An Empirical Analysis of the Cost of Borrowing*

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Abstract

We empirically study firm financing costs using a comprehensive dataset of corporate bonds and bank loans. We construct a measure of the cost of financing, the Excess Debt Premium, which controls for observable debt characteristics. We document two key findings: first, bank loans are about 97 basis points cheaper than corporate bonds when controlling for observable characteristics. Second, there is significant dispersion in borrowing costs, even within the same firm and quarter. The analysis reveals that this within-firm variation persists after accounting for instrument type, maturity, amount, and lender identity, suggesting substantial heterogeneity in the cost of debt across different financing instruments.

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1 Introduction

Firm financing decisions are widely studied in economics and finance, thanks to their relevance for real outcomes such as employment and investment. One key determinant of these decisions is the cost of borrowing. Yet, empirically, most of the research on this topic has been limited in scope to large public firms, due to lack of micro data on interest rates and other characteristics on the borrowing instruments of firms in the United States. This paper fills this gap by analyzing the cost of borrowing of both large and small firms in the United States, using a novel debt instrument-level database that encompasses both bank loans and corporate bond issuances.

We construct a dataset of borrowing instruments for US nonfinancial firms that covers the universe of bond issuances and loans issued by major US bank holding companies (BHC). We then develop a measure of the cost of borrowing at the firm level that extends the Excess Bond Premium (EBP) of Gilchrist and Zakrajsek (2012) (GZ hereafter) to a set up with multiple debt instrument types and that controls for observable characteristics, such as amount, maturity, and firm default probability. We call this measure the Excess Debt Premium (EDP), to reflect the fact that it encompasses borrowing instruments beyond senior unsecured bonds. We use this measure to arrive at two main results. First, we document that there is a significant bond-loan spread: when controlling for observable characteristics, loans are about 97 bps cheaper than bonds. Second, there is significant variation in the cost of borrowing as measuring by the EDP. A significant share of this variation arises within a firm and a quarter, across issued instruments: even the same firm, issuing multiple types of debt instruments in a given quarter, faces substantial dispersion in the cost of debt.

Section 2 explains how we construct our dataset, by merging individual bond issuance data with regulatory BHC balance sheet data that contains details on individual loan arrangements. Most existing studies on firm borrowing costs rely on syndicated loan data from Dealscan, which only covers large syndicated loans, and firm financial data from Compustat, which contains financial information for US publicly traded firms only. Our main dataset results from merging the Mergent Fixed Income Securities Database (FISD) with the Federal Reserve's FR Y-14Q Schedule H.1, which contains detailed information on loan facilities originated by large US BHCs. Unlike traditional approaches, our data includes detailed information on borrowing by both public and private firms, large and small. Our final dataset encompasses 335 thousand loans and about 15 thousand bonds issued by 160 thousand firms; it effectively covers the universe of bond issuances and 91 percent of commercial and industrial lending undertaken by major BHCs in the US.

In Section 3, we detail the construction of the EDP and present our first main result. Our measure differs from the EBP along two important dimensions. First, we consider a much larger set of instruments that goes beyond unsecured senior bonds including not only other types of bonds but also multiple types of loans: term loans, credit lines, syndicated and non-syndicated loans, among others. Second, due to the absence of secondary market data on prices for these types of loans, our measure is computed at instrument origination. The EDP is the residual credit spread after controlling for many observable instrument characteristics, such as amount, maturity, default probability, loss given default (which reflects seniority) and instrument type, among others. The construction of the EDP delivers our first main result: that bank loans are systematically "cheaper" than bonds when conditioning on observable firm and instrument characteristics. This is consistent with previous studies, such as Schwert (2020). In particular, we find that interest rates on loans tend to be 97 basis points (bps) lower than interest rates on bonds.

When aggregated, the EDP is imperfectly correlated with the EBP, suggesting that our data includes new information about credit conditions that is not captured by looking solely at unsecured bond issuances. We find a large amount of dispersion in this measure within a firm and a period. This suggests that the cost of borrowing is heterogeneous even within the boundaries of each individual firm.

In Section 4, we present a variety of variance decomposition exercises for the EDP that delivers our second main result. The EDP already controls for many observable characteristics that should explain dispersion in borrowing costs according to most models of credit risk, namely the default probability of the borrower, as well as maturity or size of the instrument. Still, a significant amount of residual variation remains after controlling for these factors. We decompose this variation into components arising from aggregate time variation, firm-time variation, and within firm-time variation. We find that the latter component remains large: there is significant dispersion in the cost of borrowing across multiple instruments issued by the same firm in the same quarter.

Related Literature. There is a large literature in economics and finance that studies the cost of external finance for firms. Hennessy and Whited (2007) combine data with a structurally estimated model to find significant dispersion in financing costs between small and large firms. More recently, Gormsen and Huber (2025) estimate series for the cost of capital and corporate discount rates from earnings call data. They argue that corporate discount rates are a more proximate driver of investment decisions than the cost of financing. Pengfei Wang (2025) uses aggregate data to document that default risk cannot explain the spread between the average bank loan rate and the interbank rate, and studies its aggregate implications. We view our paper as complementary to theirs, by presenting a new estimated measure for firm-level cost of external financing based on security prices instead of earning call announcements.

Our paper is closely related to Schwert (2020), who studies differences in interest rates between bonds and syndicated loans, finding a significant spread between the two. We extend his analysis beyond large publicly traded firms and syndicated loans, and find similar results. Our methodology to derive the Excess Debt Premium is closely inspired by that of Gilchrist and Zakrajsek (2012), who document a sizeable spread that is not explained by individual firm default risk when considering a panel of senior unsecured bonds.

One of the main contributions of our paper is that we use an extremely large panel of loans and bonds to estimate proxies for the cost of external financing. We achieve this by leveraging the Federal Reserve's Y-14 data, which has also been utilized by a series of recent papers. Chodorow-Reich et al. (2022) and Faria-e-Castro et al. (2024) use this data to investigate how lending varies across banks, while Caglio et al. (2021) and Greenwald et al. (2021) study the transmission of monetary policy, and Ivanov et al. (2024) examine how taxes affect corporate borrowing. Bräuning et al. (2021) use the data to motivate a model of heterogeneous firm borrowing to study credit supply shocks. Our contribution is to exploit this micro-level data to derive new estimates of borrowing costs for small and large firms.

2 Data Description

We begin by describing the construction of our main dataset. We build a panel of debt instruments spanning 2013Q1 to 2023Q3 that contains information on borrowing from large bank holding companies (BHC) and corporate bonds.

Main Datasets and Scope. We rely on two main sources of data: (i) the Federal Reserve's FR Y-14Q H.1 schedule (Y-14), which contains information on loan facilities, and (ii) Mergent Fixed Income Securities Database (FISD), which provides information on corporate bond issuances. Here we briefly describe each of the datasets, and relegate a more detailed explanation of how we assemble the main dataset to Appendix A.

