directly comparable to firms that do not. Researchers have been careful about such selection effects, leveraging for example company fixed effects [Schenone (2010)] or propensity score matching (PSM) to overcome selection bias [Hale and Santos (2009)].

However, bringing a company to a share IPO or issuing the maiden bond are sizable corporate undertakings with significant internal transformation necessary to achieve these milestones. IPOs or entry into bond markets are active, endogenous choices made by

¹ To be clear, in the dataset, we observe Group B companies to issue bonds and not contract syndicated loans. However, it is possible that firms in this group contract private debts or take on ordinary bank loans (that is, non-syndicated), such as for working capital, liquidity etc.

companies. These events are also not purely information releasing but require significant internal efforts. It is thus highly likely that there will be unobservable factors and confounders (e.g., changes in firm quality, unobserved risks, business model, management effort) that are not properly picked up by fixed effects regressions or PSM estimates. We also show that PSM yields very similar estimates to “naïve” OLS regressions, suggesting that it does not overcome selection bias.

In this paper, we thus estimate the impact of bond market access on firms’ loan costs using endogenous treatment effect models where the choice to enter bond market financing (“treatment”) is jointly estimated with the impact on bank loan costs (“effect”). As we are able to leverage on the data of public companies across many developed economies, our sample coverage is also considerably larger than existing studies. We confine our analysis to publicly listed companies. Having gone through a share IPO which is a major information-releasing event, public companies are known to investors. Hence, public companies are a group that should in principle have a realistic chance to access bond markets, much more so than small and medium enterprises or privately held firms. Public companies have audited and verified accounts and are regulated by the stock exchanges, and thus there should be reduced information asymmetry between potential financiers. Furthermore, being larger organizations, they should have the capacity to source for the best finance for their needs. All these point to less likelihood of capture by any single financier. On a practical note, focusing on public companies allows us to have more firm-level covariates to work with.

We show that companies that have both bonds and loans (Group C) are significantly larger, have higher financing needs, and are more leveraged than those with loans only (Group A). Our key result confirms that firms that have both bonds and syndicated loans record lower loan spreads, compared to firms that use syndicated loans only.² We find that companies would potentially face an average of 114 to 185 bps higher loan spreads in counterfactual absence of bond market access – significantly higher than the observational difference of 57 bps or the existing estimates in the literature.

Our result casts some doubt on the argument that companies value bank services and are willing to pay higher loan spreads for such services. Companies with both bond and loan financing (which are larger and more leveraged) are observed to have lower loan spreads; these companies do not appear to value banking services any less than those that use syndicated loans only. Our result provides some support that bond issuance is an information-releasing event that leads to lower spreads, though we emphasize that it is bond market access (rather than a single maiden bond) that drives the results. Our result points to the market power of bank lenders, potential frictions in accessing bond markets, and other market imperfections, in line with existing literature. This result also underscores the importance of bond market development in capping bank lending costs.

Section 2 provides a review of literature. Section 3 provides a detailed explanation of data sources. Section 4 documents the empirical approach and results. Section 5 provides a discussion of key results and policy implications. Section 6 concludes.

² During the course of the research, we also tested for the yield difference between Groups B and C but were not able to draw any conclusions due to the small number of Group B transactions.

2 Review of Literature

Large bank loans would typically be done through syndication, which allows large loans to be shared across many lenders, thereby providing diversification of risks and/or overcoming constraints of any single lender [see Simons (1993); Dennis and Mullineaux (2000); Ivashina and Scharfstein (2010); Lim et al. (2013); Thia (2019); Thia (2020)]. In the syndicated market, there is the additional advantage of banks coming together to pool information. Even though lead banks typically would have more information on the borrower, the terms of each loan are almost always *pari passu* amongst all lenders. This arrangement overcomes information asymmetry between lead banks and the rest of the lenders.³ With a number of lenders in each deal, the syndicated loan market is also more transparent compared to private debts, with loan amounts, spreads, tenor, etc. recorded.

In pricing the spreads of loans, it is industry practice for lenders to find the relevant benchmarks.⁴ For example, the loan spreads of companies with similar characteristics, the spreads of past loans to the borrower, credit history, the bond yields and credit default swap spreads of the borrower, if available, are all possible data points in the price discovery process. Critically, banks also exercise bargaining power and extract surplus, such as when the borrower is more financially constrained, or when the borrower is informationally captured.

On the other hand, bond yields are determined by a larger pool of investors and are much less susceptible to information capture (to be discussed below). Of course, bonds carry the disadvantages of more costly contracting and costly renegotiation, and hence may not be suitable for some companies. Bank spreads are expected to be tighter if banking competition is stronger or when the borrower has other financing options. Hence, fitting with the observational data in Fig. 1 below, the maintained hypothesis is that loan spreads are higher in the absence of bond market access.

Unlike private or bilateral bank loans, syndicated loans have characteristics similar to publicly issued bonds, with strong secondary market activity. This similarity allows syndicated loans to be seen as a tradable asset. Banks within the lending syndicate can sell down their respective portion of the loan to other lenders (including to those outside the syndicate) without affecting the borrower or other lenders in the syndicate. Altunbas et al. (2010), for example, highlight the strong expansion in the European syndicated loan market as an asset class with the adoption of the Euro. While not perfect substitutes, the market depth of both syndicated loans and public debts are helpful for the research as we have less concern that the prices of loans are reflecting idiosyncrasies of the otherwise thin markets.

There is a large literature on bank loans versus bonds. Evident in this literature is the fact that the choice of corporate finance has multiple equilibria. Indeed, firms are observed to use loans exclusively, bonds exclusively, or a mix of both (though the share of companies using bonds exclusively is small). Empirical research is unsurprisingly diverse in their conclusions.⁵

Denis and Mihov (2003) provide empirical evidence that firms with high credit quality borrow from public markets, those with medium quality borrow from banks, and finally those with low credit quality borrow from non-bank financial institutions. In contrast,

³ Other lenders in the syndicate in turn pay an up-front fee to lead banks to participate in the deal.

⁴ There are also non-bank financing institutions in the syndicated loan market, often working in the same syndicate with banks [see Lim et al. (2013)]. We do not make a distinction between bank or non-bank lenders in the syndicate and label all lenders as banks for convenience.

⁵ The diverse empirical conclusions are highlighted in Schenone (2010).

Altunbas et al. (2010) find that larger firms with greater leverage, more verifiable profits, and higher liquidation values prefer syndicated loans.

Similarly, there are also contrasting findings on loan pricing. Hale and Santos (2009) and Schenone (2010) show that information-releasing events – such as equity or bond initial public offerings (IPOs) – result in lower bank loan spreads. This finding implies that public companies ought not to face such high loan costs. On the other hand, using a structural model to compare loan spreads matched against bonds issued by the same firm, Schwert (2020) finds that firms that have public debt access continue to pay a sizable loan premium. Schwert (2020) posits that this loan premium is due to the valuable financial services provided by banks though this hypothesis is not firmly established in the paper.

