

TRACING THE SUPPLY CURVE OF CORPORATE DEBT*

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Abstract

Changes in credit spreads are not the only way in which financial markets adjust to shocks in investor and bank lending capacity. Firms can also respond by changing the composition of debt claims they issue across instruments and markets. We measure the price-elasticity of substitution of corporate debt supply in primary markets. Using granular data on syndicated loans and corporate bonds issued by firms worldwide, we exploit variation in borrowing costs driven by shifts in bank lending capacity and institutional demand for bonds to estimate three margins of debt supply: substitution across instruments within a market, substitution between bank and bond financing, and the scale of total debt issuance. We find that firms respond elastically along all three margins. Therefore, the composition of corporate debt supply is a key channel through which financial markets adjust to shocks in investor and bank lending capacity.

Keywords: Corporate debt supply; Capital structure; Syndicated loans; Corporate bonds; Elasticity of substitution; Asset supply.

JEL Classification: G12, G21, G23, G31, G32, E44.

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1 INTRODUCTION

Firms issue several trillion dollars of new debt every year. This flow, however, is not homogeneous: it consists of a wide range of contracts, maturities, and risk exposures. For example, a term loan, a long-dated bond, a revolving credit line and a bridge loan allocate maturity, credit risk and control rights differently across the investors who hold them. Over short horizons, the capacity of investors and banks to hold one type of claim rather than another can change. When it does, either the relative prices of these claims must move, or firms must change the mix of claims they issue, or both. How much of the adjustment falls on prices depends on how elastically firms supply debt in primary markets.

The firms best placed to make this adjustment are large non-financial corporations, which also account for a large share of debt issuance. Unlike smaller firms or sovereign issuers, these corporations often issue multiple debt instruments within a short period, either within the same asset class—e.g., several bonds or different types of syndicated loans—or across asset classes, such as bond and syndicated lending markets. They are therefore in a unique position to reallocate issuance across instruments and markets over short horizons, as if arbitraging differences in relative financings costs across debt markets due to shifts in bank lending or asset demand. The more they substitute across instruments as relative financing costs move, the more of any change in these conditions shows up in the composition of issuance rather than in prices.

We therefore ask: how elastic is the supply of corporate debt, in the short term, to shifts in the relative price of different claims? We study firms that borrow in the syndicated loan market, the corporate bond market, or both, and we measure three margins of debt supply. First, we measure the elasticity of substitution across the instruments of one market, holding the firm's financing needs fixed. Second, we measure the elasticity of substitution between bank and bond financing by looking at firms that issue in both markets. Third, we measure the elasticity of total issuance against the cost of debt, after the firm has chosen the composition of its borrowing in response to the relative price of different claims.

We find that firms respond strongly to changes in relative financing costs along every margin we measure. When one claim becomes 25 basis points more expensive than other claims issued by the same firm in the same quarter, the firm issues 8.9% less, both within syndicated lending and within corporate bonds. Substitution between the two markets is the least elastic margin: a firm active in both markets shifts its issuance split between the two by roughly 4.7% when the relative cost of bond

and loan financing moves by 25 basis points.¹ Firms also adjust the scale of their borrowing: a 25 basis point increase in the price at which a firm can place debt in a market lowers the total quantity it issues by 7.4% in bonds and 2.9% in syndicated lending. Each of these responses is measured with respect to a credit spread, the unit in which claims are quoted in both markets; on the price of the security itself, they correspond to price elasticities of 9.32, 8.52 and 3.00 for the two within-market margins and the bank–bond margin. Thus, the supply of corporate debt is highly elastic to relative changes in the cost of different financial claims: firms reallocate issuance across contracts and markets as relative prices move, effectively acting as elastic arbitrageurs of funding conditions across debt markets.

Our empirical analysis exploits highly granular data on syndicated loans and corporate bonds issued by firms around the world, from 2000 to 2023. We use Dealscan for syndicated loans, and LSEG Refinitiv for corporate bonds issued worldwide. In total we study 122,748 debt contracts issued by 7,839 firms and worth 50.5 USD trillion at issue, of which 28.6 USD trillion is corporate bonds and 21.9 USD trillion syndicated lending. Of those firms, 1,458 issue in both markets, whereby those that do so in the same quarter identify substitution between bank and bond financing. In fact, many firms issue multiple instruments within the same market in a quarter, and roughly 40 firms per quarter are active in both corporate bond and syndicated lending markets. We further find that the contract terms that vary most within a firm-quarter differ across the two markets: maturity in bonds and facility type in loans (e.g., term loans, bridge loans, revolvers, etc.).

To identify firms’ debt supply elasticities, we use variation in borrowing costs that comes from shifts in investor demand rather than from firms’ own financing needs. In corporate bond markets, we use data on investor holdings to estimate the common structure of institutional portfolio rebalancing each quarter with principal components and aggregate the fitted demand across investors within bond categories. The resulting demand shifter captures systematic changes in appetite for particular bond types that are orthogonal to individual issuers’ financing demand. In syndicated loan markets, we exploit the multi-lender structure of loan syndicates: because banks lend to many borrowers within a quarter, bank-time fixed effects recover lender-specific balance-sheet conditions, following the within-firm, across-lender decomposition of [Amiti and Weinstein \(2018\)](#). We use these demand shifters as instrumental variables to estimate the three margins of corporate debt supply: within-market substitution across the instruments of one asset class, holding firm-time financing needs fixed; cross-market substitution between bonds and loans, measured by comparing dual issuers’ issuance split with the gap in their demand-driven costs across the two markets; and the scale of total issuance

¹Bonds and loans are not priced at the same level, so a shock of a given size in basis points is a larger proportional move in the narrower market. At the median spreads of firms active in both markets, 225 basis points in bonds against 175 basis points in loans, the response is 4.2% when the move arrives through the bond market and 5.3% when it arrives through the loan market. We report the symmetric case, evaluated at the average of the two.

against the demand-driven marginal cost of debt.

A crucial feature of our identification, made possible by the granularity of our data, is that we measure substitution across debt instruments **within a firm** $\times$ **quarter**. This is the variation required to identify our parameter of interest: the elasticity of substitution across debt claims. Intuitively, when a firm issues multiple instruments in the same quarter and one becomes more expensive relative to another because of shifts in investor demand, we observe how the firm reallocates issuance away from the relatively more expensive claim. We argue that this reallocation across debt instruments is the relevant margin of risk absorption for understanding the short-run role of corporate debt supply in financial markets.

Finally, we turn to what the borrowed funds are for. We classify each instrument's stated use of funds by using web-browsing Large Language Models, separating real uses such as capital expenditure, acquisitions, and R&D from financial uses such as refinancing, liquidity management, and payouts. Stated uses of funds turn out to be tightly linked to contractual form: bonds dominate long-term general-purpose financing, bridge loans are concentrated in acquisitions, revolvers in liquidity management, and term loans in distressed or event-driven financing. This classification lets us provide additional evidence on one important determinant of debt supply: the elasticity of substitution is higher when the different debt claims a firm issues serve different financing purposes. Importantly, this result is not driven simply by the number of contracts issued, but by the diversity of uses to which the funds are allocated. This evidence suggests that the shape of corporate debt supply curves depends in part on the variety of financing needs and investment opportunities available to the firm over a short horizon. When firms can direct different debt instruments toward different uses, they have greater scope to reallocate issuance across claims in response to changes in relative financing costs.

These elasticities matter for how financial shocks, and the policies that act on them, are transmitted. Quantitative easing, bank capital requirements, liquidity regulation, and other microprudential policies generally do not move a single cost of debt uniformly; they change the relative prices of different financial claims. How much these interventions, or any shift in investor demand or bank lending, move asset prices therefore depends on how elastically firms reallocate issuance across contracts and markets. Whatever the corporate sector does not absorb through its issuance must show up elsewhere: in risk premia, in non-price terms such as covenants or collateral requirements, or in the portfolios of other investors. Our estimates show that, in the short run, firms absorb a substantial part of such relative shocks by adjusting the composition of their debt issuance.

Related literature and contribution. Our paper contributes to five strands of research. First, we contribute to the intermediary asset pricing literature, which establishes that constrained financial intermediaries are the marginal pricer of risk and that shifts in their balance sheet capacity drive fluctuations in risk premia ([Adrian and Shin, 2010, 2014](#); [He and Krishnamurthy, 2012](#); [Brunnermeier and Sannikov, 2014](#); [Adrian et al., 2014](#); [He et al., 2017](#); [He and Krishnamurthy, 2018](#); [Haddad and Muir, 2025](#)), and to the closely related demand-system agenda that formalises this logic as a system of downward-sloping asset demand curves ([Vayanos and Vila, 2021](#); [Greenwood and Vayanos, 2014](#); [Kojien and Yogo, 2019](#); [Kojien et al., 2024](#); [Kojien and Yogo, 2026](#); [Bretscher et al., 2025](#)). These literatures have measured the elasticity with which intermediaries and end investors rebalance their asset holdings in secondary markets. Our contribution is to measure the symmetric object on the liability side of the financial system: the elasticity with which firms change the claims they supply to financial markets. Whereas [Bretscher et al. \(2025\)](#) estimate the investor-side demand elasticity for corporate bonds, we estimate the issuer-side supply elasticity, which is the missing half of primary-market equilibrium. Our bond-market instrument operationalises the [Kojien and Yogo \(2019\)](#) logic directly on institutional holdings of corporate debt.

Within this strand, our paper is closest to work at the intersection of corporate finance and asset pricing that treats the supply of securities as a choice of the issuing firm. The closest existing estimate of issuer-side supply is [Siani \(2025\)](#), who uses revisions to issuance plans on the day of pricing in U.S. primary markets and finds that a 10 basis point lower credit spread raises the size of a bond issue by 1.6%, about -0.24 on the spread at our median bond spread. Our quarterly bond elasticities, -0.60 within the market and -0.59 for total issuance, imply about 3.8% for the same move, roughly two and a half times as much. The gap reflects the horizon: within the day a firm can only resize an issue it has already planned, whereas over a quarter it can also retime its issuance and reallocate it across instruments and markets. [Mota and Siani \(2026\)](#) show that firms tailor the design of their bonds to particular investors, trading the lower cost of capital from catering to temporarily elevated demand against exposure to the least stable investors. Their firms choose *which securities to design* in response to investor demand; ours choose *how much to issue, and in which instrument and market*, in response to the prices that demand generates. They establish that bond supply responds to investor demand, and we measure how elastically it does so, in bank lending as well as in bonds.

Second, we contribute to the capital structure literature, which treats the firm’s mix of debt claims as the outcome of trade-offs among taxes, distress costs, agency frictions, and information asymmetries ([Leary and Roberts, 2005](#); [Flannery and Rangan, 2006](#); [Lemmon and Zender, 2010](#); [DeAngelo et al., 2011](#); [Graham et al., 2015](#); [DeAngelo, 2022](#)). The paper closest in spirit to ours is [Greenwood et al.](#)

(2010), which documents that firms *gap-fill* when the government changes the maturity of the debt it issues, supplying more of whatever maturity the government supplies less of. That is a supply response to a demand-driven movement in the relative price of two claims, recovered on one contractual margin and from one source of variation. We generalise the object: we estimate the same kind of response across the instruments of each market, across the bank–bond margin, and in the scale of issuance, identifying it from shifts in investor demand for corporate claims themselves. A complementary strand treats corporate debt as a heterogeneous basket of instruments with distinct contracting technologies (Rauh and Sufi, 2010; Colla et al., 2013; Choi et al., 2018; Colla et al., 2020; Lian and Ma, 2021). We build on this multi-instrument view of corporate debt structure and deliver the elasticities that govern its short-run recomposition in response to demand shifts.

Third, we contribute to the literature on the substitutability of bank credit and public bonds, and on the transmission of intermediary and investor capacity to corporate financing (Faulkender and Petersen, 2006; Leary, 2009; Becker and Ivashina, 2014; Kahle and Stulz, 2013; Crouzet, 2018; Grosse-Rueschkamp et al., 2019; Holm-Hadulla and Thürwächter, 2021; Darmouni and Mota, 2024; Fleckenstein et al., 2025). This strand treats loans and bonds as distinct contracting technologies and not as interchangeable funding sources. We supply the elasticity that governs movement between them, finding that firms *do* substitute across the bank–bond margin, which is not obvious if the two are genuinely distinct technologies. But they do so less readily than they substitute within either market: the cross-market elasticity is 0.41 against within-market elasticities of 0.79 in syndicated lending and 0.60 in bonds, so movement between the two markets runs at roughly 50–70% of the rate of movement inside them. The gap is itself evidence of the distinctiveness this literature emphasises.

Fourth, our loan-side identification follows the within-firm, across-lender logic of Jiménez et al. (2012) and the Amiti and Weinstein (2018) decomposition of bilateral relationships into supply and demand components, applied to bank lending as in Chodorow-Reich (2014), Acharya et al. (2018), Bräuning and Ivashina (2020) and Ivashina et al. (2022). In those papers the estimated bank–time fixed effect is the outcome of interest, a measure of the credit supply a bank withdraws. We use it instead as an instrument for the price at which a firm can place debt. Our bond-market instrument extends Zhu (2021) from aggregate mutual-fund flows to granular cross-sectional variation in institutional portfolio weights. It is closest in spirit to Kubitzka (2026), who shifts demand for a firm’s bonds through premium inflows at the insurers that already hold them, and shows that firms respond by issuing more bonds and investing the proceeds. His shifter varies across firms, whereas ours varies across segments of comparable bonds, and therefore across the claims a single firm issues in the same quarter; this is what allows us to measure how firms recompose their issuance, and not only

how much of it they place.

Finally, a large literature traces the pass-through from credit supply shocks to real activity ([Chodorow-Reich, 2014](#); [Acharya et al., 2018, 2019](#); [Alfaro et al., 2021](#); [Gilchrist and Zakrajšek, 2012](#); [Chakraborty et al., 2020](#)), predominantly identifying from severe episodes such as crises, sovereign stress, or regulatory shocks. Our exercise is complementary on both counts. Where that literature identifies from sharp contractions in the supply of capital, we identify from continuous variation in it in normal times; and where it measures the response of the activity those claims finance, we measure the response of the claims themselves.

Bringing these strands together, our contributions are: (i) two complementary demand-side instruments that isolate variation in borrowing costs driven by investor portfolio rebalancing and by bank lending capacity, respectively; and (ii) a joint estimation of the within-market, cross-market and firm-level elasticities of corporate debt supply from a common pair of demand shifters.

Roadmap. [Section 2](#) describes the data and reports stylised facts on corporate debt issuance. [Section 3](#) develops the two asset demand shifters we use as instruments. [Section 4](#) states each specification and reports its estimates, taking the three margins in turn, within-market substitution, substitution across the bank–bond margin and the scale of issuance, and then asking how the elasticity varies with the uses a firm’s borrowing funds. [Section 5](#) concludes.

2 DATA AND DESCRIPTIVES

This section describes the different data sources that we use in our empirical analysis.

2.1 Corporate Debt Issuance and Holdings Data

Our analysis relies on a comprehensive set of data sources that capture firm-level financing and investor behavior across both bank-based and market-based channels. Our main datasets span three categories: (i) syndicated loan origination, (ii) corporate bond issuance, and (iii) institutional investor holdings of debt securities.

Syndicated Loan Data. We retrieve the origination of broadly syndicated loans worldwide from *Dealscan*. These loans are structured as credit facilities at the borrower–syndicate–tranche level,

where each syndicate consists of a group of banks partaking in distinct tranches, including lead arrangers and participant institutions. This dataset captures activity in the *primary market* for syndicated loans and will be used to analyze the supply of credit assets.

Corporate Bond Issuance. We retrieve information on the corporate bond issuance from *LSEG* (formerly Refinitiv), which covers corporate securities globally, providing detailed information on the issuer, security characteristics, and issuance terms. This dataset represents the *primary market* for market-based debt financing, and is used to analyze the supply of corporate bonds.

Institutional Investor Holdings. We retrieve information on the bond holdings of institutional investors worldwide from *Lipper* (which belongs to LSEG). This dataset provides granular information on the holdings of mutual funds and ETFs across a wide range of fixed income securities. This dataset captures the *secondary market* for corporate debt and will be used to analyze the demand side of corporate bonds, which will be crucial for our instrumental variables strategy to identify demand-driven variation in corporate bond prices.

Measuring the Credit Spread on a Bond. The two markets record the cost of borrowing in different units. Dealscan reports the spread that a syndicated tranche pays over its reference rate, so a loan enters our analysis already expressed as a credit spread. LSEG reports the coupon that a bond pays, and a coupon bundles together the risk-free term structure of the currency of issue and the credit risk compensation that investors require. The mismatch is not only across markets but inside the bond market itself: when a firm places a three year note and a twenty year bond in the same quarter, the two coupons can be very different even when investors require identical credit compensation on both, because each coupon embeds the risk-free rate at its own maturity. We therefore express the cost of every bond as a credit spread over a par interest rate swap curve matched to the currency, maturity and issue date of the security.¹

¹We prefer the swap curve because syndicated loans are priced off the interbank curve, so the same benchmark places both markets on a common footing; government bond curves, which cover thirty-four currencies against seventeen, serve as a robustness variant. Fixed coupon bonds are benchmarked at their own maturity and floating and variable coupon issues at the short end of the same curve, since they reset off a short reference rate; the latter are 6.1 percent of the bond estimation sample. Two limitations follow. First, both curve sets stop at ten years, so any term premium beyond that point stays inside the measured spread. Second, our logarithmic specification requires a strictly positive spread, so we drop the 10.6 percent of benchmarked issues whose spread falls at or below ten basis points; loan spreads are recorded directly, and fewer than 0.2 percent of tranches fall that low.

2.2 Sample Composition and Descriptive Statistics

The panel runs quarterly from 2000 to 2023, with syndicated lending covering the full window and corporate bonds entering from 2007.¹ The unit of observation is the individual contract, that is, a single security on the bond side and a single tranche on the syndicated loan side, and a contract enters the analysis only if it carries an issuance amount, a price, and a non missing demand shifter in its own market. We impose no screen on firm size. The firms in our sample are nonetheless large by nature: a firm must already be sizeable to reach a syndicate of banks or a book of institutional bond investors.

The syndicated loan sample holds 50,154 observations on 4,323 firms, and the corporate bond sample holds 72,594 issues on 4,974 firms. Note that these are the samples on which the elasticities are estimated, and not all corporate debt issuance, which is several times larger. The gap arises for three reasons: a contract enters only where its market's demand shifter exists, where its price is measurable, and where the firm-quarter it belongs to supplies a comparison that the fixed effects do not absorb. Throughout this section we give priority to the variation that identifies our estimates over the variation that describes the market as a whole.

Figure 1 plots the annual dollar flow of corporate bond issuance and syndicated loan origination on the full issuance panel from which our two samples are drawn. Both primary markets grew several times over the window: combined issuance rises from 1.7 USD trillion in 2000 to a peak of 8.3 USD trillion in 2021, and stands at 6.3 USD trillion at the end of the sample. The two series move broadly in parallel, but they diverge visibly around credit cycle episodes. Between 2007 and 2009 syndicated loan origination falls from 3.0 to 1.7 USD trillion, and in 2020 it falls from 3.4 to 3.0 USD trillion, while corporate bond issuance expands at both dates, from 1.2 to 2.0 USD trillion in the first episode and from 4.1 to 5.3 USD trillion in the second, so that the bond market absorbs a larger share of aggregate primary market activity at exactly the dates on which loan origination contracts. These aggregate reallocations across debt markets are the kind of shift that our empirical design measures at the level of the individual firm, and they motivate our decision to treat bond and loan supply as a joint system. The shaded region marks the years before 2007, over which the bond side instrument does not exist because Lipper coverage begins in that year; our bond market results therefore exploit only the portion of this series from 2007 onward.