The Y-14 contains detailed data on commercial & industrial (C&I) lending for large BHCs, who are required to report detailed balance sheet data to the Fed for stress testing purposes. For most of our sample, the data includes reporting by the largest 33 BHCs. We observe all loan facilities on the balance sheet that have committed exposures of $1 million or more.[1] We see quarterly loan facility level data on interest rates, maturity, seniority, facility type, committed and utilized exposure, collateral market value, assessed default probability (PD), loss given default (LGD), and syndicated status, among other loan characteristics. Two major advantages of the Y-14 data are the size of the data and the ability to observe both small and large firms. Commonly used loan datasets such as the Shared National Credit database or Dealscan tend to contain only syndicated loans, which restricts the sample to larger firms.

Our second main dataset is the Mergent Fixed Income Securities Database (FISD), which contains information on bond issuances. The FISD covers a significant number of US corporate issuances, and provides information on offering amount, maturity, coupon, seniority, issuer, and a number of bond type flags (callable, putable, covenant, asset-backed, or rule 144a for example).

To define a firm, we use the S&P Business Entity Cross Reference Service (BECRS). The BECRS creates a linkage between firms and their ultimate parent, allowing us to identify subsidiaries and collapse them under the parent company. This is particularly important given the disaggregated nature of the Y-14 data, where the main firm identifier is the borrower's Tax Identification Number (TIN). Large corporate groups can have dozens or even hundreds of subsidiary companies, each with their own TIN. We create a firm identifier using the 6-digit firm CUSIP, grouping together CUSIPs with the same ultimate parent. Using CUSIPs, we then merge the firm identifier to both the Y-14 and FISD. For firms in the Y-14 without a match to the BECRS data, we rely on the TIN as the firm identifier.[2]

[1] A loan facility may be comprised of many separate loan types grouped into one facility.

[2] For more details on the definition of a firm see Appendix A.3.

2.1 Descriptive statistics

Table 1 presents summary statistics for the main variables used in the empirical analysis. Each observation is a debt instrument origination (bond issuance or loan facility creation). The final dataset contains over 398 thousand observations, for 160,223 unique firms. As expected, we observe many more bank loans (335,174) than corporate bonds (14,690).

Panels A and B report summary statistics on standard contractual characteristics for bonds and loans, respectively. First, we see that the average maturity of bonds is almost twice as long as that of loans: 11.4 vs. 6.4 years.[3] A significant percentage of loans tend to have a very short maturity (the 10th percentile of loan maturities is less than 1 year), while a significant share of bonds have maturities over 30 years (the 90th percentile).

Second, bond issuances tend to be much larger in dollar amounts than loans: almost $650 million for the average bond versus $10 million for the average loan. The 90th percentile of loan sizes is considerably below the median of bond sizes.[4]

Third, average interest rates on bond issuances are higher than those of loans, which is perhaps not surprising in light of the two previous facts: the average and median interest rates are about 50 bps higher.[5] We also compute interest rate spreads by taking the difference between the interest rate at origination and the yield on a government security with equivalent maturity on the date of origination.[6] By computing the spread using a maturity-matched yield, our measure of spreads partly accounts for the term premium. We find more compressed differences in spreads: 14 bps on average and -36 bps for the median. There are many other reasons for why interest rates and spreads can vary between bonds and loans. Later, in Section 3, we conduct a more thorough analysis where we show that there are systematic differences between the prices of these two types of instruments even when other observable instrument and firm characteristics are taken into account.

Fourth, the loss given default (LGD) is much larger for bonds than for loans. The average LGD is 60 percent for bonds and 32 percent for loans. In the Y-14, we directly observe LGD

[3]Demand loans and revolving credit lines do not have an associated maturity, so we can interpret them as having infinite maturity. Given the existence of a positive term spread, we make a conservative assumption and assign a maturity of 30 years for these instruments. Our main results are robust to assuming shorter maturities.

[4]The amount for loans is the amount utilized, not the amount committed. For credit lines, many will have considerably larger committed amounts than utilized.

[5]One shortcoming of the data is that we do not observe any of the fees associated with borrowing.

[6]We use nominal yield data from Gurkaynak et al. (2007). Data available from the Federal Reserve Board at https://www.federalreserve.gov/data/nominal-yield-curve.htm.

for each loan. For the FISD, however, there is no such variable. Thus, we use the Moody's Annual Default Study to set LGD for bonds (Moody's Investors Service, 2015).[7]

Panel C of Table 1 presents summary statistics at the firm-quarter level. Only 2 percent of firms in our sample issue bonds. The loan share, defined as the ratio of issued amounts of loans to the sum of loans and bonds is 98 percent on average, which reflects the relative rare usage of bonds as a financing instrument. Once we condition on issuing bonds, the loan share becomes 13 percent, which reflects the previously discussed fact that bond issuances tend to be much larger than loans in dollar terms. The mean probability of default at the firm level is 1.8 percent.[8] Finally, the two last rows of Panel C show that debt issuance is relatively infrequent, with the average firm issuing 0.11 debt instruments per quarter, and the 90th percentile equal to zero. The following row repeats this analysis for firms that issue both loans and bonds; these tend to be larger firms that issue debt more often, and thus the average number of issued instruments is 1.27 per quarter (and the 90th percentile is no longer zero).

Panel D of Table 1 breaks down the different types of loans that we observe in the dataset. Contrary to standard datasets such as Dealscan or the SNC, the majority of the loans are non-syndicated (71 percent). The data contains slightly more credit lines than term loans (50 vs. 44 percent), both syndicated and non-syndicated. Additionally, about 6 percent of our loans are neither term loans or credit lines, with most of these being classified as capitalized lease obligations.

In Appendix A.5, we compare our merged Y-14/FISD dataset with aggregate statistics to assess its coverage. For bonds, our data captures slightly more (about 14%) than the Flow of Funds nonfinancial corporate bond measure. For loans, we cover approximately 91% of large banks' C&I lending as reported in the Federal Reserve's H.8 data, with the remainder likely representing loans below the Y-14 reporting threshold. At the firm level, our dataset captures on average 41% of total liabilities (with a 37% median), with the remaining liabilities primarily consisting of trade credit and accounts payable not covered in our dataset.

[7]Specifically, Moody's Investors Service (2015) provides the average corporate debt recovery rates measured by post-default trading prices between 1982-2014 on bonds by seniority. We use bond seniority to match the average LGD of a bond.

[8]This probability of default is reported by Y-14 lenders, and refers to the firm's expected probability of default over the next year.