Our research is also related to the broader loans versus bonds literature. Diamond (1984) shows that lenders in a syndicate can pool together for diversification which then results in reduced cost of monitoring and improvement in efficiency. Berglöf and Thadden (1994) show that contracting sources of longer-term non-bank finance reduces incentives for strategic default on shorter-term bank loans. Hence, in principle, the existence of longer-dated bonds (or higher equity commitment) should reduce incentives for ex-post negotiation on bank loans. Boot and Thakor (1994) highlight the importance of a relationship with lender in overcoming information asymmetry, leading to lower loan spreads over time. Bank loans also have lower default rates and better recovery rates upon default [Kenneth and Cantor (2005)]. All these factors, together with the seniority of loans over bonds and the fact that loans are secured against collaterals, point to lower risks for bank lenders.

Yet there is little evidence that bank loans are a cheaper form of corporate finance, which continues to be a puzzle. A strand of literature points to potential capture by the informationally advantaged bank lender. Rajan (1992) argues that outsider financing (i.e., bonds) acts as a countervailing force to the power of banks.

In comparing borrowing costs between loans and bonds, firm quality is a key confounding factor. Diamond (1991) models that higher-quality borrowers prefer bonds, but bank loan demand nonetheless increases across the board when interest rates are high (or when future discounted profits are low) because even highly rated borrowers will require bank monitoring in such scenarios as opposed to financing through unmonitored bonds. We find that there is no consensus in empirical literature that higher-quality firms prefer bond financing exclusively. In our dataset, only a relatively small set of companies use bonds exclusively.

Two studies leverage on the timing of information, or information-releasing events as briefly mentioned earlier. Schenone (2010) shows that bank interest rates vary by relationship intensity but fall after an information-releasing event such as an equity IPO. Hale and Santos (2009) find that a maiden bond issuance (or bond IPO) has the effect of lowering subsequent bank loan costs. The key idea is also that the initial bond issuance, especially if it receives an investment-grade rating, provides the market with new information about the firm's creditworthiness and thus reduces banks' informational rent.

Finally, our research is also related to the more general concern that banking concentration – that is, less competition – could be behind costly bank finance.⁶ While bond finance can act as a constraint to loan pricing, the costs of issuing and marketing bonds to investors

⁶ In the European Union (EU), banking concentration – based on assets held by the 5 largest banks in each member economy – has risen in the past decade, as measured by the median or by interquartile range (EU Structural Financial Indicators). In the United States (US), banking concentration has also risen during the 2000s [Corbae and D'Erasmus (2020)].

(flotation costs) could reduce the value of this option. Furthermore, should renegotiation or restructuring needs arise, the process involving multiple bondholders carries significantly more frictions compared to loans, hence implying a higher risk of inefficient liquidation [Harkbarth et al. (2007)]. Hence, Goel and Zemel (2018) find little evidence of firms switching from loans to bonds even when bank credit is scarce, which is consistent with the difficulty of accessing bond markets.

3 Data

Data for this study are drawn from Thomson One for bond issuance and syndicated loans and Refinitiv DataStream for borrower-level data. The data cover the period from 2000 to 2020. Syndicated loan and bond issuances are consolidated and merged using a unique company identifier.

For syndicated loan data, each data point contains three sets of information. First, it contains borrower profile (the name of borrower, its economic sector, and the headquarter country etc.). Second, it contains transaction-specific terms, including the amount, reference rate, spreads, currency type, maturity date etc. The borrowing cost is based on two components, the reference rate (usually Libor) plus the spreads, which is the key variable in this study. Using the maturity date, we are also able to compute the tenor of the loan. Third, information on the lenders' syndicate is included, such as the names of the participating banks. We can thus compute the number of lenders as a key variable in the regression later.⁷

In the dataset, the names of participating banks are recorded either as “mandated arrangers” or “bookrunners”. The former is defined as the banks originally mandated to arrange a given facility as documented in the mandate letter from the company requiring financing. The latter is defined as the banks responsible for maintaining activity of the syndicate and underwriting the largest part of the loan. Bookrunners are a subset of mandated arrangers, though the recording of bank names can be inconsistent and sometimes erroneous. To compute the number of lenders in the syndicate, we count the number of unique lenders in both variables and take the higher recorded number of lenders between the two.

For the bond data, each data point records a bond issuance containing two sets of information. First is the issuer's profile (the name of issuer, its economic sector, and the headquarter country etc.). Second is transaction-specific information, including the amount, coupon rate, yield to maturity at offering date and maturity date. The tenor of the bond can be computed as the difference between the offer and maturity dates. Unlike loans, there are no data on lenders.

As Thomson One does not record borrowers' financial information, we use Refinitiv DataStream to obtain information on the borrower or bond issuer (for each year). We understand that borrower-level information in this dataset is taken from annual reports, and it largely contains information on publicly listed companies only. As mentioned, our analysis is constrained to publicly listed companies. There are some other minor constraints such as not being able to retrieve historical annual report items for now delisted companies.

⁷ Note that each deal could be part of a wider package of financing. For example, a USD1 billion package of financing from the syndicate could be made up of separate loans, each with slightly different terms pertaining to spreads, maturity dates etc.

Table 1 Summary of sample sizes between groups. The summary statistics show that most companies are either in Group C (with syndicated loans and bonds) or Group A (syndicated loans only). Group B companies (those issuing bonds only) are relatively small and have fewer deals

	Share of deals (%)	Share of companies (%)
Group A	18.6	42.1
Group B	5.6	13.3
Group C	75.8	44.6

With the merging of the three datasets, we are able to categorize companies into three groups. Group A consists of companies that record only syndicated loans. Group B consists of companies that record only bond issuances. Group C consists of companies that record both bonds and syndicated loans.

For the dataset, loans and bonds can be denominated in various currencies. In this study, we limit our samples to those denominated in Euro and the currencies of Australia, Canada, Japan, South Korea, New Zealand, Singapore, United Kingdom, United States and Hong Kong, China. By focusing only on these more widely used currencies, we limit the extent by which the lack of liquidity in the market impacts the borrowing spreads of the syndicated loans, and potentially confounds our analysis. We also have the domicile locations of the companies. Likewise, we have included companies from Australia, Canada, Japan, South Korea, New Zealand, Singapore, United Kingdom, United States and Hong Kong, China, as well as those from the European Union economies – Germany, France, Italy, Netherlands, and Spain. We avoid dealing with loans in currencies with thin markets, which can also confound.

We spotted multiple outliers, for example, deals with negative spreads against benchmark. To drop these outliers, we keep only deals with offered yields (for bonds) and spreads (for syndicated loans) between the 1st percentile and 99th percentile ranges. After the data cleaning process, we end up with the consolidated loan/bond dataset of 87,000 transactions, across all three groups.