¹This is because the bond asset demand shifter is built from the Lipper institutional holdings panel and that panel begins in 2007; the syndicated loan instrument is available throughout.

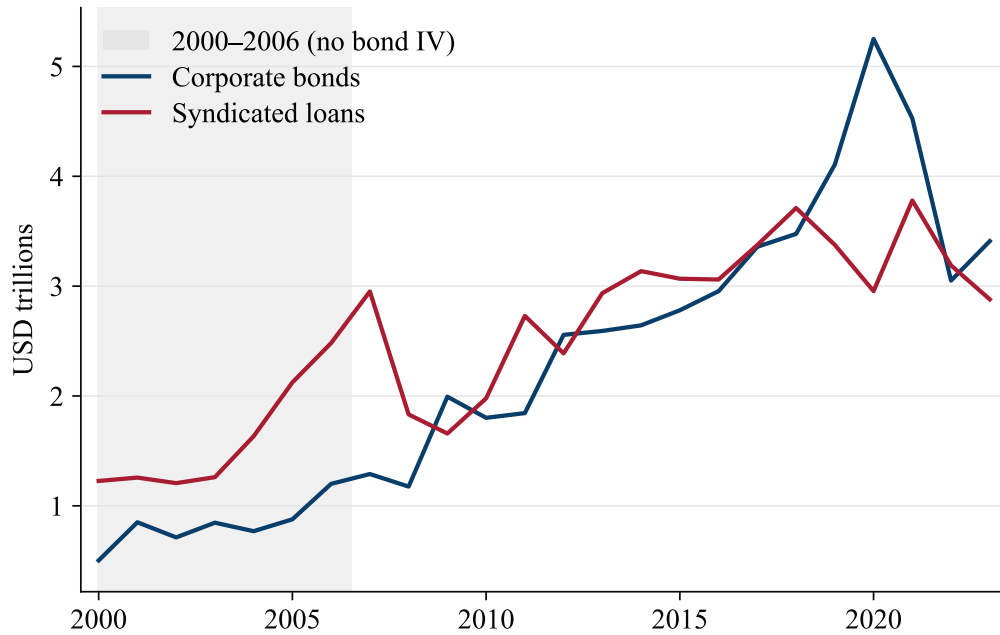


Figure 1. Annual corporate debt issuance, 2000 to 2023. The figure plots the aggregate annual dollar flow of corporate bond issuance (blue) and syndicated loan origination (red), expressed in USD trillions at issuance. Loan volumes are taken over distinct tranches. The shaded region marks the years before 2007, over which the bond asset demand shifter is not available because Lipper institutional holdings coverage begins in 2007. Sources: LSEG, Dealscan.

What identifies our estimates is not the full issuance panel but the comparisons it contains within a firm and a quarter. Each single-market sample holds several hundred firms a year: the loan sample is stable over the window, while the bond sample grows steadily after 2007 and overtakes it in 2013 (Figure A.1). In a typical quarter after 2010, 365 firms place at least two bonds and 170 firms sign at least two loan tranches, and these are the firm-quarters that identify the within-market elasticity once the firm-quarter fixed effect is absorbed (Figure A.2). Comparisons across markets are scarcer, since they require the same firm to place a bond and a loan in the same quarter. Our cross-market panel holds 2,728 such firm-quarters from 981 firms, or about 40 a quarter (Figure A.3). That is roughly three times the overlap of the two within-market samples, because the demand-driven cost index of Section 4.2 can also be built for firms that hold only a single contract on each side. The cross-market elasticity is therefore estimated on a broader set of dual issuers than the within-market samples alone would supply.

A premise of the within-market elasticity is that a firm faces a genuine menu of contractual forms inside each market, and in Figure 2 we document that menu for syndicated lending, plotting the annual share of aggregate dollar origination in the estimation sample accounted for by each of the main facility types. Term loans, in both their bank held Term Loan A and institutional Term Loan B

structures, and revolving credit lines of at least one year are the two dominant forms, and over the sample as a whole they are of almost equal size at 40 percent each, with 364 day facilities at 11 percent and bridge loans at 8 percent making up most of the remainder. The mix also moves substantially over time: the share of 364 day facilities falls from 33 percent in 2000 to 2 percent by 2010 and then recovers to 14 percent by the end of the sample, while bridge loans rise from 3 percent to a peak of 20 percent in 2017 before falling back.

This menu is what makes the within-market comparison possible, although it is not where most of the measured reallocation takes place. The firm-quarter fixed effect absorbs the firm's overall decision to tap the loan market in that quarter, leaving only the relative pricing of the contracts the firm signs at that date. As we show in [Section 4.1](#), most of the elasticity survives when we replace that fixed effect with a firm-quarter-type effect, which means that the bulk of the reallocation we measure occurs between contracts that share a facility type, and only a smaller part between one type and another.

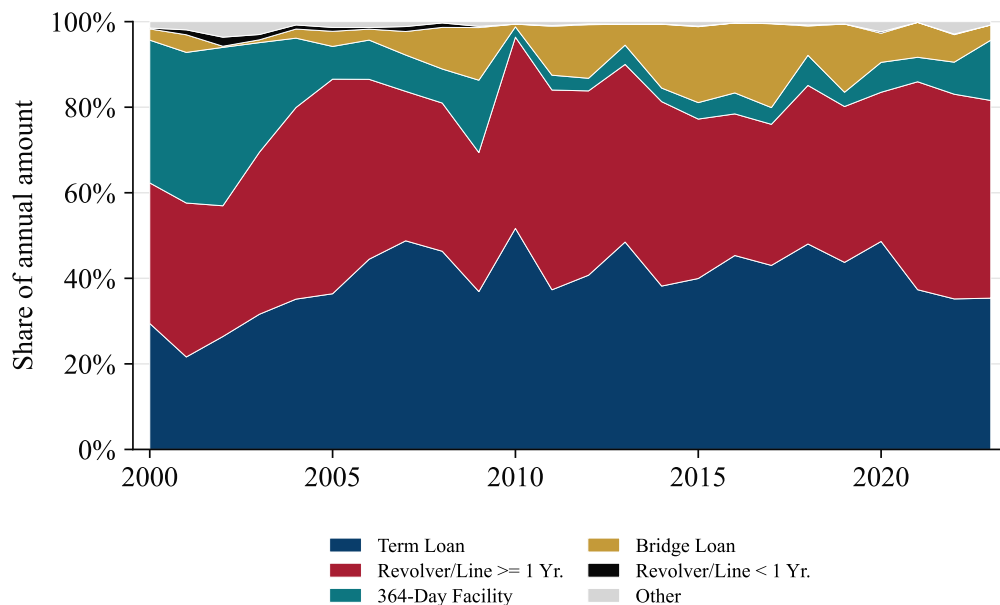


Figure 2. Syndicated loan composition by facility type. The figure plots the annual share of aggregate syndicated loan origination accounted for by each of the top five facility types; remaining facility types are pooled as Other. Shares are computed on the syndicated loan estimation sample, over distinct tranches, and not on the universe of origination. Source: Dealscan.

The menu of contractual forms is not the only dimension along which firms vary the contracts they sign in a quarter, and in [Figure 3](#) we characterise those dimensions inside the firm-quarter, separately for the two markets. The top two panels take the 21,349 bond and 18,485 loan firm-quarter cells of the estimation samples that hold at least two contracts, and report, for each contract attribute, the

share of cells in which that attribute takes more than one value. In the corporate bond market the dominant dimension is maturity: in 54 percent of cells the firm issues across more than one tenor bucket, against 9 percent for currency of denomination and 8 percent for coupon type. In syndicated lending the ordering is different: facility type is the modal dimension of variation, differing in 79 percent of cells, ahead of maturity at 45 percent and currency at 7 percent, while seniority, which is overwhelmingly senior in broadly syndicated packages, barely varies at under one percent.

This contrast is intuitive once we consider what each contract is. A corporate bond is a relatively standardised security, so the firm's principal design lever for liability management is its tenor. A syndicated loan, by contrast, is a bespoke credit facility. Its tranche type – revolver against term loan and bank held against institutional – encodes covenant, amortisation and distribution arrangements that are more contract-specific than the stated maturity. We stress that this is a statement about which contract terms firms vary, and it says nothing about how strongly firms respond to relative prices; as we show in [Section 4.1](#), the elasticities in the two markets cannot be rejected as equal.

The bottom panel reinforces this picture from the continuous side. It plots the empirical cumulative distribution of the within firm-quarter maturity range, that is, the difference between the longest and the shortest tenor among the contracts of a cell. The bond distribution dominates the loan distribution: the mean within cell maturity spread is 4.5 years for bonds against 1.3 years for loans, and the right tail of the bond distribution reaches beyond twenty years, reflecting the simultaneous issuance of short notes and long dated bonds to manage the term structure of liabilities. Roughly two fifths of bond cells and just under half of loan cells hold contracts of a single tenor. Taken together, the panels indicate that intensive margin variation in the bond market concentrates in maturity, whereas in syndicated lending it concentrates in contractual structure.

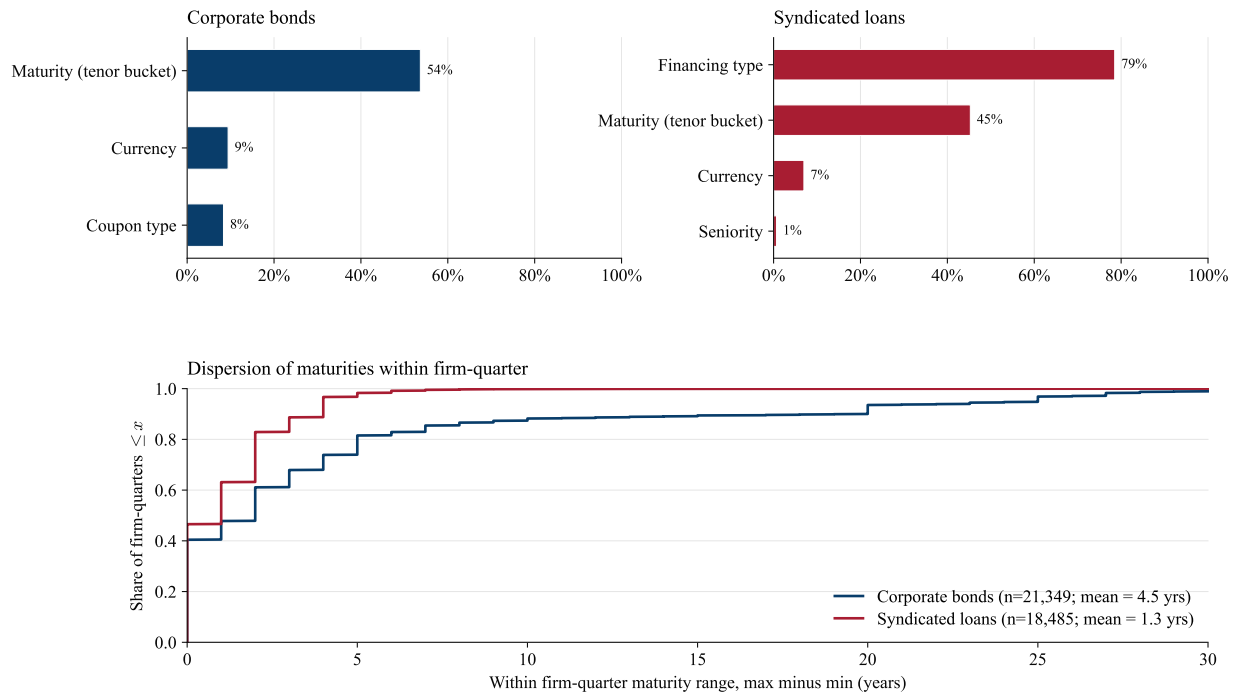


Figure 3. Within firm-quarter contract heterogeneity. The top panels take the firm-quarter cells of the two estimation samples holding at least two contracts of the same asset class, and report for each contract attribute the share of such cells in which the attribute takes more than one distinct value, separately for corporate bonds (left, blue) and syndicated loans (right, red). Maturity is bucketed into tenor bins (≤ 1 , 1 to 3, 3 to 5, 5 to 7, 7 to 10, 10 to 15, 15 to 20 and 20+ years). The bottom panel plots the empirical cumulative distribution of the within firm-quarter maturity range, the difference between the maximum and the minimum tenor across contracts in the same cell, overlaying the two markets; dashed lines mark the sample means. All panels are computed on the estimation samples and not on the universe of issuance. Sources: LSEG, Dealscan.

Table 1 provides summary statistics of our sample. Panel A reports its composition, again on the two estimation samples. The 50,154 loan observations cover 34,444 distinct tranches; in the bond market an observation is itself a security, so the distinction does not arise. Across the two markets the samples hold 122,748 contracts on 7,839 firms, of which 1,458 appear in both. Panel B shows that the two markets are broadly comparable in the contracts they price. The median loan pays 200 basis points over its reference rate against 149 basis points of credit spread for the median bond, both at a median maturity of five years and a median size close to 200 USD million, but the bond distribution is the wider of the two on both sides: its interquartile range of spreads runs from 73 to 309 basis points against 125 to 300 for loans, and its upper quartile of maturity reaches eight years against five. Panel C reports the coverage of the inputs to construct credit spreads, whereby a recorded maturity and yield are available for 95.2 percent of bond issues and 80.1 percent of loan tranches.

TABLE 1. Summary statistics

	Syndicated Loans			Corporate Bonds		
<i>Panel A: Sample composition</i>						
Contracts	50,154			72,594		
Distinct tranches	34,444			-		
Distinct firms	4,323			4,974		
Firm-quarter cells	18,485			21,349		
Amount at issue, sum (USD tn)	21.9			28.6		
Amount at issue, sum over distinct tranches (USD tn)	14.8			-		
First quarter	2000Q1			2007Q1		
Last quarter	2023Q4			2023Q4		
Contracts, both markets				122,748		
Distinct firms, both markets				7,839		
Firms present in both samples				1,458		
Firm-quarter cells, both markets				38,863		
Amount at issue, sum, both markets (USD tn)				50.5		
<i>Panel B: Contract characteristics</i>						
	25th	Median	75th	25th	Median	75th
Credit spread (bp)	125	200	300	73	149	309
Maturity (years)	3.0	5.0	5.0	3.0	5.0	8.0
Amount at issue (USD m)	52.1	165.0	450.0	67.7	201.5	501.0
<i>Panel C: Price construction coverage</i>						
Contracts with a recorded maturity and a yield (%)	80.1			95.2		
Non fixed coupon contracts (%)	-			6.1		
Benchmarked issues at or below the 10bp floor (%)	-			10.6		

All three panels are computed on the two within-market estimation samples, not on the universe of corporate debt issuance. The unit of observation is a single security in the bond market and a single tranche in a single quarter in the syndicated loan market, so a tranche carried across several quarters enters once per quarter; the two tranche rows are blank for bonds, where an observation is itself a security. Amounts are the principal raised, converted to US dollars at issue, and rows spanning both markets are taken on the union of the samples, so a firm active in both is counted once. In Panel B the loan price is the contractual spread over the reference rate and the bond price the credit spread over the par swap curve; maturity is the contractual maturity at issue. The last row of Panel C reflects the selection rule rather than the sample: the logarithmic specification requires a spread above ten basis points, so the share is zero within the bond estimation sample by construction, and the figure reported is the share of the 111,156 benchmarked rows before the floor is applied.

2.3 Use of Funds Data

We complement our data on the issuance of corporate debt with information on the stated use of funds. To our knowledge, no commercial dataset systematically tags individual bond and loan facilities with the underlying purpose of the proceeds. For each financing in our sample we deploy a multi-agent AI system equipped with online search tools, which retrieves, ranks and synthesises evidence from news articles, earnings call transcripts, press releases, regulatory filings and annual

reports around the issuance date. We instruct the agent to identify the issuer through the security identifier and the firm name, to search exhaustively across these sources, and to return a structured classification together with a free text summary of the evidence it relied on. The classification covers seven non exclusive purpose categories (mergers and acquisitions, capital expenditure, growth or expansion, innovation, refinancing, liquidity management, and shareholder returns), as well as two contextual flags for distressed and bridge financings; only the seven purpose categories define a contract’s use in what follows. When the agent cannot locate credible evidence for a given financing, all flags are set to false and the summary documents the absence of information, so that the data layer never silently imputes a purpose. The full prompt and classification protocol governing the agent are reproduced verbatim in [Section B.2](#).

The coverage of this classification is informative. Roughly 37 percent of syndicated loan contracts and 39 percent of bond issues in the estimation samples carry at least one purpose flag; for the remainder the agent could not locate credible evidence, and those contracts play no part in the analysis of [Section 4.4](#). Classified contracts are larger than average, so coverage in dollar terms is considerably higher, at 59 percent of syndicated lending and 61 percent of bond issuance. Among classified contracts, about two thirds carry more than one flag, and the average contract carries a little over two.

This overlap shapes how we define a contract’s use. Because a single financing frequently funds more than one thing, we do not treat the seven flags as separate categories; instead, we take a contract’s *use* to be the exact combination of purposes it states, so that a contract raised for both an acquisition and refinancing carries one use combining the two, and does not enter as two half uses. Uses defined in this way do not overlap and are exhaustive. 93 distinct combinations appear across the two estimation samples, out of 127 possible, with 71 in syndicated lending and 89 in corporate bonds. The combinations are concentrated: refinancing together with liquidity management accounts for 20 percent of classified contracts, refinancing alone for a further 17 percent, and liquidity management alone for 12 percent, and the five most common combinations cover between 55 and 64 percent of each market.

For each firm-quarter we then measure the variety of uses that its borrowing serves,

$$V_{i,t} = 1 - \sum_j p_{i,t}(j)^2, \quad (1)$$

where $p_{i,t}(j)$ is the share of firm i ’s contracts in quarter t carrying use j . In other words $V_{i,t}$ is the probability that two contracts drawn at random from that quarter serve different uses: it is zero

when they all serve the same use, and one half when the quarter is split evenly between two.

In [Figure 4](#) we report the distribution, across firm-quarters, of the variety of uses that results. The distribution is close to binary, because the median firm-quarter holds two contracts. In syndicated lending 51 percent of firm-quarters serve a single use and a further quarter are split evenly between two, with ca. half of loan contracts sitting in a quarter in which variety is strictly positive. In corporate bonds the mass at a single use is much heavier, at 90 percent of firm-quarters, and just under a quarter of bond contracts sit in a quarter with positive variety. The bond side of that comparison is therefore identified from a distinctly smaller part of its sample than the loan side.

