How Much Does It Cost for Firms to Switch Banks?*

July 3, 2025

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Abstract

We document significant variation in interest rates among similar loans using confidential supervisory data on commercial and industrial loans of the largest US banks. This dispersion does not appear to be due to risk. We estimate a search cost model and find search costs are highest for smaller and riskier borrowers, consistent with predictable differences in the costs of screening and monitoring. We find that half of borrowers have costs ranging from 36 to 74 basis points per dollar of loan commitment (leading them to search for only one loan quote). Less than 15 percent of borrowers have search costs that are so low (3bp) that they search broadly. In a counterfactual exercise, we estimate that a bank failure that forced its borrowers to search for new lenders would result in a deadweight loss of at least 11 percent of the bank's loans.

JEL CLASSIFICATION: E51, G21, G32

KEYWORDS: banking, credit supply, macrofinance

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1 Introduction

Reductions in bank lending and bank failures have adverse effects for a bank's borrowers. This empirical regularity motivates bank supervision and regulation as well as policy interventions in the face of bank fragility. This paper uses unique supervisory data to quantify the costs to firms of changing banks, the size of which helps to understand the importance of banks to supplying credit to the real economy.

The key observation that underlies our calculations is that comparable firms borrow from banks at very different interest rates. Even after we control for most of the factors identified by the banking literature as determining borrowing costs, the unexplained variation remains large. The profound dispersion in borrowing costs is strikingly evident for the subset of loans where banks provide their estimate of the expected loss that is associated with each loan. If risk were the primary determinant of a loan, differences in expected loss should explain the variation in interest rates. This is not what we find. Loans that are grouped on a number of dimensions do have quite similar expected loss rates, but the interest rates on these loans exhibit much greater variation than the expected loss rates. It's also notable that this variation is not necessarily a feature of all forms of corporate credit. Much of the interest rate variation in corporate bonds is explained by credit risk and bond characteristics.

Given that the rich set of observables collected by bank supervisors explain relatively little of the variation in interest rates for comparable borrowers, we explore whether the dispersion might arise from borrowers' costs of searching for loans. We develop a model of how lenders would set interest rates for a set of borrowers with homogeneous levels of risk, but differences in search costs. As in Burdett and Judd (1983), the lenders target different types of borrowers, with some setting high rates that only attract borrowers with high search costs, and others posting lower rates that will attract more customers. In equilibrium, all strategies yield the same level of expected profits because loan offers with high rates are chosen less frequently than loans with lower rates.

We thus extend the economics literature that explains how similar products have different prices to the price of bank loans. By observing the distribution of loan rates, we infer the differences in the search costs. We follow the banking literature, and the patterns in the search cost we estimate to interpret these search costs as arising because a new lender must screen and monitor the borrower

to assess creditworthiness.

Our model allows these screening and monitoring costs to vary with a host of observable characteristics like risk ratings, loan size, loan maturity, loan purpose and whether a loan has a fixed or floating rate. We group firms into "bins" that reflect these characteristics (as well as the interest rate regime that prevails at the time of a loan origination). We can then non-parametrically estimate how interest rates vary across bins.

The model supposes that even controlling for these features, i.e. within a bin, borrowers can differ in their ability to search across lenders. These idiosyncratic (and unobservable) costs can arise from many factors, such as the time costs of preparing paperwork or audited financial statements or the cognitive costs of comparing loan offers.

The estimated model suggests that these idiosyncratic switching costs differ substantially between otherwise very similar borrowers. We reach this conclusion because within a bin, some firms pay relatively high rates, which would only make sense if the cost of obtaining additional loan quotes is expensive. Simultaneously, other firms in the same bin are paying much lower rates, which is consistent with being able to search comprehensively, i.e. having low search/switching costs.

To assign a prominent role to switching costs, it is essential to accurately account for the variation in interest rates that comes from credit risk, to make sure we are really looking at a distribution of different prices for the same product. The data set we use was built by supervisors to measure credit risk, more specifically to determine how different loans would perform under stress, and thus naturally lends itself to this purpose. Hence, we have rich detail on the essential aspects of each loan in the banks' portfolios over $1 million, including banks' internal risk ratings and the other loan characteristics we use in forming bins.

Our sample includes more than 160,000 loan originations, with the average loan size around $22.36 million, which we sort into 722 bins of borrowers with similar risk characteristics. Despite the granular information used in constructing the bins, the bin characteristics account for only about 25% of interest rate dispersion in the data. Hence, the large role that is assigned to switching costs.

We estimate that approximately 36% of borrowers get one loan quote and accept it, about 49% search to get a second a quote and the remaining borrowers seem to search intensively enough to

see all quotes that are available. This search behavior is consistent with the single search borrowers (seeking a $22.36 million loan, on average) having a search cost of at least roughly $165,464, the second group of firms having a cost of at least $69,316 and the other firms having a cost of at least $6,708. These averages, however, mask a great deal of heterogeneity in imputed costs for borrowers in different bins.

The screening and monitoring hypothesis implies that borrowers whose loans are harder to evaluate or have loans that allow more discretion to the borrower require lenders to expend more resources on screening and monitoring. These loans should, therefore, have higher switching costs and this prediction is confirmed in the data. For example, holding fixed the loan size, a typical A-rated borrower who gets a second loan quote has an estimated switching cost that is about half as large as a B-rated borrower who gets the same number of quotes. This finding is driven by the empirical regularity that as the borrowers' risk in a given bin decreases (as measured by higher credit ratings), the amount of dispersion in interest rates falls. We use our estimates to compute the implied cost to the economy of having a bank fail and forcing all of its customers to obtain loans from other banks. We make this calculation by cumulating the borrower switching costs incurred at origination and dividing this number by the amount of loans outstanding to express the deadweight loss of failure as a share of bank lending. Because the 36 banks in the sample differ in terms of their customer mix, the implied costs of a failure differ too. For the median bank, the estimated deadweight loss would be 11% of the committed loans and for the average bank the loss would be 17%. In addition to informing us about the costs of a failure for a bank's borrowers, these costs also have implications for the potential costs to borrowers of changes in regulation that affect individual banks and cause them to change their lending supply as well as the role of banks in the transmission of monetary policy.

The remainder of the paper proceeds as follows. Section 2 reviews the main literature where loan supply shocks are thought to be important. It also describes the theoretical papers that underlie the screening and monitoring hypothesis. Section 3 introduces the data used in the analysis. We describe how the bins are constructed and assess the degree of interest rate variation in the different bins. Section 4 highlights new stylized facts. We present evidence suggesting that the within-bin variation does not appear to be associated with observable variables related to credit risk. We show that substantial variation in interest rates, unexplained by loan risk

characteristics collected by supervisors, remains. Section 5 introduces the theory that we use to estimate the model. Section 6 presents our estimates of the cost of switching. We first present some univariate comparisons of interest rates when we characterize loans by a single characteristic and then supplement that with a multivariate analysis of all the main characteristics. We then present the estimates of the switching costs for different types of borrowers and loans and close the section with a summary of the switching costs that a failing bank would incur. Section 7 describes several robustness checks that confirm the main findings in the paper. Section 8 concludes.

2 Literature Review

At least four well-developed literatures study shocks to lending and interpret the results as supporting the existence of switching costs. Given the depth of these literatures, we do not attempt to fully summarize all the related research and instead point to some prominent papers that give a sense of the relevant findings. The direct estimates of switching costs we provide could be used to revisit these topics to reconsider the implications of lending shocks for the economy.

One topic area concerns the impact of bank failures and bailouts on the economy. An early, influential paper by Slovin et al. (1993) examined the fate of borrowers affiliated with Continental Illinois Bank around the time of its distress in 1984. They find that share prices for the customers fell after the bank ran into trouble (as might be expected if the borrowers cannot seamlessly replace any lost loans). They could not measure which borrowers made up any reduction in lending by switching to other banks.

Following the 2008/9 Global Financial Crisis, several studies examined the consequences of the failure of Lehman Brothers and the stress at other large banks. Chodorow-Reich (2014) studies the syndicated loan market and identifies borrowers from banks that incurred large real estate-related losses and estimates how much credit they lost. He then estimates employment outcomes for the firms that lost funding and shows that the credit losses translated into employment declines.[1] The employment drops were largest for small and medium-sized firms and insignificant for large firms. This pattern is consistent with the idea that small borrowers faced disproportionately higher costs to switch lenders.

[1] Amiti and Weinstein (2011, 2018) find that a contraction in bank supply reduces their customers' export growth and investment, respectively.

Our counterfactual bank failure results produce larger results than in papers examining the direct administrative costs that are associated with bankruptcy filings. For instance, one well-known study by Warner (1977) estimates that bankrupt railroads between 1933 and 1955 incurred administrative expenses during bankruptcy of 4% of their pre-bankruptcy market value. In another widely-cited study, Weiss (1990) finds administrative costs of about 3% of market value for a set of firms that filed for Chapter 11 bankruptcy protection between 1980 and 1986. However, these studies mostly examine nonfinancial firms.

The observation that borrowers and lenders match in ways that are beneficial to both parties is also indirectly supported by the large literature on relationship lending. For instance, Bharath et al. (2011) find repeated loans between a borrower-lender pair are associated with lower loan spreads, particularly when the borrower is relatively opaque. These findings are also supportive of the view that switching costs are important. Our results also cast new light on the finding by Billett et al. (1995) that lenders with a higher credit rating are associated with larger abnormal returns upon receiving a loan, as it may also signal a lower probability of a firm being forced to incur switching costs.