Table 1: Summary Statistics

	mean	sd	p10	p50	p90
Panel A: Bonds					
Maturity (yrs)	11.40	9.78	3.04	8.13	30.04
Amount (mil$)	646.46	714.81	1.90	500.00	1,250.00
Interest Rate (bps)	418.07	183.90	195.00	400.00	675.00
Interest Rate Spread (bps)	204.54	169.48	49.32	148.11	463.42
Loss Given Default (percent)	61	5	47	63	63
Panel B: Loans					
Maturity (yrs)	6.41	7.51	0.94	4.99	15.01
Amount (mil$)	10.35	40.17	0.82	2.73	24.75
Interest Rate (bps)	366.58	159.28	180.50	348.00	583.00
Interest Rate Spread (bps)	190.44	137.54	24.44	184.81	361.76
Loss Given Default (percent)	32	17	8	32	50
Panel C: Firm issuance (quarterly)					
Share of Firms with Bonds	1.88	13.59	0.00	0.00	0.00
Loan Share, $l/(l+b)$	98.09	13.31	100.00	100.00	100.00
Loan Share given $b > 0$	13.02	17.21	0.25	5.75	37.74
Probability of Default (percent)	1.88	6.41	0.15	0.76	3.17
Securities Issued	0.11	0.52	0.00	0.00	0.00
Securities Issued given $b > 0$	1.27	2.93	0.00	0.00	4.00
Panel D: Loan Types	*Frequency*	*Percent*			
Non-syndicated Credit Line	131,607	36.51			
Non-syndicated Term Loan	128,245	35.58			
Syndicated Credit Line	46,980	13.03			
Syndicated Term Loan	30,906	8.574			
Other	22,741	6.309			

Notes: We have 398,525 debt instruments for 160,223 firms. There are 335,174 loans and 14,690 bonds.

2.2 Time series for interest rates

Table 1 shows that there is significant cross-sectional dispersion in interest rates and spreads. We now compute three simple, direct measures of firm-level interest rates and analyze their aggregate behavior.

First, we define the *Average Interest Rate* (AIR) as the average interest rate a firm pays on all outstanding instruments in a given quarter, weighted by the size of the debt instrument (amount outstanding for bonds and amount utilized for loans). This is similar to the "implied average interest rate" that can be computed from Compustat data, by dividing total interest expenditures by debt outstanding.

Second, the *New Interest Rate* (NIR) is the average interest rate a firm pays on all newly issued instruments in a given quarter, again weighted by the size of each instrument. The main difference is that the NIR reflects current market rates, while the AIR takes into account previous issuances as well.

Third, we define the *Marginal Interest Rate* (MIR) as the highest interest rate that a firm pays among all newly issued instruments in a given quarter. Note that the MIR and the NIR coincide if a firm only issues one instrument in a given quarter. In general, the MIR will be higher than the NIR and it captures the highest interest rate that the firm is willing to pay to issue debt in a given quarter.

Figure 1 plots the aggregate time series for each of the three measures of interest rates. These aggregate time series are computed as medians across firms, weighted by total amount utilized on newly issued instruments. Panel (a) shows the three measures for interest rates, while panel (b) show the three measures for interest rate spreads, computed at origination for each instrument as previously described. By construction, the MIR is always weakly greater than the NIR. In panel (a), the gap between the MIR and the NIR is about 59 bps on average.

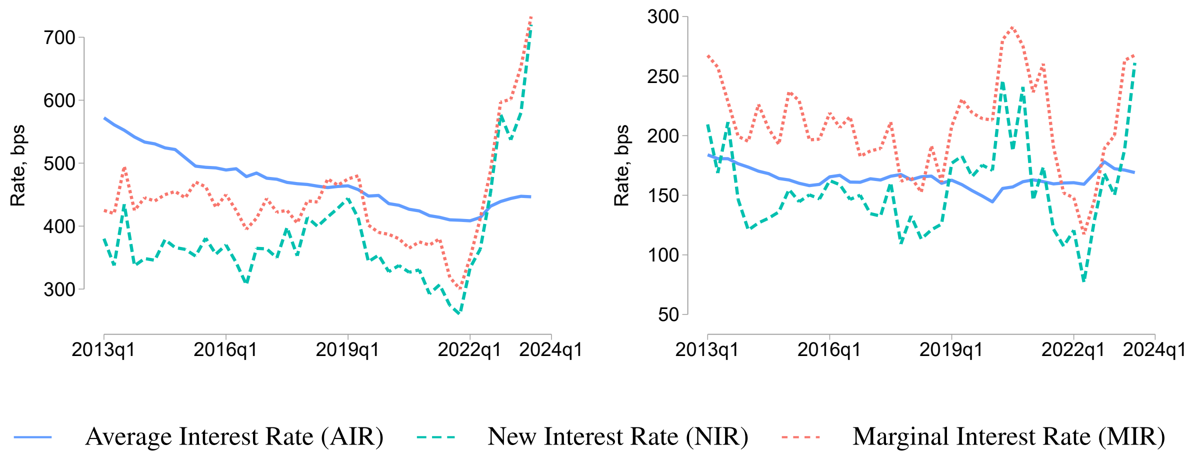
Panel (a) also shows that the AIR exceeds the NIR for most of the sample, except for two periods. This is to be expected given the low interest rate period that followed the 2007-08 Great Financial Crisis and subsequent Great Recession, with higher average interests reflecting past issuances; i.e., the AIR mechanically lags the NIR. In the latter part of the sample, the MIR is higher than the AIR, meaning that some newly issued instruments pay higher rates than the average interest rate for debt instruments in firms' balance sheets, a consequence of the Fed's rapid tightening of policy rates.

One way to partly account for this interest rate level effect is to consider instead maturity-matched interest rate spreads, as shown in Panel (b) of the same figure. This figure shows that spreads based on the AIR and the NIR display broadly similar movements. The MIR exceeds the NIR by about 53 bps on average, an indication that there significant within-firm heterogeneity persists even when variation in maturity of newly issued instruments is taken into account.

Panel (a) reveals that there can be substantial heterogeneity in interest rates paid by each particular firm within a quarter, as shown by the differences between NIR and MIR measures. This heterogeneity persists even when we compute maturity-matched spreads, as in panel (b). There are still many other instrument characteristics beyond maturity that could account for this

Figure 1: Interest Rates and Spreads

(a) Interest Rates (b) Interest Rate Spreads



heterogeneity among interest rates paid by firms, such as the type of instrument they are issuing, the amount they are borrowing, or the fact that different firms may have different probabilities of default. Next, we account for these observable characteristics by computing the Excess Debt Premium (EDP).

3 The Excess Debt Premium

To account for other observable characteristics that could explain within- and across-firm dispersion in the cost of borrowing, we construct a measure of deviations of observed interest rates from what a statistical model that conditions on observable characteristics would predict: the Excess Debt Premium (EDP). We use the EDP as the main indicator for a firm's cost of borrowing. We closely follow Gilchrist and Zakrajsek (2012), who construct a measure based on secondary market bond prices that they call the excess bond premium (EBP). There are, however, some important differences between the measure they construct and ours.

