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An Empirical Analysis of the Cost of Borrowing*

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Abstract

We examine borrowing costs for firms using a security-level database with bank loans and corporate bonds issued by U.S. companies. We find significant within-firm dispersion in borrowing rates, even after controlling for security and firm observable characteristics. Obtaining a bank loan is 132 basis points cheaper than issuing a bond, after accounting for observable factors. Changes in borrowing costs have persistent negative impacts on firm-level outcomes, such as investment and borrowing, and these effects vary across sectors. These findings contribute to our understanding of borrowing costs and their implications for corporate policies and performance.

JEL Classification: E6, G01 H00

Keywords: Credit Spreads, Bonds, Loans, Macro-finance

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1 Introduction

The firm decisions of why and how to borrow have been widely studied in economic theory. As such, the cost of borrowing is a fundamental component that underpins all questions of this nature. Yet, empirically, most of this research has been limited to studying large public firms, due to lack of micro data on interest rates and other characteristics on borrowing by 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 security-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 over 91 percent of loan borrowing from major US bank holding companies. We then develop a measure of the cost of borrowing at the firm level that adapts the Excess Bond Premium (EBP) of Gilchrist and Zakrajsek (2012), GZ hereafter, to a set up with multiple security types and that controls for observable security characteristics, such as amount, maturity, and firm default probability. We call our measure the Excess Debt Premium (EDP), to reflect the fact that it encompasses borrowing issuances beyond senior unsecured bonds. Our measure 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. We find that fluctuations in the EDP have persistent significant effects on firm-level outcomes such as investment and borrowing. Finally, we show that the sensitivity of firm investment to fluctuations in borrowing costs is heterogeneous across industries, with traditional "interest-rate sensitive" sectors such as construction and real estate showing little sensitivity to fluctuations in the EDP.

Section 2 explains how we construct our dataset, by merging individual bond issuance data with regulatory bank 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 banks, as well as detailed financial information for those borrowers. Our final dataset encompasses 335 thousand loans and about 15 thousand bonds issued by 152 thousand firms. Our dataset covers effectively the universe of bond issuances and 91 percent of commercial and industrial lending undertaken by major bank holding companies in the US.

In Section 3 we construct alternative measures for the cost of borrowing for a firm. Our preferred measure is the EDP, a reference to the EBP of GZ. Our measure differs from their measure along two important dimensions. First, we consider a much larger set of securities 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 the origination of the security. Our aggregate measure of the EDP is only imperfectly correlated with the EBP, suggesting that our new data contains additional information. We also show that loans are systematically "cheaper" than bonds, even when conditioning on observables in which these types of securities tend to differ, consistent with previous studies (Schwert, 2020). In particular, we find that interest rates on loans tend to be 132 basis points (bps) lower than interest rates on bonds, after controlling by a variety of observable characteristics.

In Section 4 we perform variance decomposition exercises for the different measures of borrowing costs. We find that time variation explains 8 percent of the dispersion in the EDP, and across-firm variation accounts for about 51 percent of the dispersion. Security characteristics (such as type, maturity or amount) and lender fixed effects explains less than 1 percent of the dispersion. As a result, about 40 percent of the dispersion in borrowing costs happen at the within-quarter-firm-lender-security level.

Given the rich amount of variation in borrowing costs, Section 5 investigates whether this variation has an impact on firm-level outcomes. We focus on the net investment rate and the growth rate of total borrowing at different horizons. We find that a one standard deviation increase in the EDP leads to a 7 percent of a standard deviation drop in the net investment rate 1-year ahead. This effect is extremely persistent and lasts for 7 years. We also find significant negative effects on total borrowing, albeit they are not significantly persistent. Finally, we investigate whether this sensitivity of the investment rate to fluctuations in the EDP varies across sectors. We uncover substantial heterogeneity across sectors (NAICS 2-digit level), with

sectors such as Administrative Services, Information and Transportation exhibiting a larger sensitivity. Firms in traditionally "interest-rate sensitive sectors" such as Construction and Real Estate do not react significantly to changes in borrowing costs, suggesting that such sensitivity operates primarily through the aggregate level of interest rates and not necessarily via the direct cost of financing.

Related Literature. There is a large literature in economics and finance that study 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. 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. More recently, Gormsen and Huber (2023) estimate series of 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 capital. 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. Moreover, we show how fluctuations in the cost of capital affect firm-level decisions, such as investment and borrowing.

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 and Favara et al. (2022) use it to study so called zombie lending. Our contribution is to exploit this micro-level data to derive new estimates of borrowing costs for small and large firms.

Finally, our analysis of firm-level outcomes relates to the literature that tries to assess the effect of changes in the cost of borrowing on investment decisions (Jeenas, 2023; Ottonello and Winberry, 2020). Given the lack of detailed micro data on firm-level borrowing costs, these authors rely on measures that proxy for changes in firm-level interest rates, such as the

interaction of identified monetary policy shocks with measures of firm sensitivity to borrowing costs, such as leverage or liquidity. We are able to directly observe a measure of borrowing costs that controls for the characteristics of that type of borrowing and therefore directly estimate an elasticity of investment to the cost of borrowing.

2 Data Description

We first describe how we construct our final database to measure the cost of borrowing. We build a security-level panel spanning 2013Q1 to 2023Q3 that contains information on lending from large bank holding companies (BHC), corporate bonds, and firms' balance sheets.

Main Datasets and Scope. We rely on two main sources of data: (i) the Federal Reserve's FR Y-14Q H.1 schedule, which contains information for loan facilities and firm balance sheet data, and (ii) Mergent Fixed Income Securities Database (FISD), which provides information on corporate bond issuances.

The FR Y-14Q H.1 schedule contains detailed data on commercial & industrial (C&I) lending for large BHCs. All BHCs with more than $50 billion in total consolidated assets prior to 2019, and $100 billion after, 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 33 BHCs. For each of these, we observe all loan facilities that have committed exposures of $1 million or more.[1] Banks only report loan facilities on their balance sheets, and so we stop observing a loan if it is sold or securitized. We see quarterly loan facility level data on interest rates, maturity, seniority, facility type, committed and utilized exposure, collateral market value, loss given default (LGD), and syndicated status, among other loan characteristics. Furthermore, we observe financial data at the firm level such as assets, liabilities, sales, income, and probability of default (PD). Two major advantages of the Y-14 data are the size of the data and the ability to see 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.

The Mergent Fixed Income Securities Database (FISD) is our main source of data for bond

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

issuances. The FISD covers a significant number of US corporate issuances, and provides information on bond issuance, 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 treat them as the same firm as their parent company. This is particularly important given the disaggregated nature of the FR Y-14 dataset, 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 id using the 6-digit firm CUSIP, grouping together CUSIPs with the same ultimate parent. Using CUSIPs, we then merge the firm id 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 id.[2]

Sample Selection. We apply a series of filters in order to clean the data and exclude observations that are not comparable for our purposes. We keep only US firms and exclude firms in finance (NAICS code 52) and public administration (NAICS code 92). We exclude convertible bonds.[3]

2.1 Descriptive Statistics

Table 1 presents summary statistics for the main variables used in the empirical analysis that follows. The final dataset contains over 433 thousand observations, for 152,482 unique firms, where each observation is a security origination. We observe many more bank loans (335,827 unique loans) than corporate bonds (14,700 unique bonds). The discrepancy between the total number of observations and the number of unique loans and bonds is related to the re-issuance of loans, which occurs if the terms of a loan are substantially altered, which we treat as new loan originations.