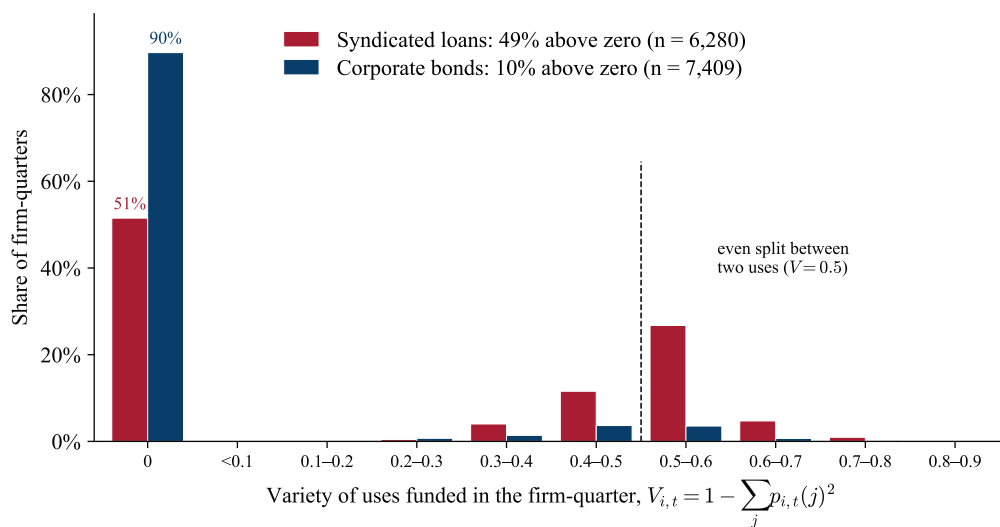


Figure 4. Distribution of the variety of uses funded, by market. The figure plots the distribution across firm-quarters of $V_{i,t}$ in Equation (1), the probability that two contracts drawn at random from a firm's borrowing in that quarter serve different uses, for syndicated lending (red) and corporate bonds (blue). A contract's use is the exact combination of purposes it states. The leftmost bar is the point mass at zero, where every contract in the quarter serves the same use; the dashed line marks one half, the value of a quarter split evenly between two uses. Computed on the estimation samples of [Section 4.4](#) and not on the universe of issuance. Sources: LSEG, Dealscan; AI classified use of funds.

In [Figure 5](#) we turn to what the debt funds over time, reporting the annual dollar volume of issuance carrying each purpose flag, separately for the two markets because the bond sample begins only in 2007. The comparison shows that the two markets fund different activities. In syndicated lending, liquidity management is the largest single purpose over the sample at 5.4 USD trillion, ahead of refinancing at 4.6 trillion and acquisitions at 3.9 trillion, while capital expenditure, at 1.1 trillion, is a minor use of syndicated credit. In corporate bonds the ordering differs: refinancing dominates at 12.6 USD trillion, which is more than a third of purpose tagged bond dollars, followed by liquidity management at 7.6 trillion, acquisitions at 4.9 trillion and growth at 4.6 trillion. Capital expenditure takes a larger share of bond issuance than of syndicated lending, although it remains under a tenth

of it, and debt raised explicitly to fund payouts or innovation is small in both markets. Liquidity management shows a sharp level shift around the 2020 shock in both markets, when firms raised precautionary debt against the sudden stop in revenues, and distressed financings cluster around the 2008 and 2020 episodes while remaining an order of magnitude smaller than the other categories in normal times.

We record one feature of these volumes explicitly, because it bears on how our elasticities should be read. Debt raised to rearrange the existing liability structure, whether by refinancing maturing debt or by managing liquidity, is the majority of purpose tagged issuance in both markets. In other words, the marginal contract in this sample is more often a balance sheet transaction than a claim on new investment, and this is one reason why the composition of borrowing can respond to relative prices at a horizon over which real investment does not.

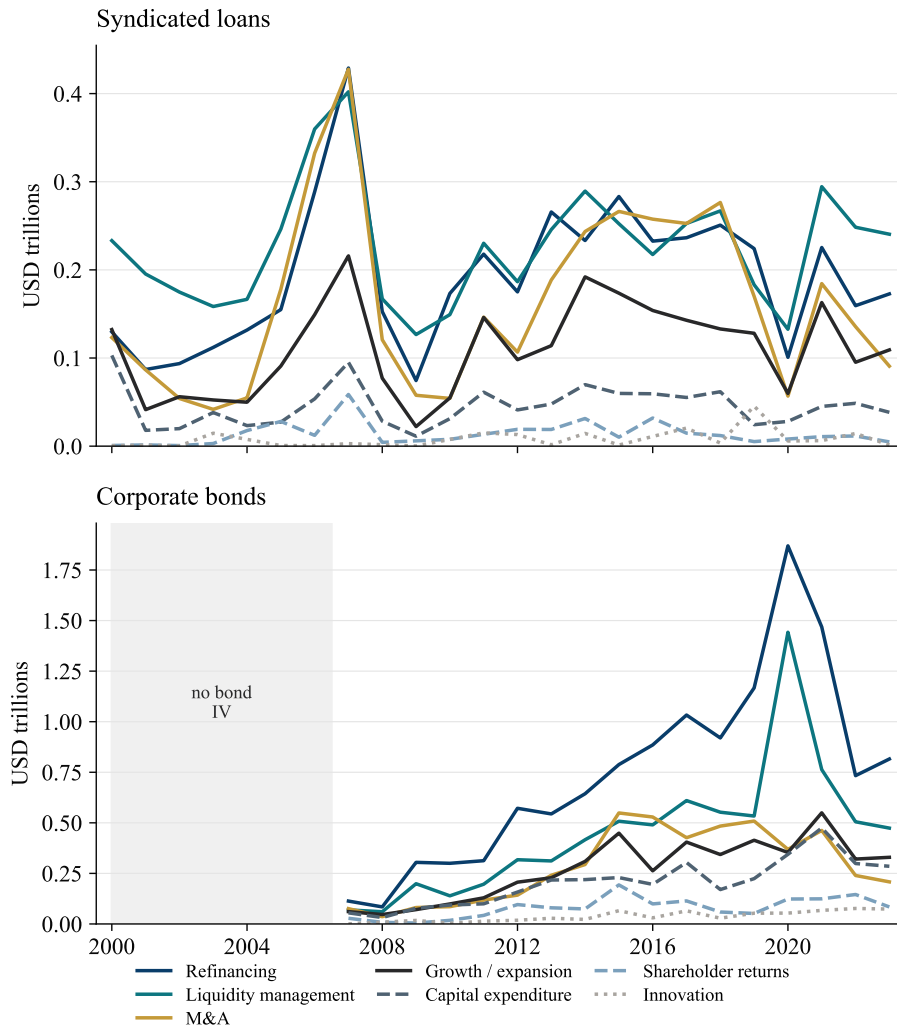


Figure 5. Annual debt issuance by stated use of funds. The figure plots the annual dollar volume of debt issuance carrying each of the seven AI classified purpose flags, separately for syndicated lending (top) and corporate bonds (bottom), on the two estimation samples rather than on the universe of issuance. The series are not mutually exclusive, since a single contract can state several purposes. The bond panel begins in 2007 and its shaded region marks the years over which the bond asset demand shifter does not exist. Loan volumes are taken over distinct tranches. The underlying classifications are produced by the AI system described in this section and detailed in [Section B.2](#). Sources: LSEG, Dealscan; AI classified use of funds.

The time series in [Figure 5](#) report how many dollars each purpose absorbs, but they do not tell us *which* financing instruments absorb those dollars. We therefore ask whether the instrument chosen by the issuer is informative about the underlying use of proceeds, or whether bonds, term loans, revolvers, bridge loans and short term facilities are drawn from a common pool that funds every purpose in the same proportions. The second possibility gives us a natural benchmark: if instrument choice and stated use of funds were statistically independent, the contractual technology would be

neutral with respect to the economic task it finances, and the same mix of instruments would fund capital expenditure, refinancing, and liquidity buffers alike. As we show below, the data reject this benchmark sharply.

To quantify the association, we compute, for each stated use of funds p and financing instrument f , the within purpose dollar share

$$s_{f|p} = \Pr(\text{instrument} = f \mid \text{purpose} = p) = \frac{A_{f,p}}{\sum_{f'} A_{f',p}}, \quad (2)$$

where $A_{f,p}$ is the total dollar volume of contracts of instrument f carrying purpose flag p . By construction the shares $s_{f|p}$ sum to one within each purpose. Under the null of independence between instrument and stated use of funds, $s_{f|p}$ would equal the unconditional market share s_f of instrument f for every purpose p . We therefore report the ratio $s_{f|p}/s_f$, the factor by which an instrument is over or under represented in a purpose relative to the market as a whole, which equals one under the null.

The reason we report the departure from the market share, and not the level of the share itself, is the asymmetry in market size. Corporate bonds account for three quarters of the dollars in our estimation samples, at 74.6 percent against 10.9 for term loans, 10.1 for revolvers, 2.6 for bridge loans and 1.5 for 364 day facilities. Bonds are consequently the largest instrument inside every purpose, so the ranking within any single purpose mostly restates the size of the bond market; the association between contract and task shows instead in how far each purpose departs from that common baseline.

In [Figure 6](#) we report these ratios for the eight classified flags and the six largest instrument buckets. The departures from the independence benchmark are large, and they line up with the contractual logic of each instrument. Bridge loans are 3.7 times over represented in acquisitions, consistent with their institutional role of providing certainty of funds at announcement, funding that is later refinanced through permanent bond or loan issuance after closing ([Kahl et al., 2015](#)). Committed credit lines concentrate in liquidity management: 364 day facilities are 2.6 times and revolvers 2.1 times over represented there, in line with the contractual fit between a committed line and a precautionary need. Term loans are 1.6 times over represented in acquisitions and in distressed borrowing alike, consistent with the comparative advantage of relationship lenders in renegotiation intensive situations ([Qian and Strahan, 2007](#)). Corporate bonds, by contrast, sit close to their market share in every purpose, tilting only mildly towards payouts, capital expenditure and innovation, which is what we expect of the general purpose long term funding instrument.

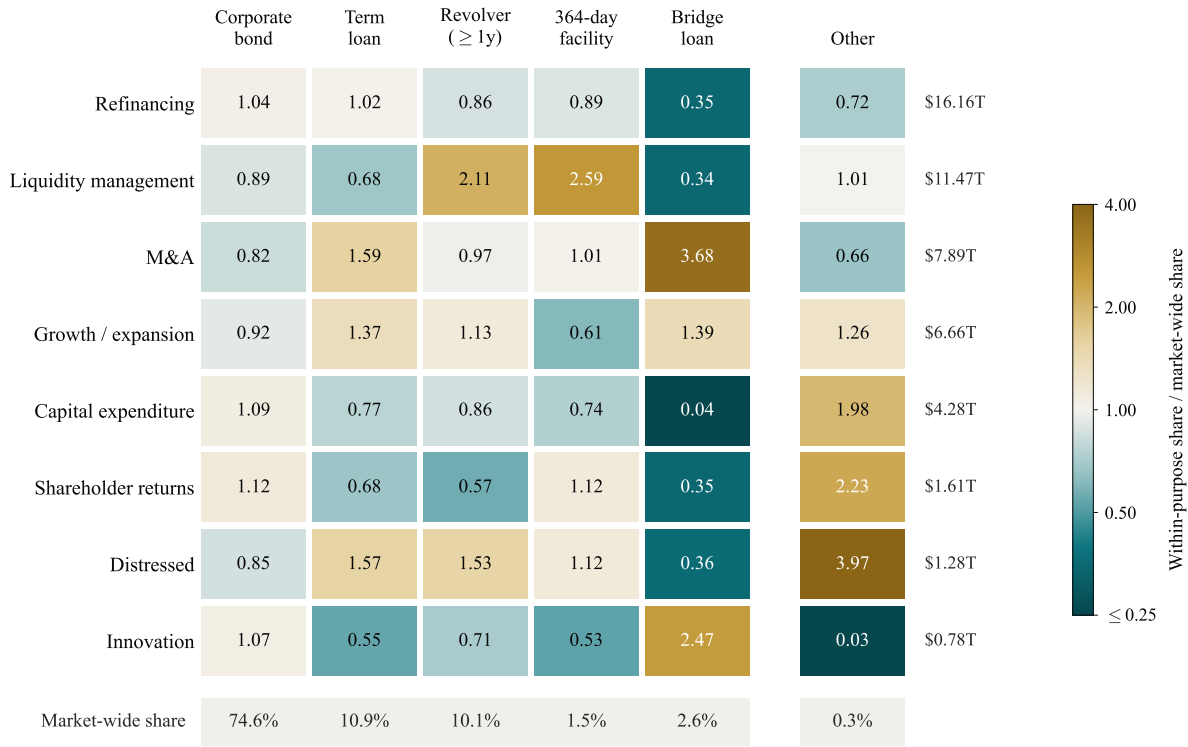


Figure 6. Over and under representation of financing instruments within each stated use of proceeds. The figure reports the ratio $s_{f|p}/s_f$ of the within purpose dollar share defined in Equation (2) to the same instrument’s market-wide dollar share, for each of the eight AI classified flags and the six largest instrument buckets. A value of one means the instrument funds that purpose in the same proportion as it funds the market as a whole, and departures from one are the signature of an association between contractual technology and the economic task it finances. Computed on the two estimation samples over the common 2007 to 2023 window, with loan volumes taken over distinct tranches. The instrument categories are corporate bonds, term loans, revolvers with maturity of at least one year, 364 day facilities, bridge loans, and all remaining instruments pooled in an “Other” category. Sources: LSEG, Dealscan; AI classified use of funds.

Read jointly, the departures across the rows of Figure 6 establish that the stated use of funds and the financing instrument are strongly dependent in the corporate debt market. The departures form a coherent map of contractual specialisation, and are not idiosyncratic noise around a common unconditional mix: bridge loans finance acquisitions, revolvers and 364 day facilities finance liquidity, term loans finance distressed and event driven transactions, and bonds provide the general purpose long term funding behind capital expenditure, innovation and refinancing. This specialisation matters for our purposes because it ties each contract to the task it finances. A firm whose borrowing in a quarter serves a single use is typically executing one committed transaction, and that task largely dictates the instrument and the size. A firm funding several uses at once can choose which of them to fund now, in what size and through which contract, and so has more room to tilt its borrowing towards whichever claim has become relatively cheap. This is the hypothesis we take to the data in

Section 4.4, where we ask whether a firm’s within-market elasticity rises with the variety of distinct uses its borrowing serves in a quarter.¹

3 EMPIRICAL STRATEGY

Identifying corporate debt supply elasticities requires isolating variation in borrowing costs driven by shifts in investor demand for corporate debt rather than by firms’ own borrowing decisions. We construct two *asset demand shifters*, one per market, and refer to the variation they isolate as *demand-driven*. The label is immediate for bond markets, where the marginal holder of the security is an investor choosing a portfolio, so that a shift in the willingness to hold corporate bonds *is* a shift in asset demand and requires no translation. For syndicated loans it follows from the same logic: banks’ lending capacity reflects either their ability to hold loans on balance sheet, itself a form of asset demand, or their capacity to distribute loans to institutional investors. Any shift in financing conditions that does not come from firms’ borrowing decisions must therefore, directly or indirectly, reflect a shift in the demand for those assets.

3.1 BOND MARKETS: INVESTOR PORTFOLIO REBALANCING

Shifts in institutional investor demand manifest as changes in portfolio allocation across bond segments. A stylized mean-variance framework, formalized in Appendix C.1, shows that with heterogeneous, specialized investors who price risk using a small number of common factors, demand for a portfolio of *comparable debt securities* $\mathcal{B}$ – securities sharing issuer country, rating, coupon type, currency, maturity year and industry, viewed as close substitutes (Haddad et al., 2026; Chaudhary et al., 2025) – has an approximately low-rank structure: latent portfolio factors $x_k(\mathcal{B})$ summarize common risk characteristics, and investor-specific loadings λ_{ik} summarize each investor’s sensitivity to those factors.² By the law of one price, a new security comparable to $\mathcal{B}$ must be priced relative to that portfolio, so latent factors extracted from secondary-market holdings summarize the marginal will-

¹We take the specialisation documented here to the data through the *variety* of uses a firm funds in a quarter, rather than through the individual uses themselves. Estimating a separate elasticity for each use would require a firm to place several contracts of the same asset class, in the same quarter, all carrying the same purpose combination, and the classified sample is too thin at that level to support it: we lack the power to say whether the elasticity differs for, say, acquisitions against liquidity management.

²While demand for individual securities also admits a low-rank representation, we work with portfolios of comparable securities so that secondary-market data can proxy for the supply of capital available to a new, similar primary-market issuance.

ingness of investors to absorb additional risk in comparable bonds.¹

Proposition 1. Asset-demand shifter from bond markets. *Let n be a new security issued in primary markets, which is comparable to the set of securities $\mathcal{B}$ in secondary markets. We define:*

$$z_t(n) = \sum_i a_{i,t-1} \hat{w}_i(\mathcal{B}) = \sum_i a_{i,t-1} \sum_{k=1}^r \lambda_{ik} x_k(\mathcal{B})$$

where $\hat{w}_i(\mathcal{B})$ is the demand for the portfolio of comparable bonds at time t that is explained by common factors, $a_{i,t-1}$ is the investor weight on total holdings of bonds in $\mathcal{B}$ in period $t - 1$. The demand shifter $z_t(n)$ captures the aggregate willingness of investors to absorb additional risk in comparable bonds at time t . The **exclusion restriction** requires that $z_t(n)$ is independent of firms' financing needs.

Instrumental Variables We construct the empirical analog to $z_t(n)$ from the Lipper holdings panel as follows. Each quarter, we compute investor portfolio weights $w_{j,t}(n) = V_{j,t}(n) / \sum_{n'} V_{j,t}(n')$ across bond types, standardize each bond type column to zero mean and unit variance across investors, and extract the leading $K = 65$ principal components.² The fitted portfolio weight $\hat{w}_{j,t}(n)$ is the projection of $w_{j,t}(n)$ onto these components, capturing the systematic component of each investor's allocation while stripping out idiosyncratic variation. The demand shifter is the aggregate fitted dollar demand,

$$Z_t^{\text{bond}}(n) = \sum_j A_{j,t} \cdot \hat{w}_{j,t}(n),$$

where $A_{j,t} = \sum_{n'} V_{j,t}(n')$ is investor j 's total assets under management.

Two features of this construction support the exclusion restriction. First, the shifter never sees the issuer: it is built entirely from institutional holdings of the segment $\mathcal{B}$ in the secondary market, weighted by investor size, so the identity, the characteristics and the financing needs of the firm coming to market enter nowhere, and any single issuer's own bonds are a negligible share of the segment they belong to. Second, projecting each investor's weights onto the leading principal components retains the systematic component of how that investor allocates across segments and discards the idiosyncratic residual, including any position taken because of one particular issuer. What remains is the willingness of investors as a group to hold the segment, measured before the new security is placed.

¹This reflects the common practice of pricing new issues against secondary-market comparables during the investor roadshow. [Zhu \(2021\)](#) uses a similar logic in aggregating flows from a firm's existing bond holders.

²Within-segment standardization ensures that the PCA captures variation in how investors shift their relative allocation across segments, not level differences in the size of bond categories. The partition described above divides the universe into roughly thirty thousand segments.