The first important difference is that we focus not only on fixed-rate senior unsecured bonds, but also include other types of bonds and, more importantly, bank loans observed in the Y-14. We therefore consider a much larger set of debt instruments than what is considered for the EBP, and explicitly control for instrument type. This raises a number of issues, however. We do not have secondary market prices for bank loans, as these instruments are not traded in secondary markets. This means that instead of considering the secondary market spreads of a bond at any point in time while it is outstanding, we consider only spreads at origination. Since we only need to control for the term premium at origination, we compute simple spreads at origination, without undertaking the procedure of constructing maturity-matched cash-flows that Gilchrist and Zakrajsek (2012). This allows us to include a wider set of debt instruments in our measure, such as variable rate or credit lines, for which constructing maturity-matched cash-flows would be non-trivial.

Let $r_{i,f,t}$ be the interest rate for instrument i issued by firm f at quarter t. Let $r^{treasury}_{t,m(i)}$ be the interest rate on a US Treasury with maturity $m(i)$: the same maturity as instrument i at quarter t. The spread at origination is computed as the simple difference between the two:

$$y_{i,f,t} = r_{i,f,t} - r^{treasury}_{t,m(i)}$$

We then follow Gilchrist and Zakrajsek (2012) and estimate the following specification:

$$\log y_{i,f,t} = \sum_j \gamma_j \mathbb{I}(\text{debt type}_{i,f,t} = j) + \Gamma X_{i,f,t} + \varepsilon_{i,f,t} \tag{1}$$

where $\mathbb{I}(\text{debt type}_{i,f,t} = j)$ is a dummy that is equal to 1 if debt instrument i is of type j. In our baseline specification, we separately consider the following debt instrument types: (i) callable bond, (ii) non-callable bond, (iii) syndicated credit line, (iv) syndicated term loan, (v) non-syndicated credit line, and (vi) non-syndicated term loan. $X_{i,f,t}$ is a vector of other observable instrument characteristics that includes maturity, size, probability of default, and LGD. The inclusion of LGD, in particular, is important as it captures not only expected recovery rates, but also differences in seniority across instruments.

The estimation results are reported in Panel A of Table 2. We consider six alternative specifications. Column (1) includes no fixed effects, column (2) includes sector fixed effects (NAICS 3-digit), column (3) includes firm fixed-effects, column (4) includes time fixed effects, column (5) includes sector-time fixed effects, and finally column (6) includes firm-time fixed effects. Note that the specification with firm fixed effects (column 3) restrict the sample to firms that have issued at least two instruments during the period of analysis, and the specification with firm-time fixed effects (column 6) considers only firms that issue multiple instruments within a quarter, which leads to a lower number of observations (a reduction in the sample size by about 30 and 60 percent, respectively). For that reason, our benchmark is the specification with time-sector fixed effects, column (5). Longer maturity and larger amounts are associated with lower spreads, which is likely to reflect selection and the fact that we observe equilibrium borrowing only. We do not consider this to be a problem since our goal at this stage is to simply control for these characteristics. As one would expect, a higher probability of default is associated with higher spreads. Higher LGD also result in higher spreads; again, this partly reflects differences in seniority across instruments, with more senior instruments having lower LGD, everything else constant.

Our reference category are non-callable bonds. We find significant differences between the spreads of bonds and loans, regardless of syndication status and type (credit lines or term loans). Loans tend to be significantly cheaper than bonds, especially if syndicated, even after controlling for observable characteristics. We explore this further in the following subsection.

3.1 The Bond-Loan Spread

As highlighted in our description of Panel A of Table 2, loan spreads appears to be consistently lower than those of bonds, regardless of the type of loan or bond. This finding was suggested by the summary statistics in Table 1, where we find lower interest rates on average for loans than for bonds, and Panel A of Table 2 shows that it seems to survive the inclusion of controls such as maturity and amount, which are quite different across instrument types.

We further investigate this difference by estimating a variant of equation 1 that pools all loan types together, so that we can interpret the coefficient γ as the average difference in (log) spreads, when controlling for other observable characteristics of the instrument. We report the results in Panel B of Table 2, with the different columns corresponding to combinations of fixed effects as in Panel A.

These results reinforce the fact that loans are, on average, cheaper than bonds. Consider the most conservative specification, which is presented in Column (6), as it includes firm-time fixed effects. The estimate for γ captures average differences in spreads between loans and bonds issued by the same firm in the same period. We find that loans have, on average, spreads that are 0.41 log points lower than those of bonds issued by the same firm, in the same period, and controlling for both amount and maturity. Hence, for the average firm, the spread of a bond is 51 percent larger (i.e., $\exp(0.41)$) than those of equivalent loans. A back-of-the-envelope calculation using the summary statistics in Table 1 (i.e, an average spread of about 190 basis points for loans) suggests that the spread between the average loan and a bond with the same characteristics is around 97 bps (i.e., 190×0.51).[9]

These findings are closely related to, and extend, those of Schwert (2020), who uses data on large public firms and finds that syndicated loans tend to have lower interest rates than bonds issued by the same firm and with equivalent residual maturity. Using a calibrated model of firm default, Schwert (2020) argues that the difference between spreads is actually smaller than what a model would predict (meaning that loan rates are actually higher than what a model would predict), which he attributes to bank market power in commercial & industrial lending. We find that even when controlling for loan seniority and recovery rates, by including LGD as an explicit control, and in a much larger and broader sample, a substantial spread persists between bonds and loans.

3.2 Time series: the EDP for bonds and loans

Using the estimation results from equation 1, column (5) of Table 2, we construct a predicted log spread at origination, $\widehat{\log y}_{i,f,t}$. The EDP for a given instrument is then defined as the difference between the observed spread and the predicted value from the regression:

$$EDP_{i,f,t} = y_{i,f,t} - \exp[\widehat{\log y}_{i,f,t}] \tag{2}$$

This is our preferred measure of the cost of debt, since it controls for several observable characteristics of the debt instrument. Panel (a) of Figure 2 plots time series for the average *EDP*, aggregated across instruments and firms. The solid blue line. There was a positive trend in the pre-pandemic period that seems to have reverted around 2020. This is followed by a significant drop and subsequent increase in the latter part of the sample. The dashed black line plots the Excess Bond Premium of GZ, which contains information on secondary market pricing for bonds only. While the two measures comove at some specific periods of the sample, the overall correlation is rather low, 11%, suggesting that our measure contains information that is not present in the EBP.