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. 6.3 years.[4] A significant percentage of loans tend to have a very short

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

[3]Appendices A.1, and A.3 provide additional details on the cleaning and construction of the variables.

[4]Demand loans and revolving credit lines do not have an associated maturity, so we can interpret them as

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 50th percentile of bond sizes[5].

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. 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. As a result, we find more compressed differences in spreads: 14 bps on average and -38 bps for the median. There are many other reasons and characteristics for why interest rates and spreads can vary between bonds and loans. Later, in section 3.4, we conduct a more thorough analysis where we show that there are systematic differences between the prices of these two types of securities even when other observable security and firm characteristics are taken into account.

Panel C of Table 1 presents summary statistics of bonds and loans issuances at the firm-quarter level. Only 2.03 percent of firms in our sample issue bonds. The loan share, defined as the ratio of loans to the sum of loans and bonds is 97.96 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 14.4 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 1.82 percent.[7] Finally, the two last rows of Panel C show that security issuance is relatively infrequent, with the average firm issuing 0.12 securities 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 securities more often, and thus the average number of issued securities is 1.81 per quarter.

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 securities. Our main results are robust to assuming shorter maturities.

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

[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.

[7]This probability of default is reported by the FR Y-14Q lenders, and refers to the expected probability of default over the next year.

Panel D of Table 1 provides firm financial data that we later use in Section 5. In order to increase the number of observations, we take yearly means of all quarterly financial reports by the firms.[8] Total assets show that our coverage of firms is wide and right-skewed–the median firm has about 14 million in total assets, while the mean firm has over 750 million. Total debt, which we measure as observed liabilities, or the sum of loans and bonds in the dataset is also skewed right, with a mean of just under 13.4 million and a median of 2.34 million. The leverage ratio in our sample is of 40.8 percent, in line with common estimates for non-financial firms. The mean liquidity ratio is around 13 percent and the mean sales growth is around 7.9 percent. The net investment rate, measured as capital expenditures less depreciation and amortization over fixed assets from last period, has a mean of about 6.8 percent with a large standard deviation of approximately 86 percent.

Table 2 breaks down the different types of loans that we observe in the dataset. Contrary to standard datasets such as Dealscan the SNC, the majority of the loans are non-syndicated (72 percent). The data contains slightly more credit lines than term loans (50 vs. 43 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.

Coverage. To understand the aggregate coverage of our Y-14/ FISD merged dataset, we compare our data to aggregate measures of outstanding bonds and C&I lending. Figure 1 compares amounts outstanding in our merged dataset to these aggregate measures. For bonds, we compare our data to a measure of bonds issued by the nonfinancial corporate sector from the Flow of Funds (FL103163003Q). 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 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, 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.

[8] We do not necessarily observe firm financial information on every quarter.

Table 1: Summary Statistics

	mean	sd	p10	p50	p90
Panel A: Bonds					
Maturity (yrs)	11.40	9.77	3.04	8.12	30.04
Amount (mil$)	646.34	714.61	1.91	500.00	1,250.00
Interest Rate (bps)	418.82	184.67	195.85	400.00	675.00
Interest Rate Spread (bps)	207.16	173.10	49.64	149.25	471.26
Panel B: Loans					
Maturity (yrs)	6.29	7.47	0.92	4.95	15.01
Amount (mil$)	10.19	39.01	0.80	2.73	24.53
Interest Rate (bps)	368.91	160.79	182.44	349.00	589.76
Interest Rate Spread (bps)	193.32	138.64	26.68	187.14	365.53
Loss Given Default	32.08	17.15	8.00	32.14	50.00
Panel C: Firm Issuance					
Share of Firms with Bonds	2.03	14.11	0.00	0.00	0.00
Loan Share, $l/(l+b)$	97.96	13.70	100.00	100.00	100.00
Loan Share given $b > 0$	14.42	18.11	0.39	6.87	41.26
Probability of Default	1.82	6.21	0.16	0.76	3.06
Securities Issued	0.12	0.66	0.00	0.00	0.00
Securities Issued given $b > 0$	1.81	3.78	0.00	0.00	5.00
Panel D: Firm Financial					
Total Assets (mil$)	780.90	9,371.13	1.76	13.66	276.21
Total Debt (mil$)	13.37	56.15	0.92	2.34	19.38
Leverage	40.83	69.16	3.26	22.32	80.94
Liquidity Ratio	13.15	15.44	0.69	7.54	33.73
Sales Growth	7.92	31.83	-16.86	5.51	35.28
Net Investment Rate	6.84	86.03	-29.16	-0.82	50.40

Notes: We have 433,364 securities, for 152,482 firms. There are 335,827 loans and 14,700 bonds.

Figure 2 plots the histogram of liability coverage at the firm-level. From the Y-14, we can 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 being 37 percent. A significant share of liabilities for nonfinancial firms consists of trade credit and accounts payable, which our dataset does not cover.

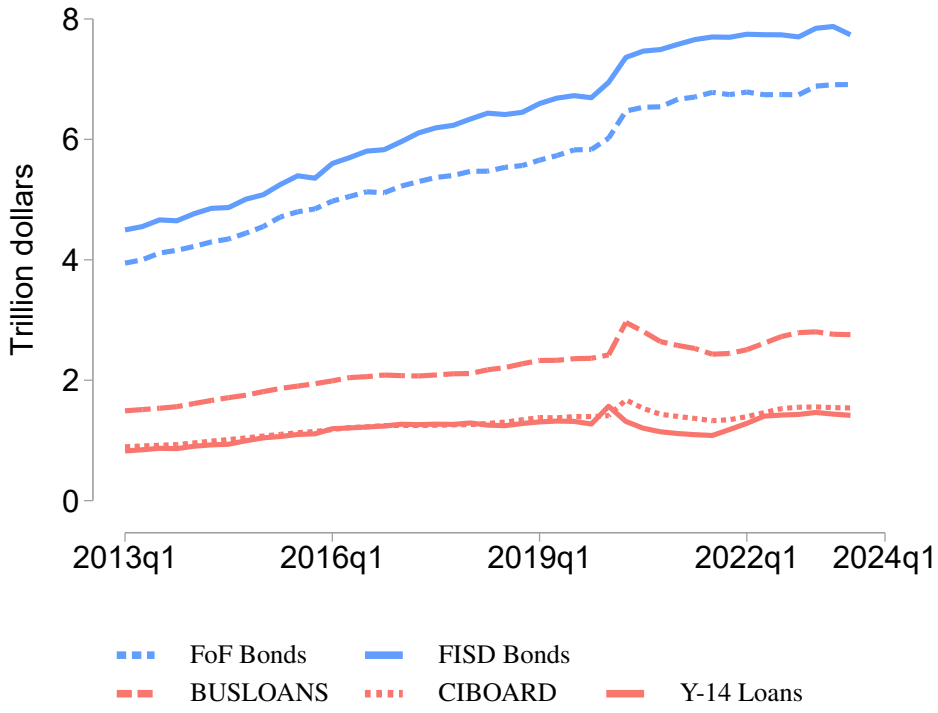
3 Measuring the Cost of Borrowing

We begin our analysis by computing simple direct measures of interest rates at the firm level, and documenting their aggregate behavior. We then present the Excess Debt Premium (EDP),

Table 2: Loan Types

	Freq.	Percent
Non-syndicated Credit Line	146075	37.01
Non-syndicated Term Loan	137486	34.83
Syndicated Credit Line	53291	13.50
Syndicated Term Loan	32740	8.30
Other	25111	6.36