The fixed effects of our within-market specification then narrow what has to be assumed. The firm-quarter-asset-class effect absorbs the firm’s borrowing need, its credit quality and its investment opportunities at that date, and the currency by quarter effect absorbs conditions common to the bond market of that currency in that quarter. What remains to be assumed is therefore considerably weaker than exogeneity of investor demand as such: it is enough that, among the segments into which a single firm issues in a given quarter, relative fitted demand be unrelated to that firm’s relative willingness to place debt in one segment rather than another. Common credit news, shifts in aggregate risk appetite and the state of the market as a whole reach the firm at that date, and are absorbed before they can bias the estimate; what would remain is a shock that moved investor demand differentially across the very segments a single firm issues into within one quarter.

3.2 SYNDICATED LOAN MARKETS: BANK LENDING CAPACITY

Our instrument exploits the multi-lender structure of bank syndicates: the same bank participates in loans to many different borrowers within a quarter, allowing bank-specific lending conditions to be disentangled from borrower demand. Following [Amiti and Weinstein \(2018\)](#), we estimate at the bank-borrower-tranche-quarter level on the Dealscan universe,

$$\log(\text{spread}_{b,i,t}(n)) = \alpha_{i,t} + \gamma_{b,t} + \delta_{b,i} + \phi_{n,t,c} + \varepsilon_{b,i,t}(n), \quad (3)$$

where b indexes lenders, i indexes borrowers, t indexes quarters, n indexes tranche types, and c indexes currencies. The specification includes four sets of high-dimensional fixed effects. Firm-time fixed effects $\alpha_{i,t}$ absorb all time-varying borrower characteristics, including investment opportunities, credit risk, and business cycle exposure. Bank-time fixed effects $\gamma_{b,t}$ capture each lender’s time-varying supply conditions. Bank-firm fixed effects $\delta_{b,i}$ absorb persistent relationship-specific pricing, such as information rents from repeated lending relationships. Tranche type by quarter by currency fixed effects $\phi_{n,t,c}$ control for aggregate market conditions specific to each loan segment and denomination.

Lead banks arrange the syndicate, negotiate terms, and monitor the borrower, so their pricing reflects relationship rents that are firm-specific; participant banks play a more passive capital-providing role. We therefore aggregate $\hat{\gamma}_{b,t}$ to the tranche level using only non-lead syndicate members, weighted by

their lending shares.¹

Proposition 2. Asset-demand shifter in syndicated loan markets. Let $\hat{\gamma}_{b,t}$ denote the estimated bank-time fixed effect from equation (3). We define the tranche-level loan demand shifter as:

$$z_{lt} = \sum_{b \in \mathcal{B}_{lt}} \omega_{b,lt} \hat{\gamma}_{b,t} \quad (4)$$

where $\mathcal{B}_{lt}$ is the set of participant banks in tranche l at time t and $\omega_{b,lt}$ is bank b 's share in the total lending amount. The demand shifter z_{lt} aggregates time-varying pricing behavior of passive syndicate members, weighted by their lending contribution. The **exclusion restriction** requires that z_{lt} is plausibly exogenous to firm-specific loan demand.

Instrumental Variables After absorbing borrower demand through $\alpha_{i,t}$, relationship premia through $\delta_{b,i}$, and segment-level conditions through $\phi_{n,t,c}$, the bank-time fixed effect $\hat{\gamma}_{b,t}$ captures the bank's residual propensity to price loans in a given quarter, reflecting capital adequacy, liquidity conditions, deposit dynamics, regulatory pressures, or internal risk appetite. The tranche-level instrument is the amount-weighted average across non-lead syndicate members,

$$Z_{i,t}^{\text{loan}}(l) = \sum_{b \in \mathcal{B}_{lt}} \omega_{b,lt} \hat{\gamma}_{b,t}.$$

The exclusion restriction rests on where this variation comes from. A bank's fixed effect is identified from the many borrowers it lends to in the same quarter, with each of *their* firm-time effects netted out, so $\hat{\gamma}_{b,t}$ carries the bank's own supply conditions and not the demand of any one borrower; $\delta_{b,i}$ removes what is persistent in a given lending relationship, and $\phi_{n,t,c}$ removes conditions common to a loan segment and denomination. Restricting the aggregation to non-lead members sharpens this further: participants are brought into a syndicate by the lead arranger in order to place the paper, so which banks appear reflects the lead's distribution network rather than the borrower's own circumstances. Within a firm-quarter, two tranches therefore differ in $Z_{i,t}^{\text{loan}}$ only through the composition of the syndicates that fund them, the borrowing need itself having been absorbed.

Syndicates are of course matched rather than randomly assigned. Matching that persists between a bank and a borrower is absorbed by $\delta_{b,i}$ in the regression above and by the firm-quarter effect in the estimation that follows, so the restriction would fail only if, within a single quarter, a firm assembled

¹Syndicates in the loan estimation sample are granular: the median tranche carries eight participant banks, the interquartile range runs from five to fourteen, and only 0.8 percent of tranches are financed by a single lender (Figure A.4 in Appendix A). Because each bank lends alongside many others and to many borrowers within a quarter, lender-specific conditions can be separated from borrower-specific ones in the bank-time fixed effects.

systematically different syndicates across its own tranches for reasons correlated with how much it wished to borrow on each.

In [Figure 7](#) we provide a first visual assessment of the two shifters. We plot the credit spread a firm pays against the asset demand shifter of its market, residualising both variables on the fixed effects of our within-market specification, firm by quarter and segment by quarter, so that we compare the pricing of the contracts that the same firm signs at the same date. We orient both shifters so that a higher value corresponds to weaker investor demand. Weaker demand for a claim means that investors will pay less for it, and a lower price for a given stream of promised payments is precisely a wider credit spread, so the shifter and the spread should move together. They do: in both markets the spread rises with the shifter, and a one standard deviation movement widens it by 9.4 percent in syndicated lending and by 5.5 percent in corporate bonds. In other words, when the investors of a market become less willing to absorb its debt, the firms issuing in that market pay more for the claims they place at that date. The fitted lines correspond to the first stage regressions with which we instrument the relative price, and we report them in full in [Appendix D](#).

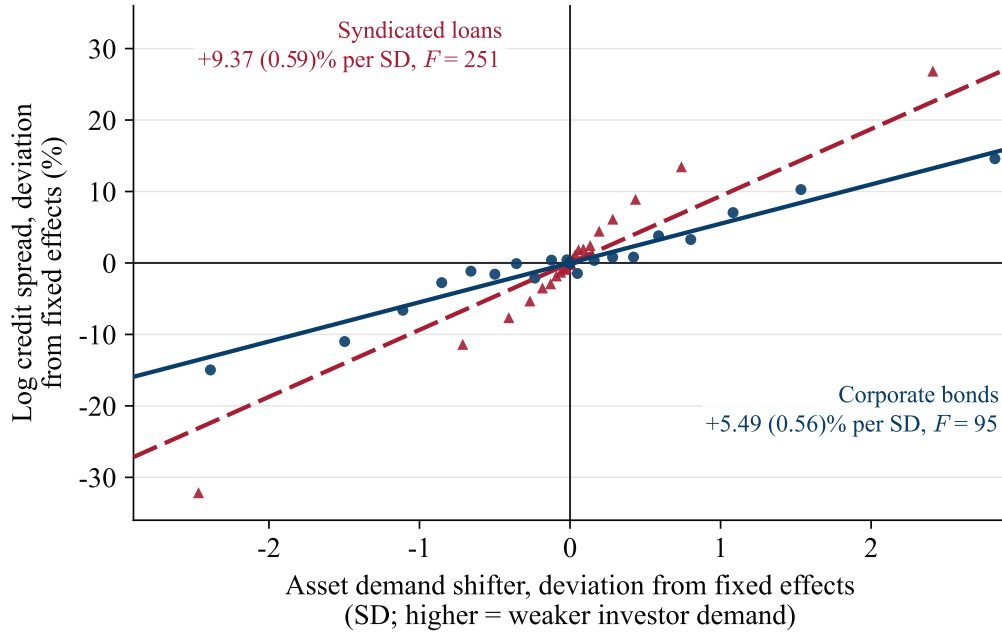


Figure 7. The asset demand shifters and the price of corporate debt. The figure plots binned means of the log credit spread against the asset demand shifter of the market, for syndicated lending (red) and corporate bonds (blue), on the two within-market estimation samples. Both variables are residualised on the fixed effects of the within-market specification: firm by quarter and financing type by quarter by currency in syndicated lending, firm by quarter and currency by quarter in corporate bonds. The horizontal axis is in standard deviations of the residualised shifter and the vertical axis in percent. Each market is split into twenty five equal count bins. Both shifters are oriented so that a higher value corresponds to weaker investor demand; the bond shifter measures fitted investor dollar demand, which is higher when demand is stronger, and is therefore multiplied by -1 to place it on the same orientation as the loan shifter. The fitted lines are the first stage coefficients reported in [Appendix D](#). Sources: LSEG, Dealscan, Lipper.

4 ESTIMATING THE SUPPLY OF CORPORATE DEBT

We specify a parsimonious reduced-form model for the quantity of corporate debt issued by firm i at time t as a function of the relative cost of borrowing across different financing types, each indexed by $n|a$, where a denotes the asset class (corporate bonds or syndicated loans) and n denotes the financing type (term loan, credit line, specific bond maturity, etc.).

This section reports the estimates of the specifications developed in [Section 3](#). Every coefficient we report is an elasticity with respect to the credit spread, the unit in which corporate debt is quoted in both of the markets we study, and this is the object we interpret throughout. For comparison with asset demand elasticities, which are defined on the price of the security, our tables also restate the leading estimates on the price of the claim; [Appendix E](#) derives that conversion. Standard errors are clustered at the firm level throughout, and where an estimate rests on a constructed price index we

report a pairs cluster bootstrap over firms.

4.1 WITHIN-MARKET SUPPLY ELASTICITY OF SUBSTITUTION

Within each asset class a , we model the intensive margin of debt issuance:

$$\log(X_{i,t}(n|a)) = \alpha_{i,t}(a) + \alpha_t(n, c|a) + \beta \log(R_{i,t}(n|a)) + \varepsilon_{i,t}(n|a), \quad (5)$$

where $X_{i,t}(n|a)$ is issuance in contract n of asset class a , and $R_{i,t}(n|a)$ is its cost of borrowing, which we measure as a credit spread in both markets, as described in [Section 2](#). The specification includes two sets of fixed effects. First, $\alpha_{i,t}(a)$ is a firm-time-asset-class fixed effect, which holds the asset side of the firm’s balance sheet fixed; β is therefore identified from *within firm-quarter-asset-class* reallocation across contract types in response to relative pricing, which is exactly the substitution margin defined in [Section 3](#). Second, $\alpha_t(n, c|a)$ is a segment fixed effect over the contract type n and the currency of issue c : in corporate bonds, which carry a single contractual form, it is a currency by quarter effect, while in syndicated lending it is a financing type by quarter by currency effect. Finally, because $R_{i,t}(n|a)$ is a credit spread, β is an elasticity with respect to a spread.

We begin with substitution across the instruments of a single asset class. Equation (5) is estimated within firm, quarter and asset class, so that the instruments entering the comparison share the borrower’s investment opportunities, its credit quality and the date on which it comes to market, and differ only in the price at which each is placed. The firm-quarter fixed effect therefore absorbs the borrowing need itself, and β is identified from the relative pricing of the claims a firm signs at the same date. Intuitively, we compare the claims a firm sells in the same quarter and ask whether the ones with a wider spread are the ones it sells less of. We instrument that relative price with the demand shifter of the market in question, so that the variation identifying β originates in shifts in investor appetite and not in the firm’s own financing decisions.

The estimated elasticity of substitution is -0.79 in syndicated lending, with a standard error of 0.10 on $50,154$ tranches, and -0.60 in corporate bonds, with a standard error of 0.19 on $72,594$ issues. Testing for equality of the two coefficients does not reject: the difference is 0.19 with a standard error of 0.21 , so firms substitute across their loan tranches at a rate we cannot distinguish from the rate at which they substitute across their bonds. On the price of the claim these correspond to 9.32 and 8.52 ([Table 4](#), Panel A; [Appendix E](#)).

[Table 2](#) reports these estimates. The baseline in column (1) absorbs firm-quarter fixed effects and

rests on a first stage F statistic of 251. The least squares counterpart, in Panel A of [Table D.2](#), is -0.59 , and it is smaller in absolute value than the instrumented estimate in every column, by between 0.04 and 0.30. This is the direction simultaneity predicts: a firm that needs to raise more through a particular contract accepts a wider spread on it, so its own borrowing needs move price and quantity together and bias the least squares estimate towards zero. The instrumented estimate is -0.84 on the subsample of borrowers who also issue bonds and -1.01 for tranches maturing beyond three years, both significant at the 1% level. In column (4) we replace the firm-quarter fixed effect with a firm-quarter-*type* effect, so that a tranche is compared only with other tranches of the same facility type, and the estimate is -0.61 , again significant at the 1% level. This comparison exists only where a firm signs two tranches of one type in a quarter, so the sample falls to 27,447; in other words, the finer fixed effect changes the sample as well as the variation it exploits. Most of the elasticity remains under this stricter comparison, which tells us that much of the reallocation we measure takes place between contracts that share a facility type.

TABLE 2. Substitution across financing types: Syndicated lending

	(1)	(2)	(3)	(4)
$\log R_{i,t}(n a)$	-0.79^{***} (0.10)	-0.84^{***} (0.11)	-1.01^{***} (0.10)	-0.61^{***} (0.11)
Dependent variable	Log loan issuance			
Firm-Quarter FE	Yes	Yes	Yes	-
Firm-Quarter-Type FE	-	-	-	Yes
Quarter-Currency-Type FE	Yes	Yes	Yes	Yes
Only firms which issued bonds	No	Yes	No	No
Maturity	All	All	>3y	All
First-stage F	251	191	119	156
N	50,154	29,128	30,653	27,447

Syndicated lending within-market elasticity. The outcome is log issuance amount and $\log R_{i,t}(n|a)$ is the log loan price: the contractual spread over the reference rate, in basis points. The price is instrumented with the tranche level loan demand shifter $Z_{i,t}(l)$ of Equation (4), the lending share weighted average of the estimated bank-time effects of the non-lead members of the syndicate. The corresponding least squares estimates, on the same rows column by column, are in Panel A of [Table D.2](#). Column (1) absorbs firm-quarter fixed effects; column (2) restricts to firms that also issued bonds; column (3) restricts to maturities longer than 3 years; column (4) replaces firm-quarter with firm-quarter-type fixed effects, where type is the facility type, so the coefficient is identified only from tranches sharing a facility type within a firm-quarter and the sample falls accordingly. The first stage statistic is a test of instrument strength (the Kleibergen-Paap rk Wald F), computed on the same firm clustered variance matrix as the standard errors. Robust standard errors clustered at the firm level are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

[Table 3](#) reports the bond market. Instrumenting the price gives -0.60 on 72,594 issues, on a first stage F statistic of 95. The least squares bias is considerably larger here than in syndicated lending: the corresponding estimates in Panel B of [Table D.2](#) range from -0.10 to 0.01 and none can be distinguished

from zero, consistent with a bond spread at issue reflecting the issuer’s own placement conditions more directly than a loan margin does. As in syndicated lending, we obtain similar estimates on the subsample of issuers who also borrow from syndicates, at -0.54 , and on issues maturing beyond three years, at -0.56 , both significant at the 1% level. Confining the sample to fixed coupon bonds gives -0.41 , significant at the 5% level. Benchmarking the spread against government curves in place of the par swap curve gives -0.83 , on the wider sample of 79,156 issues that those curves reach, since they cover thirty-four currencies against seventeen; [Table D.3](#) reports that variant in full.

TABLE 3. Within-market own-elasticity: Bond issuance

	(1)	(2)	(3)	(4)
$\log R_{i,t}(n a)$	-0.60^{***} (0.19)	-0.41^{**} (0.19)	-0.54^{***} (0.16)	-0.56^{***} (0.16)
Dependent variable	Log bond issuance			
Bond price	Swap	Swap	Swap	Swap
Coupon type	All	Fixed	All	All
Spread above the 10bp floor	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes
Quarter-Currency FE	Yes	Yes	Yes	Yes
Only firms which obtained syndicated loans	No	No	Yes	No
Maturity	All	All	All	>3y
First-stage F	95	34	190	263
N	72,594	67,433	39,299	43,703

Bond within-market elasticity of substitution. The outcome is log issuance amount and $\log R_{i,t}(n|a)$ is the log bond price, the credit spread in basis points over the par swap curve. The spread is measured against the maturity matched point of the curve for fixed coupon bonds, which take the ten year benchmark when they mature beyond ten years, and against the short end of the curve for floating, variable and range coupon bonds whatever their maturity; spreads at or below 10 basis points are dropped. The price is instrumented with $\log Z_{i,t}(n)$, the log factor fitted dollar demand of institutional investors for comparable bonds. Column (1) pools fixed and floating coupon bonds; column (2) keeps fixed coupon bonds only; column (3) restricts to firms that also obtained syndicated loans; column (4) restricts to maturities longer than three years. The corresponding least squares estimates, on the same estimation sample column by column, are in Panel B of [Table D.2](#). N counts the observations remaining once the fixed effects are absorbed. The first stage statistic is a test of instrument strength (the Kleibergen-Paap rk Wald F), computed on the same firm clustered variance matrix as the standard errors. Robust standard errors clustered at the firm level are in parentheses.

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

[Table 4](#) translates these elasticities into basis points, which is the unit in which both markets are quoted. At the median syndicated loan spread of 200 basis points, widening one tranche’s spread by 25 basis points relative to the other claims the firm signs in that quarter reduces issuance of the tranche by 8.9%; at the median bond spread of 149 basis points, the same experiment reduces issuance by 8.9% as well. The proportional response is correspondingly larger at narrow spreads and smaller at wide ones, since a fixed widening of 25 basis points is a larger relative move the lower the spread

from which it starts: at the first quartile it is worth 13.5% in syndicated lending and 16.3% in bonds, and at the third quartile 6.2% and 4.6%.

How much weight these estimates can bear depends on how much identifying variation lies behind them, which we report in Panel E of [Table 4](#). What remains after the fixed effects is a movement in the demand-driven price worth 9.8% of the spread in syndicated lending and 5.6% in bonds, which at the median spread of each market is 20 and 8 basis points, respectively. Realised dispersion across the claims a single firm issues in one quarter, measured after the same fixed effects, is considerably wider, at 52 and 74 basis points; in other words, the movement our shifters price is a portion of the relative pricing firms actually face. A 25 basis point experiment is accordingly close to the scale of variation we identify in syndicated lending and beyond it in bonds, and the 100 basis point rows of Panel C lie well beyond it in both markets; we report those rows only to give the scale of the mapping.