A second set of analyses investigates lending disruptions that are created as a result of bank mergers. Berger et al. (1998) study over 6,000 mergers and find that small business lending drops at the time of a merger. In subsequent quarters, however, they find that lending recovers.[2] Karceski et al. (2005) look at stock price reactions for publicly traded customers of Norwegian banks that are involved in mergers. Customers of acquired banks have negative share price reactions, though when borrowers are dropped by the bank, the share price reaction is less negative. They interpret this evidence as reflecting different switching costs for different customers, whereby the borrowers with low switching costs move and are less likely to be held up, while the firms that stay behind are charged higher loan rates because their switching costs are prohibitive.

A third related area of study looks at the monetary policy transmission process, emphasizing the impact of policy changes on bank lending. Kashyap and Stein (2000) show that U.S. banks differ systematically in the extent to which they reduce lending after a tightening of monetary policy. Smaller banks with less liquid assets tend to cut lending more than similar-sized banks

[2]This is reinforced by Peek and Rosengren (1998), who find that loan portfolios converge towards the structure of the acquiring bank. Because most mergers involve small banks, this will mean that small borrowers are not necessarily cast aside after a merger.

with high levels of liquid assets. They interpret this result as arising because smaller banks cannot raise market financing easily, so banks have to shrink when deposits are reduced (via the monetary policy tightening). Those with abundant liquidity can insulate their lending business, whereas the banks with few liquid assets have to reduce lending. Large banks that presumably can better raise alternative financing do not show this pattern. Because small banks tend to lend to small borrowers, the effect of a monetary tightening will differ for different firms.[3] Kashyap and Stein (2000) find that a given monetary policy tightening has different effects on different types of borrowers. Implicit in these cross-sectional analyses is that borrowers do not switch away from banks that are differently affected by changes, and unanswered in that literature is how many firms can switch and replace funding. One contribution of this paper is to offer numbers that are relevant to interpreting the literature on the impact of bank supply shocks.

Using even better data from Spain, Jiménez et al. (2012) find similar results. They rely on the Spanish credit register that tracks all lending and loan applications. They find that when monetary policy tightens, loans granted by less well-capitalized banks with low levels of liquid assets decline significantly compared to strong-capitalized, highly liquid banks. They can also see if firms that were denied credit make successful applications elsewhere, and they find that about one-third of the borrowers that were turned down have another application successfully approved within the next three months. So, while there appears to be some substitutability, it seems to be imperfect. Therefore, this research also suggests that when bank-borrower relations are disrupted, the borrower incurs some costs.

Finally, there are many analyses of how changes in bank regulation, primarily capital regulation, affect bank customers. If only some banks are affected by regulatory changes and switching costs are low, the impact on borrowers should be limited. However, most studies do find significant costs to borrowers when bank capital standards are increased. Using Spanish data, Jiménez et al. (2017) document that when capital standards increase for some banks, their borrowers struggle to replace the funding. In the US, Cortés et al. (2020) examine lending to small businesses by the largest US banks after they become subject to stress testing and find that banks more affected by stress tests pass the implied increase in capital requirements into loan rates in markets where they

[3] Drechsler et al. (2017) present complementary evidence that emphasizes differences in market power in the deposit market as a source of heterogeneity of monetary policy changes on lending.

have local knowledge, a price increase suggesting that borrowers face high costs of switching.

In addition to these empirical literatures, a large theoretical literature rationalizes the existence of switching costs and predicts how they might differ across borrowers. We use this literature to assess the plausibility of our estimates for different types of borrowers and loans. This theoretical literature highlights the problems created by asymmetric information between borrowers and lenders, whereby borrowers know more about their creditworthiness than lenders do. Financial intermediaries are valuable in such settings because they invest in information production (in particular, screening borrowers before making loans and monitoring them afterward to ensure repayment).[4] Switching costs, however, are still likely to arise because once a lender becomes informed about a borrower, that lender has an edge in extending credit relative to uninformed lenders.

This reasoning suggests that switching costs are likely to be highest in cases where information asymmetries are largest. Standard proxies for the extent of information problems include borrower size (where smaller firms are assumed to be more opaque), loan purpose (where loans that allow more discretion in their use are assumed to be less transparent) and the nature of the borrower's business (with more complex organizations or complicated competitive environments assumed to be more opaque).[5] We refer to these types of predictions as "the screening and monitoring hypothesis". We provide some comparisons of our estimates along these dimensions to assess this hypothesis.

Past research finds that loan interest rates tend to vary in ways consistent with this hypothesis. For example, smaller firms or firms without credit ratings pay more to borrow (Hubbard et al. (2002)). Similarly, loans for general corporate purposes are more expensive than those restricted to working capital. These kinds of findings, however, do not directly tie the loan pricing to the presence of switching costs.

[4]Classic references include Pyle and Leland (1977); Diamond (1984) who investigate how lenders can screen and monitor borrowers to address the information problems.

[5]Similar kinds of predictions can be made for consumer lending. In that case proxies might be based on the length of an individual's borrowing history, the variability in their income, and the exposure to unexpected spending requirements.

3 Data

Our analysis uses a unique matched U.S. bank-firm data set collected by the Federal Reserve for Dodd-Frank Act mandated stress testing (FR Y-14). We focus on the H.1 schedule, which includes a comprehensive dataset of all loans to commercial and industrial borrowers (C&I loans) made by stress-tested banks. This supervisory data is collected quarterly for US bank holding companies, intermediate holding companies of foreign banks, and savings and loan holding companies with more than $100 billion in total assets, making it the most comprehensive data source for US bank loans.[6]

The Y-14 data collection since its inception includes information on 42 bank holding companies, accounting for approximately 70% of all US commercial bank lending. Our sample (after cleaning) contains 36 banks over the time period, reflecting that some of the stress tested banks do not have a large number of C&I loans, consistent with their business models and organizational structure. While the United States does not maintain a credit registry, these data are as close as possible to a registry for the set of large banks subject to stress testing because they are required to report detailed information on all loans with committed amounts greater than $1 million. One benefit of these data relative to the extensive literature on syndicated lending is that we can gain information about smaller businesses, which are more likely to be bank-dependent.

3.1 Sample Description

The Y-14 data include quarterly observations, with the dataset beginning in 2011:Q3. Because of potentially inconsistent reporting in the first year of the sample, we limit the analysis to loans made between 2012:Q4 and 2024:Q4. An advantage of this comprehensive supervisory data is that it includes a full set of fields designed to allow supervisors to estimate potential loan losses in a stressed economic environment. The data include the committed and outstanding amount of the loan as well as key characteristics such as the loan type and purpose, interest rate, base rate,

[6]Most studies on U.S. bank lending rely on data from syndicated loans, using either LPC DealScan data or the confidential Shared National Credit data, which cover only loans held by multiple banks, and mostly loans greater than $100 million. Some studies have also used Community Reinvestment Act (CRA) data, which capture loans smaller than $1 million for banks with more than $1 billion in assets and do not have data on interest rates. See https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_Y-14Q for detailed instructions on the Y-14 data collection, H.1 schedule. The FR Y-14Q data collection has been used in several papers. For example, Chodorow-Reich et al. (2022) compare the Y-14 data to Compustat firms, DealScan, and SNC, highlighting the differences between the large borrowers in those databases and the smaller borrowers in this sample. They also note that loans collected in the Y-14 account for more than 90% of total C&I and real estate-backed-lending by stress-tested banks.

interest rate spread, maturity, borrower location, industry, and collateral. We track borrowers in the sample through their taxpayer identification number. Because there may be data-entry errors, we drop reported interest rates over 30 percent and observations where interest rates are equal to zero.

Banks directly report measures of loan risk, including an internal loan risk rating, which captures the bank's estimated probability of default. We make use of a confidential Federal Reserve concordance table that translates banks' internal loan risk ratings into a common rating scale, which mimics the one used for syndicated loans, in which loans are rated from AAA to D. Some banks opt in to the "advanced approach" to assessing capital requirements whereby they make use of their own risk models approved by supervisors rather than being subject to the default capital requirements. For banks and loans subject to advanced approaches, our data also include information on a numeric probability of default, loan exposure at default and loss given default, each expressed as a percentage of the committed amount of the loan. The expected loss ratio is the product of these numbers and, when multiplied by the committed amount, determines the expected dollar loss on a given loan. We exploit this information in some of our analyses.

4 Stylized Facts

There are many reasons why loans to similar borrowers might be made at different interest rates. At one extreme, suppose borrowers are identical. If they can costlessly find the cheapest loan, then competition would push all loan rates to be identical. If search is costly, however, and especially if different borrowers have different costs of searching, then there will be interest rate dispersion even for borrowers that are otherwise the same. These search costs can range from financial costs associated with finding lenders and disclosing information to them as well as any cognitive and time costs associated with expending the effort needed to search.

At the other extreme, if borrowers differ in their default risk, or in other dimensions, then equilibrium interest rates will differ even if there are no search costs. The degree of dispersion may differ depending on the source of the heterogeneity, but some dispersion would be expected.

Reality undoubtedly involves both heterogeneity in loan/borrower characteristics and search costs. The implications for how loan supply disruptions are transmitted to the economy depend on the relative importance of these two considerations.