3.1 Key Observations

First, there are few deals by companies that have bond issuances but not syndicated loans (Table 1). This constrains our ability to analyze Group B companies, and the rest of the research thus focuses more on Group A versus Group C only.

Group C companies, those that have both syndicated loans and bond issuance, have higher sales and assets (Figs. 2 and 3). They also have higher debt to asset ratios, indicating higher leverage (Fig. 4). Group C companies are thus larger and more highly leveraged, consistent with Faulkender and Petersen (2006). In terms of debt servicing, Group A firms have slightly wider P25 – P75 earnings before interest and tax (EBIT) over liability ratios (Fig. 5), indicating a somewhat higher heterogeneity in debt-service capacities.

A key advantage of endogenous treatment effect models is that it is not necessary for a treated sample to be closely matched to an untreated sample. Certain endogenous treatment models, which are employed in this paper, are also robust to the presence of unobserved variables. However, it is important for the “overlap condition” to be satisfied – that

Fig. 2 P25 and P75 Sales (log) of Groups A and C. The figure shows that while Group C companies have higher sales on average, there is a distribution overlap between Group A and Group C sales (which is important to be able to model bond market access)

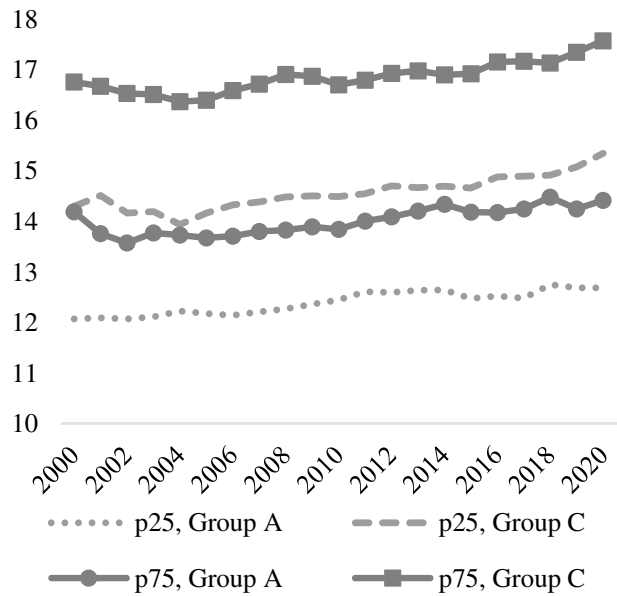
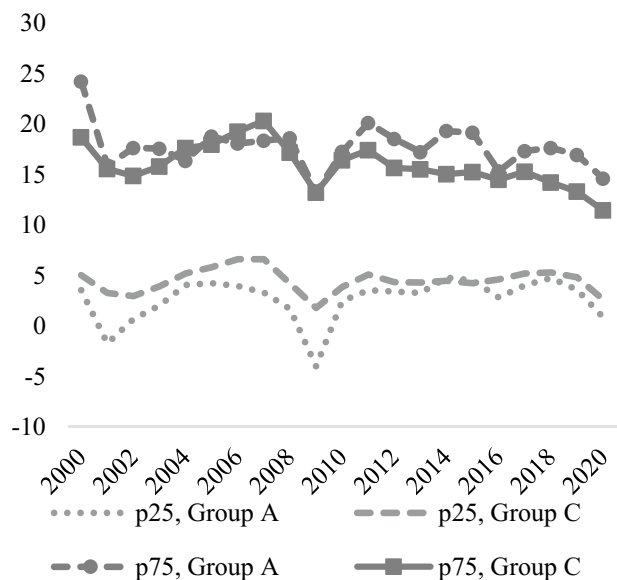


Fig. 3 P25 and P75 Total Asset (log) of Groups A and C. The figure shows that Group C companies have more assets on their balance sheets



there should be a positive probability of being selected into treatment for both treated and untreated groups. From Fig. 2, it can be seen that the P75 level of sales for Group A overlaps with the P25 level of Group C, highlighting the overlap as sales is used as one of the key selection variables.

We also checked for timing effects. For Group C companies – those that have both syndicated loans and bonds – loan spreads following a bond issuance within two years are considerably lower than loans spreads following a bond issuance more than two

Fig. 4 P25 and P75 Debt to Asset Ratios of Groups A and C. The figure shows that Group C companies have higher leverage

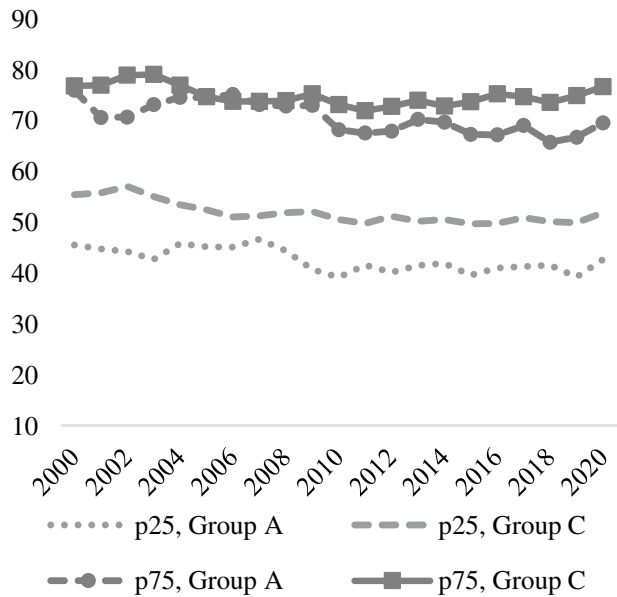
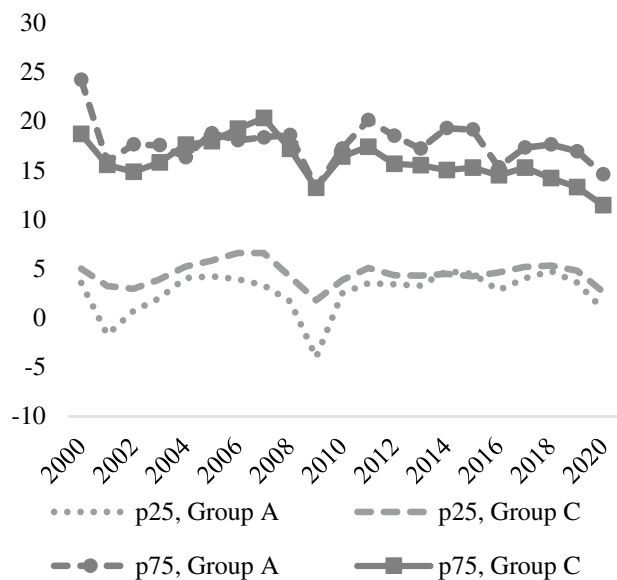


Fig. 5 P25 and P75 EBIT/ Liability of Groups A and C. The figure shows that Group A and Group C companies have similar debt-servicing capacity



years prior, by an average of 60 bps between 2002 and 2020 (Fig. 6).⁸ No such timing effect is observed if the loan follows another loan (Fig. 7). Furthermore, average loan spreads following a bond within two years are lower than loan spreads following another loan within two years by an average of 26 bps (i.e., the broken line in Fig. 6 is

⁸ For Fig. 6, we also checked loan size and tenor (factors which are known to have an impact on spreads). We find that average loan size is in fact larger for subsamples where there was a bond issuance within the last two years, though tenor is on average around two years shorter.