Figure 1: Aggregate Data vs. Merged Y-14/FISD dataset

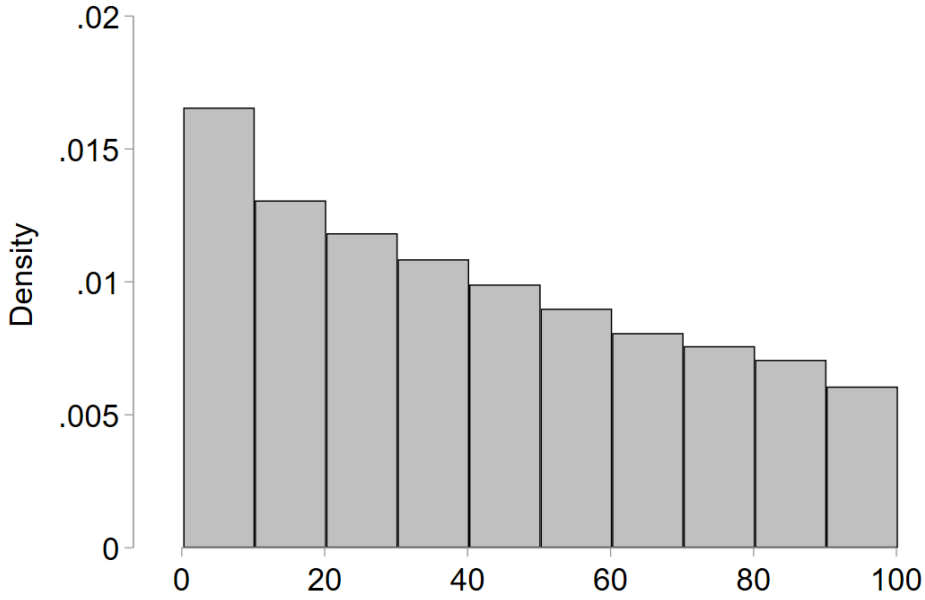


a measure of the cost of borrowing that accounts for heterogeneity in observable characteristics of borrowing, such as security type, size of the security, and maturity, and which we use as the main indicator for the cost of borrowing throughout the paper.

3.1 Interest Rate Measures

First, we define the *Average Interest Rate* (AIR) as the average interest rate a firm pays on all outstanding securities in a given quarter, weighted by the size of the security (measured as amount outstanding for the case of bonds and amount utilized for the case of 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.

Figure 2: Histogram of Utilized Exposure over Liabilities by Firm-quarter



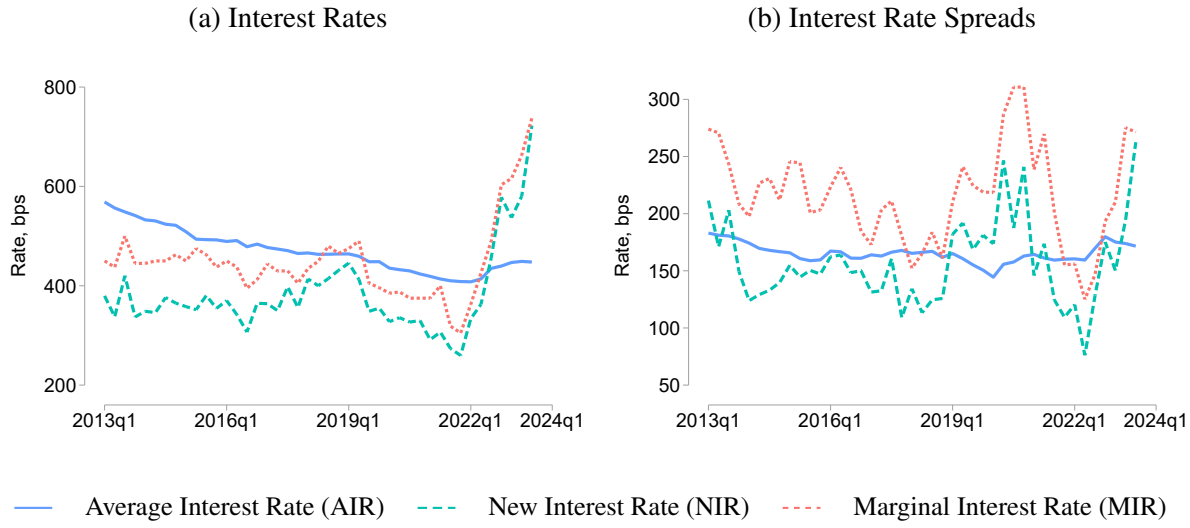
Second, the *New Interest Rate* (NIR) is the average interest rate a firm pays on all newly issued securities in a given quarter, again weighted by the size of each security. Hence, the main difference is that the NIR reflects current market rates, while the AIR takes into account previous issuances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

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

To understand the differences between the AIR, NIR, and MIR in the data consider the following hypothetical examples. First, if we only observe one security for a firm, the three measures (average, new, and marginal) will be equal. Second, if we observe multiple securities for a firm, but only one new issuance in a given quarter, the NIR and MIR will be equal, but the AIR will not. Third, if the firm issues multiple securities each quarter, then the three measures can potentially be different. Therefore, these measures capture the within-firm variation both across and within each quarter.

Figure 3 plots the aggregate time series for each of the three measures of the cost of capital. These aggregate time series are computed as medians across firms, weighted by total amount

Figure 3: Interest Rates and Spreads



utilized on newly issued securities. 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 security. By construction, the MIR is always weakly larger than the NIR. For the interest rate, the gap between the MIR and the NIR is about 59 bps on average. This reveals that there can be substantial heterogeneity in interest rates paid by each particular firm within a quarter.

For almost the entire sample of the interest rates, shown in panel (a), the AIR is higher than the NIR. 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. Additionally, both during and after the COVID-19 crisis, the MIR is higher than the AIR, meaning that some newly issued securities pay higher rates than the average interest rate for securities in firms' balance sheets. This happened for two different reasons. During COVID-19 we observed an increase in credit spreads while starting in 2021 we observed an increase in the underlying risk-free rate as the Fed started tightening monetary policy.

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, with the only significant deviations between the two occurring during the COVID crisis. 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 securities is taken into account.

There are still many other security characteristics beyond maturity that could account for this heterogeneity among interest rates paid by firms, such as the type of security 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).

3.2 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. 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 measures 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 from the Y-14 dataset. We therefore consider a much larger set of securities than what is considered for the EBP, and allows us to explicitly control for security type. This raises a number of issues, however. We do not have secondary market prices for bank loans, as these loans are not traded (otherwise they would not be observed in our dataset, as they would have left the bank's balance sheet). 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 securities, such as variable rate securities or credit lines, for which constructing maturity-matched cash-flows would be non-trivial.

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

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

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

$$\log y_{s,f,t} = \sum_i \gamma_i \mathbb{I}(\text{security type}_{s,f,t} = i) + \Gamma X_{s,f,t} + \varepsilon_{s,f,t} \tag{1}$$

where $\mathbb{I}(\text{security type}_{s,f,t} = i)$ is a dummy that is equal to 1 if security s is of type i. In our baseline specification, we separately consider the following security 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. $X_{s,f,t}$ is a vector of other observable security characteristics that includes the maturity and the size of the security, among others.

The estimation results are reported in Table 3. 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 securities during the period of analysis, and the specification with firm-time fixed effects (column 6) considers only firms that issue multiple securities 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 (as opposed to the full menu of interest rates that is potentially offered to the firm). 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. Our reference category are non-callable bonds; we do not find any significant differences between the spreads at origination of callable and non-callable bonds when controlling for other characteristics. We do 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 these differences in greater detail in Section 3.4.