This dichotomy motivates our empirical strategy. In Section 4.1, we explain how we form the bins that underlies most of the subsequent analysis. Section 4.2 demonstrates that only a small fraction of the variance in adjusted interest rates can be explained by the risk proxies and other observable loan and borrower characteristics. Section 4.3 further characterizes the properties of the observed dispersion in loan rates. We find that even accounting for the bin characteristics that should reflect risk differences and estimating the determinants of adjusted interest rates non-parametrically, the fraction of interest rate variation in our sample that can be explained by observable heterogeneity is modest. Section 4.4 confirms these findings and explores other variables that proxy for loan differences such as variation in relationship length, access to public markets and other variables identified in the banking literature. We also estimate the variation explained by expected loan losses, which should reflect banks' best estimates of the risk of loans, incorporating many more observable characteristics than those we use (and potentially soft, unobservable to us, information too). We find that controlling for all of these factors fails to substantially shrink the dispersion in interest rates for observably similar firms. That finding leads us to explore whether search cost variation might explain the dispersion.

4.1 Observable and Unobservable Heterogeneity

We seek to study the dispersion of interest rates for similar borrowers and to explain the origin of any differences. We are broadly interested in separating differences that can be traced to observable characteristics from those that we cannot measure, so that we can confirm that the dispersion we study is really dispersion in the price of similar products.

One challenge in doing this is correcting for the movements in the overall level of interest rates. In the Y14 data, most loans are made relative to a reference (or base) rate such as LIBOR. Some loans, however, are based on one-month LIBOR, others are based on 3-month LIBOR and for some loans, the reference rate may have to be imputed. When we use the word "spread" we are referring to the difference between the level of the interest rate and the reference rate.

As a simpler and more transparent way to correct for changes in the level of interest rates, we have also compared the loan rate at origination to the upper end of the effective range for the Federal Funds Rate that prevails at the time of origination. We refer to that difference as the adjusted interest rate. In this draft, the regression analysis is primarily performed on the adjusted

interest rate. We denote the adjusted interest rate that firm j pays when originating loans with a set of characteristics k from bank b by r_{jbkt}.

We assume that these adjusted rates can be explained by a vector of observable borrower and loan characteristics given by $\boldsymbol{X_k}$. In forming $\boldsymbol{X_k}$, we group loans so that all originations within a "bin" are similar on six dimensions (committed amount, risk-rating, maturity, loan purpose, loan type and the interest rate regime). The first five of these are the main variables that banks commonly collect to measure loan risk and that were included in the Y14 data to estimate the performance of loans in a stressed environment. By grouping loans on these dimensions, we aim to limit the unobserved heterogeneity within each bin. A naive hypothesis would be that just grouping loans based on the risk-rating alone should be sufficient to assure that adjusted loans would be very similar, so we view our groupings as being conservative.

We also pool loans across dates that have similar overall interest rate environments, in case the price of risk varies according to whether interest rates are at the effective lower bound. Our first regime runs from 2012:Q4 to December 16, 2015, when rates were near the zero-interest-rate lower bound. The second interval spans December 17, 2015 to December 31, 2019, and includes a period of positive interest rates. We drop the first two quarters of 2020 to avoid the initial period of the pandemic where borrower risk may be harder to estimate. The third period starts on July 1, 2020, and continues until March 17, 2022, capturing the second interval, where rates were again at the effective lower bound. The last period covers March 18, 2022 through 2024Q4, when rates were non-negative.

In order to further minimize unobservable borrower heterogeneity in each bin, we limit our sample in several other ways. We include only non-financial, for-profit borrowers. The Y-14 reporting schedule lists 19 types of loans and 30 loan purposes. We restrict our sample to include only loans for corporate purposes and working capital. We do this because loans made to fund acquisitions may have a different set of risk characteristics depending on the scale and scope of an acquisition. We also exclude loans for project-financing and real-estate related purposes, where the collateral may be hard to compare, as well as other miscellaneous loan purposes. Approximately a quarter of loan observations remain after we impose these restrictions on loan purpose. Within the corporate purpose and working capital loan purposes, we sort loan types into four loan categories, separating revolvers from term loans as well as loans for short-term or seasonal working capital

from those for permanent working capital or general corporate purposes. On average, there are approximately 3,750 originations per quarter, peaking in 2012 and with a minimum in 2020Q3.

4.2 How Much Interest Rate Variation Exists and Can be Explained by Observable Heterogeneity?

Table 1: Loan Characteristics

	Share of obs (%)	Share of committed (%)	Mean interest rate (pp.)	Median interest rate (pp.)	Mean spread (pp.)	Median spread (pp.)	Mean utilization (%)	SD interest rate (pp.)
Rating:								
A	1.1	2.6	2.57	2.24	1.55	1.30	60.48	1.53
BBB	26.2	38.3	3.36	2.97	1.88	1.65	65.95	1.83
BB	56.6	47.2	4.05	3.66	2.54	2.40	69.36	1.87
B	16.0	11.9	4.66	4.25	3.14	3.00	69.09	1.97
Committed (millions):								
1-5	52.8	7.5	4.12	3.75	2.68	2.60	71.73	1.80
5-10	12.1	5.6	3.90	3.41	2.45	2.25	68.88	1.94
10-25	15.5	16.3	3.77	3.25	2.32	2.10	68.13	1.99
25-100	17.9	54.6	3.65	3.08	1.96	1.70	60.17	2.11
100-250	1.8	15.7	3.83	3.26	1.59	1.35	47.81	2.28
Maturity (years):								
0-1	32.3	11.1	4.18	3.75	2.74	2.75	61.67	1.91
1-4	32.3	35.8	3.92	3.44	2.40	2.25	67.63	2.01
4-5	28.3	50.4	3.75	3.38	2.22	1.95	71.45	1.91
5-8	5.8	2.6	3.78	3.60	2.32	2.10	87.87	1.51
8-15	1.4	0.2	4.28	4.20	2.20	2.08	94.81	1.32
>15	0.0	0.0	4.60	4.66	2.19	2.20	94.50	0.88
Loan type:								
Revolver, short-term capital	30.5	17.3	4.43	4.00	2.64	2.60	60.82	2.03
Revolver, general working capital	41.8	64.4	3.70	3.25	2.41	2.25	56.75	1.87
Term, short-term capital	6.4	2.2	3.34	3.18	2.20	1.93	96.75	1.48
Term, general working capital	21.4	16.1	3.95	3.64	2.36	2.15	93.18	1.83

Notes: This table reports summary statistics for the 160,627 estimation sample of loan originations for 36 stress-tested banks from 2012:Q4 to 2024:Q4 (we drop 2020Q1 and 2020Q2 from the sample) after we have restricted the data. Bins are constructed by splitting by banks' internal risk rating, commitment amount, maturity, loan type, and loan purpose. We drop the revolver loans that were never drawn on over the life of the loan, bins with less than 6 unique banks and bins that have less than 20 loans. The first two columns show the share of originations by number and committed value. The next columns show the mean, median, and standard deviation of the interest rate and interest rate spread for all loan originations in each category calculated as of origination date. Interest rate spreads are calculated based on spreads to 3-month LIBOR, and use forward curves at origination for fixed-rate loans. Mean utilization is the mean of the loans in the category, defined as utilized divided by committed, calculated for each loan over the loan's lifespan in the dataset.

Table 1 shows summary statistics for the loans in our sample. The table reveals several stylized facts about these loans. Most of the loans are rated BBB or BB. The median loan spread, which we define as the difference between the interest rate on the loan and the three-month London

Interbank Offered Rate (LIBOR) (and SOFR once LIBOR ceased), monotonically increases with loan risk. This variation motivates our bin structure, grouping firms with different risk ratings into different bins. Loans rated above A are rare in the Y-14 data, which means that we typically do not observe enough originations to form bins. Therefore, we drop these loans from the analysis.

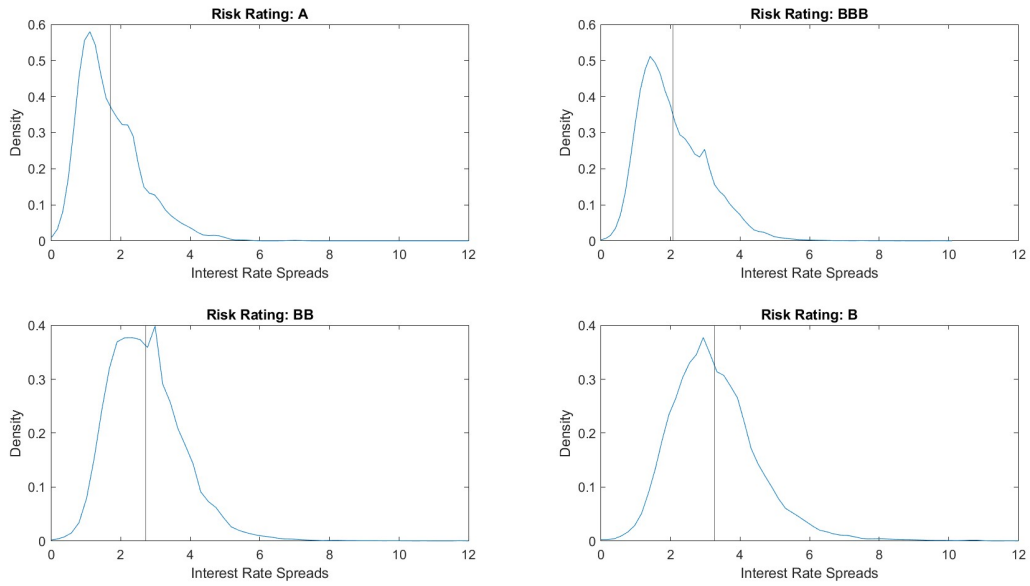
Spreads fall with the amount committed and maturity, which probably reflects that, all else equal, long-term borrowers and larger firms tend to be those with lower default risk. Revolvers, which account for about 72 percent of all loans and 82 percent of the value of all lending, have systematically higher spreads than term loans, which motivates our decision to divide these two types of loans into four separate categories: revolvers for short-term capital, revolvers for general working capital, term loans for short-term capital, and term loans for general working capital. We also divide loans according to whether or not they have fixed or variable interest rates.