Fig. 6 Average Loan Spreads Following Bond Issuance (Group C). The figure shows that loan spreads are lower when loans are contracted within two years of a bond issuance

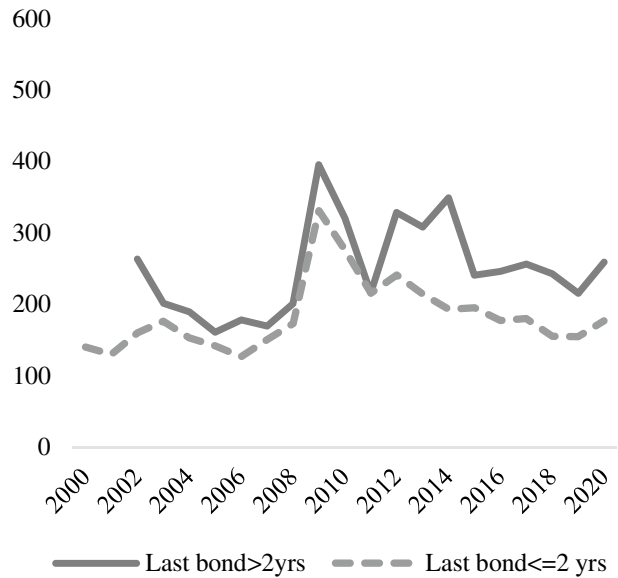
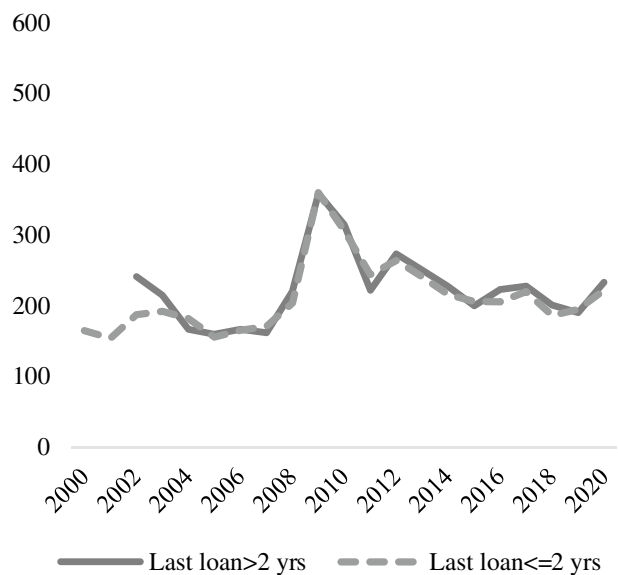


Fig. 7 Average Loan Spreads Following Another Loan (Group C). The figure shows that there is no difference in loan spreads, whether the loans are contracted within or beyond two years of another loan



lower than the broken line in Fig. 7). To complete the picture, we also checked Group A. Average loan spreads, following a recent loan, are slightly higher (Fig. 8). Finally, for Group B, there is no clear pattern on yield spreads (over Libor) (Fig. 9).⁹

⁹ Note that there are relatively fewer bond issuances coming from companies that do not have syndicated loans.

Fig. 8 Average Loan Spreads Following Another Loan (Group A). The figure shows that there is no difference in loan spreads, whether the loans are contracted within or beyond two years of another loan

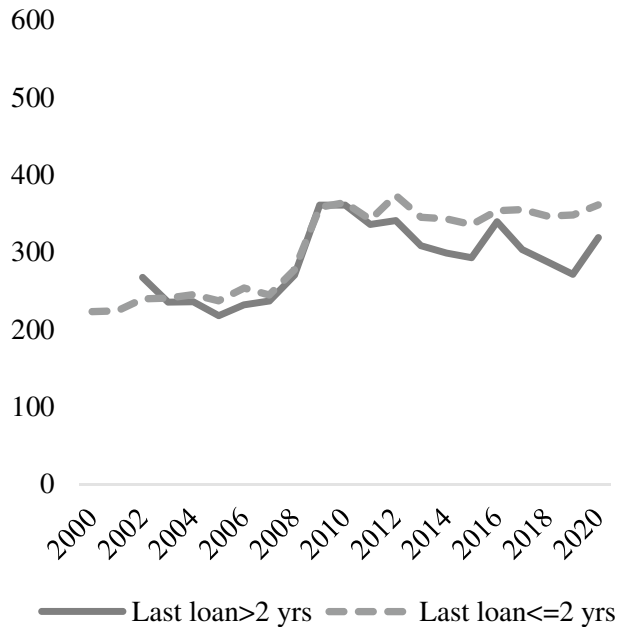
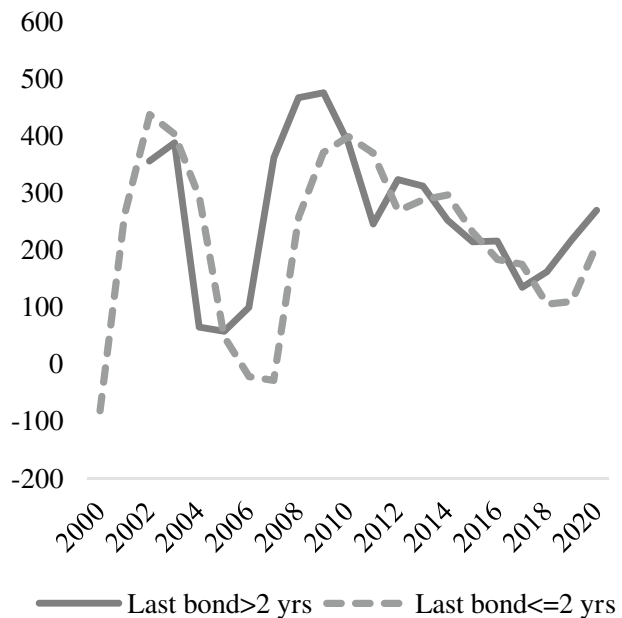


Fig. 9 Average Bond Spreads (over Libor) Following Another Bond (Group B). The figure shows that there is little difference between bond yields, whether the bond is issued within or beyond two years of another bond



These patterns in observational data provide further *prima facie* evidence that sustained bond market access (not just a single information-releasing event like the maiden bond issuance) is the key to constraining banks' loan pricing. We will revisit and discuss this observation in a later section. The full list of variables is provided in Appendix 2.