Using the estimation results from equation 1, we construct a predicted log spread at origination, $\widehat{\log y}_{s,f,t}$. The EDP for a given security is then defined as the difference between the

Table 3: Excess Security Premium Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Maturity	-0.02***	-0.02***	-0.03***	-0.02***	-0.02***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Amount	-0.90***	-0.95***	-0.82***	-1.14***	-1.20***	-0.53***
	(0.11)	(0.11)	(0.12)	(0.11)	(0.12)	(0.15)
Default Probability	0.02***	0.01***	0.01***	0.02***	0.01***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Callable Bond	0.08*	0.14***	-0.01	0.04	0.11***	0.02
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Non-Syndicated Term Loan	-0.12***	-0.08*	-0.48***	-0.18***	-0.12***	-0.47***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)
Non-Syndicated Credit Line	-0.03	0.01	-0.43***	-0.09**	-0.03	-0.40***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)
Syndicated Credit Line	-0.22***	-0.21***	-0.61***	-0.28***	-0.25***	-0.56***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)
Syndicated Term Loan	-0.24***	-0.22***	-0.64***	-0.28***	-0.24***	-0.59***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)
Constant	5.30***	5.27***	5.68***	5.37***	5.32***	5.64***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)
Observations	292662	291933	223159	292662	291811	171693
Adjusted R^2	0.048	0.078	0.278	0.119	0.178	0.532
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

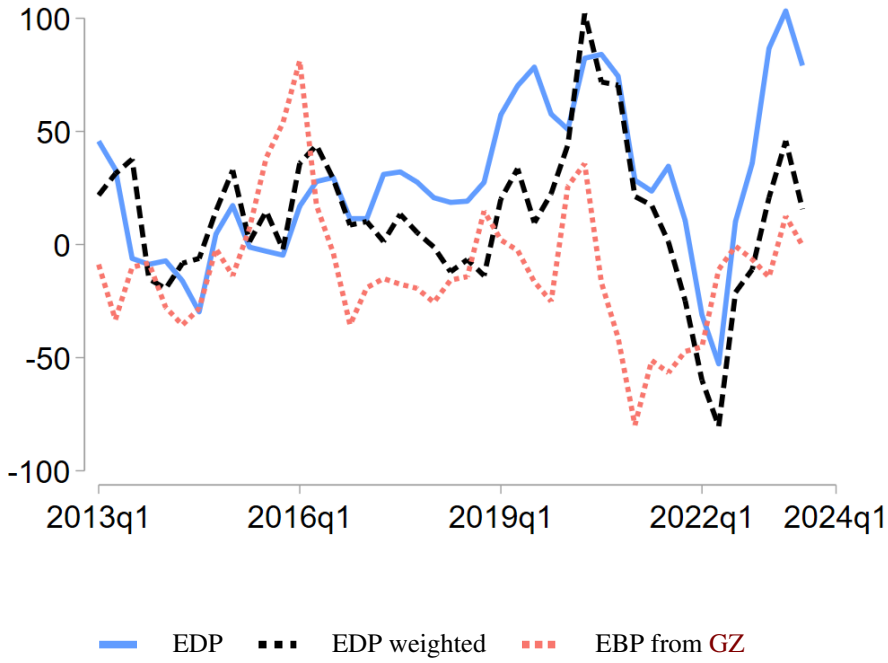
Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. *The left-hand side is the log of the spread in basis points. The controls in the right-hand side are maturity in years, amount in 10 billions, and default probability in percent.*

observed spread and the predicted value:

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

This is our preferred measure of costs of borrowing, since it controls for several observable characteristics of the borrower security. Figure 4 plots time series for the average EDP, aggregated across securities and firms. The solid blue line corresponds to the unweighted average of the EDP on each quarter, while the dashed black line corresponds to the aggregate EDP, weighted by the size of each origination. This latter measure attributes much larger weight to bonds, which tend to correspond to larger issuances. In spite of some differences, the overall movements are similar: There was a positive trend in the pre-pandemic period that seems to

Figure 4: Excess Debt Premium



have peaked in 2020. This is followed by a significant drop and subsequent increase in the latter part of the sample. The dotted red line plots the Excess Bond Premium of GZ, whose movements tend to follow more closely those of the weighted EDP, which attributes greater weight to bonds.

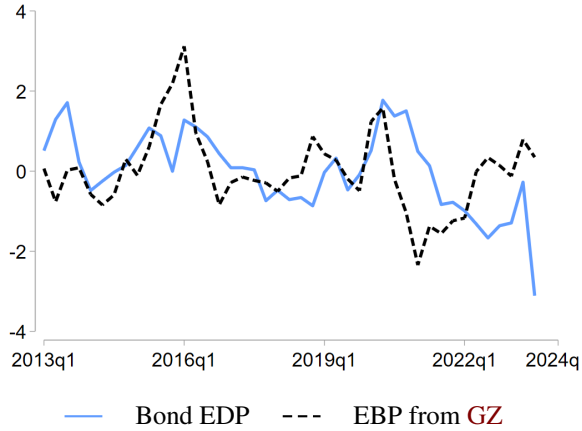
3.3 The EDP for Bonds and Loans

Next, we compute our EDP measure once again, but this time only considering loans or bonds in 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) on bank lending practices. In order to directly compare these measures, we create a "z-score" of each measure by subtracting from each quarterly observation the time series mean, and then diving by the time series standard deviation.

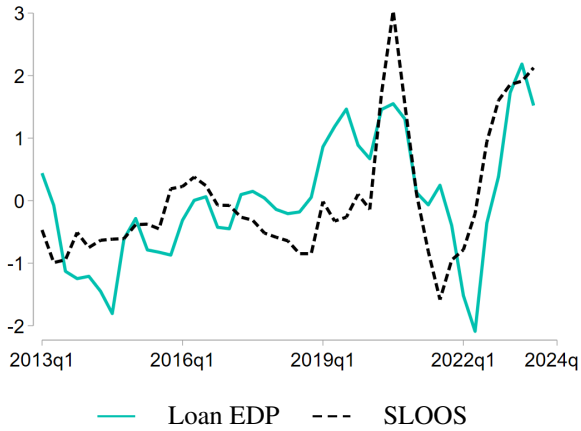
The first panel of Figure 5 shows the EDP with only bonds and the EBP from GZ. The bond EDP is similar to the aggregate EDP, with a spike during the COVID recession. However, our bond EDP shows that there was a large increase in tightening on bonds near the end of 2021. This increase was not captured by the GZ EBP z-score, which in fact, was negative in the same

Figure 5: Excess Debt Premium vs. Risk Measures

(a) Bond EDP vs. EBP from GZ



(b) Loan EDP vs. SLOOS



period. The main difference between the two measures is that the EBP uses secondary market prices so it captures the spreads of all the bonds outstanding. In contrast, the EDP consider spreads at origination. The second panel shows the EDP with only loans and the SLOOS measure of loan lending tightness. The loan only EDP matches the shape of the SLOOS loan tightning measure quite well. The COVID shock was higher in SLOOS than our loan EDP, and was quicker to fall after COVID.

In the next sections we use the EDP as the main cost of borrowing measure. First, in Section 4 we perform variance decomposition exercises to study what generates variations in the EDP. Then, Section 5 studies how fluctuations in the EDP affect firm-level outcomes such as investment and borrowing.

3.4 The Role of Security Type

One noticeable feature of the results in Table 3 is that loan spreads appears to be consistently lower than those of bonds, regardless of the type of loan (term loan or credit line, syndicated or not). 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 Table 3 shows that it seems to survive the inclusion of controls such as maturity and amount, which are quite different across security types.