Next, we specialize our EDP measure to bonds and loans only, using the estimates from

[9]In Appendix B, we show that the results are not driven by the fact that loan sizes tend to be much smaller than bond issuances (even though we explicitly control for issuance amount).

two separate regressions. We then compare the bond EDP to the EBP from GZ and the loan EDP to the net percentage of domestic banks tightening standards from the senior loan officer opinion survey (SLOOS). We standardize each measure so as to facilitate comparison.

Panel (b) of Figure 2 compares the bond EDP to the EBP from GZ. As with the aggregate EDP, The bond EDP also spikes during the COVID crisis. The main difference with respect to the GZ measure is that the EBP uses secondary market prices, and so it captures the spreads of all bonds outstanding. In contrast, the EDP considers spreads at origination. While the two measures also contain different information, the correlation between the two rises to 29%.

Panel (c) compares the loan EDP to the SLOOS measure. The loan EDP matches the movements in the SLOOS quite well, especially in the post-2020 time period during the Fed's tightening and the crash of Silicon Valley Bank. Logically, our loan EDP measure seems to be slightly lagged compared to SLOOS. SLOOS is based on survey questions where bank officers answer how they are currently enacting tightness in lending standards, while our measure is the ex-post observation of said standards. The two measures exhibit a correlation coefficient of 64%.

4 What explains dispersion in the EDP?

The results in Table 2 show that while instrument characteristics are important to explain variation in credit spreads, the adjusted R^2 from the different specifications is relatively low. This suggests that there remains significant residual dispersion in the EDP. We now turn our attention to investigating the potential sources of this dispersion across different dimensions: time, across firms, and within firms.

To this end, we specify a statistical model that helps us quantify how much of the dispersion is due to within-firm dispersion versus other factors, such as aggregate time variation of certain instrument characteristics. Let $EDP_{t,f,a,i}$ be the EDP for instrument i, issued by firm f, of type a, at time t. We can decompose the EDP into a time-average component γ_t, a time-firm component $\beta_{t,f}$, a time-firm-type component $\alpha_{t,f,a}$ and a residual $\varepsilon_{t,f,a,i}$. We consider different definitions of type: maturity bins, amount bins, and/or the instrument type (bond vs. loan).[10] We decompose the variance by taking averages in an iterative manner following Daruich and

[10] The maturity and amount bins are described in Appendix A.4.

Kozlowski (2023), such that:

$$EDP_{t,f,a,i} = \gamma_t + \beta_{t,f} + \alpha_{t,f,a} + \varepsilon_{t,f,a,i} \tag{3}$$

Panel A of Table 3 presents the decomposition results for the EDP. In the first row, we consider only time and firm-time fixed effects. In this specification, time variation accounts for close to 8% of the variance, with the bulk (over 65%) being explained by within-time, across-firm variation. However, a significant amount of residual variation persists (over 26%), which reflects that the EDP is heterogeneous even for firms that issue multiple instruments in the same time period. The following rows show that these results are roughly unchanged even when accounting for other potential sources of variation (instrument type, maturity, amount, or identity of the lender).

4.1 Small vs. large issuers.

There is significant variation in the number of instruments that firms issue per quarter, as shown in Section 2, which can play an important role in driving the within-firm dispersion for the variance of the EDP. On the one hand, larger firms tend to issue more instruments, as well as more varied types of instruments, which tends to raise this within-firm dispersion component. On the other hand, larger firms tend to be more transparent due to reporting requirements, which could contribute to interest rate compression and a reduction in the importance of this component. Ex-ante, it is not clear whether the within-firm dispersion component should increase or decrease depending on the share of large firms in our sample.

Panel B of Table 3 repeats the variance decomposition of the EDP for subsets of firms that have more than two, four, six, and eight issuances in at least a quarter.[11] The share of within-firm dispersion seems to increase as we restrict the sample to firms that issue larger numbers of instruments, suggesting that the "variety" effect dominates. The residual dispersion for the overall data (shown in Panel A) was about 26 percent, and it increases to up to 58 percent if we consider firms with more than eight issuances.

[11] Results are similar if we look at firms that have more than two, four, six, and eight issuances on average across quarters.

4.2 The role of instrument type for large issuers.

The previous analysis suggests that instrument type explains an extremely small share of the total variation of the EDP. This could be, however, a direct consequence of the fact that our sample includes many more loans than bonds: bonds are just over 4 percent of all the issuances in our sample (see Table 1). To account for this imbalance, we repeat the baseline decomposition for a sub-sample of firm-quarters in which firms issue both loans and bonds. Panel C of Table 3 shows that about 60 percent of the variation comes from within-firm dispersion, even after controlling for firm, instrument type, maturity, amount, and lender (bank) effects. This result is not surprising in light of the results in Panel B, which suggest that within-firm variation becomes more important for larger issuers. These larger issuers are also more likely to issue bonds. Overall, our results suggests that there is substantial residual variation even among large firms that issue both types of instruments.

5 Conclusion

We construct a comprehensive dataset that combines information on corporate bond issuances and loans issued by large BHCs in the US. We use this data to construct a measure of the cost of financing: the Excess Debt Premium. We obtain two main results. First, we find that bank loans tend to be cheaper than corporate bonds, even when controlling for observable characteristics. Second, we find significant heterogeneity in borrowing rates across different debt instruments within the same firm, even after accounting for observable characteristics.

These findings have important implications for our understanding of corporate financing decisions, capital structure choices, and the transmission of credit conditions to the real economy. Faria-e-Castro et al. (2025), for example, provide a measurement framework to illustrate how dispersion in borrowing costs affect the allocative efficiency of capital in the US. Our results highlight the importance of monitoring borrowing costs and their dispersion across firms and sectors. Future research could further explore the underlying mechanisms driving the heterogeneity in borrowing costs and their real effects.