TABLE 4. Economic magnitude of the within-market elasticities

	Syndicated Loans			Bonds		
	25th (1)	Median (2)	75th (3)	25th (4)	Median (5)	75th (6)
Dependent variable	Log loan issuance			Log bond issuance		
<i>Panel A: Estimated elasticity, and the same estimate on the price convention</i>						
$\log R_{i,t}(n a)$		−0.79*** (0.10)			−0.60*** (0.19)	
Implied elasticity on the security price, at the median		9.32			8.52	
<i>Panel B: Credit spread (bp)</i>						
Spread at this percentile	125	200	300	73	149	309
<i>Panel C: Issuance response to a relative spread shock (%)</i>						
+25 bp	−13.5	−8.9	−6.2	−16.3	−8.9	−4.6
+50 bp	−23.5	−16.2	−11.5	−27.1	−16.0	−8.7
+100 bp	−37.3	−27.5	−20.4	−40.7	−26.7	−15.6
<i>Panel D: Response per basis point at the pooled elasticity (%)</i>						
Issuance per bp	0.64	0.40	0.26	0.83	0.41	0.20
<i>Panel E: Scale of the identifying variation</i>						
Demand-driven price variation, one s.d. (% of spread)		9.8			5.6	
One s.d. at the median spread (bp)		20			8	
Issuance response to a one s.d. shock (%)		−7.2			−3.3	
Realised spread dispersion after the fixed effects, one s.d. (bp)		52			74	

The within-market elasticities of substitution restated in the units in which the two markets are quoted, and the scale of the variation behind them. $\log R_{i,t}(n|a)$ is the log contract price: the loan spread over the reference rate in columns (1) to (3) and the bond spread over the par swap curve in columns (4) to (6). Columns are the 25th percentile, the median and the 75th percentile of each market's own credit spread distribution on its estimation sample, the levels themselves reported in Panel B. Panel A repeats the baseline within-market elasticities and restates each on the price of the security as $-\beta/u - 1$, the conversion of [Appendix E](#); it is a change of units applied to the coefficient above it, not a separate estimate. That restatement is evaluated at the median spread of Panel B and the market's median spread duration, and it moves with the point of evaluation: at the 25th and the 75th percentile spread it is 15.03 and 6.14 for loans and 17.85 and 3.91 for bonds. Panel C evaluates $100[(S + \Delta)/S]^\beta - 1$ and Panel D the local response $-100\beta/S$, with S the spread level of Panel B in basis points and β the coefficient of Panel A; the shock is a movement in the spread of one claim relative to the other claims the same firm issues in the same quarter, which is the variation the firm-quarter fixed effect leaves. Panel E reports the residual standard deviation, after the same fixed effects, of the demand-driven price component, which is the first stage slope on the demand shifter multiplied by the shifter and not the whole fitted price, and of the realised log spread. Standard errors clustered at the firm level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

4.2 CROSS-MARKET SUPPLY ELASTICITY OF SUBSTITUTION

Equation (5) tells us how a firm redistributes debt issuance across instruments conditional on being active in a market. However, it does not tell us anything about two further objects that we want to measure: how the firm divides its borrowing between the bank and the bond market, and how it

scales the total it places when the price at which investors will hold its debt moves. To measure either of these margins we need a price that is defined at the level of the firm and the market, and not at the level of the individual contract. We therefore use the contract level estimates as building blocks to construct such a price, and we then write the two specifications that follow in terms of it.

THE DEMAND-DRIVEN MARGINAL COST OF DEBT

For each firm i , date t , and asset class a , we construct a firm–asset-class marginal cost of debt from the first stage of equation (5). Let $\widehat{\log R_{i,t}}(n|a)$ denote the fitted value of $\log R_{i,t}(n|a)$ from projecting the log rate on the asset demand shifter of that market, absorbing the same fixed-effect structure. That fitted value is the sum of three components,

$$\widehat{\log R_{i,t}}(n|a) = \hat{\alpha}_{i,t}(a) + \hat{\alpha}_t(n, c|a) + \hat{\gamma}_a Z_{i,t}(n|a),$$

a firm-time component, a segment component, and the loading $\hat{\gamma}_a$ of the price on the demand shifter $Z_{i,t}(n|a)$. Of these three components, only the third captures a shift in investor demand, and it is therefore the only one that we carry into the index.

To aggregate the shifter channel across the instruments of a cell we need weights, and we take them to be the quantities that the firm would place at its estimated $\hat{\beta}$ given the fitted prices,

$$\hat{X}_{i,t}(n|a) = \exp(\hat{\beta} \cdot \widehat{\log R_{i,t}}(n|a)), \quad \hat{s}_{i,t}(n|a) = \frac{\hat{X}_{i,t}(n|a)}{\sum_{n' \in \mathcal{N}_{i,t}(a)} \hat{X}_{i,t}(n'|a)},$$

We use these projected shares, and not the observed ones, because observed shares respond to transitory firm-time shocks and are therefore endogenous to them. Note also that the firm-time component is common to every instrument in the cell, so it cancels from these shares; in other words, the projected composition is determined by the relative pricing inside the cell alone. We then define the demand-driven marginal cost of debt as the share-weighted average of the shifter channel, taken in logs,

$$\widehat{\log R_{i,t}}(a) = \sum_{n \in \mathcal{N}_{i,t}(a)} \hat{s}_{i,t}(n|a) \hat{\gamma}_a Z_{i,t}(n|a). \quad (6)$$

We discard the other two components because each of them would contaminate the index, although in different ways. Consider first the firm-time component $\hat{\alpha}_{i,t}(a)$. It is fitted to the average log rate inside the cell, so an index that retained it would track the firm’s own realised cost of debt almost one for one. Consider next the segment component $\hat{\alpha}_t(n, c|a)$. It does not capture a shift in investor

demand either: it varies by currency and quarter in bonds, and by financing type, date and currency in loans, and the firm itself chooses the currency it issues in and the contractual form it signs.

We use the demand-driven index of equation (6) in the cross-market specification of equation (7) and in the total debt issuance regression of equation (8) below. In Table 5 we report one alternative beside it, the firm’s amount-weighted realised cost of debt, which serves as an explicit least squares benchmark.

Because we build $\widehat{\log R_{i,t}}(a)$ from first stage fitted values, the variation it carries is already demand-driven, and we therefore estimate the two specifications that use it by ordinary least squares. Both specifications take the firm’s total issuance in a market, $X_{i,t}(a) = \sum_{n \in \mathcal{N}_{i,t}(a)} X_{i,t}(n|a)$, as the outcome: in equation (7) we set the two markets against one another within the firm-quarter, and in equation (8) we relate the level of issuance to the level of the index.

SPECIFICATION AND INFERENCE

With the marginal cost of debt of equation (6) in hand, we can measure directly the margin at the heart of the capital structure literature: the substitution between capital market and bank based financing. Consider a firm that is active in both markets in the same quarter. The two demand-driven cost indices $\widehat{\log R_{i,t}}(L)$ and $\widehat{\log R_{i,t}}(B)$ summarise the relative price of bank and bond financing that this firm faces, and the split of its issuance across the two markets reveals its willingness to substitute between them. We therefore stack the two asset classes at the firm-quarter level and estimate, on the strict-match panel of firm-quarters in which the firm issues in *both* markets,

$$\log X_{i,t}(a) = -\sigma \widehat{\log R_{i,t}}(a) + \alpha_{i,t} + \alpha_t(a) + \varepsilon_{i,t}(a), \quad a \in \{L, B\}, \quad (7)$$

where $X_{i,t}(a)$ is total firm issuance in asset class a , as above, $\alpha_{i,t}$ is a firm-quarter fixed effect and $\alpha_t(a)$ a quarter-asset-class fixed effect. With exactly two asset classes, the firm-quarter fixed effect reduces the regression to a within-firm-quarter comparison, so that σ is the elasticity of substitution between bank and bond financing.¹

We impose two rules on this sample. First, we drop any firm-quarter whole if it holds a bond whose spread is missing or at or below the ten basis point floor: the market level price is then undefined on one side of the comparison, so the pair carries no information. Second, we winsorise the loan minus

¹Every cell of this panel holds exactly two observations, one per market, so demeaning within the firm-quarter is differencing across the two: writing Δ for the loan minus bond difference, Equation (7) has the same slope as $\Delta \log X_{i,t} = -\sigma \Delta \widehat{\log R_{i,t}} + \Delta \alpha_t + \Delta \varepsilon_{i,t}$. The relative price notation of Appendix E.5 is this differenced form.

bond difference in log issuance at the first and the ninety-ninth percentiles. That is, we cap how far apart the two sides of a cell may be, and then rebuild the two observations from the capped difference while holding their mean fixed, so that the firm’s total issuance in the quarter is unchanged and only the split between the two markets is trimmed.

We report that estimate alongside the amount-weighted actual CoD, which serves as an explicit ordinary least squares benchmark. For the demand-driven columns we conduct inference with a pairs cluster bootstrap over firms on the fixed estimation panel. The procedure has three steps: we estimate the index once on the full sample and hold it fixed; we resample firms with replacement, with repeated firms entering as distinct clusters; and we re-estimate the second stage on each draw. For the actual CoD column we report analytic standard errors clustered at the firm level.

The resulting standard errors are conditional on the estimated index. Resampling with replacement mechanically alters which firm-quarters the first stage can price, so a bootstrap that rebuilds the pipeline inside each draw estimates on a different panel than the point estimate, and its draws are then no longer comparable to it. Holding the index fixed, by contrast, keeps every draw on the estimation panel of the point estimate. Moreover, the price regressions behind the index are estimated on tens of thousands of instrument level observations, so the first stage uncertainty that we forgo by conditioning is small relative to the sampling uncertainty of a second stage that rests on a few thousand pairs.

ESTIMATES

We turn next to substitution between the two markets, an exercise that requires firms active in both at the same date. Equation (7) uses exactly those firm-quarters: we set the split of issuance across the two asset classes against the gap between their demand-driven marginal costs of debt, so that the comparison is internal to the firm and to the quarter. With two asset classes and a firm-quarter fixed effect, the regression reduces to a within cell comparison of the two markets, and σ is therefore identified from the relative movement of the two markets’ demand-driven costs for the same borrower in the same quarter; intuitively, we ask whether the firm tilts its borrowing towards the market that has become relatively cheaper for it.

The estimated elasticity of substitution between bank and bond financing is 0.41, with a bootstrap standard error of 0.22, and it is significant at the 10% level. We estimate it on the 2,728 firm-quarters, drawn from 981 firms, in which a firm issues in both markets and carries a usable price and a usable demand shifter on each side. The 95% percentile interval covers zero, running from -0.03 to 0.88

on the elasticity of substitution.¹ We therefore read this estimate as fixing the sign and the order of magnitude of substitution across the bank–bond margin rather than as pinning it to a decimal place. On the price of the claim it corresponds to 3.00 ([Appendix E.5](#)).

Note that the panel on which this estimate rests is wider than the first stage that feeds it. The index retains only the part of the fitted rate that loads on the demand shifter, and we can therefore construct it for any firm-quarter whose segment is estimated, including the firms that the first stage itself drops for holding a single observation in their firm-time cell. Recovering these firm-quarters is what makes the exercise feasible in the first place: the firm that signs one loan and one bond in the same quarter is exactly the firm whose choice between the two markets we want to measure, and yet, because it holds a single contract on each side, it supplies no within cell comparison for the first stage to price. Firm-quarters lacking a usable price or a usable demand shifter on one side of the comparison are excluded. Replacing the demand-driven index with the firm’s amount-weighted realised cost of debt, an explicit least squares benchmark, gives an elasticity of substitution of 0.20 on the same firm-quarters.

Substitution across the bank–bond margin is therefore the least elastic of the margins we measure, and the ordering holds on the price of the claim as well. The size of that restatement depends on which market the relative price shock arrives through, since dual issuers’ bonds are longer and wider than the loans they sign alongside them ([Appendix E.5](#)); [Table 5](#) reports the symmetric case.

¹Equation (7) is written with $-\sigma$, so the interval [Table 5](#) reports on the estimated coefficient, $[-0.88, 0.03]$, becomes $[-0.03, 0.88]$ on σ itself once the sign is reversed.

TABLE 5. Cross-market substitution: the elasticity of substitution between bank and bond financing

	Demand-driven CoD (1)	Actual CoD (2)
$\log \widehat{\text{CoD}}_{i,t}$	-0.41* (0.22)	-0.20*** (0.04)
95% CI	[-0.88, 0.03]	[-0.28, -0.12]
Elasticity of substitution σ	0.41	0.20
Implied elasticity on the security price	3.00	-
Implied issuance response to a +25 bp relative cost shock (%)	-4.7	-
Dependent variable	Log issuance in the market	
Firm-Quarter FE	Yes	Yes
Quarter-Asset class FE	Yes	Yes
Strict match (L & B)	Yes	Yes
Pairs	2,728	2,728
Firms	981	981
N	5,456	5,456

Estimates of $\log X_{i,t}(a) = -\sigma \log \widehat{\text{CoD}}_{i,t}(a) + \alpha_{i,t} + \alpha_t(a) + \varepsilon_{i,t}(a)$, for $a \in \{\text{loans, bonds}\}$, on the strict match panel of firm quarters in which the firm issues in *both* markets. With two asset classes and a firm quarter fixed effect the regression is a within cell comparison, and σ is the elasticity of substitution between bank and bond financing; the coefficient in the first row and the interval below it are minus that elasticity, and the row beneath reports σ itself. Column (1) uses the demand-driven cost of debt, which retains only the loading of the fitted first stage rate on the demand shifter; column (2) is the amount weighted mean of the log spread the firm actually paid, an ordinary least squares benchmark. The bond price is the credit spread over the par swap curve and the loan price the spread over the reference rate. Firm quarters holding a bond without a usable spread are dropped whole, and the loan minus bond difference in log issuance is winsorised at the 1st and 99th percentiles. The last two rows of the estimate block apply the conversion of [Appendix E](#) and involve no further estimation. Both are evaluated symmetrically across the two markets and shown only for the identified column: on the price of the claim the elasticity runs from 1.90 through the bond market to 5.44 through the loan market, and the response to a +25 basis point move in the relative cost of the two markets from -4.2% to -5.3%. Standard errors in column (1) are from a pairs cluster bootstrap over firms on the fixed estimation panel ($B = 200$), the index being estimated once on the full sample and held fixed, so they are conditional on the estimated index, with stars from the bootstrap normal p -value and the interval the bootstrap percentile interval. Column (2) reports analytic standard errors clustered at the firm level. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

[Figure 8](#) plots the three substitution margins as supply curves, with the price of the claim on the vertical axis and the quantity of claims on the horizontal axis, both obtained from the spread and the amount raised by the mapping of [Appendix E](#). The figure involves no new estimation: the slope of each line is the coefficient reported above. The two within-market curves are almost identical and nearly flat, whereas the bank–bond curve is about three times as steep. All three are much flatter than the dotted line, which marks unit elastic supply.

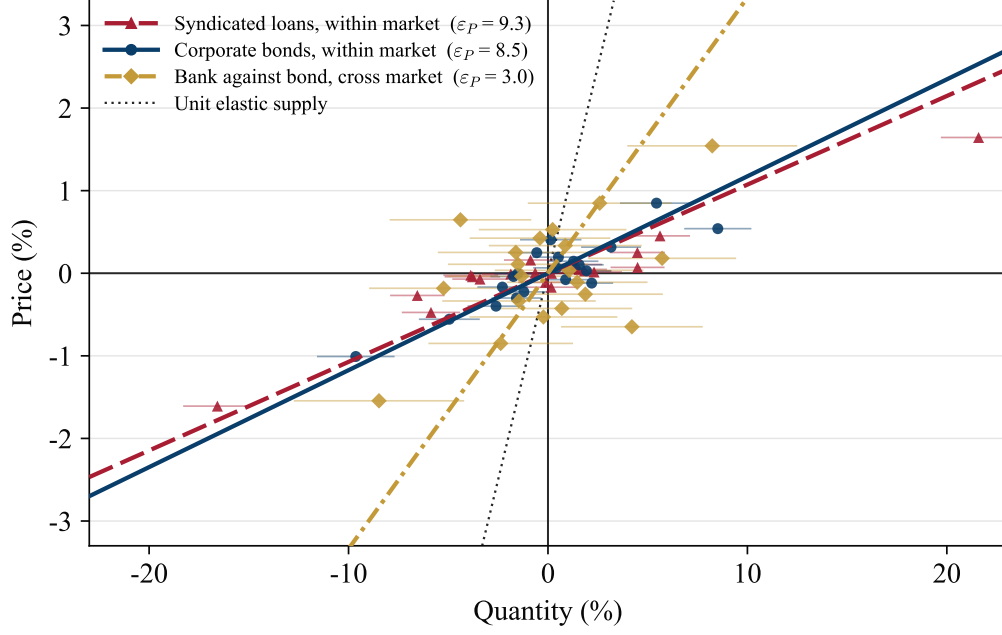


Figure 8. The fitted supply curves of corporate debt. The three estimated supply schedules, for syndicated lending within the market (red), corporate bonds within the market (blue) and the bank against bond margin across markets (gold), each on its own estimation sample. Both axes are deviations from the fixed effects of the specification behind each schedule, so that the slope of each line is the coefficient reported for it. The vertical axis is the price of a claim and the horizontal the quantity of claims created, both in percent and obtained from the log credit spread and the log amount raised by the mapping of [Appendix E](#); the price rises as the spread narrows, which orients each schedule upwards. Markers are equal count binned means, twenty per margin, and horizontal bars one standard error of the binned mean of issuance. The vertical axis is scaled by a factor of seven relative to the horizontal so that the three slopes are distinguishable; the dotted line is unit elastic supply on the same axes. Sources: LSEG, Dealscan, Lipper.

4.3 TOTAL DEBT SUPPLY ELASTICITY

The two margins we have examined so far take the size of a firm's borrowing as given and trace how that borrowing is divided across claims. A shift in the price of debt, however, can be met by changing the composition of what a firm issues, by changing how much it issues, or by both. To measure the second of these channels we relate the quantity of debt a firm places to the demand-driven price of placing it, in the firm-quarter regression

$$\log X_{i,t}(m) = \delta \widehat{\log R_{i,t}}(m) + \alpha_i + \alpha_t + \varepsilon_{i,t}, \quad (8)$$

where m indexes the market the price is taken over and $X_{i,t}(m)$ is the firm's issuance in that same market. We estimate three versions of this regression. In the first, we price bond issuance off the bond CoD $\widehat{\log R_{i,t}}(\text{bonds})$, and in the second we price syndicated loan issuance off the loan CoD $\widehat{\log R_{i,t}}(\text{loans})$. In the third, we take total issuance across both asset classes, $X_{i,t} = \sum_a X_{i,t}(a)$, and

we set it against a price constructed over the firm’s full quarterly menu of instruments, whichever market they were issued in, using each market’s own first stage and projected shares analogous to (6). Before pooling the two markets into that third index, we centre each market’s shifter channel on the sample it serves, so that a change in the mix of bonds and loans a firm places cannot move the index mechanically.

In every version we define the price and the quantity over the same set of instruments. Issuance in both markets in the same quarter is uncommon, so a total issuance outcome would in most firm-quarters coincide with the own market quantity; the firm-quarters in which the two differ, however, are large ones, and roughly a fifth of the issuance entering the bond specification would then be syndicated lending, carrying no price on the right-hand side. We sum issuance over every instrument the firm placed in that market in the quarter, and across both markets in the third version, including instruments that the price index does not cover.