We further investigate this difference by estimating a variant of equation 1 that pools all bond and 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 security. We report the results in Table 4, with the different columns corresponding to combinations of fixed effects as in Table 3.

These results reinforce the fact that loans are, on average, cheaper than bonds. The most conservative specification is presented in Column (6), as it includes firm-time fixed effects. The estimate for γ therefore 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 -0.52 log points lower than those of bonds issued by the same firm, in the same period, and controlling for amount and maturity. Hence, for the average firm, the spread of a bond is 68 percent larger (i.e., $\exp(0.52)$) than those of equivalent loans. A back-of-the-envelope calculation using the summary statistics in Table 1 (i.e, an average spreads of about 193 basis points for loans) suggests that the spread between the average loan and a bond with the same characteristics is around 132 bps (i.e., 193×0.68).

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. We arrive at the same result using a much larger and broader sample that includes private firms and non-syndicated loans.

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 security being a different size. Table 5 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 smallest one.

Table 4: The Bond-Loan Spread

	(1)	(2)	(3)	(4)	(5)	(6)
Maturity	-0.02***	-0.02***	-0.03***	-0.02***	-0.02***	-0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Amount	-1.09***	-1.10***	-0.97***	-1.33***	-1.35***	-0.61***
	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.16)
Default Probability	0.02***	0.01***	0.01***	0.01***	0.01***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Loan	-0.20***	-0.24***	-0.54***	-0.22***	-0.26***	-0.52***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Constant	5.38***	5.42***	5.71***	5.41***	5.44***	5.66***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	292662	291933	223159	292662	291811	171693
Adjusted R^2	0.040	0.068	0.273	0.112	0.170	0.528
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

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 in percent.*

4 What Explains the Dispersion in Borrowing Costs?

The previous section focuses on the first moments for the different measures of the cost of borrowing: AIR, NIR, MIR, and EDP. These series mask a substantial amount of heterogeneity, however. In this section, we investigate the drivers of dispersion for these measures across different dimensions: across time, and both across and within firms. To this end, we specify a statistical model that allows us to perform a variance decomposition of the different measures of the cost of borrowing. This helps us quantify how much of the dispersion is due to within-firm dispersion versus other factors, such as aggregate time variation of certain security characteristics. Let $r_{t,f,a,s}$ be the borrowing cost measure of firm f at quarter t for security type a, and security s. We can decompose this rate 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 $\varepsilon_{t,f,a,s}$. We consider different definitions of type: maturity bins, amount bins, and/or the type of security (bond vs. loan).[9] We decompose the variance by taking averages in an iterative manner following Daruich and

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

Table 5: The Bond-Loan Spread: Similar Sized Security Bins

	(1)	(2)	(3)	(4)	(5)	(6)
Maturity	-0.04***	-0.04***	-0.03***	-0.01**	0.01***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Amount	-484.33***	-88.91*	-20.83***	2.02	-6.04***	0.25
	(26.66)	(50.55)	(3.53)	(6.76)	(1.83)	(0.17)
Loan	0.18**	-0.29	-1.29***	-1.14***	-0.81***	-0.61***
	(0.09)	(0.20)	(0.14)	(0.29)	(0.10)	(0.19)
Constant	5.23***	5.46***	6.35***	5.84***	5.28***	4.66***
	(0.09)	(0.20)	(0.15)	(0.30)	(0.08)	(0.02)
Observations	71064	11508	35308	3942	2919	5116
Adjusted R^2	0.479	0.634	0.752	0.828	0.751	0.766
Firm-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N Loans	69458	11375	35209	3901	1375	81
N Bonds	1606	133	99	41	1544	5035
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 default probability in percent.*

Kozlowski (2023), such that:

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

We estimate this decomposition for the different measures of interest rates, interest rate spreads, and for the EDP.

4.1 Interest Rates

The first panel of Table 6 presents the results of the variance decomposition for different types of models. In the first row, we consider only time and time-firm effects. The second row considers the full set of controls, which also include time-firm-type, time-firm-type-maturity and time-firm-type-maturity-amount effects. The following rows include each of these additional factors individually. Finally, the sixth row goes back to the original firm-time specification, and controls for the identity of the lending bank.[10] The table shows that, regardless of the specification, nearly 25 percent of the total variance in interest rates is accounted for by within-firm dispersion. Variation across time accounts for around 39 percent of total variance, while

[10]When including bank fixed effects, we treat bonds as being originated by a single lender.

Table 6: Variance Decomposition

	Time	Firm	Bank	Security Type	Maturity	Amount	Residual
				A. Interest Rate			
(1)	39.68	35.52					24.8
(2)	39.68	35.52		.74	.05	.12	23.89
(3)	39.68	35.52		.74			24.06
(4)	39.68	35.52			.14		24.66
(5)	39.68	35.52				.61	24.19
(6)	39.68	35.52	.97				23.83
N Firms	152481						
N Securities	433364						
				B. Interest Rate Spread			
(1)	5.28	57.73					36.99
(2)	5.28	57.73		.3	1.56	.19	34.94
(3)	5.28	57.73		.3			36.69
(4)	5.28	57.73			1.44		35.54
(5)	5.28	57.73				.44	36.55
(6)	5.28	57.73	.84				36.15
N Firms	152365						
N Securities	432689						
				C. Excess Security Premium			
(1)	7.79	51.4					40.81
(2)	7.79	51.4		.29	.41	.2	39.92
(3)	7.79	51.4		.29			40.52
(4)	7.79	51.4			.32		40.5
(5)	7.79	51.4				.28	40.54
(6)	7.79	51.4	.8				40.01
N Firms	107887						
N Securities	311590						

Notes: Each cell presents the share of the total variance explained by each component. By construction, each row adds up to 100 percent of the total variance.

dispersion across firms accounts for 35.5 percent. Security type within a firm-quarter only accounts for 0.74 percent of the variation, while maturity and amount explain less than 1 percent. Differences between banks accounts for less than 1 percent of variation. [11]

[11] The order in which we place the controls can potentially matter for the results. For example, if you have two controls that are exactly equal, by construction the control you put second will explain 0 percent of the variance. Nevertheless, we corroborated that regardless of the ordering, security type, maturity, amount, and bank have a very small explanatory power.

4.2 Interest Rate Spreads

The second panel of Table 6 repeats the exercise for maturity-matched credit spreads as opposed to interest rate levels. The contribution of aggregate time variation is substantially lower at 5.28 percent, as most of this aggregate time variation arises from interest rate level effects. Across-firm variation now explains close to 57.7 percent of total variation, while the contribution of other observable factors is still very small. This leaves over 35 percent of variation unexplained at the within-firm-quarter level, a larger share to that obtained using interest rates instead of spreads.

4.3 Excess Security Premium

The third panel of Table 6 performs a variance decomposition of the ESP. While the EDP already accounts for the impact of maturity, amount, and security type, it does so only linearly, and so we include these characteristics to make the results comparable to those in the previous tables. The results are overall similar to those for interest rate spreads: time-variation accounts for less than 10 percent of the variance, with the bulk (over 50 percent) being explained by across-firm variation. Finally, there is a substantial within-firm and period share of variance, close to 40 percent, that is not explained by observable characteristics of the contract.

4.4 Robustness

Small vs Large Issuers There is significant variation in the number of securities 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 interest rate, spreads, and the EDP. On the one hand, larger firms tend to issue more securities, as well as more varied types of securities, 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.