The distribution of loans is skewed towards small borrowers. Although 53 percent of loans are for amounts between $1 million and $5 million, small borrowers account for less than 8 percent of the total amount committed. Conversely, loans of $25 million or more account for about 20 percent of the observations but represent about 70 percent of the dollars lent. One way to say this succinctly is that the median loan is small but the median dollar lent is part of a large loan. Finally, just under 93 percent of all loans have a maturity of five years or less. So most of our loans are relatively short-term.

A more important stylized fact that also emerges from the data is the substantial variance in loan spreads even within loans that have identical risk ratings. Although the median spread only rises from 1.3 percentage points to 3.0 percentage points as we move from A-rated loans to B-rated ones, the standard deviation of interest rates for loans of the same rating ranges from 1.5 to 2.0 percentage points. This means that holding the risk rating fixed, there is a high degree of variation in spreads paid by identically rated borrowers. While this fact motivates our inclusion of additional observable characteristics to compose bins of similar borrowers, it's worth observing that these high standard deviations also imply that there is substantial overlap in the borrowing costs for firms with different risk ratings.

This overlap is more clearly seen in Figure 1, which presents Kernel Density estimates of the adjusted interest rates at the time of loan origination by rating. The distributions are similar in that they are bounded below by zero and exhibit a positive skew. Moreover, we see considerable

Figure 1: Kernel Density Estimates of Borrowing Costs by Rating (Interest Rate Adjusted by FFR)



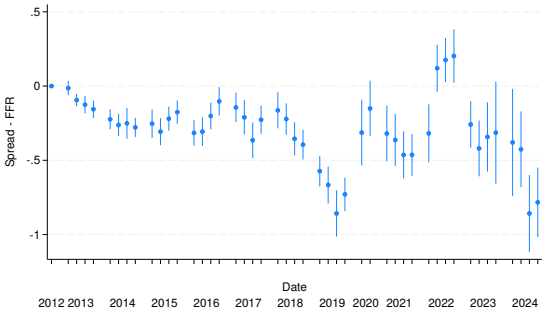
Notes: Above are the Kernel Density Estimates, which are smoothed versions of the probability distributions, for the estimation sample of 160,627 observations. We split the densities by rating. The vertical line shows the mean of the interest rates for each rating. The mean and standard deviations of interest rates for loans with A ratings are 2.57 and 1.53 respectively. The mean and standard deviations of interest rates for loans with BBB ratings are 3.36 and 1.83 respectively. The mean and standard deviations of interest rates for loans with BB ratings are 4.05 and 1.87 respectively. The mean and standard deviations of interest rates for loans with B ratings are 4.66 and 1.97 respectively.

dispersion in these adjusted rates, and the variance clearly rises as loan quality falls. The data make plain that although higher risk is associated with higher interest rates, risk ratings only account for a small portion of the variance.

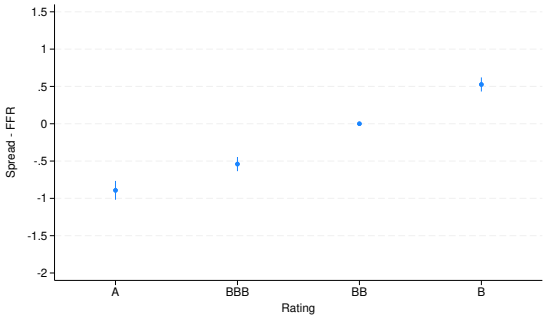
To formalize the role of these observables in explaining interest rate variation, Figure 2 plots the estimated coefficients and 5/95 confidence levels from a multivariate regression of the adjusted interest rate on dummy variables for risk rating, committed amount, maturity, loan type, loan purpose, date, and industry fixed effects. There are five main takeaways from this regression. First, there appears to have been a drop in the adjusted rate in 2018-2019 and 2022-2023, coinciding with the monetary policy tightening. This is an artifact of using the adjusted interest rate rather than the more complicated adjustments that go into computing spreads relative to LIBOR. Second, we see in Panel B that riskier loans are charged higher adjusted rates. Third, we observe in Panel E that loans with maturities exceeding five years have higher adjusted rates than those with shorter maturities, which likely reflects banks charging a premium for longer time horizon loan commitments. Fourth, adjusted interest rates fall with loan size. This may be because larger borrowers have a better set of options, something that is consistent with other evidence presented below. Finally, we see that permanent and short-term capital loans and term and revolver loans have similar adjusted rates. In these multivariate specifications, which include controls for all the characteristics shown in the various panels, the industry of the borrower typically does not matter much for interest rates.

Perhaps the most striking thing in this regression is that the R^2 is only 0.25, indicating that these variables explain only a quarter of the variation in adjusted interest rates at the time of origination. Put differently, three-quarters of what matters for the determination of borrowing costs are factors that are not captured by a linear combination of the variables that are collected by regulators to estimate loan losses in adverse macroeconomic scenarios. As outlined at the beginning of this section, there are two categories of explanations for why the R^2 is so low. One explanation is that these bins are not capturing important variation in borrower risk. For example, there could be important interactions between variables that are not captured in linear specifications that restrict loan characteristics to have the same impact for all loans. It is also possible that there are other variables that generate heterogeneity that should be included in the regression that have not been collected. Alternatively, search costs could be generating the dispersion in the adjusted rates for

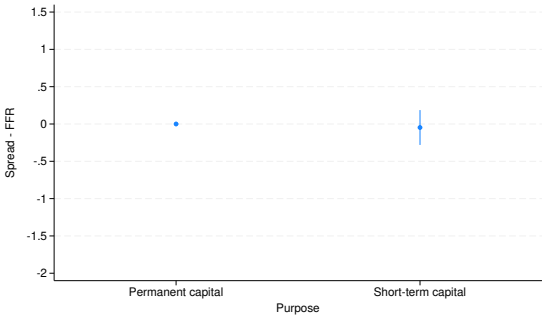
Figure 2: Impact of Loan Characteristics on Adjusted Interest Rates



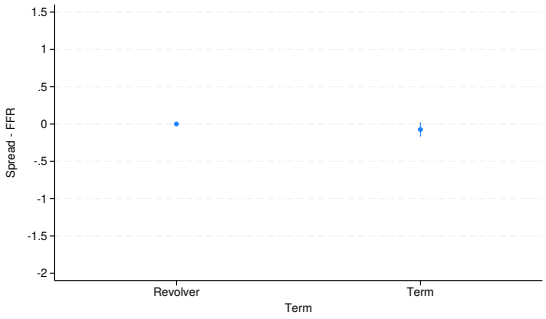
(a) Loan Origination Date Fixed Effect



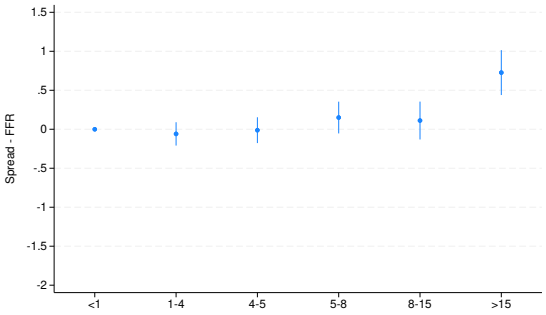
(b) Loan Rating Fixed Effects



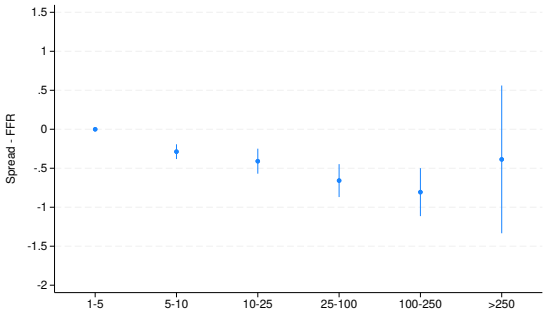
(c) Loan Purpose Fixed Effects



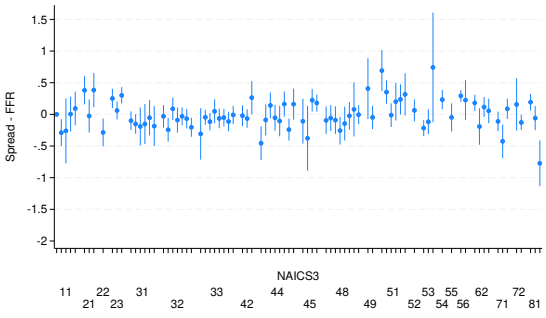
(d) Term Loan vs. Revolver Fixed Effects



(e) Maturity Fixed Effect (years)



(f) Committed Loan Size Fixed Effect (millions)



(g) NAICS Fixed Effect

Notes: These charts show the coefficients of a regression of the adjusted interest rates (at the origination date of the loan) on various fixed effects. These controls include binary variables equal to one for categories of internal risk rating and fixed effects for the dollar amount of loan commitment, maturity in years, loan type, loan purpose, quarter of origination, and North American Industrial Classification System (NAICS) 3-digit industry. The sample is the estimation sample of 160,627 originations (the same sample as Table 1) from 2012:Q4 to 2024:Q4. Blue bars represent 95% confidence intervals. The Y axis is percentage points.

otherwise identical loans.