All three indices are the demand-driven index of equation (6), in which we retain only the loading of the fitted price on the asset demand shifter. For inference we use the same fixed panel bootstrap as in the cross-market regression: we estimate each index and its firm-quarter panel once on the full sample and hold them fixed, and we then run a pairs cluster bootstrap at the firm level, re-estimating the firm-level regression on each draw, with repeated firms entering as distinct clusters.

Panel A of Table 6 reports issuance falling with the price in all three specifications. The estimated elasticity is -0.59 against the bond market price, -0.25 against the loan market price, and -0.38 against the firm’s full menu of instruments, each of them significant at the 1% level. On the price of the claim these correspond to 6.87, 2.31 and 4.07 (Appendix E). The response to a typical shock is nonetheless modest, because the demand-driven index isolates a narrow component of the price, and Panel B of Table 6 reports that variation. The residual standard deviation of the index after the fixed effects is 6.9% in bonds, 12.3% in syndicated lending and 10.4% over the firm’s full menu of instruments, so that a one standard deviation movement in the index shifts quarterly issuance by 4.0%, 3.1% and 3.9% respectively. When we set these estimates beside those of Section 4.1, the two margins rank differently in the two markets. In syndicated lending the scale response is the less elastic of the two, at -0.25 against a within-market elasticity of -0.79 . In bonds the two are of the same size on the credit spread, at -0.59 against -0.60 . A firm meeting a shift in the cost of syndicated credit therefore adjusts mainly by re-cutting which contracts it signs rather than how much it borrows, whereas in bonds the two channels carry roughly equal weight.

TABLE 6. The scale of debt issuance and the marginal cost of debt

	Bond market (1)	Loan market (2)	Both markets (3)
<i>Panel A: Estimated elasticity, and the same estimate on the price convention</i>			
$\log \widehat{\text{CoD}}_{i,t}$	-0.59*** (0.07)	-0.25*** (0.06)	-0.38*** (0.04)
95% CI	[-0.73, -0.45]	[-0.36, -0.14]	[-0.46, -0.29]
Implied elasticity on the security price	6.87	2.31	4.07
<i>Panel B: Scale of the identifying variation</i>			
Residual price variation, one s.d.	0.069	0.123	0.104
Issuance response to a one s.d. shock (%)	-3.97	-3.05	-3.89
Issuance response to a +25 bp shock (%)	-7.4	-2.9	-4.6
Dependent variable	Log bond issuance	Log loan issuance	Log total issuance
Price	Bond spread	Loan spread	Full menu
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Sample	Bond issuers	Loan issuers	All issuers
Adjusted R-squared	0.70	0.57	0.63
N	42,190	36,257	76,100

The response of a firm's total issuance in a market to the demand-driven marginal cost of debt it faces there. The unit of observation is the firm quarter. Issuance is summed over every instrument the firm issued in that market in the quarter, including those the price index does not cover, and the price is taken over the same market. Firm quarters containing a bond whose spread is missing or at or below ten basis points are dropped whole from columns (1) and (3). The bond price is the credit spread over the par swap curve; the loan price is the spread over the reference rate. The demand-driven index is the instrument channel of the fitted first stage rate alone, aggregated with projected quantity weights. Standard errors in parentheses are from a pairs cluster bootstrap over firms on the fixed estimation panel ($B = 200$), the index being estimated once on the full sample and held fixed, so they are conditional on the estimated index, with stars from the bootstrap normal p -value and the reported interval the bootstrap percentile interval. The implied elasticity on the security price applies the conversion of [Appendix E](#), evaluated at u of 0.075, 0.076 and 0.075 in the three columns, the last an amount weighted blend of the two markets. Panel B reports the residual standard deviation of each column's own log price, after the fixed effects of the regression above. The response rows apply the coefficient of Panel A to a movement of one such standard deviation, $100(e^{\beta \text{s.d.}} - 1)$, and to a widening of $\Delta = 25$ basis points, $100[(S + \Delta)/S]^\beta - 1$ at S each panel's own median credit spread, 178.31, 200.00 and 188.85 basis points. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

4.4 HETEROGENEITY BY USE OF FUNDS

Everything so far treats the elasticity as a single number for each market. We close the section with the purpose that the borrowing serves. Firms frequently borrow for more than one reason in the same quarter, and a bond raised to fund an acquisition need not be a close substitute for one raised to refinance maturing debt, even for the same firm at the same date. To measure this, we need a summary of how widely a firm's borrowing is spread across purposes in a given quarter.

We set out the construction in [Section 2.3](#) and recall its two elements here. A contract's *use* is the exact

combination of purposes it states, so that a contract raised for both an acquisition and refinancing carries a single use combining the two, not two half uses, and $V_{i,t}$ of Equation (1) is the probability that two of a firm's contracts in a quarter serve different uses. Half of loan contracts and just under a quarter of bond contracts are issued in quarters in which it is positive.

Variety cannot be read on its own, because it rises mechanically with the number of contracts a firm signs, and a firm signing more contracts may substitute more elastically for that reason alone. The two characteristics we must separate are therefore the *variety of uses* $V_{i,t}$ of Equation (1) that a firm's borrowing serves in a quarter and the *number of contracts* $N_{i,t}(a) = |\mathcal{N}_{i,t}(a)|$ it signs in that market, which we take in logs. We hold one fixed while the other varies: we interact the price of equation (5) with each in turn, and we instrument the product with the demand shifter interacted with the same characteristic. Each enters as a deviation from its mean within a stratum of firm-quarters that share the same calendar quarter and the same value of the rival characteristic. The variety coefficient is therefore identified from firms that borrowed in the same quarter and signed the same number of contracts, and the contract count coefficient from firms that borrowed in the same quarter and served the same number of uses. Both comparisons are formed across firm-quarters and never across the contracts of a single issuer. The sample retains the firm-quarters holding at least two contracts with a stated purpose in the market, and for inference we again use a pairs cluster bootstrap over firms.

Of the two interactions, we find information only in variety. The estimated coefficient on the number of contracts is -0.07 in syndicated lending and 0.27 in corporate bonds; the two are of opposite sign across the markets and insignificant in either. The coefficient on variety is -0.82 in syndicated lending and -1.27 in bonds, each of them approximately 1.7 bootstrap standard errors from zero and therefore significant only at the 10% level. The two markets are identified from different demand shifters on separate sets of contracts, and they nonetheless agree in sign and in order of magnitude.

The implied difference is large relative to the elasticity itself. Moving from a quarter in which every contract serves the same use to one split evenly between two raises $V_{i,t}$ from zero to one half, so the interaction contributes half the estimated coefficient: 0.41 in syndicated lending and 0.64 in bonds. Against subsample baselines of -0.83 and -0.60 without the interaction, that is close to a 50% increase in syndicated lending and a doubling in bonds. The intuition is that variety captures discretion in what the borrowing has to fund. A firm serving several purposes at once has some latitude over which of them to fund now, and in what size, so it can tilt towards whichever claim has become relatively cheap; a firm whose quarter serves a single purpose is more often executing one committed transaction, and takes the price it is offered.

TABLE 7. Substitution, the number of contracts and the variety of uses funded

	Syndicated Loans		Corporate Bonds	
	(1)	(2)	(3)	(4)
Dependent variable	Log loan issuance		Log bond issuance	
$\log R_{i,t}(n a)$	-0.80*** (0.15) [0.15]	-0.80*** (0.15) [0.15]	-0.75*** (0.16) [0.17]	-0.59*** (0.16) [0.16]
$\log R_{i,t}(n a) \times \log N_{i,t}(a)$	-0.07 (0.22) [0.28]		0.27 (0.35) [0.34]	
$\log R_{i,t}(n a) \times V_{i,t}$		-0.82* (0.49) [0.47]		-1.27* (0.74) [0.76]
Firm-Quarter FE	Yes	Yes	Yes	Yes
Quarter-Currency FE	-	-	Yes	Yes
Quarter-Currency-Type FE	Yes	Yes	-	-
N	17,474	17,474	27,862	27,862
Firm-quarters	6,280	6,280	7,409	7,409
First-stage F (system)	74	51	6.3	40

Whether the within-market elasticity of substitution varies with the number of contracts a firm signs in a quarter and with the variety of uses they fund. $\log R_{i,t}(n|a)$ is the log contract price: the loan spread over the reference rate in columns (1) and (2) and the bond spread over the par swap curve in columns (3) and (4). Within-market elasticities of substitution, estimated by IV with firm-quarter and segment fixed effects. Each column takes the baseline specification and multiplies $\log R_{i,t}(n|a)$ by one firm-quarter variable. $\log N_{i,t}(a)$ is the log number of contracts the firm issues in that market that quarter. $V_{i,t}$, the variety of uses, is the chance that two of those contracts, drawn at random, serve different uses, where a contract's use is the exact combination of purposes it states. The price and the product are both instrumented, by the demand shifter and by the demand shifter multiplied by the same variable. Each variable enters as a deviation from the average over one stratum, a group of firm-quarters held identical on the calendar quarter and on the rival variable, so that the two coefficients are never identified off the same variation: for $\log N_{i,t}(a)$ the stratum is the calendar quarter and the number of distinct uses, and for $V_{i,t}$ it is the calendar quarter and the exact number of contracts. The sample keeps firm-quarters carrying at least two contracts with a stated purpose in the market. On that sample the same specification estimated without any interaction, which is the baseline the interactions shift, gives -0.83 in columns (1) and (2) and -0.60 in columns (3) and (4). The first stage statistic is a test of instrument strength (the Kleibergen-Paap rk Wald F), computed on the same firm clustered variance matrix as the standard errors. With two instrumented regressors it is the statistic for the system of first stages and not for the price equation alone. Standard errors clustered at the firm level in parentheses; firm bootstrap standard errors from 200 draws in brackets, from which the stars are taken. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5 CONCLUSION

We measure how elastically firms adjust the supply of their debt claims when the relative cost of those claims moves, and the answer, on every margin we examine, is that they respond strongly within the quarter. When one claim becomes 25 basis points more expensive than the other claims

the firm issues in the same quarter, the firm issues 8.9% less of that claim, and it does so both in syndicated lending, where the median spread is 200 basis points, and in corporate bonds, where it is 149. The elasticities behind this response, -0.79 and -0.60 on the credit spread, differ by 0.19 with a standard error of 0.21, so we cannot call either market the more adjustable one. Restated on the price of the claim, the same two coefficients are 9.32 and 8.52: firms supply debt elastically.

The same response appears between the two markets and in the total quantity of debt placed. When the cost of bond financing rises by 25 basis points relative to the cost of loan financing, a firm active in both markets shifts its issuance split between the two by roughly 4.7%; the elasticity of substitution behind this margin is 0.41, with a bootstrap standard error of 0.22, or 3.00 on the price of the claim. Firms adjust the scale of their borrowing as well, and not only its composition: a 25 basis point rise in the demand-driven price at which a firm can place debt in a market lowers the quantity it issues there by 7.4% in bonds and 2.9% in syndicated lending, with elasticities of -0.59 , -0.25 and, over the firm's full menu of instruments, -0.38 , each significant at the 1% level. In other words, when investor demand for a firm's debt weakens, the firm tilts its issuance towards the market that remains cheaper and places less debt overall.

Taken together, these margins describe a corporate sector that absorbs financial risk elastically. In the short run, large corporations meet shifts in investor demand by rebalancing the liability side of their capital structure: they substitute most freely across the contracts of a single market, they substitute across the bank and bond margin at 50–70% of that rate on the credit spread (30–40% on the price of the claim), and they vary how much they place as well as where they place it. The ranking of the margins holds on either basis. Because firms meet part of a shift in investor demand by recomposing and rescaling their liabilities, prices need to move less to clear the market, and the cost of debt absorbs only the remainder. Our estimates suggest that this price response should be largest at the bank and bond margin, the least elastic margin we identify.

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A DATA AND DESCRIPTIVES: IDENTIFYING VARIATION

This appendix collects the descriptive figures on the identifying variation in our estimation samples that are summarised in [Section 2](#).

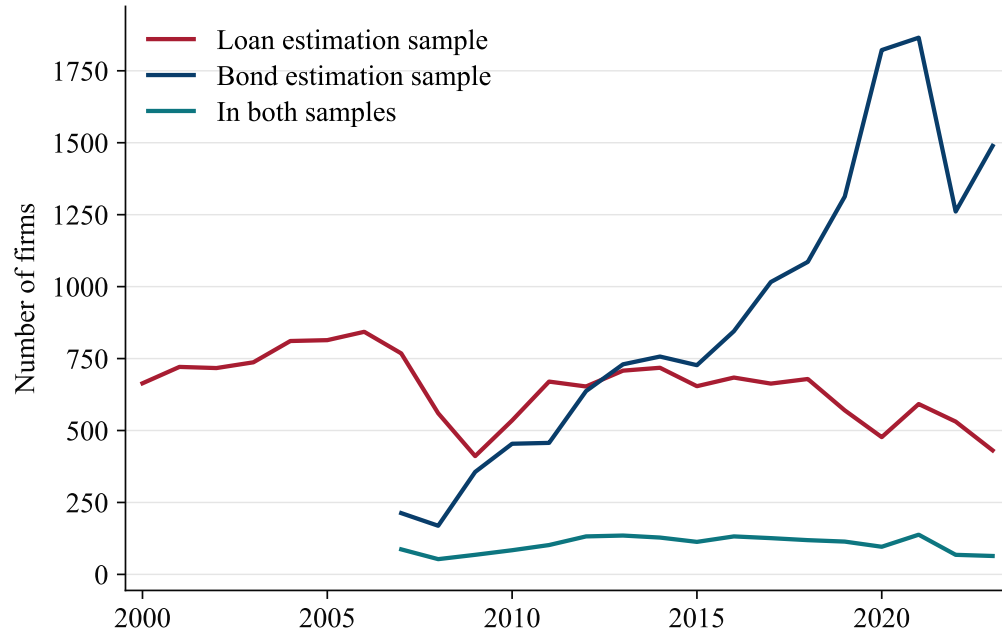


Figure A.1. Unique firms per year in each estimation sample. The figure plots the number of distinct firms appearing in each calendar year in the syndicated loan estimation sample (red), the corporate bond estimation sample (blue), and in both (teal). Counts are taken on the samples the elasticities are estimated on, not on the universe of corporate debt issuance. The bond series begins in 2007, when Lipper institutional holdings coverage starts. Sources: LSEG, Dealscan, Lipper.

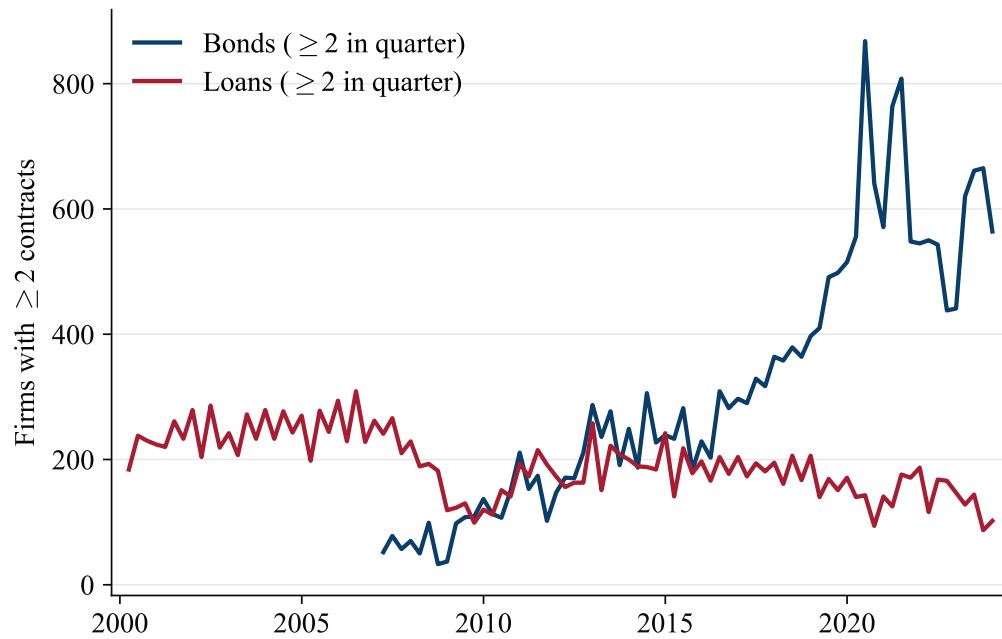


Figure A.2. Within market repeat issuers, by quarter. The figure plots the number of firms placing at least two contracts of the same asset class in the same quarter, for corporate bonds (blue) and syndicated loans (red), counted on the two estimation samples rather than on the universe of issuance. These firm-quarter observations supply the identifying variation for the within-market elasticity of substitution once the firm-quarter and other fixed effects are absorbed. Sources: LSEG, Dealscan, Lipper.

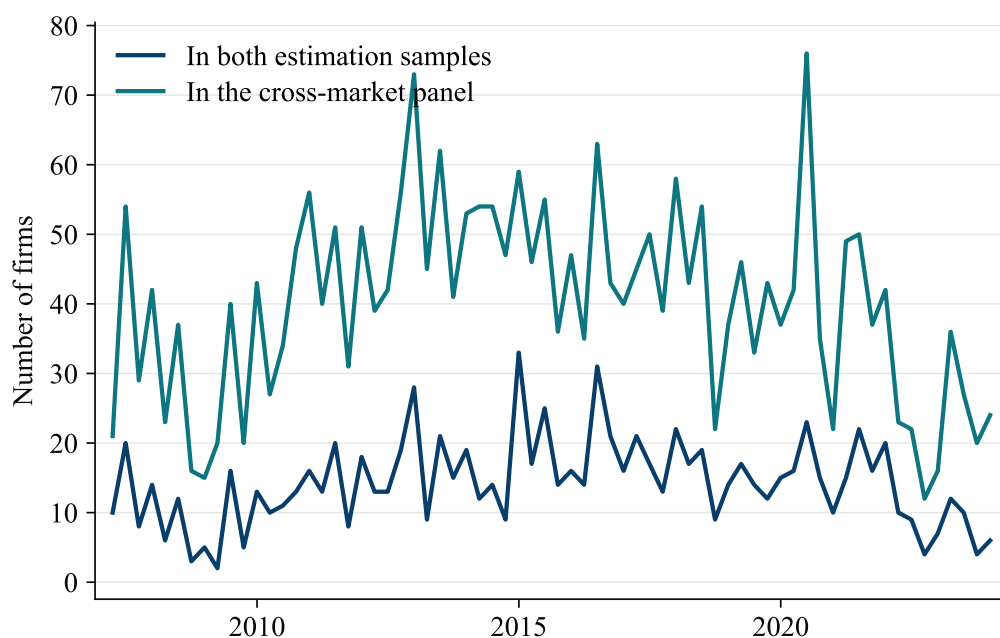


Figure A.3. Cross market dual issuers, by quarter. The figure plots the number of firms placing at least one corporate bond and at least one syndicated loan tranche in the same quarter, on two definitions: firm-quarters appearing in both within-market estimation samples, and the wider panel on which the cross-market elasticity of substitution is estimated. Both are counts on the samples used in estimation and not on the universe of issuance. Sources: LSEG, Dealscan, Lipper.