In panel A of Table 7, we repeat the variance decomposition of the ESP (row 2 of Panel C

of Table 6) for subsets of firms that have more than two, four, six, and eight issuances in at least a quarter.[12] The share of within-firm dispersion seems to increase as we restrict the sample to firms that issue larger numbers of securities, suggesting that the "variety" effect dominates. The residual dispersion for the overall data (shown in Panel C of Table 6) was about 40 percent, while it increases to up to 73 percent if we consider firms with more than eight issuances.

The Role of Security Type for Large Issuers The previous subsections suggest that the security type (whether the credit facility is a loan or a bond) explains an extremely small share of total variation of interest rate spreads. 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 (more than 335 thousand loans and about 15 thousand loans, see Table 1). To account for this imbalance, we repeat the baseline decomposition for a sub-sample of firms-quarters in which firms have both loans and bonds. Panel B of Table 7 shows that over 70 percent of the variation comes from within-firm dispersion, even after controlling for firm, security type, maturity, amount, and lender (bank) effects. This result is not surprising in light of panel A, which suggests that the 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 the large firms that issue both bonds and loans.

5 Firm-level outcomes

We now investigate whether changes in our measures of borrowing costs have an impact on firm-level outcomes such as fixed asset investment and firm borrowing. To this end, we estimate panel regressions of outcomes y at varying time horizons h on borrowing cost measures alongside a set of controls. The baseline panel specification is given by:

$$y_{i,t+h} = f_{s,t} + \beta R_{i,t} + \gamma X_{i,t} + u_{i,t} \tag{4}$$

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

Table 7: Variance Decomposition Robustness, Excess Security Premium

Issued	Time	Firm	Bank	Security Type	Maturity	Amount	Residual
			A. By Number of Securities Issued				
2+	9.08	31.36		.36	1.09	.25	57.87
4+	9.61	19.92		.48	1.28	.27	68.44
6+	9.82	16.32		.56	1.48	.3	71.53
8+	9.92	14.43		.6	1.57	.3	73.18
N Firms: 20085							
N Securities: 237210							
			B. Firms With Loans and Bonds Only				
(1)	7.67	16.61					75.72
(2)	7.67	16.61		1.03	1.14	.38	73.17
(3)	7.67	16.61		1.03			74.69
(4)	7.67	16.61			.86		74.86
(5)	7.67	16.61				1.03	74.69
(6)	7.67	16.61	3.28				72.44
N Firms: 1614							
N Securities: 75175							

Notes: Each cell presents the share of the total variance explained by each component. By construction, each row adds up to 100 percent of the total variance.

where $h = 1, \ldots, H$ denotes the horizon at which the relative effect is being estimated. We consider two types of outcomes: the net investment rate in period $t+h$, or the log change in debt between the current period and $t+h$, $\log B_{t+h} - \log B_t$. $X_{i,t}$ is a vector of of firm-level controls that includes leverage, size (log of total assets), liquid assets over total assets, and sales growth. Our benchmark model studies variation across firms, so it includes industry-time dummies at the NAICS 3-digit level, $f_{s,t}$. We also report additional specifications with other type of fixed effects, so we can also measure within firm variation across time. Firm financial data is obtained from the Y-14 dataset, where firms tend to report their financial data to the lending bank when obtaining a new loan, with infrequent updates. For this reason, and in order to maximize the number of observations, our analysis is conducted at a yearly frequency.[13] Finally, we standardize both the dependent and independent variables of interest, so that the reported coefficients can be interpreted as the number of standard deviations impact of a change of one standard deviation in the regressor.

[13]Most firms report financial data only once a year, so this also increases the sample size, since we need two observations in a row.

5.1 Investment

We start by analyzing the effects on the net investment rate. Panel A of Table 8 reports the 1-year ahead effects of changes in the EDP on the net investment rate, i.e. $h = 1$.

First, Columns (1) to (4) consider variation across-firms: (1) no FE, (2) sector FE, (3) time FE, and (4) sector-time FE. Our preferred specification is column (4), which controls for sector-time FE. This specification focuses on cross-sectional variation across firms, controlling by aggregate variation across sector-time. We find that firms with higher borrowing costs have lower investment rates, with coefficients that are statistically significant. A one standard deviation increase in borrowing costs imply about 7 percent of a standard deviation decrease in the investment rate. Second, we consider within-firm variation: Column (5) has firm FE, and column (6) has firm and time FE. We find that the effects are smaller when considering variation within firms over time (controlling for aggregate changes over time).

Panels B and C repeat the analysis for the MIR and NIR spreads, respectively. Overall, We find quantitatively similar results regardless of the borrowing cost measure that we use.

While Table 8 reports the results for the 1-year ahead impact of changes in borrowing costs on the investment rate, we also investigate the dynamics over longer horizons. Panel (a) of Figure 6 plots local projections where we consider the impact of $R_{i,t}$ on net investment rates over the following 8 years.[14] The plotted results follow specification (4) in the table, which includes sector-time FE. We find that the effects on the net investment rate are quite persistent, lasting for over 6 years after the initial shock.

5.2 Borrowing

We repeat the analysis but for firm-level borrowing. We measure borrowing as the log change in total observed debt borrowed by the firm over horizon h. Table 9 presents the results for the 1-year ahead change, and panel (b) of Figure 6 plots the dynamic effects. Regardless of the measure, an increase in borrowing costs has a significant negative impact on firm borrowing. Differently from the investment regressions, we find that the quantitative effects are larger for variation within firms over time, instead of across firms. These effects are not as persistent as those on investment, however, and cease to be statistically significant after a year or longer,

[14] Appendix B.2 presents local projection results for other borrowing cost measures.

Table 8: Investment Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
			A. EDP			
EDP	-0.09***	-0.06***	-0.09***	-0.07***	-0.02**	-0.01*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	36995	36993	36995	36955	23178	23178
Adjusted R^2	0.024	0.046	0.024	0.047	0.388	0.388
Firm FE	no	no	no	no	yes	yes
NAICS FE	no	yes	no	no	no	no
Time FE	no	no	yes	no	no	yes
NAICS-time FE	no	no	no	yes	no	no
			B. MIR spread			
MIR spread	-0.07***	-0.05***	-0.08***	-0.05***	-0.01**	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	47706	36993	47706	36955	29773	29773
Adjusted R^2	0.022	0.045	0.022	0.045	0.352	0.352
Firm FE	no	no	no	no	yes	yes
NAICS FE	no	yes	no	no	no	no
Time FE	no	no	yes	no	no	yes
NAICS-time FE	no	no	no	yes	no	no
			C. NIR spread			
NIR spread	-0.08***	-0.07***	-0.09***	-0.07***	-0.02***	-0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	47706	36993	47706	36955	29773	29773
Adjusted R^2	0.023	0.046	0.023	0.046	0.352	0.352
Firm FE	no	no	no	no	yes	yes
NAICS FE	no	yes	no	no	no	no
Time FE	no	no	yes	no	no	yes
NAICS-time FE	no	no	no	yes	no	no