4.3 Other explanations for differences in interest rates for loans of similar risk

To explore the possibility that the poor fit of the last regression might be due simply to missing interaction effects, we move to analyzing our bins. We run a regression of the adjusted interest rate on bin fixed effects that correspond to $\boldsymbol{X_k}$. We drop bins that have fewer than 20 loans or where there are fewer than six banks in the bin. This leaves us with 722 bins and 160,627 loan originations.[7] So our specification is

$$r_{jbkt} = f(\boldsymbol{X_k}) + \epsilon_{jbkt}, \tag{(1)}$$

where ϵ_{jbkt} is an error term that captures the impact of unobserved loan heterogeneity and search costs in interest rate determination. We can estimate this non-parametrically by allowing an arbitrary relationship between the adjusted interest rates and $\boldsymbol{X_k}$.

Table 2 shows the results of our estimation of equation (1). The first column shows the results when only bin fixed-effects are accounted for. The R^2 for this specification is 0.25, almost exactly the same value as we observed by including the loan characteristics as linear explanatory variables. This finding leads us to conclude that failing to account for possible interactions among the characteristics that are used in forming the bins is not why we see so much interest rate dispersion.

As a further diagnostic, we compute measures of the dispersion within bins by defining the "adjusted rate gap" as the difference between the ninetieth percentile in the residuals and the tenth percentile of the residual in the same bin. The lower portion of the table shows the distribution of adjusted rate gaps. Notice that the median adjusted gap is 2.295, so that within the typical bin, there is a 229 basis point spread in adjusted rates after controlling for bin fixed effects.

The rest of the table adds more and more control variables to see whether we can shrink the adjusted interest rate gaps. We start by exploring the explanatory power of more granular time periods. Adding origination quarter fixed effects to this regression has almost no effect—the R^2 rises to 0.28. This result suggests that very little of the variation in adjusted interest rates spreads is due to differences across time.

[7] Although we could have further subdivided our sample by restricting the analysis to only periods when FFR was close to zero, we found that this did not qualitatively affect our results, so we report these results in the Appendix.

Table 2: Bin Level Regressions

	(1) Rate-FFR	(2) Rate-FFR	(3) Rate-FFR	(4) Rate-FFR	(5) Rate-FFR
Relationship Length			-0.033***		-0.015***
			(0.001)		(0.001)
Log Sales (millions)				-0.018***	-0.009***
				(0.001)	(0.001)
Observations	160,627	160,627	160,627	138,697	136,683
Number of Bins	722	722	722	722	722
R-Squared	0.248	0.278	0.281	0.291	0.406
RMSE	0.998	0.978	0.976	0.960	0.880
Mean(p90 - p10 Residuals Within Bin)	2.441	2.371	2.362	2.305	2.140
p10(p90 - p10 Residuals Within Bin)	1.495	1.465	1.463	1.408	1.354
p25(p90 - p10 Residuals Within Bin)	1.925	1.870	1.862	1.776	1.642
p50(p90 - p10 Residuals Within Bin)	2.295	2.241	2.227	2.202	1.994
p75(p90 - p10 Residuals Within Bin)	2.825	2.725	2.721	2.697	2.511
p90(p90 - p10 Residuals Within Bin)	3.414	3.355	3.352	3.318	3.057
Bin FE	Y	Y	Y	Y	Y
Quarter FE		Y	Y	Y	Y
Risk Proxies FEs					Y
Interest Rate Index FEs					Y
Industry/Regional FEs					Y

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The sample is the same as Table 1. Variables are defined the same as in Table 12. Column (1) regresses the interest rate adjusted by subtracting the FFR on bin fixed effects. (2) includes bin and quarter FE. Column (3) adds the relationship length variable as defined in Table 12. Column (4) adds the log of net sales. Columns (5) adds additional fixed effects as described in Table 12. The fixed effects included are the risk proxy fixed effects, interest rate index fixed effects, and industry/regional fixed effects. The risk proxy fixed effects are comprised of a binary variable equal to 1 if a Stock Ticker or Cusip is present and 0 otherwise, a fixed effect for lien position and a fixed effect for collateral type. The industry/regional fixed effects are comprised of fixed effects for NAICS3 codes and MSAs. Each bin has a set of residuals, for each bin we subtract the 10th percentile residual from the 90th. We then report the mean, 10th, 25th, 50th, 75th, and 90th percentile of the bin p90-p10 residuals within a bin.

The next column adds a control for the length of the bank relationship. If banks have soft information about borrowers that comes from knowing them well, for example, if long-term relationships enable banks to better understand firms, they may choose to jettison high-risk borrowers and retain low-risk ones, thereby offering lower interest rates on average. We compute the length of a bank-firm relationship at the time of a loan's origination as the number of quarters between the time that we first observe a bank lending to a firm and the current loan origination date. We normalize this measure by the average relationship of all bank- firm pairs so that the early years of the sample do not have mechanically lower relationships than do later years. On average banks with longer relationships pay lower rates, but the mean of the 90th and 10th percentile residuals is barely changed by controlling for bank relationship and remains at approximately 2.4 percentage points. The R^2 also hardly moves.

It is also possible that loan pricing could reflect opportunities for cross-selling to the borrower, with lower interest rates for borrowers who could be profitable for banks' other business units. Generally, we would expect loan size to be a reasonable proxy for cross-selling opportunities, so our bins would already partially capture this. We can also add a control for borrower sales, to rule out interest rate differences arising from more cross-selling, for example to businesses with more sales and thus more deposits. Column (4) adds the logarithm of sales to the specification and that boosts the R^2 to 0.291, though the median adjusted interest rate gap is still more than 220 basis points.

Finally, we also control for other potential risk proxies such as: whether or not the borrower is public (ticker and CUSIP fixed effects), loan collateral, the base rate (typically 1-month or 3-month LIBOR) in case this also suggests differences in business characteristics that may be valued by lenders. We can also control for the extent of bank competition (or other place-specific factors) by including industry and MSA fixed effects. The last column of Table 2 is a "kitchen sink" regression that includes loan size as an explanatory variable, our relationship proxy as well as fixed effects corresponding to industry, region, risk proxies, and interest rate indexes. Even with all of these fixed effects, the R^2 only rises to 0.406, indicating that most of the variation in loan interest rates remains unexplained. The dispersion in the residuals remains very large even in this specification, coming in at 199 basis points for the median bin.

To further explore this dispersion, Table 3 presents bin-level statistics for loans with ratings

Table 3: Average Loan Characteristics Across Bins

	All Bins	A	BBB	BB	B	1-5	5-10	10-25	25-100	100-250
number of banks	13.00	8.76	12.46	14.04	12.81	13.15	12.95	13.44	12.92	10.64
	(4.88)	(2.65)	(4.39)	(5.28)	(4.59)	(5.18)	(4.55)	(4.90)	(4.76)	(3.41)
number of loans	222.48	53.36	178.46	318.15	154.25	322.17	139.99	172.57	202.05	87.06
	(379.65)	(51.21)	(246.61)	(517.16)	(226.60)	(546.01)	(150.16)	(194.97)	(296.52)	(87.66)
maturity (years)	3.72	3.34	3.69	3.91	3.50	4.02	3.42	3.57	3.52	3.99
	(2.33)	(1.69)	(2.20)	(2.58)	(2.14)	(3.03)	(1.98)	(1.83)	(1.70)	(1.08)
loan size (millions)	22.36	45.57	26.71	19.24	16.96	2.35	7.55	17.14	48.57	144.09
	(34.24)	(47.53)	(41.46)	(28.95)	(24.60)	(0.35)	(0.33)	(0.92)	(5.52)	(8.55)
min(interest rate - FFR)	0.57	0.49	0.41	0.54	0.87	0.70	0.63	0.61	0.32	0.33
	(0.68)	(0.46)	(0.66)	(0.70)	(0.61)	(0.75)	(0.57)	(0.43)	(0.75)	(0.69)
max(interest rate - FFR)	6.27	3.93	4.89	6.81	7.78	6.81	6.21	6.38	5.64	4.57
	(2.16)	(2.00)	(1.30)	(1.94)	(2.02)	(2.20)	(1.84)	(2.24)	(2.00)	(1.90)
p90-p10 range(interest rate - FFR)	2.45	1.63	1.92	2.55	3.17	2.57	2.54	2.46	2.21	1.99
	(0.88)	(0.68)	(0.56)	(0.67)	(0.99)	(0.95)	(0.79)	(0.80)	(0.87)	(0.67)
interquartile range(interest rate - FFR)	1.24	0.83	0.96	1.29	1.62	1.30	1.26	1.26	1.14	0.97
	(0.47)	(0.38)	(0.33)	(0.37)	(0.52)	(0.50)	(0.42)	(0.43)	(0.50)	(0.43)

Notes: This table presents summary statistics for the estimation sample of 160,627 loan originations (the same sample as Table 1) for which we can compose bins of loans with similar characteristics. Numbers represent the mean across 722 bins for each variable. The minimum (maximum) interest rate is therefore an average of the minimum (maximum) interest rate across 722 bins. We first calculate the average of a variable within a bin and then average the means across bins sharing a specific characteristic (rating, committed amount, or across all bins for column (1)). Column (1) shows the cross-bin averages across all bins, columns (2-5) show the cross-bin averages based on bin rating, and columns (6-10) show the cross-bin averages for committed amount in millions.

ranging from A to B. We have 33 bins of high-grade A-rated loan originations, 236 bins of BBB originations, 286 bins of BB originations, and 167 bins of B originations. We also have a single bin with originations greater than 250 million which is not tabulated due to limitations on data disclosure. There are typically a substantial number of loan originations within each bin. The number of banks per bin ranges from 8.76 for A-rated originations to 14.04 for BB originations. As we noted before, average interest rates rise with loan risk, with B-rated firms paying interest rates that are around 2 percentage points higher than A-rated firms.