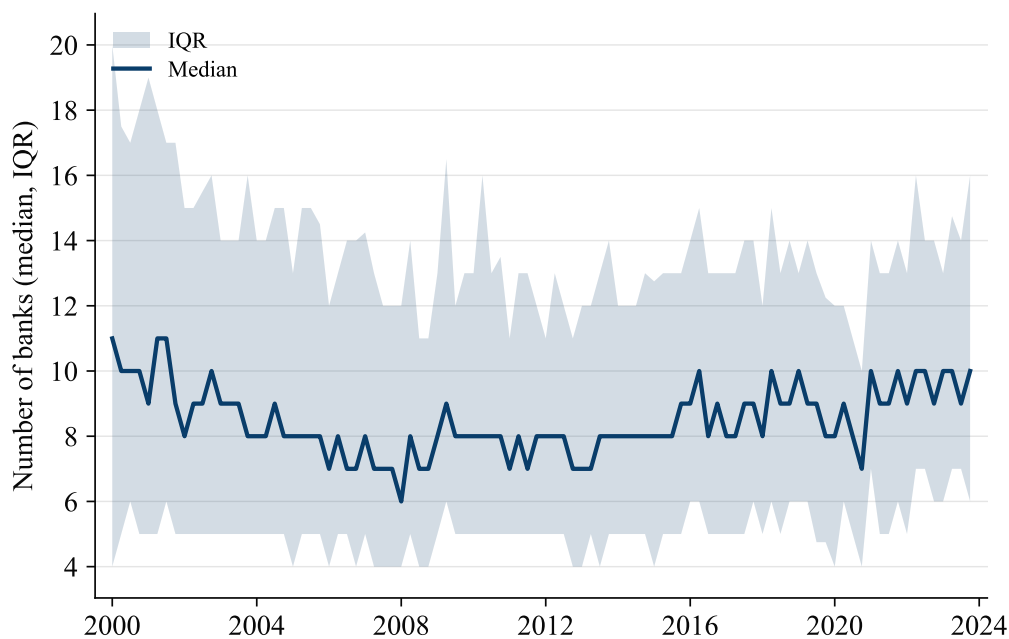


Figure A.4. Syndicate granularity, by quarter. The figure plots the median (solid line) and interquartile range (shaded area) of the number of participant banks per syndicated loan tranche, over the tranches of the syndicated loan estimation sample rather than the universe of origination. This granularity underpins the identification of the bank-time fixed effect and the aggregation of those fixed effects into the tranche level loan asset demand shifter Z^{loan} . Source: Dealscan.

B USE OF FUNDS: CONSTRUCTION AND PROMPT

B.1 *Construction of the dataset*

For each financing in our sample we deploy a multi-agent AI system equipped with online search tools, in order to identify the stated use of proceeds. Inputs to the agent are the security identifier (ISIN where available), the issuer name, the asset class, the financing type, the issuance amount, the issuance date, and the contractual maturity. The agent first attempts to retrieve issuance level information from the most authoritative source available (typically the issuer’s annual report or the corresponding 8-K, 10-K or prospectus filing), and falls back to news articles, earnings call transcripts and press releases dated around the issuance when filings are silent or when the financing is privately placed. For each financing the agent must return both a structured set of boolean purpose flags and a free text summary documenting the evidence on which the classification rests. When no credible evidence on the use of proceeds can be located after an exhaustive search, all flags are returned as false and the summary explicitly records the absence of information, so that downstream code can distinguish between a financing that was not classified and a financing that was classified into the no purpose category.

The agent is restricted to a fixed schema of nine boolean flags. Seven of these capture purpose: `ma` (mergers, acquisitions, joint ventures), `capex` (capital expenditure on physical assets, real estate, plants), `growth_expansion` (organic expansion, market entry, new locations), `innovation` (research and development, intellectual property, technology), `refinancing` (repayment, redemption or refinancing of existing debt), `liquidity_management` (working capital and cash management, narrowly defined), and `shareholder_return` (buybacks, repurchases, dividends). Two further flags capture context: `is_distressed` (issuance under restructuring or to avoid default) and `is_bridge_financing` (temporary financing pending a larger transaction or refinancing event). Multiple purpose flags can be true for the same financing, since the proceeds of a single bond or facility frequently fund more than one type of activity.

In the analysis we do not aggregate the seven purpose flags. Because a single financing frequently carries more than one, we take a contract’s use of funds to be the exact combination of flags it carries, so that a financing tagged for both an acquisition and refinancing has one use combining the two rather than two half uses. Uses defined in this way are mutually exclusive and exhaustive, which is what the diversity measure of Equation (1) requires, and 93 of them appear across the two estimation samples. The two contextual flags play no part in the definition of a use. A financing for which no

purpose flag is true is unclassified and enters neither that definition nor the estimates that rest on it.

B.2 *Verbatim prompt*

The prompt below is supplied verbatim to the AI agent for every batch of financings. It is reproduced here exactly as deployed, including formatting and emphasis.

The input contains a list of corporate debt financings: bonds and loans. Your task is to determine the purpose of each debt financing by conducting an online search.

Search Instructions

- For every financing entry, use the available variables (asset_class, financing_type, date (end of month), amount, company_name, maturity (years), and ISIN) to guide your search.
- For debt securities, prioritize searching by ISIN and company name. If you don't find results with ISIN, try searching by company name, asset class, date and amount.
- For loans or cases where ISIN brings no results, use the date, asset class, and financing type to refine your search.
- ****Search strategy****: Use credible sources such as news articles, earnings transcripts, press releases, company filings, and especially the annual reports of the relevant companies around the financing date. It must be an exhaustive search; dig deep into multiple sources to find the intended use of proceeds. Be flexible in your search terms, combining the company name with keywords like "debt issuance", "bond issuance", "loan purpose", "use of proceeds", "financing announcement", etc.

JSON File Structure

For each financing, in the JSON file:

```
"debt_id": from the CSV,  
"date": from the CSV, format YYYY-MM-DD,  
"ma": (true/false),  
"capex": (true/false),
```

```
"growth_expansion": (true/false),
"innovation": (true/false),
"refinancing": (true/false),
"liquidity_management": (true/false),
"shareholder_return": (true/false),
"is_distressed": boolean (true/false),
"is_bridge_financing": (true/false),
"details": a detailed summary of the intended use of proceeds,
            including specific projects, liabilities refinanced, sectors
            involved, and any other relevant information. A lot of detail
            and comprehensive as possible, a long paragraph. This must be
            unique and specific for each financing row.
```

The json should ONLY contain these entries, one row per financing.

Classification Categories

Purpose Questions

Answer the following questions with true or false

- ****ma****: True if the proceeds are used for Mergers & Acquisitions, buying other companies, funding joint ventures/partnerships, etc.
- ****capex****: True if the proceeds are used for Capital Expenditures, purchasing physical assets, Real Estate, building factories/stores, etc.
- ****growth_expansion****: True if the proceeds are used for business expansion, market entry, opening new locations, geographic expansion, scaling operations, organic growth initiatives, etc.
- ****innovation****: True if the proceeds are used for Research & Development (R&D), intellectual property development, technology innovation, etc.
- ****refinancing****: True if the proceeds are used to repay, redeem, or refinance existing debt.
- ****liquidity_management****: True if the proceeds are used for working capital, liquidity and cash management, etc (do not use this as a catch-all

- option, it truly has to be for liquidity purposes).
- **shareholder_return**: True if the proceeds are used for share buybacks, repurchases, paying dividends to shareholders, etc.
 - **is_distressed**: True if the financing was issued under financial distress, restructuring circumstances, to avoid bankruptcy/default, etc.
 - **is_bridge_financing**: True if this is temporary or bridge financing pending a larger transaction, refinancing event, asset sale, etc.

Important guidelines

- Multiple Purposes: Set multiple flags to true if the financing serves multiple purposes (e.g., both refinancing and M&A). Be thorough and capture all stated uses.
- If after exhaustive research NO specific use of proceeds can be identified from any credible source, set all flags to false. The ‘details’ field MUST explain why no information was found.

C ASSET DEMAND: BOND MARKETS

C.1 *Motivating Mean-Variance Framework*

This appendix collects the formal demand-side model summarized in [Section 3](#). There is a continuum of investors in bond markets, each indexed by i . Each investor is specialized and can only invest in one type of asset class (e.g., commercial paper, high-yield bonds, investment-grade bonds, etc.). Although investors share identical beliefs about expected returns and betas, they differ in the set of assets available to them, which leads to differences in their overall portfolio characteristics. We model investors as having mean-variance preferences over next-period wealth. They maximize:

$$\max_{\mathbf{w}_i} \left\{ \mathbf{w}_i' \mathbb{E}[\mathbf{R}] - \frac{\gamma_i}{2} \mathbf{w}_i' \text{Var}[\mathbf{R}] \mathbf{w}_i \right\}$$

where $\mathbf{w}_i$ is the vector of portfolio weights, $\mathbf{R}$ is the vector of asset returns available in the investor’s investment set, γ_i is the investor’s risk aversion, and the expectation $\mathbb{E}[\cdot]$ and variance $\text{Var}[\cdot]$ are

common to all investors. In particular, we assume that beliefs about asset returns are determined via:

$$R(n) = \mathbb{E}[R(n)] + \beta(n)' \mathbf{f} + u(n)$$

where all investors share the same beliefs about factor loadings $\beta(n)$ and risk factors. The shock $u(n)$ is independent across assets and is mean zero with variance σ^2 .

The first-order conditions yield a linear asset demand function:

$$w_i(n) = \frac{1}{\gamma_i \sigma^2} \left[\mathbb{E}[R(n)] - \beta(n)' \Lambda_i^{-1} \sum_m \beta(m) \mathbb{E}[R(m)] \right] \quad (9)$$

where $\Lambda_i \equiv (\sigma^2 \mathbf{I} + \mathbf{B}_i' \mathbf{B}_i)$ and $\mathbf{B}_i$ collects the common betas corresponding to the asset set available to investor i . Differences in Λ_i across investors arise solely because they have access to different investment sets.

We now consider the demand for a portfolio of *comparable debt securities*. Let $\mathcal{B}$ be a set of securities that are close substitutes (similar credit rating, maturity, or industry). Since all investors share the same beliefs about expected returns and betas, the factor loadings $\beta(m)$ for any security $m \in \mathcal{B}$ are very similar, leading to strong substitution effects (Haddad et al., 2026; Chaudhary et al., 2025). Summing the individual demands in (9) over $\mathcal{B}$ and rearranging, the demand for the portfolio of comparable bonds simplifies to:

$$w_i(\mathcal{B}) = \frac{1}{\gamma_i \sigma^2} \left[\sum_{m \in \mathcal{B}} \mathbb{E}[R(m)] - \beta(\mathcal{B})' \kappa_i \right],$$

where $\beta(\mathcal{B}) = \sum_{m \in \mathcal{B}} \beta(m)' \Lambda_i^{-1}$ and $\kappa_i \equiv \sum_k \beta(k) \mathbb{E}[R(k)]$ is the aggregate expected return characteristic of investor i 's investment set.

As shown below in [Appendix C.3](#), the demand for a portfolio of comparable bonds exhibits a low-rank structure. For each investor, demand simplifies to:

$$w_i(\mathcal{B}) = \sum_{k=1}^r \lambda_{ik} x_k(\mathcal{B}) + \varepsilon_i,$$

where $r \ll |\mathcal{B}|$, λ_{ik} are investor-specific loadings, and $x_k(\mathcal{B})$ are comparable-portfolio factors that aggregate the collective characteristics of securities in $\mathcal{B}$. The error term ε_i captures idiosyncratic deviations. The variation in portfolio demand across investors is therefore driven by differences in their sensitivities to a small set of latent factors that summarize common investment characteristics

of the portfolio.

C.2 Optimal asset demand: matrix derivation

We have a typical mean-variance portfolio problem, with first order conditions given by:

$$\mathbf{w}_i = \frac{1}{\gamma_i} \text{Var}_{i,t}(\mathbf{R}_i)^{-1} \mathbb{E}_i[\mathbf{R}_i]$$

The covariance matrix of returns is given by:

$$\text{Var}_{i,t}(\mathbf{R}_i) = \mathbf{B}_i \mathbf{B}_i' + \sigma^2 \mathbf{I}$$

where $\mathbf{B}_i$ is the matrix of factor loadings with each column containing the factor loadings for each asset, and σ^2 is the idiosyncratic variance. Thus, the optimal portfolio weights are

$$\mathbf{w}_i = \frac{1}{\gamma_i} (\mathbf{B}_i \mathbf{B}_i' + \sigma^2 \mathbf{I})^{-1} \mathbb{E}_i[\mathbf{R}_i]$$

Since $\mathbf{B}_i \mathbf{B}_i'$ is a low-rank matrix, we can apply the Woodbury matrix identity to rewrite the optimal portfolio weights as:

$$\mathbf{w}_i = \frac{1}{\gamma_i \sigma^2} \left(\mathbf{I} - \mathbf{B}_i (\sigma^2 \mathbf{I} + \mathbf{B}_i' \mathbf{B}_i)^{-1} \mathbf{B}_i' \right) \mathbb{E}_i[\mathbf{R}_i]$$

We define $\mathbf{\Lambda}_i \equiv (\sigma^2 \mathbf{I} + \mathbf{B}_i' \mathbf{B}_i)$, and we get:

$$\mathbf{w}_i = \frac{1}{\gamma_i \sigma^2} \left(\mathbf{I} - \mathbf{B}_i \mathbf{\Lambda}_i^{-1} \mathbf{B}_i' \right) \mathbb{E}_i[\mathbf{R}_i]$$

Thus, for each asset n , the optimal portfolio weight is:

$$w_i(n) = \frac{1}{\gamma_i \sigma^2} \left[\left(1 - \beta_i(n)' \mathbf{\Lambda}_i^{-1} \beta_i(n) \right) \mathbb{E}_i[R(n)] - \beta_i(n)' \mathbf{\Lambda}_i^{-1} \sum_{m \neq n} \beta_i(m) \mathbb{E}_i[R(m)] \right]$$

C.3 Asset Demand as Exhibiting a Low-Rank Structure

Investors typically price risk using the same K systematic factors alongside a common idiosyncratic variance. Consequently, the overall demand for nearly identical bonds depends solely on (i) the scalar sum of those bonds' expected returns and (ii) a K -dimensional vector summarizing their factor

loadings. This observation implies that the $I \times J$ matrix (where rows represent investors and columns represent bond portfolios) can vary along at most $K + 1$ directions, regardless of how large I or J are, rendering the demand matrix inherently low-rank.

We can rewrite the demand of investor i for portfolio $\mathcal{B}_j$, in (C.1), as:

$$W_i(\mathcal{B}_j) = \frac{1}{\gamma_i \sigma^2} \left[S_0(\mathcal{B}_j) - \beta(\mathcal{B}_j)^\top \kappa_i \right],$$

with $S_0(\mathcal{B}_j) = \sum_{m \in \mathcal{B}_j} \mathbb{E}[R(m)]$ representing the sum of expected returns for bonds within portfolio $\mathcal{B}_j$. We now stack the demands of the I investors into the $I \times J$ matrix

$$\mathbf{W} = [W_i(\mathcal{B}_j)].$$

For each investor i , define the vector

$$\mathbf{L}_i = \frac{1}{\gamma_i \sigma^2} \begin{bmatrix} 1 \\ -\kappa_i \end{bmatrix} \in \mathbb{R}^{K+1},$$

and for each portfolio $\mathcal{B}_j$, define

$$\mathbf{s}(\mathcal{B}_j) = \begin{bmatrix} S_0(\mathcal{B}_j) \\ \beta(\mathcal{B}_j) \end{bmatrix} \in \mathbb{R}^{K+1}.$$

Then Equation (1) can be written as the inner product

$$W_i(\mathcal{B}_j) = \mathbf{L}_i^\top \mathbf{s}(\mathcal{B}_j).$$

By stacking $\mathbf{L}_i$ into an $I \times (K + 1)$ matrix

$$\mathbf{L} = \begin{bmatrix} \mathbf{L}_1^\top \\ \vdots \\ \mathbf{L}_I^\top \end{bmatrix},$$

and arranging $\mathbf{s}(\mathcal{B}_j)$ as the columns of a $(K + 1) \times J$ matrix

$$\mathbf{S} = [\mathbf{s}(\mathcal{B}_1) \quad \cdots \quad \mathbf{s}(\mathcal{B}_J)],$$

we obtain the compact factorization

$$\mathbf{W} = \mathbf{L}\mathbf{S}$$

Since $\mathbf{W}$ is the product of an $I \times (K + 1)$ matrix and a $(K + 1) \times J$ matrix, it follows that

$$\text{rank}(\mathbf{W}) \leq K + 1.$$

Given that the number of priced factors K is usually small relative to I and J , Equation (2) reinforces that the demand matrix $\mathbf{W}$ is low-rank.

C.4 Asset demand as a function of asset characteristics

Similar to [Kojien and Yogo \(2019\)](#), we assume that investors do not know the true data-generating process of asset returns. Instead, each investor has subjective beliefs about the stochastic process driving asset returns:

$$\begin{aligned} R_{i,t,n} &= \mathbb{E}_i[R_{i,t,n}] + \beta'_{i,n} \mathbf{f}_t + u_{t,n} \\ \beta_{i,k,n} &= \boldsymbol{\pi}'_{i,k,n} \mathbf{x}_{t,n} \\ \mathbb{E}_i[R_{i,t,n}] &= \boldsymbol{\theta}'_{i,k,n} \mathbf{x}_{t,n} \end{aligned}$$

where $\mathbb{E}_i[R_n]$ is the return of asset n expected by investor i , $\mathbf{f}$ is a $k \times 1$ vector of orthogonal risk factors with mean zero and variance unity, and $\beta_{i,n}$ is the vector of asset-specific factor loadings, as believed by investor i . We assume factors are orthogonal to each other, have mean zero and variance unity. Finally, u_n is an idiosyncratic shock with mean zero and variance σ^2 . Investors use observable asset characteristics or information signals to form beliefs about the expected returns and factor loadings. We denote by $\mathbf{x}_n$ the vector of characteristics of asset n , and by $\pi_{i,k}$ the vector of coefficients that determine the strength of the relationship between characteristics and the factor loadings. We assume that investors' beliefs are linear in these characteristics.