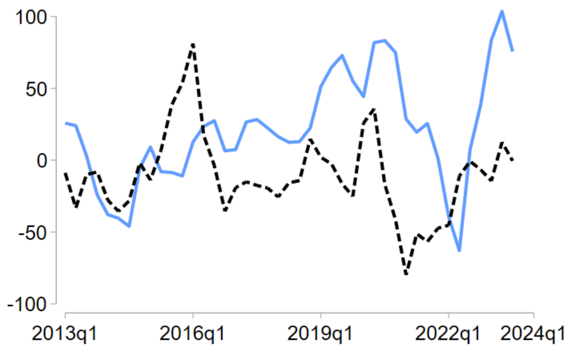
Table 2: Excess Debt Premium Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: all debt types						
Maturity	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Amount	-0.65***	-0.70***	-0.48***	-0.90***	-0.98***	-0.18
	(0.10)	(0.10)	(0.12)	(0.10)	(0.11)	(0.13)
Default probability	1.57***	1.34***	0.75***	1.52***	1.25***	
	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	
Loss given default	0.08***	0.01	0.09***	0.10***	0.05***	0.18***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Non-syndicated term loan	-0.13***	-0.16***	-0.42***	-0.16***	-0.17***	-0.28***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Non-syndicated credit line	-0.05***	-0.08***	-0.49***	-0.08***	-0.09***	-0.35***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)
Syndicated credit line	-0.23***	-0.30***	-0.63***	-0.26***	-0.33***	-0.50***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Syndicated term loan	-0.23***	-0.29***	-0.62***	-0.25***	-0.29***	-0.50***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Constant	5.27***	5.33***	5.58***	5.30***	5.34***	5.33***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)
Observations	238224	237457	166147	238224	237250	88589
Adjusted R^2	0.045	0.087	0.383	0.112	0.186	0.682
Firm FE	no	no	yes	no	no	no
NAICS FE	no	yes	no	no	no	no
Time FE	no	no	no	yes	no	no
NAICS-time FE	no	no	no	no	yes	no
Firm-Time FE	no	no	no	no	no	yes
Panel B: loans vs. bonds						
	(1)	(2)	(3)	(4)	(5)	(6)
Maturity	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Amount	-0.81***	-0.85***	-0.57***	-1.06***	-1.12***	-0.21
	(0.10)	(0.10)	(0.12)	(0.11)	(0.11)	(0.14)
Default probability	1.55***	1.34***	0.74***	1.50***	1.26***	
	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	
Loss given default	0.04***	-0.01	0.09***	0.06***	0.03***	0.18***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Loan	-0.15***	-0.21***	-0.55***	-0.17***	-0.22***	-0.41***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Constant	5.30***	5.37***	5.62***	5.32***	5.37***	5.34***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)
Adjusted R^2	0.039	0.079	0.379	0.106	0.178	0.679

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *The left-hand side is the log of the spread in basis points. The controls in the right-hand side are maturity in years, amount in 10 billions, and default probability and LGD in percent.*

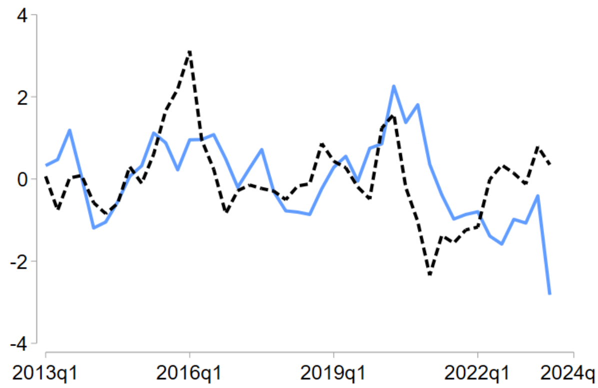
Figure 2: Excess Debt Premium and risk measures

(a) Excess Debt Premium



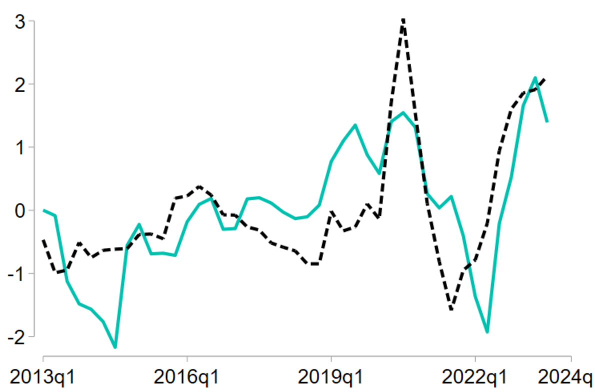
EDP --- EBP from GZ

(b) Bond EDP vs. EBP from GZ



Bond EDP --- EBP from GZ

(c) Loan EDP vs. SLOOS



Loan EDP --- SLOOS

Table 3: Variance decomposition of the EDP

				Panel A: Baseline			
	Time	Firm	Bank	Instrument Type	Maturity	Amount	Residual
	7.51	65.68					26.81
	7.51	65.68	.44				26.37
	7.51	65.68		.36	.14	.08	26.23
111,626 firms, 253,868 instruments.							
				Panel B: By Number of Instruments Issued			
# of Instruments	Time	Firm	Bank	Instrument Type	Maturity	Amount	Residual
2+	9.29	47.54		.62	.43	.17	41.95
4+	10.86	35.49		1.09	.47	.19	51.91
6+	11.64	30.06		1.51	.64	.23	55.92
8+	11.99	27.07		1.74	.76	.18	58.26
21,115 firms, 191,432 instruments.							
				Panel C: Firms with Loans and Bonds Only			
	Time	Firm	Bank	Instrument Type	Maturity	Amount	Residual
	8.24	28.66					63.1
	8.24	28.66	3.18				59.93
	8.24	28.66		2.35	.84	.22	59.69
1,543 firms, 40,389 instruments.							

Notes: Each cell presents the share of total variance explained by each component. By construction, rows sum to 100 percent of total variance. Panel A reports the baseline decomposition. Panel B provides robustness checks by (i) number of instruments issued and (ii) restricting to firms with both loans and bonds.

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Appendix

A Data

A.1 FR Y-14Q Data

This section explains the sample selection of the Y-14 data, and the construction of the variables used in the empirical analysis.

A.1.1 Sample Selection

Our sample selection criteria follow standard practice in the literature. We exclude all firm-quarters for which:

(i) The loans are not in the U.S. (`Field 6 Country` is not U.S.).

(ii) Industry is finance or public administration (`Field 8 IndustryCode` is 52, 92, 551111, or 5312).

(iii) Committed Exposure is negative or zero (`Field 24 CommittedExposure` ≤ 0).

(iv) Utilized Exposure is negative (`Field 25 UtilizedExposure` < 0).

(v) Utilized exposure is larger than committed (`Field 25 UtilizedExposure` $>$ `Field 24 CommittedExposure`).

(vi) The posted date is after the maturity date of the facility (`Field 0 D_DT`, the date of observation, is after `Field 19 MaturityDate`).

(vii) The posted date precedes the origination date of the facility (`Field 0 D_DT` is before `Field 18 OriginationDate`).

(viii) The loan is classified as municipal or foreign (`Field 26 LineReportedOnFRY9C` loan type is not 3, 4, 8, 9, or 10).[12]

[12] The codes are: 3) Loans to finance agricultural production and other loans to farmers, 4) Commercial and industrial loans to U.S. addresses, 8) All other loans, excluding consumer loans, 9) All other leases, excluding consumer leases, 10) Loans secured by owner-occupied nonfarm nonresidential properties originated in domestic offices.

(ix) The interest rate reported is 0 (`Field 38 InterestRate` = 0).

(x) The observation date (`Field 0 D_DT`) is before 2013 Q1.