4 Regression Estimates

4.1 Regression Without Selection

We first present a regression with no selection or treatment (“naïve” regression). In this regression, the dependent variable is loan spreads ($s_{i,j,t}$) of the i syndicated loan of company j at time t . We can potentially draw from the following as explanatory variables (or regressors). Firstly, we have loan characteristics including tenor, currency type, and the number of lenders. Secondly, we draw firm characteristics including asset, liability, gross profit margins, EBIT. From there, we can compute liability to asset ratio and EBIT to liability. The liability to asset ratio will capture the leverage of the firm, which is expected to increase spreads since higher leverage represents increased risk. The EBIT to liability ratio captures the ability of the firm to service its debts. The level of assets in the regression captures the effects of what firms can put up as collaterals, or as a proxy for recovery rates upon any default, or just simply diversification through size effects. We estimate the following outcome equation,

$$s_{i,j,t} = \alpha + X_{i,j,t}\theta_1 + Y_{j,t}\theta_2 + \delta I_j + \varepsilon_{i,j,t} \quad (1)$$

where α denotes a vector of constant and fixed effects (e.g., year, country, sector dummy variables); $X_{i,j,t}$ is a vector of loan characteristics (tenor, number of lenders); $Y_{j,t}$ is a vector of firm-level characteristics (debt to asset ratio, gross profit margin, EBIT to liability ratio, assets in logs, initial sales); and $\varepsilon_{i,j,t}$ is the error term. I_j is an indicator set to 1, should firm j be observed to contract both syndicated loan and bond at any time during the sample period. Note that this variable is thus a firm-specific indicator rather than a transaction-specific one. All regressions are carried out using clustered standard errors at firm level.

A priori, one would expect the coefficient for tenor to be positive, and the coefficient for the number of lenders to be negative given the diversification effect. The coefficient for debt to asset ratio is expected to be positive as companies with higher debt ratios should be deemed more risky. On the other hand, companies with higher gross profit margins and EBIT to liability ratios should be deemed less risky, with negative coefficients thus expected. Lending due diligence often focuses on the expected debt service coverage ratio (DSCR) capacity of the firm, which is approximated by the ratio of EBIT to liability. Finally, the sign of assets should be negative. A higher level of book assets could imply higher level of collaterals or liquidation value, or it could simply reflect diversification that comes with a larger scale. Results of the regression are shown in column (1) of Table 2. In column (2), we replace the indicator I_j with an indicator that is set to 1 for any loan transaction after the first observed bond issuance (i.e., post maiden bond).

Having included covariates for regression, it is possible that conditional mean independence (CMI) is achieved. If so, the coefficient can then be interpreted as the effects of having bond access, conditioned on $Y_{j,t}$, the other firm-level characteristics. After controlling for lender-specific characteristics and loan-specific characteristics, firms that participated in both syndicated loan and bond market enjoyed slightly less than 10 bps lower spreads (but insignificant).¹⁰ We also find lower bank spreads post-bond IPO, based on regression in column (2) in Table 2—companies saw a lower spread of 21 bps

¹⁰ This small effect is consistent with Hale and Santos (2009). Their research finds that post-bond IPO effect is very small when regression does not control for ratings of the bond issuance. Their research also shows very small difference between OLS regressions (investment grade) and PSM.

Table 2 Regressions without controlling for Treatment. This table reports the OLS regressions for the model described in Eq. 1. Column 1 shows the results when the indicator takes the value of 1 for firms with bond issuance. Column 2 shows the results when the indicator takes the value of 1 after the first bond issuance is observed for the company

	1	2
Both loan and bond ($I_j = 1$)	-9.879 (4.435)	
Post first bond issuance		-21.34*** (4.125)
Tenor	5.630*** (0.6780)	5.119*** (0.7197)
Number of lenders	-4.189*** (0.5023)	-4.647*** (0.5271)
Debt to asset ratio (or leverage)	1.316*** (0.1917)	1.428*** (0.2068)
EBIT to liability ratio (debt servicing)	-0.0983 (0.06103)	-0.1039* (0.06221)
Gross profit margin	-0.1208** (0.05663)	-0.1339** (0.06180)
Total assets (natural log)	-16.94*** (1.9330)	-17.13*** (2.028)
Initial (first) sales	-10.76** (1.815)	-10.19*** (1.851)
Constant	483.4*** (58.29)	477.8*** (27.72)
Year fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Sector fixed effects	Yes	Yes
Observations	21,814	21,870
R-squared	0.3182	0.3042
F-statistics	64.76	59.45
p-value	0	0

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

on average, an estimate comparable with Hale and Santos (2009) for non-investment-grade companies.

Nevertheless, there is a strong presumption that CMI does not hold for either of the above regressions. As mentioned, management quality, prospects, and business risks are all potentially unobserved confounding factors. It is highly likely that the error $\varepsilon_{i,j,t}$ is correlated with I_j – that is, the part of the spreads that is unexplained by covariates is in fact correlated with a company's decision to enter bond issuance. This likelihood also implies that treatment estimators that do not deal with unobserved factors will not produce the right estimates.¹¹

¹¹ For example, treatment effect methods such as regression adjustments also require conditional independence and do not work when treatment and potential outcomes are correlated. PSM is also ineffective in the presence of unobserved factors.

Table 3 Average Treatment Effect (ATE) Using PSM. This table reports the results for the model described in Eq. 1 using PSM estimation to account for selection effects. It can be seen that the average treatment effect is almost the same as the coefficients estimated by simple OLS, in particular the coefficient post-first observed bond issuance in column 2 of Table 2

	Coefficient	Standard error
Both loan and bond ($I_j = 1$ vs. 0)	-21.90***	3.813

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

There is also a need to discuss the effect of firm size. The literature has extensive evidence on the borrowing constraints faced by small firms. To be clear, the research here focuses only on publicly listed companies; therefore, borrowing constraints should not, in principle, be a key factor resulting in different spreads. Nonetheless, there could be several other channels where firm size can reduce borrowing cost. First, larger companies may have greater bargaining power against lenders for being more valuable clients with larger loan deals. Second, the debt instruments of larger companies may be more liquid in the secondary market. This explanation may be true even for the syndicated loan market where the individual lender in the syndicate can sell down its portion to other lenders within or outside of the syndicate. Larger companies may be deemed more diversified and better able to withstand shocks. All these factors can potentially explain why spreads are negatively correlated with size.

As noted, companies that issue bonds are also systematically larger in size. The inclusion of total assets into regression thus reduces the significance of coefficient δ . In other words, firm size is also a confounding factor. In this and all subsequent regressions presented in this paper, we include total assets as a variable in the outcome equation. This inclusion is to ensure greater robustness that the coefficient δ is not merely picking up the effect of size and overstating the effects of bond market access.