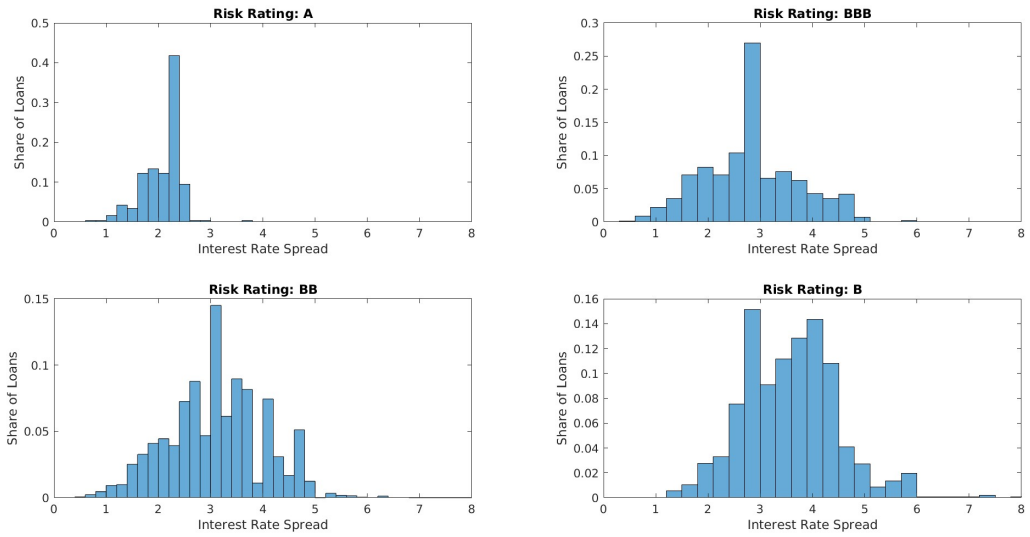
We compute measures of the dispersion within bins between the ninetieth percentile in the adjusted rate distribution and the tenth percentile in the same bin. We find that there is a large amount of dispersion in adjusted interest rates within each bin. On average, this gap is 2.45 percentage points. But the dispersion is pervasive, even in the A-rated bins the adjusted interest rate gap is 1.63 points.

To see this more concretely, Figure 3 presents histograms of the adjusted interest rates for the bins with the most loan originations by rating. These figures are strikingly similar to those in Figure 1, which portrayed the unconditional distributions of interest rate spreads. One might have concluded from Figure 1 that we were simply learning that much of the variation in interest rates is due to variables unrelated to loan rating, such as size, maturity, etc. The fact that the within-bin variation is comparable to the overall level of variation, combined with the results from Table 2 indicates that observable loan heterogeneity cannot easily explain the dispersion in interest rates. The natural response to seeing this scale of variation within loans with the same rating is to appeal to unobserved heterogeneity. We dedicate Section 4.4 to a discussion of omitted variables and seek out explanations for what these specifications are missing. However, it is difficult to think of what unobserved characteristic could be accounting for so much of the variance, especially given the overlap between loan rates in different risk bins.

4.4 In Search of the Unobservables

While we cannot rule out the possibility that an omitted variable explains the large amount of interest rate dispersion observed within bins, in this section, we address its plausibility by bringing additional data to bear to show that many, *a priori*, other ways to account for unobservable heterogeneity fail to have much additional predictive power. It is possible that the dispersion exists

Figure 3: Adjusted Interest Rates for Largest Bins by Rating



Notes: The above figure plots histograms of adjusted interest rates for bins with the most loan originations by rating for the sample in Table 1 The A-rated bin with the most loan originations (263) has loans from 7 banks, a mean adjusted interest rate of 2.1, a range of 3.0 ($r_{max} - r_{min}$), mean maturity of 7.0 years, mean committed of 1.6 million, and is a term, permanent capital loan. The BBB rated bin with the most loan originations (1752) has 22 banks, a mean adjusted interest rate of 2.9, a range of 6.75 ($r_{max} - r_{min}$), mean maturity of 0.84 years, mean committed of 2.3 million, and is a revolver, permanent capital. The BB with the most loan originations (4765) has 20 banks, a mean adjusted interest rate of 3.1, a range of 7.7 ($r_{max} - r_{min}$), a mean maturity of 0.85 years, mean committed of 2.2 million, and is a revolver, permanent capital. The B with the most loan originations (1620) has 12 banks, a mean adjusted interest rate of 3.6, a range of 6.65 ($r_{max} - r_{min}$) with a mean maturity of 0.70 years, mean committed of 2.16 million, and is a revolver, short-term capital.

because the bins do not capture the right characteristics. For example, if there is significant within-bin variation in expected losses, maturity, committed amounts, or some other variable that we cannot measure that could generate dispersion in interest rates. Alternatively, it could be the case that movements in expected economic conditions cause interest rates for otherwise identical loans to vary.

One way to check if we have properly grouped loans in forming bins is to see how well they predict spreads in other debt markets for corporate borrowers. We test this hypothesis by estimating equation (1) using data on bonds. Just as we did when looking at loans, we group bonds based on their size, rating and maturity. We report the result in the first column of Table 13 in the Appendix.

The R^2 when estimating equation (1) using bond data is 0.77, more than triple what we found using loan data. This result suggests that the source of the poor fit in estimating loan spreads is unlikely to come from an omitted variable or an inherent difficulty in finding the right observables to explain corporate borrowing costs. It must be related to a phenomenon that makes it more difficult to predict interest rates on loans, rather than bonds.

Another possible explanation for adjusted rate dispersion could be due to differences between banks' estimation of the true risk of borrowers and the ratings that they submit to their regulators. Since the Y-14 data collection is part of an extensive supervisory effort and subject to supervisory review, and because the same set of supervisors also monitor banks risk models, we believe this explanation to be unlikely, as systematic differences between banks' risk evaluations and data submitted to supervisors would have consequences for that bank's supervisory ratings. Y-14 data collections were designed to capture all relevant information that could inform the estimation of loan losses. However, it is possible that some banks rely on additional specialized information to evaluate borrower risk and that information is not widely used across all banks and thus not part of the Y-14 data collection. [8]

Fortunately, we have access to additional data for some banks that allow us to further test for the role that risk differences might play in creating adjusted rate gaps. Those banks that utilize the advanced method for determining their capital requirements must calculate the expected loss for

[8] One consideration in designing regulatory requirements is the regulatory burden on banks to submit that information.

each loan. Supervisors must approve the model that is used to estimate these losses. In addition to the models that banks use, banks occasionally supplement their calculation with judgmental overlays which adjust for potential credit risk. This allows us to determine whether knowing the banks' internal loan risk assessments adds significant explanatory power for understanding adjusted rate gaps, and thus proxies for any information banks have that is used to estimate credit risk.

Table 4: Interest Rates and Expected Loan Losses

	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate	(4) Interest Rate Standardized
Expected loss ratio			0.105***	
			(0.006)	
Standardized Expected loss ratio				0.0384***
				(0.002)
Bin FE	Yes	Yes	Yes	Yes
Observations	160627	90214	90214	90214
R-Squared	0.620	0.618	0.619	0.619
RMSE	1.189	1.256	1.254	0.620