A.1.2 Construction of variables

We construct two types of variables in the Y-14: first, variables at the loan facility level-quarter level, and second, variables at the firm-quarter level, which are constructed by aggregating all loan facilities owed by a firm in a given quarter.

Variables at the facility-quarter level:

(i) Maturity: the difference between maturity (`Field 19 MaturityDate`) and origination date (`Field 18 OriginationDate`).

(ii) Amount: the utilized exposure on a loan (`Field 25 UtilizedExposure`).

(iii) Loan type: we use the credit facility type to create broad categories of revolving credit lines and term loans (`Field 20 FacilityType` - credit lines defined as 1-6, term loans defined as 7-13).

(iv) Syndicated loans: we use a participation flag to classify a loan as syndicated or not (`Field 34 ParticipationFlag` - 1 is not syndicated, 2-5 syndicated).

(v) Interest rate: the interest rate on the loan (`Field 38 InterestRate`).

(vi) Interest rate spread: we calculate the interest rate spread using the nominal yields from Gurkaynak et al. (2007). For each loan, we calculate the maturity remaining to the nearest year, and subtract from the interest rate the nominal treasury yield with maturity equal to maturity remaining at the date of origination (`Field 38 InterestRate`, nominal interest yields from the Board of Governors).

Variables at the firm-quarter level:

(i) Loan Share: we define the loan share as the total utilized value of loans divided by the total observed utilized value of loans and bonds. For firms with no bonds, the loan share will be $= 1$. For firms with no loans, the loan share will be $= 0$.

(ii) Probability of default: the median probability of default that is reported across lenders for a firm on a given quarter.

A.2 FISD data

This section explains sample selection in the FISD data, as well as the construction of the variables used in the empirical analysis.

A.2.1 Sample Selection

Our sample selection criteria follow standard practices in the literature. Our period of study is 2013Q1-2023Q3. Since the FISD lists only bonds at origination, we consider all bonds issued after 1990Q1 for purposes of measuring coverage. Thus if a bond has a maturity of 20 years and originates in 2000Q1, we consider this bond in our 2013Q1-2023Q3 sample.

We exclude all firm-quarters for which:

(i) Industry is finance or public administration (`Issuer NAICS_Code` is 52, 92, 551111, or 5312).

(ii) Bond issuer or issue is not in the US (`Issuer or Issue Country_Domicile` not USA).

(iii) Issuer or issue industry was government (`Issue industry_group` is 4).

(iv) Currency is not USD (or missing).

(v) Bond is not a corporate bond (`Bond_type` not CCOV, CCPI, CDEB, CLOC, CMTN, CMTZ, CP, CPAS, CPIK, CS, CUIT, CZ, RNT, UCID, or USBN).

(vi) Bond is convertible (`convertible` equals yes).

Further, we augment the dataset with information from Bloomberg on whether bonds have been called or not, and the date in which they are called. We retire these bonds after the call period.

A.2.2 Construction of variables

We construct the key variables employed in the empirical analysis as follows.

(i) Maturity: difference between maturity and origination dates (`Issue Maturity-Issue Offering`

(ii) Amount: the offering amount of the bond (`Issue Offering_amt`).

(iii) Bond type: we have flags for a number of bond types. Specifically, if a bond is convertible, putable, callable, asset backed, rule 144a, or if it has a covenant (Issue convertible, putable, announced_call asset_backed, rule_144a, and covenants respectively).

(iv) Coupon type: type of interest rate, i.e. zero-coupon, floating, etc. (`Issue coupon_type`).

(v) Interest rate: coupon rate.

(vi) Interest rate spread: we follow the same procedure as with the Y-14 data, see previous section.

A.3 Firm-level data

This section explains how we create the final firm identifier and how we assign bonds and loans to a firm. The Y-14's main firm identification variable is the tax identification number (TIN). To begin, we define a firm by grouping TINs. For any loans that are missing TINs, we define the firm by grouping loans that share an `ObligorName`, `ZipCode`, and `IndustryCode`. In order to merge the Y-14 and FISD, we use S&P's Business Entity Cross Reference Service (BECRS). The BECRS contains CUSIP level information, and contains the ultimate parent for each CUSIP. It also contains the start and end date of any relationships. We create an ultimate ID for a firm that contains the ultimate parent, and every CUSIP associated with that firm or its subsidiaries. Then, we merge the BECRS ultimate ID to the Y-14 using the 6-digit firm CUSIP. After merging the BECRS to the Y-14, we carry forward the ultimate ID by firm for any firm missing ultimate IDs. Then, we drop any matches that take place before or after the period of relationship, as reported by the BECRS. To settle any within firm-quarter discrepancies (i.e., a Y-14 firm, as defined by TIN, with multiple CUSIPs in the same quarter, that point to different ultimate parents in the BECRS), we assign the ultimate ID with the most observations in a firm-quarter to all observations in that firm-quarter. The FISD uses the firm CUSIP identifier, so we can simply merge with the BECRS, and follow the same procedure for dropping relationships outside of the scope. For bonds that are not matched, we define the firm by the issuer identifier provided by the FISD.

A.4 Maturity and Amount Bins

In order to compute the variance decomposition in Section 4, we create categorical bins. Instrument types are already categorical. For instrument maturity and amount, which are continuous variables, we discretize them into buckets. For maturities less than 11 years we use two-year buckets. Then we consider one bucket for maturities between 11 and 29 years, because most of our debt instruments are either less than 11 years maturity, or 30 year maturity. Next, we have a group for 29 to 31 years, and a group above 31 years. For amounts, we use the same buckets as described in Table B1.