4.2 Controlling for Selection Through Propensity Score Matching (PSM)

Typical in the literature, the selection effect is controlled for using PSM. We run a simple version of PSM, using the same set of variables as above. The results are presented in Table 3.

The results show that companies with bond market access have on average lower bank spread of around 22 bps. This spread reduction is only slightly larger than 10 bps estimated reported in column 1 and almost the same as the 21 bps in column 2 of Table 2, where selection effect is not controlled for. At face value, these results suggest that there are hardly any selection effects into bond market access, which seems implausible as observational data already show that firms entering bond financing are larger and more leveraged. A more likely explanation is that PSM itself does not adequately control for the selection effect. As it is well known, PSM does not work in the presence of unobserved variables or endogenous efforts. We develop this line of thinking further in subsequent subsections.

4.3 Endogenous Treatment Linear Regression (ETR)

In this subsection, we present the estimation using the linear regression with endogenous treatment, as explained in Wooldridge (2010) and StataCorp (2015). The outcome equation remains the same as before, but with an additional treatment equation for I_j . The full model setup is given as follows, with the potential outcome equation as

$$s_{i,j,t} = \alpha + X_{i,j,t}\theta_1 + Y_{j,t}\theta_2 + \delta I_j + \varepsilon_{i,j,t} \quad (2)$$

And the treatment equation given as

$$I_j = \begin{cases} 1, & \text{if } Z_j\gamma + v_j > 0 \\ 0, & \text{otherwise} \end{cases}$$

with the following error structure for $\varepsilon_{i,j,t}$ and v_j as

$$\begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{bmatrix}$$

As discussed, there are good reasons to believe that CMI does not hold in the previous regression, and the estimated coefficients there are unreliable even if the covariates are not themselves correlated to error terms. The endogenous treatment regression accounts for unobservable factors that affect both treatment and outcomes by allowing $\varepsilon_{i,j,t}$ and v_j to be modelled as bivariate normal distribution. The error structure links the treatment and outcome equations. Estimation is then carried out using the maximum likelihood of this joint distribution.

Guided by observational data, we see that sales, total assets and total liabilities are all larger for Group C companies. Yet despite assets and liabilities being highly correlated with bond issuance, we avoid using these variables to model treatment out of concern that these can be influenced by bond market access itself. Sales is also strongly correlated to size and entry into bond issuance. Unlike assets and liabilities, sales would be the least likely to be affected by financing mix or financing cost.¹²

Sales thus is a good variable to be included in Z_j . For companies included in the regression, we use the initial sales (first recorded observation) as the selection variable. We use the initial sales, rather than average sales over the sample period for the company, to avoid concerns that sales would be affected by loan spreads.¹³ In addition, country and sector dummies are also included in Z_j to capture country or sector industry dynamics. The same set of $X_{i,j,t}$ and $Y_{j,t}$ covariates are used to model outcomes (as per earlier regressions). The results are reported in Table 4.

From the regression seen in column 2 of Table 4, the coefficient points to an average of 114 bps lower bank lending spreads for firms with bond market access. The Wald test rejects the null hypothesis of no correlation between treatment and spreads. The

¹² We show, by way of regression in the Appendix 1, that spreads have very little explanatory power on sales once assets and liabilities are included. Sales is thus correlated with assets and liabilities – providing a measure of company size.

¹³ The estimation requires Z_j to be unrelated with the error terms, and unobserved factors affecting outcomes can be modelled as the joint mean zero normal distribution between $\varepsilon_{i,j,t}$ and v_j . This fact explains why first sales is used (instead of average sales).

Table 4 Linear Regression with Endogenous Treatment. This table reports the results for the model described in Eq. 2. The results of the treatment equation are provided in column 1, where initial sales (i.e., first observed sales the firm in the sample) is seen a good predictor for bond market access. Column 2 shows that the average effects for bond market access is -114 bps

	1 Probit treatment model	2 Linear regression with endogenous treatment
Initial (first) sales	0.2581*** (0.02272)	
Both loan and bond ($I_j = 1$)		-114.1*** (20.56)
Tenor		5.945*** (0.6850)
Number of lenders		-3.974*** (0.4917)
Debt to asset ratio		1.276*** (0.1824)
EBIT to liability ratio		-0.1051* (0.06352)
Gross profit margin		-0.1155** (0.05168)
Total assets (natural log)		-20.48*** (1.814)
Constant	-2.789*** (0.3339)	485.4*** (23.12)
Year Fixed Effect	No	Yes
Country Fixed Effect	Yes	Yes
Sector Fixed Effect	Yes	Yes
rho (ρ)	0.5289*** (0.09181)	
Athrho	0.5887*** (0.1274)	
Ln Sigma	4.756*** (0.02881)	
Observations	21,814	

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

estimate of ρ is 0.53, which shows the positive correlation between the error terms of the treatment and outcome equations. In other words, the unobservable factors that contribute to companies entering into bond financing are positively correlated with higher loan spreads. This finding presents a considerably more nuanced picture, and also highlights the importance of modelling endogenous treatment to deal with the unobserved factors as potential confounders.

Table 5 Endogenous Treatment Effect (ETE) Estimation. This table reports the results for the model described in Eq. 3. Unlike other sections, δ is not directly estimated but inferred through the difference in POMs, which is provided in Table 6 below. Column 1 reports the Probit treatment estimation, column 2 is the outcome estimation for the untreated ($I_j = 0$) which is for the companies without bond issuance, and column 3 is the outcome estimation for the treated ($I_j = 1$) group which is those with bond issuance

	1	2	3
	Treatment	Untreated	Treated
Initial (first) sales	0.2664*** (0.01982)		
Tenor		7.619*** (1.806)	5.203*** (0.6900)
Number of lenders		-6.812*** (1.146)	-3.360*** (0.5431)
Debt to asset ratio		0.786*** (0.285)	1.616*** (0.1084)
EBIT to liability ratio		-0.1263 (0.09373)	-0.09042 (0.07633)
Gross profit margin		0.02730 (0.04060)	-0.1960* (0.1026)
Total assets (natural log)		-7.435 (4.530)	-21.23*** (1.924)
Constant	-2.866*** (0.3050)	387.9*** (50.22)	354.6*** (37.35)
Year fixed effect	No	Yes	Yes
Country fixed effect	Yes	Yes	Yes
Sector fixed effect	Yes	Yes	Yes
Observations		21,814	

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Firms with bond issuance have higher financing needs and are more leveraged. What motivates them to tap the bond market also leads to higher bank loan spreads (ρ being positive). Hence, without bond market access, Group C companies could have had significantly higher bank borrowing costs.