Next, we express (C.4) in matrix form by stacking all assets:

$$\mathbf{R}_i = \mathbf{X}'\boldsymbol{\Theta}_i\mathbf{1} + \mathbf{X}'\boldsymbol{\Pi}_i\mathbf{f}_t + \mathbf{u}_t$$

where $\boldsymbol{\Pi}_i \equiv \text{diag}[\pi_{i,1}, \pi_{i,2}, \dots, \pi_{i,k}]$, $\pi_{i,k} \equiv (\pi_{i,k}(1), \dots, \pi_{i,k}(n))'$, $\mathbf{X} \equiv \text{diag}[\mathbf{x}(1), \dots, \mathbf{x}(n)]$, $\boldsymbol{\Theta} = \text{diag}[\boldsymbol{\theta}(1), \dots, \boldsymbol{\theta}(n)]$, and $\mathbf{1}$ is a conformable vector of ones. Since the covariance matrix is given

by:

$$\text{Var}_{i,t}(\mathbf{R}_{i,t}) = \mathbf{X}'\mathbf{\Pi}_i\mathbf{\Pi}_i'\mathbf{X} + \sigma^2\mathbf{I}$$

After applying the Woodbury matrix identity on the covariance matrix, we can rewrite the optimal asset weights as:

$$\mathbf{w}_{i,t} = \frac{1}{\gamma_i\sigma^2} \left(\mathbf{I} - \mathbf{X}'\mathbf{\Pi}_i (\sigma^2\mathbf{I} + \mathbf{\Pi}_i'\mathbf{X}\mathbf{X}'\mathbf{\Pi}_i)^{-1} \mathbf{\Pi}_i'\mathbf{X} \right) (\mathbf{X}'\mathbf{\Theta}_i\mathbf{1})$$

We define the vector $\boldsymbol{\lambda}_i \equiv \frac{1}{\gamma_i\sigma^2} \left(\mathbf{\Theta}_i\mathbf{1} - \mathbf{\Pi}_i (\sigma^2\mathbf{I} + \mathbf{\Pi}_i'\mathbf{X}\mathbf{X}'\mathbf{\Pi}_i)^{-1} \mathbf{\Pi}_i'\mathbf{X}\mathbf{X}'\mathbf{\Theta}_i\mathbf{1} \right)$, and we can rewrite the optimal portfolio allocation as a linear function of asset characteristics:

$$\mathbf{w}_{i,t} = \mathbf{X}'\boldsymbol{\lambda}_i$$

which, for each asset, takes the form:

$$w_{i,t}(n) = \mathbf{x}(n)'\boldsymbol{\lambda}_i(n)$$

D WITHIN-MARKET ESTIMATES: FIRST STAGE AND LEAST SQUARES

This appendix reports the first-stage estimates and the least squares counterparts of the within-market IV specifications of [Section 4.1](#). [Table D.1](#) pairs each first-stage column with the corresponding second-stage IV column in [Table 2](#) and [Table 3](#).

TABLE D.1. First stage: instrument relevance for syndicated loans and bonds

<i>Panel A: Syndicated lending substitution specification</i>				
	(1)	(2)	(3)	(4)
$Z_{i,t}(l)$	2.22*** (0.14)	2.30*** (0.17)	1.98*** (0.18)	2.18*** (0.17)
Dependent variable	Log loan spread			
Firm-Quarter FE	Yes	Yes	Yes	-
Firm-Quarter-Type FE	-	-	-	Yes
Quarter-Currency-Type FE	Yes	Yes	Yes	Yes
Only firms which issued bonds	No	Yes	No	No
Maturity	All	All	>3y	All
R-squared	0.92	0.90	0.92	0.92
N	50,154	29,128	30,653	27,447
First-stage F	251	191	119	156

<i>Panel B: Bond within-market specification</i>				
	(1)	(2)	(3)	(4)
$\log Z_{i,t}(n)$	-0.049*** (0.005)	-0.050*** (0.009)	-0.075*** (0.005)	-0.075*** (0.005)
Dependent variable	Log bond price			
Bond price	Swap	Swap	Swap	Swap
Coupon type	All	Fixed	All	All
Spread above the 10bp floor	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes
Quarter-Currency FE	Yes	Yes	Yes	Yes
Only firms which obtained syndicated loans	No	No	Yes	No
Maturity	All	All	All	>3y
R-squared	0.84	0.87	0.86	0.89
N	72,594	67,433	39,299	43,703
First-stage F	95	34	190	263

First stage estimates for the within market IV specifications. Panel A mirrors [Table 2](#): the dependent variable is the log loan spread and the instrument is the tranche level loan demand shifter $Z_{i,t}(l)$ of Equation (4), the lending share weighted average of the estimated bank-time effects of the non-lead members of the syndicate. Panel B mirrors [Table 3](#): the dependent variable is the log bond price of the corresponding column, the log spread over the par swap curve, and the instrument is $\log Z_{i,t}(n)$, the log factor fitted dollar demand of institutional investors for comparable bonds. The first stage statistic is a test of instrument strength (the Kleibergen-Paap rk Wald F), computed on the same firm clustered variance matrix as the standard errors. Robust standard errors clustered at the firm level are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

[Table D.2](#) reports the least squares estimates of Equation (5) for syndicated lending (Panel A) and corporate bonds (Panel B), column by column on the samples of [Table 2](#) and [Table 3](#); the comparison with the instrumented estimates is discussed in [Section 4.1](#).

TABLE D.2. Within-market elasticity of substitution: least squares estimates

<i>Panel A: Syndicated lending</i>				
	(1)	(2)	(3)	(4)
$\log R_{i,t}(n a)$	-0.59*** (0.04)	-0.65*** (0.04)	-0.71*** (0.04)	-0.57*** (0.04)
Dependent variable	Log loan issuance			
Firm-Quarter FE	Yes	Yes	Yes	-
Firm-Quarter-Type FE	-	-	-	Yes
Quarter-Currency-Type FE	Yes	Yes	Yes	Yes
Only firms which issued bonds	No	Yes	No	No
Maturity	All	All	>3y	All
R-squared	0.80	0.77	0.79	0.81
N	50,154	29,128	30,653	27,447
<i>Panel B: Corporate bonds</i>				
	(1)	(2)	(3)	(4)
$\log R_{i,t}(n a)$	-0.10 (0.09)	-0.10 (0.10)	0.01 (0.04)	-0.08 (0.10)
Dependent variable	Log bond issuance			
Bond price	Swap	Swap	Swap	Swap
Coupon type	All	Fixed	All	All
Spread above the 10bp floor	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes
Quarter-Currency FE	Yes	Yes	Yes	Yes
Only firms which obtained syndicated loans	No	No	Yes	No
Maturity	All	All	All	>3y
R-squared	0.88	0.88	0.84	0.89
N	72,594	67,433	39,299	43,703

Ordinary least squares counterparts of the instrumented within-market elasticities of substitution. Panel A mirrors [Table 2](#) and Panel B mirrors [Table 3](#), column by column and on the same estimation samples. The outcome is log issuance amount and $\log R_{i,t}(n|a)$ is the log credit spread: the contractual spread over the reference rate for loans, and the spread over the par swap curve for bonds. Column definitions and fixed effects are as in the corresponding main text table. Robust standard errors clustered at the firm level are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

[Table D.3](#) reproduces the bond within-market estimates with the government curve in place of the par swap curve as the benchmark.

TABLE D.3. Within-market own-elasticity: Bond issuance, government benchmarked spread

<i>Panel A: OLS</i>				
	(1)	(2)	(3)	(4)
$\log R_{i,t}(n a)$	-0.08 (0.09)	-0.09 (0.10)	0.02 (0.05)	-0.08 (0.10)
Dependent variable	Log bond issuance			
Bond price	Gov.	Gov.	Gov.	Gov.
Coupon type	All	Fixed	All	All
Spread above the 10bp floor	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes
Quarter-Currency FE	Yes	Yes	Yes	Yes
Only firms which obtained syndicated loans	No	No	Yes	No
Maturity	All	All	All	>3y
R-squared	0.86	0.88	0.84	0.87
N	79,156	72,230	43,263	47,198

<i>Panel B: IV</i>				
	(1)	(2)	(3)	(4)
$\log R_{i,t}(n a)$	-0.83*** (0.20)	-0.54*** (0.19)	-0.68*** (0.18)	-0.74*** (0.18)
Dependent variable	Log bond issuance			
Bond price	Gov.	Gov.	Gov.	Gov.
Coupon type	All	Fixed	All	All
Spread above the 10bp floor	Yes	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes	Yes
Quarter-Currency FE	Yes	Yes	Yes	Yes
Only firms which obtained syndicated loans	No	No	Yes	No
Maturity	All	All	All	>3y
First-stage F	80	31	136	267
N	79,156	72,230	43,263	47,198

Government benchmarked twin of Table 3. $\log R_{i,t}(n|a)$ is the log bond price, the credit spread in basis points over the government curve. The sample and specification choices, column by column, are those of Table 3; the realised samples are wider, because the government curves cover 34 currencies against 17 for the par swap curves, so more bonds carry a benchmarked spread. Panel A presents OLS and Panel B the IV estimate on the same estimation sample, column by column. N counts the observations remaining once the fixed effects are absorbed. The first stage statistic is a test of instrument strength (the Kleibergen-Paap rk Wald F), computed on the same firm clustered variance matrix as the standard errors. Robust standard errors clustered at the firm level are in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

E FROM CREDIT SPREADS TO PRICES

This appendix derives the mapping between credit spreads and the price of a claim that we use to restate our estimates in price units, sets out how we construct the annuity factor on which it depends, and extends it to the cross-market case.

E.1 *Why restate spread elasticities as price elasticities*

Our regressions measure prices in credit spreads. This is the natural unit in the primary corporate debt market: a syndicated loan is quoted as a margin over a reference rate, while a bond's yield can be written as a spread over a currency- and maturity-matched benchmark curve. Every elasticity we interpret in the main text is therefore an elasticity with respect to a credit spread. Asset demand elasticities, by contrast, are usually defined with respect to the price of the security ([Kojien and Yogo, 2019](#)). To compare our supply elasticities with that literature, we translate a percentage change in the credit spread into the corresponding percentage change in the price of the claim.

The key distinction is between the *amount of funds raised* and the *quantity of claims supplied*. Let X denote the amount the firm raises at issuance, Q the quantity of promised cash flows it must sell in order to raise X , and P the price received per unit of those promised cash flows, so that $X = PQ$ by definition. A wider credit spread means that the firm receives a lower price per unit of promised payment; equivalently, to raise the same amount X it must promise more cash flows. The coefficients we estimate describe the response of X to the spread; the price elasticity describes the response of Q to P .

E.2 *The price of a claim*

Consider a contract issued at par with contractual spread s and maturity T , and let

$$A(y, T) = \sum_{\tau=1}^T \frac{1}{(1+y)^\tau} = \frac{1 - (1+y)^{-T}}{y}$$

denote the present value of one unit paid annually for T years, where y is the contract's total yield. Thus A is an annuity factor: an additional annual payment of one dollar over the life of the contract has present value A .

The contractual spread requires the firm to make an additional payment of sX per year, whose present

value is sAX . Measuring the quantity of claims relative to the amount raised, the total quantity of promised claims is

$$Q = X + sAX = X(1 + sA).$$

Since the firm receives X in exchange for these claims, the price per unit of promised cash flow is

$$P = \frac{X}{Q} = \frac{X}{X(1 + sA)} = \frac{1}{1 + sA}.$$

This gives the mapping from a credit spread into a price. Holding the contract-specific annuity factor A fixed, differentiating with respect to the spread gives

$$-\frac{\partial \ln P}{\partial s} = \frac{A}{1 + sA} \equiv D^s,$$

where D^s is the claim's spread duration. Spread duration therefore differs from the annuity factor itself: A is the present value of one unit of annual spread payments, whereas D^s measures the percentage sensitivity of the claim price to a one-unit change in the spread. Because our elasticities use percentage changes in spreads, the relevant object is

$$u \equiv -\frac{\partial \ln P}{\partial \ln s} = sD^s = \frac{sA}{1 + sA},$$

the share of the promised cash-flow stream accounted for by the spread annuity, so that $d \ln P = -u d \ln s$. A 1% increase in the credit spread lowers the price of the claim by $u\%$; conversely, a 1% decrease in the price corresponds locally to a $1/u\%$ increase in the spread. The mapping can be large because the credit spread is only one component of the payments promised by the borrower: a large proportional movement in that component can correspond to a much smaller proportional movement in the price of the entire claim.

E.3 From the estimated coefficient to a price elasticity

Define

$$\beta \equiv \frac{\partial \ln X}{\partial \ln s},$$

the elasticity of the *amount raised* with respect to the credit spread. This is the coefficient we estimate. What we ultimately want is the elasticity of the *quantity of claims supplied*, Q , with respect to their price, P . From $X = PQ$,

$$\ln Q = \ln X - \ln P,$$

and differentiating with respect to the log spread gives

$$\frac{\partial \ln Q}{\partial \ln s} = \frac{\partial \ln X}{\partial \ln s} - \frac{\partial \ln P}{\partial \ln s} = \beta + u.$$

The two terms in this expression are the two channels through which a wider spread moves the number of claims: the firm chooses to raise less, which is β and is negative, and each claim fetches a lower price, so that more of them must be sold to raise any given amount, which is the $+u$.

Because the demand shifter moves only the spread, the amount raised, the price per claim and the quantity of claims all respond through s alone. Both responses are therefore taken along the same supply curve, parameterised by s , and their ratio is the derivative of $\ln Q$ with respect to $\ln P$. Using $\partial \ln P / \partial \ln s = -u$, the conventional price elasticity of supply is

$$\varepsilon_P \equiv \frac{\partial \ln Q}{\partial \ln P} = \frac{\partial \ln Q / \partial \ln s}{\partial \ln P / \partial \ln s} = \frac{\beta + u}{-u} = -\frac{\beta}{u} - 1. \quad (12)$$

The two terms have different origins. The term $-\beta/u$ converts the firm's estimated response in the amount raised from spread units into price units. The additional -1 is mechanical: even if the firm kept X completely unchanged, $X = PQ$ implies $d \ln Q = -d \ln P$, so a 1% lower price per claim requires the firm to create 1% more claims simply to raise the same amount of money. This response is present independently of any behavioural adjustment in X .

E.4 *Constructing the annuity factor*

For each contract we evaluate A using its maturity and total yield. For a par instrument,

$$A(y, T) = \frac{1 - (1 + y)^{-T}}{y},$$

which is also the modified duration of a standard par bullet bond with annual payments.¹

This construction also explains why a floating-rate syndicated loan does not have zero spread duration. The floating reference-rate component resets periodically and therefore remains close to par. The contractual margin over that reference rate, however, is fixed. A loan with spread s therefore still promises an additional payment of sX at every payment date until maturity. Those fixed spread

¹The conversion is local: we evaluate A at the contract's observed maturity and yield and hold this annuity factor fixed when taking the derivative with respect to s . Using the benchmark rate rather than the total yield to discount the annuity produces very similar conversions. Replacing A by contractual maturity T , by contrast, overstates the relevant duration and changes the conversion by roughly 15%.

payments form an annuity, and it is their present value that enters A and hence u .

For bonds, we construct the total yield using the recorded coupon, which equals the yield for an issue placed at par. For loans, we add the contractual margin to the short end of the par swap curve for the tranche's currency and quarter.¹

On the within-market estimation samples we obtain $u_L = 0.077$ for loans and $u_B = 0.063$ for bonds, so that $1/u_L \simeq 13.0$ and $1/u_B \simeq 15.9$. A 1% movement in the price of a loan claim therefore corresponds to approximately a 13% movement in its credit spread, while a 1% movement in the price of a bond corresponds to approximately a 16% movement in its spread. The conversion is therefore quantitatively large: the same response by the firm can look small in the unit the market quotes and large in the unit the asset demand literature uses. Applying Equation (12) to the within-market estimates of Section 4.1, the elasticities of -0.79 in syndicated lending and -0.60 in corporate bonds correspond to price elasticities of 9.32 and 8.52, and the total issuance elasticities of Section 4.3 to 6.87, 2.31 and 4.07.

E.5 Cross-market substitution

The same logic applies to substitution between loans and bonds, with one additional complication. A cross-market elasticity is defined with respect to a *relative* price, and since the spread-to-price mapping can differ between the two markets, we need to know which market's spread generates the relative-price movement.

Let X_B/X_L denote bond issuance relative to loan issuance and P_B/P_L the corresponding relative price. Using the sign convention of our cross-market specification, let $\sigma > 0$ denote substitution away from the market whose spread rises, so that

$$\frac{\partial \ln(X_B/X_L)}{\partial \ln(s_B/s_L)} = -\sigma.$$

Because $Q_i = X_i/P_i$ in each market,

$$\ln\left(\frac{Q_B}{Q_L}\right) = \ln\left(\frac{X_B}{X_L}\right) - \ln\left(\frac{P_B}{P_L}\right).$$

Suppose first that the relative-spread shock comes entirely from the bond market, so that s_L is un-

¹The loan panel records the contractual margin but not the reference rate against which it is set. We reconstruct the missing reference-rate component from the short end of the par swap curve, aggregated by currency and quarter. The conversion can be computed for contracts with both a recorded maturity and a yield, covering 80% of the loan estimation sample and 95% of the bond estimation sample.

changed. Then $d \ln(P_B/P_L) = -u_B d \ln(s_B/s_L)$, and the elasticity of relative claim supply with respect to the relative price is

$$\varepsilon_{P,\text{cross}}^B = \frac{\sigma}{u_B} - 1.$$

If instead the shock comes entirely from the loan market, the same argument gives $\varepsilon_{P,\text{cross}}^L = \sigma/u_L - 1$. A symmetric relative-spread shock, in which the bond and loan spreads move equally in opposite directions in logs, uses $\bar{u} = (u_B + u_L)/2$ and gives $\varepsilon_{P,\text{cross}}^{\text{sym}} = \sigma/\bar{u} - 1$. We use this symmetric conversion as our baseline and report the bond- and loan-driven conversions as a range.

The distinction is quantitatively important for dual issuers. In firm-quarters in which the same firm issues both bonds and loans, sA equals 0.16 for bonds and 0.07 for loans, which correspond to

$$u_B = \frac{0.16}{1.16} = 0.138, \quad u_L = \frac{0.07}{1.07} = 0.065.$$

The difference reflects the contracts issued in the two markets. The median bond of a dual issuer carries a spread of 225 basis points and a maturity of eight years, compared with 175 basis points and five years for the median loan. The same proportional spread movement consequently generates a substantially larger price movement when it occurs in the bond market than when it occurs in the loan market: on the dual-issuer panel the spread annuity accounts for 0.14 of what a bond promises against 0.06 of what a loan promises, so a given proportional move in the bond spread is worth more than twice as much in price terms. Applied to the cross-market elasticity of substitution of 0.41 in [Section 4.2](#), the conversion gives 3.00 in the symmetric case that we report as our baseline, and runs from 1.90 when the shock arrives through the bond market to 5.44 when it arrives through the loan market.

E.6 Comparing elasticities across specifications

The conversion also makes clear when comparisons are sensitive to the choice of units. An individual elasticity is always unit-dependent: its numerical value changes when we move from spreads to prices.

If two coefficients are converted using the same u , the transformation $\varepsilon_P = -\beta/u - 1$ is the same for both, so a test of equality is unaffected:

$$\beta_1 = \beta_2 \iff \varepsilon_{P,1} = \varepsilon_{P,2}.$$

Whenever a common conversion factor applies to both coefficients, therefore, a test of equality be-

tween them carries over unchanged from one unit to the other.

Ratios, however, are *not* invariant, because the conversion contains the additive -1 ; nor are comparisons invariant when the relevant values of u differ. This matters when comparing the loan and bond estimates. On the within-market samples $u_L = 0.077$ and $u_B = 0.063$, and correspondingly the ratio of the two estimated elasticities is 0.76 in spread units but 0.91 in price units. The difference is larger still when a within-market elasticity is compared with the cross-market elasticity, for which the relevant values of u are computed on the dual-issuer sample and differ substantially across the two markets. For this reason we always state the unit of an elasticity explicitly, and a test of equality between two coefficients converted with the same u is the only comparison that is unaffected by the choice: spread elasticities are the objects estimated directly from the data, and price elasticities are their economically equivalent restatements using the mapping derived above.