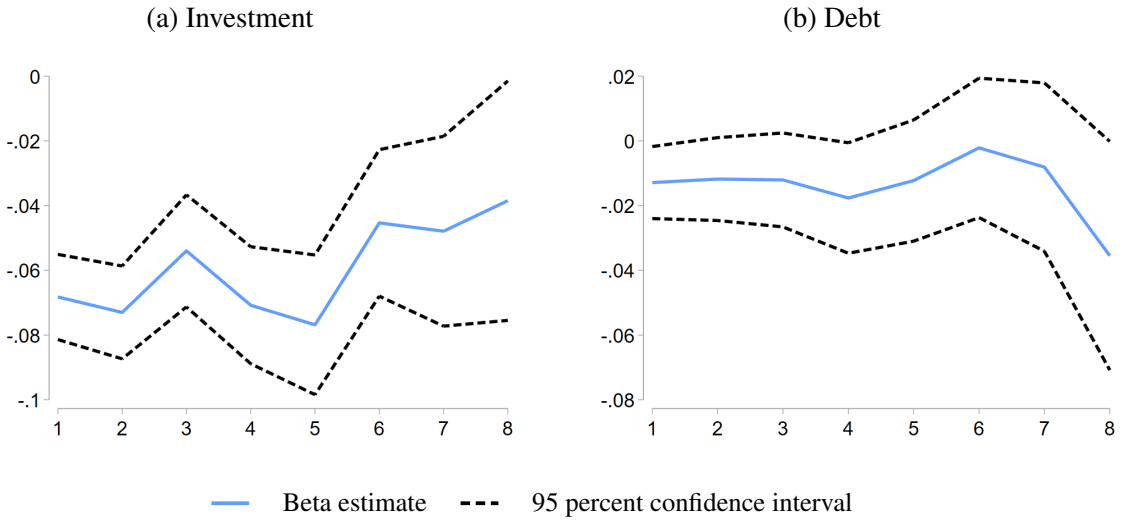
Notes: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

depending on the measure of borrowing costs.

5.3 Sectoral Heterogeneity

Finally, we investigate whether there is significant variation in how firms react to changes in borrowing costs across different sectors. Due to our relatively limited sample, we focus on NAICS 2-digit industries (excluding Finance and Government). Essentially, we re-estimate equation 4 for each sector separately. Figure 7 plots the resulting coefficients for the effect of EDP on the net investment rate, along with 95 percent confidence intervals. The figure shows that there is considerable heterogeneity in how investment reacts to changes in borrowing

Figure 6: EDP Local Projections



costs across sectors, with particularly large effects in sectors such as Information, professional services, and administrative services.

Note that we do not find statistically significant effects for sectors that are traditionally thought of as being interest rate sensitive, such as construction and real estate. We do not see our results as being inconsistent with this standard view: it is well understood that activity in these sectors is sensitive to the overall level of interest rates. Since our measure of borrowing costs contains time-sector fixed effects, what we effectively find is that investment activity in these sectors is not particularly sensitive to changes in borrowing rates in excess of aggregate fluctuations in interest rates.

6 Conclusion

We provide novel insights into the determinants and implications of firms' borrowing costs by exploiting a comprehensive security-level database covering both bank loans and corporate bonds. Our analysis reveals significant heterogeneity in borrowing rates across different debt instruments within the same firm, even after accounting for observable characteristics. Consistent with previous research, we find that bank loans tend to be cheaper than corporate bonds, even when controlling for observable characteristics.

Moreover, our results demonstrate that changes in borrowing costs have persistent negative effects on key firm-level outcomes, such as investment and leverage decisions. Importantly,

Table 9: Debt Regressions

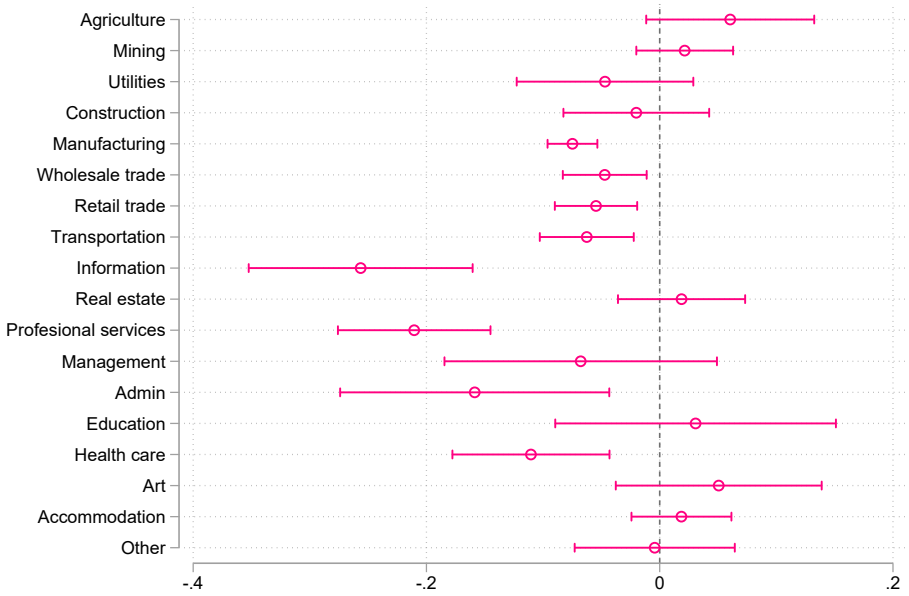
	(1)	(2)	(3)	(4)	(5)	(6)
			A. EDP			
EDP	-0.03***	-0.03***	-0.01*	-0.01**	-0.08***	-0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Observations	70979	70975	70979	70951	37771	37771
Adjusted R^2	0.012	0.015	0.019	0.032	0.019	0.034
Firm FE	no	no	no	no	yes	yes
NAICS FE	no	yes	no	no	no	no
Time FE	no	no	yes	no	no	yes
NAICS-time FE	no	no	no	yes	no	no
			B. MIR spread			
MIR spread	-0.03***	-0.05***	-0.02***	-0.03***	-0.08***	-0.05***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Observations	93482	70975	93482	70951	51428	51428
Adjusted R^2	0.011	0.015	0.017	0.032	0.015	0.027
Firm FE	no	no	no	no	yes	yes
NAICS FE	no	yes	no	no	no	no
Time FE	no	no	yes	no	no	yes
NAICS-time FE	no	no	no	yes	no	no
			C. NIR spread			
NIR spread	-0.02***	-0.04***	-0.01***	-0.02***	-0.07***	-0.03***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Observations	93482	70975	93482	70951	51428	51428
Adjusted R^2	0.011	0.015	0.017	0.032	0.014	0.027
Firm FE	no	no	no	no	yes	yes
NAICS FE	no	yes	no	no	no	no
Time FE	no	no	yes	no	no	yes
NAICS-time FE	no	no	no	yes	no	no

Notes: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

these effects exhibit substantial variation across sectors, highlighting the differential impact of financing costs on different industries.

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. For policymakers, our results underscore the relevance 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.

Figure 7: Investment Effects Across Sectors



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Appendix

A Data

A.1 Y14 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 financial 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 higher than committed (`Field 25 UtilizedExposure` $>$ `Field 24 CommittedExposure`).

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

(vii) The date is before the origination date (`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).[15]

[15]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 the key variables employed in the empirical analysis as follows. In the Y-14 we have two levels of analysis: security level and firm level. Therefore, we have a few sets up variables. First, security level variables. Then, firm-quarter level variables. Finally, firm-year level variables that are used in Sction 5.

Variables at the security-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 define if a loan is syndicated or not (`Field 34 ParticipationFlag` - 1 is not syndicated, 2-5 syndicated).

(v) Interest rate: The interest rate on a 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. (`Field 38 InterestRate`, nominal interest yields from the Board of Governors).

Variables at the firm-quarter level:

(i) Coverage: We define the coverage as the total utilized value of loans and bonds divided by a firm's total liabilities.

(ii) 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 $= 0$.

(iii) Probability of default: the median of a firm across observations (i.e., across different securities from potentially different banks) in a quarter.