4.4 Endogenous Treatment Effect (ETE) Estimation

The ETE estimator also deals with endogenous treatment and outcomes. The key advantage of ETE (over ETR) is that it is somewhat less restrictive. ETE allows for coefficients of the covariates to differ between the treated and untreated groups. For example, once a company achieves bond market access, bank lenders may behave differently with regard to various firm- or loan-specific factors. Such effects can then show up in the coefficients of tenor or the number of syndicators, just to give a few plausible scenarios. ETE also does not require the error structure to take a joint normal distribution and can be estimated by the moment conditions of the control functions.¹⁴ The treatment-effect model is given by

¹⁴ See StataCorp (2015) for estimation of the control functions.

Table 6 ATE of Endogenous Treatment Effect Model. This table reports the potential outcome means based on the regression results seen in Table 5, which is for the model in Eq. 3. The average loan spreads for the untreated (companies without bond issuance) and the treated (companies with bond issuance) are 342 bps and 157 bps respectively

Both loan and bond ($I_j =$)	Coefficient	Standard Error
0	341.8***	43.39
1	156.8***	6.791

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7 ATET of Endogenous Treatment Effect Model. This table reports difference in potential outcome means based on the model in Eq. 3, but for group C companies only

	Coefficient	Standard error
Both loan and bond ($I_j = 1$ vs. 0)	-193.5***	54.90

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

$$\begin{aligned}
 s_{i,j,t|I_j=1} &= \alpha_1 + X_{i,j,t}\theta_{11} + Y_{j,t}\theta_{12} + \beta_1\hat{v}_j + \varepsilon_{i,j,t} \\
 s_{i,j,t|I_j=0} &= \alpha_0 + X_{i,j,t}\theta_{01} + Y_{j,t}\theta_{02} + \beta_0\hat{v}_j + \varepsilon_{i,j,t} \\
 I_j &= Z_j\gamma + v_j > 0 \\
 s_{i,j,t} &= I_j s_{i,j,t|I_j=1} + (1 - I_j) s_{i,j,t|I_j=0}
 \end{aligned} \tag{3}$$

where the first two equations are the potential outcome estimations of Group C (treated) and Group A (untreated) respectively, while endogenous treatment estimation is achieved by estimating the third equation with Probit treatment variables with first recorded sales, as well as country and sector dummies (the same variables used in Section 4.3). For the ETE estimation, the estimated residuals of the treatment estimation \hat{v}_j enter into outcome equations.

In essence, $\hat{v}_j = I_j - Z_j\hat{\gamma}$ picks up the part of I_j that is not explained by the exogenous factors Z_j . Entering into the potential outcome equations, \hat{v}_j then picks up the effects of unobserved factors affecting both treatment and outcomes (endogenous treatment). With the unobserved factors accounted for, the effects of treatment can be estimated by comparing the potential outcome means (POMs) between the treated and untreated groups. The results are reported in Table 5.

A simple test is also performed to check whether the treatment-assignment is well behaved. The propensity scores of entering treatment group and control group are calculated for each sample, and with confirmed overlaps between Groups A and C.

The Wald test for endogeneity rejects the null hypothesis that there is no correlation between the unobserved variables of the treatment-assignment and the potential-outcome models. The results suggest that the unobservable factors that determine the loan spreads are correlated with whether a company chooses to finance through the bond market as well. The ATE estimation is presented in Table 6. The potential outcome means for the treated and untreated are 157 bps and 342 bps, respectively, with a difference of 185 bps.

Average treatment effect on the treated (ATET) is also calculated. The ATET provides the counterfactual estimates on how many bps higher loans would be, had companies in Group C financed through loan market only. ATET is estimated at -193.5 (Table 7), which

implies that they would suffer on average around 194 bps loan price increase, if they did not have bond financing.

The Wald Test on endogeneity rejects the null hypothesis of no endogeneity. Our checks show the predicted error term \hat{v}_j takes on positive coefficients, consistent with the positive ρ in ETR presented in Section 4.3 – that is, evidence that unobserved factors are driving both bond issuance and higher loans spreads. It is the positive effects of \hat{v}_j that explain the large (negative) ATE effects, which would be underestimated otherwise.

5 Discussion and Implications

Companies that have both syndicated loans and bonds are larger (by sales, by assets, and by liabilities) and are more leveraged than companies that use only syndicated loans. Controlling for treatment and outcomes using two estimation methods, we find that bond market access is associated with a reduction of bank loan spreads by 114 bps and 185 bps, respectively, against the counterfactual absence of bond financing.

The fact that bond market access reduces bank loan costs is not a surprising finding; there are many studies confirming this finding. It is thus important that we situate our findings against estimates in the literature. Firstly, our estimates are larger than those in Hale and Santos (2009) which show that maiden bonds reduce bank loan costs by 35 to 50 bps if the bond is rated as investment grade, and by 5 to 20 bps only otherwise. Schenone (2010) reports that firms see an average reduction in banking spreads of around 50 bps post-equity IPOs (but does not directly analyze the impact of bonds on bank loan prices). Both results support informational release as the channel. On the other hand, Schwert (2020) finds substantial average loan premium over bonds estimated at 143 bps (of an average 305 bps total spreads) even for publicly listed companies with bond market access.

To be clear, our results do not capture the loan premium over bonds per se but point to the higher loan spreads companies would have to pay if they did not have bond market financing. Our estimates (114 bps to 185 bps) are two to three times larger than the observational difference of 57 bps between Groups A and C.

The key reason here is that Group C companies take on larger borrowings (in absolute terms) and have higher leverage. They are systemically different from Group A, those without bond issuances. In 2018, on a deal-by-deal basis, the average size of a syndicated loan for a Group C company is USD825 million with an average of 4.8 banks per syndicate. For Group A, the average deal size is much smaller at USD163 million with an average of 2.5 banks per syndicated loan. Based on 2018 transactions reported on a company basis, Group C companies that contracted syndicated loans borrowed USD155 million per syndicating bank it contracted with, and this size was around 2.5 times as large as that for a Group A company. In other words, because of the large funding needs of Group C companies, each lender is more exposed on average to any single company despite the higher number of banks in the syndicate.

We see these effects reflected in the estimates. Take the ETE estimation. We see that the coefficient on the debt to asset variable (indicating leverage) is twice as large for Group C, compared to Group A. In other words, Group C companies pay a larger spread penalty for additional leverage. Furthermore, the impact of additional lenders in the syndicate is smaller for Group C, compared to Group A, indicating less diversification effects as loan per lender becomes large.

The natural question, also posed by various researchers, is why we do not observe all publicly listed companies issuing bonds. Our results are broadly consistent with flotation costs of bonds explanation, as with other researchers. Companies would need to build up a bond investor base. There is often also a need to issue bonds at different maturities in order to address the cash needs of different time horizons, build up a yield curve, and optimize borrowing costs. There are significantly more regulatory costs to financing through bonds. Industry experts speak of building a bond program as opposed to a one-off borrowing. Companies without seasoned offerings face significant underpricing of bonds [Cai et al. (2007) and Schenone (2010)]. Bond yields are also more volatile, exposing companies to the liquidity conditions in the market at time of issuance. Of course, as discussed, bonds also carry a higher risk of inefficient liquidation.