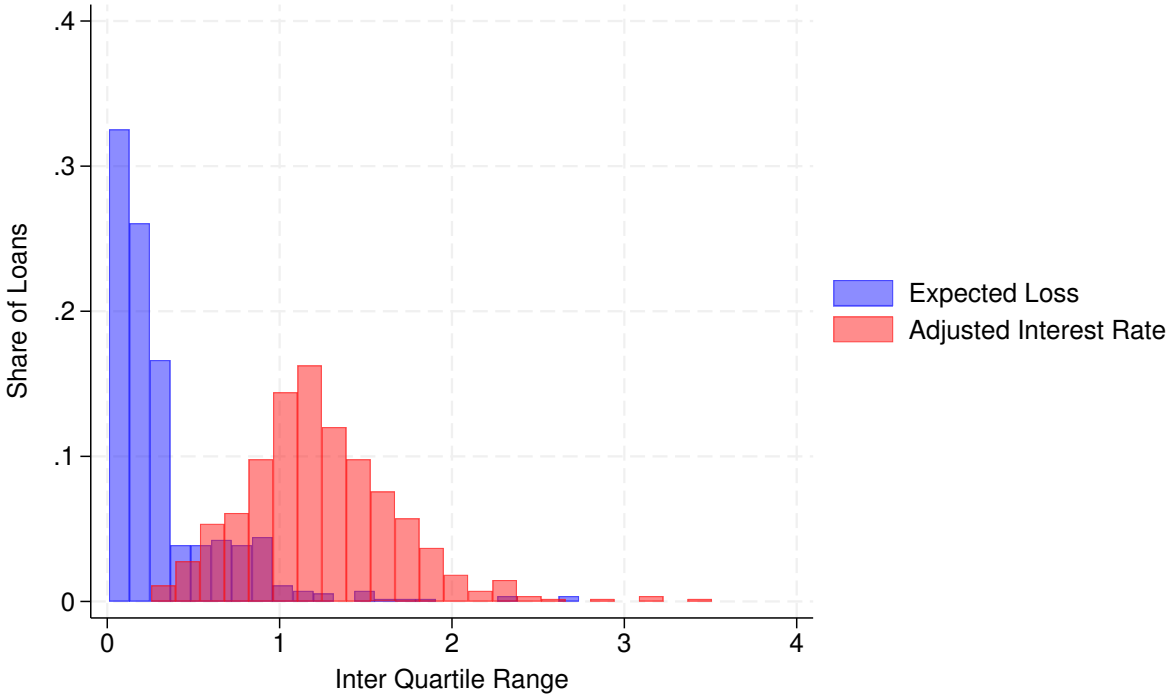
Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Results from regressing interest rates on an indicator variable for each loan bin where bins are based on monetary policy cycle, rating, maturity, size, type, and purpose. The first column estimates the regression for the estimation sample of 160,627 observations (the same sample as Table 1), while Column 2 limits the specification to the sample of 90,214 observations for which the expected loss ratio data is available. The third column adds the expected loss ratio (denoted as the probability of default times loss given default times the exposure given default, divided by the committed size of the loan) as an explanatory variable and the fourth column standardizes both the expected loss ratio and the interest rate to mean 0 and standard deviation 1. The median interest rate and expected loss ratio for column 3 is 3.99 percentage points and 0.18 percentage points, respectively. The standard deviation interest rate and expected loss ratio for column 3 is 2.02 percentage points and 0.74 percentage points, respectively.

We employ two approaches to show that additional information used by banks to model credit risk does not explain much of the variation in borrowing costs. First, we assess the extent to which banks perceive loan risk variation within our bins by computing the interquartile ranges of the expected loss ratio and the adjusted rate gap within each bin. We should expect to see expected loss ratios varying substantially if banks perceive substantial heterogeneity in risk within bins. Figure 4 presents histograms of these interquartile ranges. We see that most of the expected loss interquartile ranges are less than 50 basis points—far less than the dispersion of the adjusted interest rates —which suggests that this variable is going to have difficulty explaining interest rate

Figure 4: Distribution of Interquartile Ranges of Expected Loss and Adjusted Interest Rates



Notes: The above histograms are created from 541 bins created by first dropping all loans where we can not calculate expected loss, and then restricting bins to have at least 6 unique banks and 20 loans. The mean, median, and standard deviation of the interquartile range of Expected Loss within a bin are 0.32, 0.21, and 0.36, respectively. The mean, median, and standard deviation of the interquartile range of interest rates - FFR within a bin are 1.24, 1.19, and 0.44, respectively.

dispersion.

Second, regression analysis in Table 4 confirms this intuition. Column 1 shows a regression for the full sample of the interest rate on bin fixed effects. The second column of Table 4 presents the same specification using only the set of bins for which we have both the Fed's risk rating and expected loss ratings to ensure that any gains in R^2 are not due to differences in sample sizes. The third column adds the expected loss ratio as an explanatory variable to this regression. We find that while there is a significant association between expected loan losses and interest rates, the economic significance of the impact of expected loan losses on interest rates is trivial. Adding expected loan losses to the regression increases the adjusted R^2 by 0.001, indicating that finer gradations of risk captured in the banks' risk models do not explain much of the variation in interest rates within bins.

This finding also rules out a significant role for covenants in loan pricing. Covenants that affect the risk of the loan should be captured in expected loss calculations, either through their impact on the probability of default (through covenants restricting payouts) or through their impact on exposure at default (through covenants preventing drawdowns) will be captured in expected loss.[9]

The last unobservable factor that we consider is whether variation in borrower-specific search costs might help explain the data. There are several hints in the data presented so far that such costs might help explain some of the otherwise puzzling patterns.

If high-risk borrowers need to work harder to convince lenders to extend credit, they are likely to search less. Lower search frequency will result in more price dispersion because some borrowers will get lucky and be charged low rates, while others will be unlucky and be charged high rates. This implies that we should observe more interest rate dispersion for loans with low ratings. This pattern is clearly present in Table 3, where the dispersion in adjusted interest rates vary systematically with bin risk characteristics. For instance, the interquartile range of adjusted rates for A-rated bins is 83 compared to 162 basis points for B-rated bins.

We also observe similar patterns when comparing dispersion within bins across other variables that are likely correlated with the payoff to searching. For example, the cost of paying a high interest rate is greater for a large loan than for a small one, and indeed, we find that the gap between the

[9] Y-14 data do not collect information on loan covenants. Generally these covenants are associated with the bin characteristics, particularly rating but also commitment size.

ninetieth and tenth percentile of the adjusted interest rate within bins falls monotonically with loan size. The gap for loans in the $1-5 million range equals 2.57 percentage points, and the spread for loans in the $100-250 million range equals 1.99 percentage points. By contrast, as we report in the Appendix, we see no pattern in the adjusted rate gaps for different maturities or across interest rate regimes. The fact that zero interest rate regimes have an average 90-10 gap of 2.5 percent while regimes with rate increases or decreases have a gap of 2.4 percent is *prima facie* evidence that movements in average interest rates are not driving the dispersion of interest rates within bins.

Search costs can also possibly provide an explanation for the differences we documented between bank loans and bonds. Bonds are marketed to arm's-length investors and come with considerable standardized disclosure about the borrower. Rating agencies also have reputational incentives to assess borrower risk correctly. So, judging the risk associated with a bond is likely easier than assessing the creditworthiness of bank customers, many of whom are relatively opaque.[10] So it is perhaps not so surprising that bin characteristics explain much more of the dispersion in bond yields than in bank loan rates.

Our limited ability to correlate dispersion with most proxies for unobservable heterogeneity other than search costs, leads us to focus on them in the remainder of the analysis.

5 The Bank Search Model

The difficulty in finding variables that can explain the amount of variation in loan interest rates, in the face of similar variables explaining rates for other corporate credit such as bonds, motivates us to construct a model in which interest rate dispersion arises from search costs. Our approach to estimating borrower search costs closely follows the approach of Hong and Shum (2006) and Moraga-González and Wildenbeest (2008). While these papers consider the problem of estimating consumer search costs for low-cost sellers when the econometrician can only observe prices, we adapt this approach to a case in which we want to estimate borrower search costs when we can observe interest rates. We assume that it is possible to create loan bins such that borrowers are homogeneous within a bin and loans offered by different banks are viewed as equivalent.

[10] Another difference is that the distribution of bond issuance sizes is shifted far to the right of the distribution of loans. However, there is very little difference in interest rate dispersion across and within loan size categories. For example, the average interest rate for loans of $1-5 million is 4.1 percent, while for loans of 100-250 million it is 4.0 percent. Similarly, the median adjusted rate gap for these bins are 2.4 and 2.1 percentage points, respectively.

We start by establishing some notation. We estimate the search costs within a bin—i.e., for set of loans (k)—so without loss of generality, we suppress the k subscript on all variables in this section because it does not vary within a bin. Let ρ be the common cost for a bank to offer a loan of amount L. Each borrower has a reservation interest rate of $\bar{r}$ above which it will not borrow, and we assume that every borrower costlessly observes an interest rate offered by one random bank. Borrowers can also obtain $i-1 \geq 0$ additional interest rate quotes from other banks *before* choosing a lender at a cost of $(i-1)\,cL$, where c is the search cost per dollar borrowed. We assume that c differs for each borrower and is drawn from a distribution of search costs F_c.[11]

Following Burdett and Judd (1983), the interest rates offered by the N banks arise from a mixed strategy equilibrium in which the equilibrium distribution of interest rates that banks choose, F_r, makes each bank indifferent between charging any interest rate between the lower bound of the support for F_r ($\underline{r} > \rho$) and the upper bound ($\bar{r}$). This distribution of interest rates ensures that the per-loan gains (losses) associated with offering a higher (lower) interest rate are exactly offset by the loss (gain) of customers associated with the higher (lower) interest rate. The optimal number of interest rate price quotes a borrower will obtain is given by

$$i(c) = \arg\min_{i>1} \left\{ (i-1)\,cL + \int_{\underline{r}}^{\bar{r}} irL\,(1-F_r(r))^{i-1} f_r(r)\,dr \right\}, \tag{(2)}$$

where the second term is the expected annual interest payment conditional on doing i searches. As Honka et al. (2019) note, the intuition for this expression can be obtained by noting that probability that all interest rate quotes are greater than r after obtaining i interest rate quotes is $(1-F_r(r))^i$ so the cumulative distribution function (CDF) for the minimum price draw is $\left[1-(1-F_r(r))^i\right]$. The probability density function is just the derivative of the CDF $\left[i\,(1-F_r(r))^{i-1} f_r(r)\right]$. Multiplying this by rL and integrating gives us the expected annual interest payment associated with obtaining i interest-rate quotes.