Variables at the firm-year level: Created by taking the mean of quarterly variables when available:

(i) Total Assets: We use the log of total assets (`Field 70 TotalAssetsCurrent`).

(ii) Total Debt: We use the total amount utilized on all loans and bonds in a quarter (`Field 25 UtilizedExposure`).

(iii) Leverage: We define leverage as total liabilities divided by total assets.

(iv) Liquidity Ratio: We define the liquidity ratio as the difference between current assets and current liabilities (`Field 61 CashMarketableSecurities`) divided by total assets.

(v) Sales Growth: Sales growth is defined as the change in log net sales (`Field 54 NetSalesCurrent`).

(vi) Net Investment Rate: the difference between capital expenditures (`Field 82 CapitalExpenditures`) and depreciation and amortization (`Field 57 DepreciationAmortization`), divided by fixed assets from last period (`Field 69 FixedAssets`).

A.2 FISD data

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

A.2.1 Sample Selection

Our sample selection criteria follow standard practice in the literature. Our final sample is 2013Q1 - 2023Q3, but we view the FISD bonds only at origination. Because of this, we start the "sample"–the bonds that we are viewing at origination–in 1990Q1. Thus if a bond has a maturity of 20 years and originates in 2000Q1, we will have this bond in our sample from 2013q1-2020q1.

We exclude all firm-quarters for which:

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

(ii) Bond issuer or issue not in 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 (Currency not either 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 not convertible (`convertible not` equal yes).

Further, we download data from Bloomberg on bonds that have been called, and the date they were called. We merge that data to FISD using the nine digit security level cusip, and drop bond observations that are in or after the quarter the bond was called.

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_date`).

(ii) Amount: The offering amount of the loan (`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) Interest rate: Issue coupon (`Issue coupon_type`).

(v) 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 of 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 of that firm or their 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 missing ultimate ids. Then, we drop any matches that take place before or after the relationship, as reported by the BECRS. To settle any within firm-quarter discrepancies (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 the scope. For bonds that are not matched, we define the firm by the issuer id provided in the FISD.

A.4 Maturity and Amount Bins

In order to calculate the variance decomposition in Section 4, we must create categorical bins. For security type, it is already categorical. For security maturity and amount, which are continuous variables, we use the buckets. For maturities less than 11 years we use two year periods. Then we consider a group for maturities between 11 and 29 years, because most of our securities 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 5.

B Robustness

B.1 Firms with Loans and Bonds

In this Appendix, we show that the benchmark regressions are robust to consider only the sample of firms that contains firm-quarters in which a firm has both loans and bonds. Hence, table B1 uses only firms that originate both a loan and a bond in a given quarter. Our estimates of the Bond-Loan spread are very similar to the benchmark.

Table B1: The Bond-Loan Spread: Firms That Originate Both a Loan and Bond

	(1)	(2)	(3)	(4)	(5)	(6)
Maturity	-0.01***	-0.01***	-0.00***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Amount	-0.25**	-0.23**	-0.53***	-0.51***	-0.50***	-0.83***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.13)
Default Probability	0.03***	0.03***	0.01***	0.03***	0.02***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Loan	-0.27***	-0.29***	-0.34***	-0.31***	-0.29***	-0.38***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	5.16***	5.16***	5.21***	5.20***	5.17***	5.28***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	19556	19553	19523	19556	19484	22292
Adjusted R^2	0.029	0.072	0.229	0.095	0.278	0.388
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

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Local Projections

In this Appendix, we provide robustness to our results in Section 5. Specifically, in Figure B1, we provide the local projection estimates for both investment and debt for two alternative borrowing cost measures: the NIR and MIR. For investment, both the NIR and MIR local projections show a depression in investment, albeit at a slightly lower magnitude than the EDP.

Similarly for debt, the NIR and MIR local projections show an initial decrease in debt, which is persistent for 1-3 years before the results are no longer statistically significant.
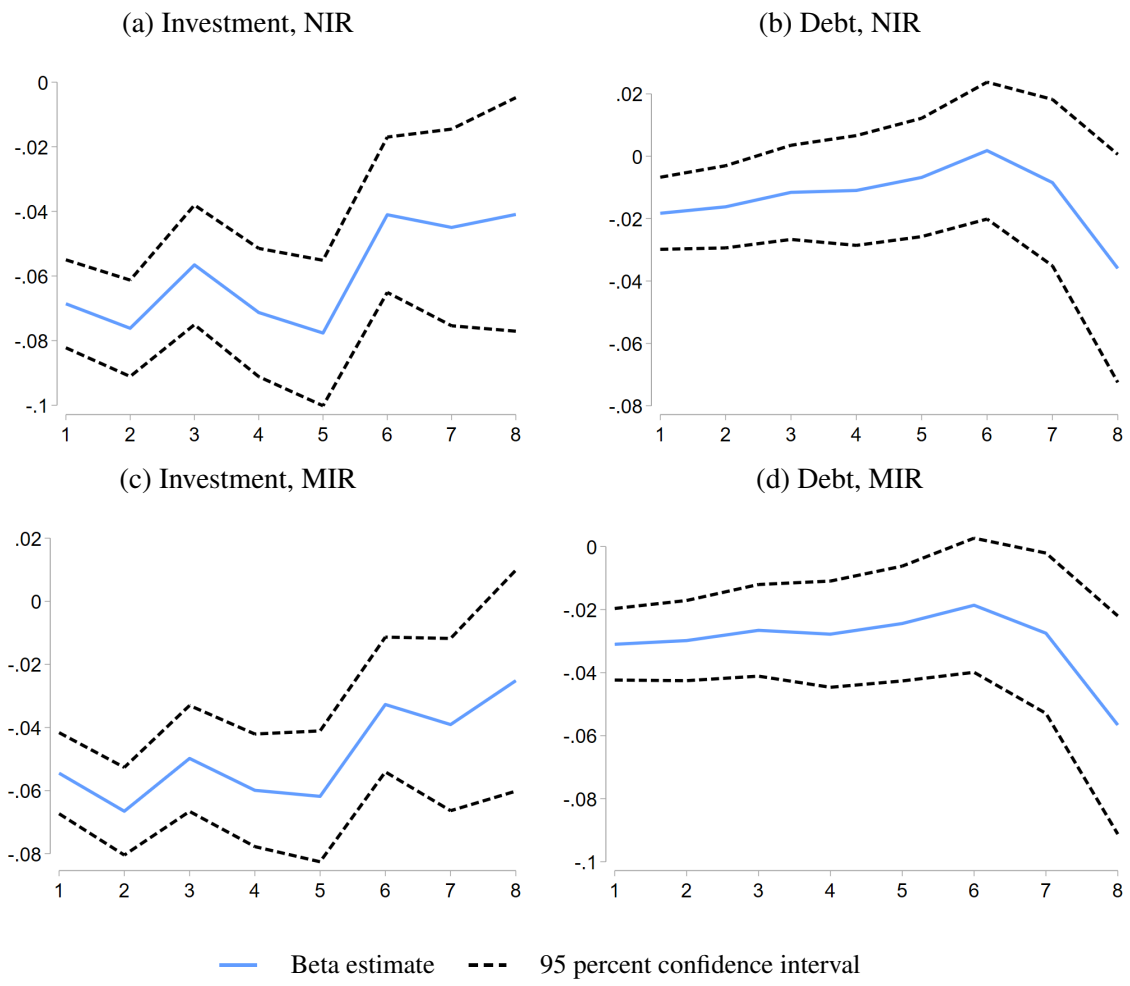
Figure B1: NIR & MIR Spread Local Projections