It is also important to interpret the results in light of endogenous treatment versus other estimation methods. Propensity scores, or more generally matched sample methods, do not work well in the presence of unobserved variables. Bond market access is an active choice and where considerable efforts have to be undertaken by companies ahead of bond issuances. Similarly, methods exploiting events such as pre and post IPOs also do not account for the significant corporate effort required – that is, the active choice with much corporate undertaking – to achieve such event milestones.

More generally, it is difficult to interpret estimates based on propensity scores. Suppose we observe from matched samples that bond issuance results in lower bank spreads; one would then have to provide an explanation on why firms in the matched control group do not then tap into the bond market – are they not sub-optimizing as a result? One would likely have to again question if the matched samples are, in fact, a good control group, or if there is something missing.

Rather than arguing that non-bond access companies are good matches for those that enter into bond financing, this paper provides a new and more nuanced insight through endogenous treatment. This paper does not argue that companies that do not access the bond market are being sub-optimal in their corporate finance. Rather, only companies with large financing needs and aiming for higher leverage will find it necessary to incur flotation costs and seek bond market access. Both regressions show that unobserved factors that motivate companies to enter bond financing also raise loan spreads. The choice to seek bond market financing and bank loan spreads are, in fact, positively correlated.

These results provide supporting evidence that large borrowers do face constraints should they rely solely on bank financing. The results here also cast doubt that companies are paying higher bank loan spreads to enjoy the financial services provided by banks. It is difficult to conceive that companies with both bonds and loans – being larger, more leveraged and yet with lower observed spreads – would value financial services any less.¹⁵

There is also a need to discuss exactly how bond market access reduces loan spreads. One school of thought is that this reduction operates through information release. Our result is consistent with this thinking but also adds some nuances to this argument. First and foremost, there is the information-releasing effect of the maiden bond, which we find some support of, as seen in the regression in Table 2.

¹⁵ In some research, it is noted that larger loans have lower spreads, and the explanation is economies of scale. This explanation is somewhat counterintuitive, given that larger loans would come with greater risks, liquidity constraints, or regulatory constraints for lenders such as capital charge. Thia (2020) shows that corrected for the endogeneity between loan size and loan pricing, the size of loans would have a positive impact on spreads.

However, subsequent bond issuances do matter. Even post maiden bond, loans following a bond within two years saw observed lower spreads (Fig. 6). This finding is consistent with the idea that bond issuance is a program, not a one-off. Bank lenders too update their beliefs about companies' debt raising capacity in the capital market, thus affecting loan spreads. This explanation is consistent with the data in Fig. 7 where loan spreads following another loan are less volatile and with no timing effect as to whether the previous loan was within or more than two years ago.

We thus surmise that maiden bond issuance reduces bank loan costs as an information releasing event is a partial explanation. Information release by bond issuance is unlikely to be a one-time affair; subsequent bond market capacity continues to matter. Finally, our research is consistent with the possibility that bank lenders do exercise some market power or behave strategically towards borrowers, providing loans with lower costs depending on their record at bond issuances. This conclusion is consistent with recent work by Paukowitz and Prabhala (2023) who find evidence that banks raise lending spreads when credit rating agencies tighten rating standards, suggesting strategic pricing based on borrowers' perceived capacity for bond market access.

6 Conclusion

It is quite clear from observational data that companies that used both syndicated loan and bond financing saw lower average loan spreads (57 bps). We employ two treatment and outcome estimations and find that bond financing, in fact, reduces syndicated bank loan spreads on average by 114 bps and 185 bps, respectively, against counterfactuals. The bond market access effect is thus significantly larger than what is suggested by observational data.

Admittedly, the exact channels for this effect are less clear. We find large-sized loans and leverage to be a potential explanation. Absent of bond issuance, these firms would have faced higher loan costs due to large financing needs and leverage. We find that the information-release hypothesis is a partial explanation at best, as it does not fully explain some characteristics in the data. We find little support to suggest that companies are willing to pay higher loan spreads over bonds for valuable banking services.

In summary, our research supports the literature that shows that bond financing plays a role in capping banks' power on pricing loans. Given the rising concentration in the bank sectors in many economies over the years, research of bank loan spreads is an area that will continue to benefit from further research. This result also underscores the importance of bond market development.

Appendix 1

We use initial sales as the variable to model "treatment" into bond issuance. Sales (which is a measure of company scale) is highly correlated with assets and liabilities. We present the ancillary regression to show that despite sales being correlated with company scale, there is very little correlation between sales and the syndicated loan spread. We take the average of each company's financials (e.g., the average of total assets from 2000 to 2020) and the average of each syndicated loan spread to obtain a company-level cross-sectional

Table 8 Regression of Average Sales (natural log). This table shows the correlation between average sales and different variables

Average total assets (natural log)	0.4362*** (0.04457)
Average liabilities (natural log)	0.4512*** (0.04156)
Average syndicated loan spread	-0.000961*** (0.0001250)
Constant	1.632*** (0.1826)
Sector Fixed Effect	Yes
Country Fixed Effect	Yes
Observations	3,739
R-squared	0.8480

Clustered standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

data. We regress average sales against the following variables. Sales is highly correlated with assets and liabilities, as these are all measures of scale. Controlling for scale, syndicated loan spreads have little impact on sales (Table 8).

Appendix 2

Table 9 below provides the list of variables for the regressions in the paper.

Table 9 List of Variables. This table provides the list of variables used in the regression, the period covered, and the data source

Firm-level characteristics	Time coverage	Source
Initial sales (sales in the first occurrence of the panel)	2000–2020	DataStream
EBIT to liability ratio (debt servicing)	2000–2020	DataStream
Total assets	2000–2020	DataStream
Debt to asset ratio	2000–2020	Calculated by authors using data retrieved from DataStream
Gross profit margin	2000–2020	DataStream
Country	2000–2020	Thomson One
Sector	2000–2020	Thomson One
Bond/loan level information		
Tenor	2000–2020	Thomson One
No. of lenders in the loan	2000–2020	Calculated by authors using deal data retrieved from Thomson One
Year	2000–2020	Thomson One
Spread	2000–2020	Thomson One
Market access information		
Both bond and loan (dummy variable indicates that the company has access to both markets)	2000–2020	Calculated by authors using deal data retrieved from Thomson One

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Data Availability Data for this research has been provided in an open-access depository (<https://data.mendeley.com/datasets/nrs7c8v4m2/1>).

Declarations

Conflicts of Interests/Competing Interests There is no conflict or competing interest.

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