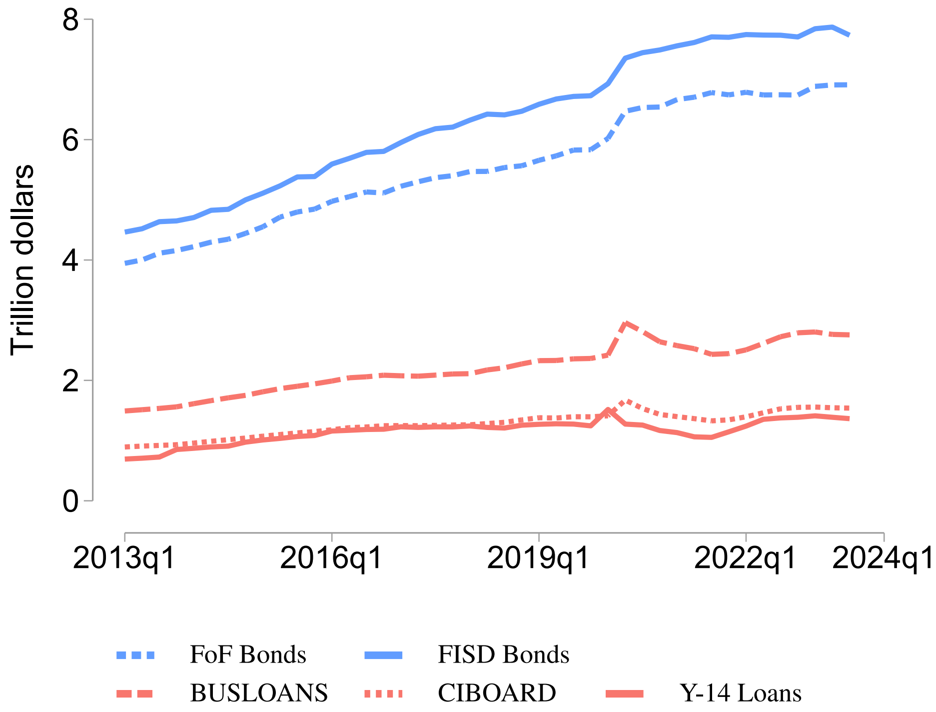
A.5 Coverage

To understand the aggregate coverage of our Y-14/ FISD merged dataset, we compare it to aggregate measures of outstanding bonds and C&I lending, which we do in Figure A1. For bonds, we compare our data (solid blue) to a measure of bonds issued by the nonfinancial corporate sector from the Flow of Funds (FL103163003Q, dashed blue). We consistently obtain slightly larger amounts outstanding than what is reported in the flow of funds (around 14 percent more), which could reflect either the fact that we miss some bonds that have been called, or imputation issues with the flow of funds.

For loans, we compare total amounts outstanding in our dataset (solid red) to measures of all C&I lending, and C&I lending by large banks from the Board of Governors H.8 data (BUSLOANS and CIBOARD in FRED, dashed and dotted red lines, respectively). We cover an average of 91 percent of C&I lending by large banks, with the remaining 9 percent likely representing loans under the Y-14 reporting threshold. This is supported by the fact that we tend to miss a larger share in 2020, at a time when many firms were tapping into their credit lines and increasing their borrowing supported by public programs such as the Paycheck Protection Program.

Figure A2 plots the histogram of liability coverage at the firm-level. From the Y-14, we can

Figure A1: Aggregate Data vs. Merged Y-14/FISD dataset

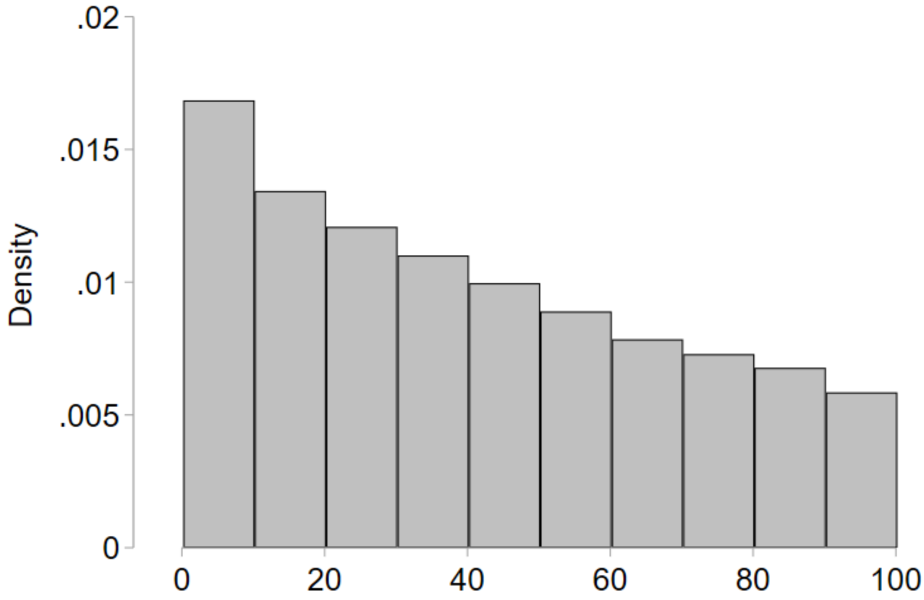


observe firm financial data, including total liabilities, at certain quarters. For those quarters, we compute the ratio of total loans and bonds outstanding to total liabilities of the firm. The average coverage is 41 percent, with median coverage equal to 37 percent. A significant share of liabilities for nonfinancial firms consists of trade credit and accounts payable, which our dataset does not cover.

B EDP: Robustness

Even though we explicitly control for facility size in our baseline regression, the summary statistics in Section 2 raise the possibility that we may be comparing large bonds to small loans, and that bonds are therefore more expensive simply because they are so much larger in terms of size. To try to account for this, we run our benchmark regression with firm-time fixed effects on different facility size bins. In each of our bins, we condition on the instrument being of a different size. Table B1 reports the results, with each column corresponding to our baseline regression specification for a different size bin. We also report the number of loans and bonds in each size bin. We find a statistically significant bond-loan spread for all bins except for the

Figure A2: Histogram of Utilized Exposure over Liabilities by Firm-quarter



two smallest binds (less than \$ 10 M), and the largest bin (over \$ 500 M). Note that both the smallest and largest bins are extremely unbalanced, with the smaller bins containing very few bonds and the largest bins containing very few loans. Importantly, for our purposes, we find that a significant bond-loan spread persists in the most balanced bin, which contains loans and bonds between \$100 M and \$500 M (column 5).

Table B1: The Bond-Loan Spread: similar sized instrument bins

	(1)	(2)	(3)	(4)	(5)	(6)
Maturity	-0.02***	-0.02***	-0.02***	-0.00	0.01***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Amount	-281.97***	-143.37***	-7.77**	0.11	-6.90***	0.25
	(36.72)	(55.05)	(3.89)	(7.24)	(1.91)	(0.18)
Loss given default	0.18***	0.05	0.03	-0.23**	-0.13	1.74***
	(0.05)	(0.08)	(0.03)	(0.11)	(0.12)	(0.30)
Loan	-0.13	-0.43	-1.38***	-1.52***	-0.76***	-0.30
	(0.22)	(0.33)	(0.20)	(0.28)	(0.12)	(0.21)
Constant	5.28***	5.55***	6.36***	6.33***	5.35***	3.59***
	(0.21)	(0.33)	(0.20)	(0.29)	(0.12)	(0.19)
Observations	31253	5255	18905	2598	2539	5095
Adjusted R^2	0.663	0.765	0.835	0.850	0.738	0.770
Firm-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N Loans	29655	5124	18809	2560	1027	71
N Bonds	1598	131	96	38	1512	5024
Amount Bin	1-5	5-10	10-50	50-100	100-500	500up

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *The left-hand side is the log of the spread in basis points. The controls in the right-hand side are maturity in years, amount in 10 billions, and LGD in percent.*