We also can also use this structure to characterize the optimal number of interest-rate quotes a borrower will obtain. Since $i(c)$ is an integer, we divide borrowers into B subsets of size q_i, $i = 1, 2, ..., N$, with $\sum_{i=1}^{N} q_i = 1$, where q_i is the fraction of borrowers obtaining i interest-rate

[11] Morgan and Manning (1985) show that simultaneous search may be optimal if agents need to make decisions rapidly and sequential search is time consuming.

quotes. We denote the expected minimum interest rate in a sample of i prices drawn from F_r by $E[r_{1,i}]$. We can write the search cost that would render a borrower indifferent (in expectation) between sampling i interest rates and $i+1$ interest rates as

$$\Delta_i \equiv E[r_{1,i}] - E[r_{1,i+1}], \quad i = 1, 2, \ldots, N-1 \tag{(3)}$$

Since Δ_i is a non-increasing function of i, the number of banks a borrower with a search cost of c will be inversely related to the size of the firm's search cost. This property guarantees that we can write the fraction of borrowers searching i times is given by:

$$\begin{aligned} q_1 &= 1 - F_c(\Delta_1) \\ q_i &= F_c(\Delta_{i-1}) - F_c(\Delta_i), \quad i = 2, 3, \ldots, N-1 \\ q_N &= F_c(\Delta_{N-1}), \end{aligned} \tag{(4)}$$

where F_c is the CDF of the distribution of costs.

We can use this structure to estimate the search-cost distribution, F_c, using only the interest-rate data. It is optimal for banks to set prices using mixed strategy for interest rates in this setup. In equilibrium, one bank will charge the maximum interest rate, $\bar{r}$, which will equal the borrowers' reservation interest rate and gives us the upper value of the support for the equilibrium interest-rate distribution, F_r. This bank will only lend to borrowers who only obtain one interest-rate quote (i.e., q_1) because borrowers who obtained two or more quotes could always do better. In equilibrium, other banks must be indifferent between charging the maximum interest rate and any other interest rate in the equilibrium support $\left[\underline{r}, \bar{r}\right]$, i.e.,

$$(\bar{r} - \rho) q_1 L = (r - \rho) L \left[\sum_{i=1}^{N} i q_i \left(1 - F_r(r)\right)^{i-1} \right], \tag{(5)}$$

where the left-hand side of this equation denotes the fraction of profits going to bank charging the maximum interest rate, and the right-hand side denotes the fraction of profits going to a bank charging r. Hong and Shum (2006) solve the system by noting that the empirical counterpart of

this equation is given by

$$(r_1 - \rho)q_1 L = (r_i - \rho)L \left[\sum_{i=1}^{N} i q_i \left(1 - \hat{F}_r(r_i)\right)^{i-1} \right] \quad i = 2, 3, \ldots, N-1, \tag{(6)}$$

where r_i is the observed interest rate charged by bank i, r_1 is the maximum observed interest rate, and $\hat{F}_r(r_i)$ is the fraction of banks offering an interest rate below r_i. Since we also have $q_N = 1 - \sum_{i=1}^{N-1} q_i$, we have N equations and N unknowns (ρ and the q_i), so we can solve the system. Once we have estimates for the q_i, we can use equation (4), to solve for the CDF of the search-cost distribution $[F_c(\Delta_1), F_c(\Delta_2), ...F_c(\Delta_{N-1})]$.

Moraga-González and Wildenbeest (2008) note that one can improve on the Hong and Shum (2006) estimation by using a maximum likelihood estimator because estimating $\hat{F}_r(r_i)$ using the empirical distribution is not efficient. They rewrite the system of equations described above as a maximum likelihood problem that is efficient and provides us with standard errors for the estimated variables. They show that this method performs well in Monte Carlo trials even when one does not observe loans offered by some banks (prices offered by firms in their implementation). We will therefore follow their approach.

6 Estimating Switching Costs

We can obtain intuition for what the estimates of switching costs are likely to be by looking at Figures 1 and 3. Interest variation within bins maps directly to our estimates, as the presence of rate variation for borrowers with similar risk suggests that search costs must be high. In particular, the model will assign high search costs to those in the right-hand tail of the distribution of each bin. Conversely, the borrowers with low search costs are pinned down by the left tail of the adjusted interest rate distribution. In this section, we begin by mapping our estimates from the model at the borrower level. We then aggregate those estimates to the bank level, to allow for calculations of the potential impact of bank failure or changes to bank lending supply.

6.1 Switching costs for borrowers

Table 5 reports the estimates for the model when all bins are treated equally. The search cost estimates are the minimum number that is needed to rationalize the data. So the 74 basis point

estimate for the firms that search once is a lower bound, meaning that 36% of the borrowers are estimated to have switching costs that are at least that large. Since the average bin has a mean loan size of $22.36 million, this estimate implies that the typical firm would have switching costs of at least $165,464. We estimate that another 49% of firms get one additional quote. The associated search cost estimate of 31 basis points implies that firms are behaving as if the switching cost for a $22.36 million loan is at least $69,316.

To estimate the model we must make an assumption about how many banks that a borrower could possibly consider. We set that parameter equal to the number of banks that are observed to make a loan in each bin. The last row in the table shows that for the average bin, 14% of the borrowers are found to have very low switching costs, just over $6,700. As indicated above, the size of this set of borrowers is determined by the number of borrowers that find the lowest rates in the bin.

Table 5: Number of Searches and Average Search Costs Across Bins

	share	search cost
number of searches=1	0.36	0.74
	(0.14)	(0.25)
number of searches=2	0.49	0.31
	(0.12)	(0.11)
number of searches=3	0.00	0.18
	(0.04)	(0.07)
number of searches=4	0.00	0.12
	(0.01)	(0.05)
number of searches=n-1	0.00	0.04
	(0.02)	(0.03)
number of searches=n	0.14	0.03
	(0.07)	(0.02)

Notes: This table presents summary statistics for the estimation sample of 160,627 loan originations (the same sample as Table 1) for which we can compose bins of loans with similar characteristics. Numbers represent the mean across 722 bins for each variable. In the search model interest rates are adjusted by subtracting the Federal Funds Rate at the origination date of the loan.

The next two tables are intended to explore whether the model estimates are consistent with the screening and monitoring hypothesis. That hypothesis implies that borrowers that require more ex-ante effort to judge their creditworthiness or loans that require more ex-post monitoring should come with higher rates and higher switching costs. As empirical proxies for borrowers that would require more screening and monitoring we use the credit rating and loan size.

Table 6: Number of Searches and Average Search Costs Across Bins by Rating

Rating	A	BBB	BB	B	A	BBB	BB	B
	share	share	share	share	search cost	search cost	search cost	search cost
number of searches=1	0.37	0.36	0.35	0.37	0.46	0.58	0.80	0.91
	(0.19)	(0.14)	(0.15)	(0.14)	(0.23)	(0.18)	(0.20)	(0.24)
number of searches=2	0.45	0.49	0.50	0.47	0.19	0.25	0.33	0.39
	(0.15)	(0.12)	(0.12)	(0.11)	(0.09)	(0.09)	(0.08)	(0.09)
number of searches=3	0.01	0.00	0.00	0.01	0.11	0.14	0.19	0.22
	(0.06)	(0.03)	(0.03)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)
number of searches=4	0.00	0.00	0.00	0.00	0.07	0.10	0.13	0.15
	(0.00)	(0.01)	(0.00)	(0.01)	(0.03)	(0.05)	(0.04)	(0.04)
number of searches=n-1	0.00	0.00	0.00	0.00	0.04	0.03	0.04	0.05
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)
number of searches=n	0.16	0.14	0.14	0.14	0.03	0.03	0.03	0.04
	(0.10)	(0.06)	(0.07)	(0.07)	(0.02)	(0.02)	(0.02)	(0.03)

Notes: This table presents summary statistics for the estimation sample of 160,627 loan originations (the same sample as Table 1 for which we can compose bins of loans with similar characteristics. Numbers represent the mean across N bins for each variable (N for A ratings = 33, BBB ratings = 236, BB ratings = 286, and B ratings = 167). In the search model interest rates are adjusted by subtracting the Federal Funds Rate at the origination date of the loan.

Table 6 shows the results when we group bins according to their credit rating. The estimated search costs follow the same pattern as was found when the estimation was done with all bins. Specifically, for each rating, there are about 30 to 40 percent of borrowers who are estimated to accept the first rate they are presented with, while between 45 and 50 percent of the borrowers seek a second loan quote. The remaining 14 to 17 percent of the borrowers shop heavily and find the lowest rates available.

The estimated size of the search costs align with the predictions of the screening and monitoring

hypothesis. The A-rated borrowers have switching costs that are about half the size of the costs of the B-rated borrowers. For instance, the A rated firms that get a second quote act as if their switching costs were at least 19 basis points, so that for a $10 million loan they would have costs of at least $19,000. The B rated borrowers are estimated to have costs of at least 39 basis points, implying a switching cost of at least $39,000 for the same $10 million loan. the BBB and BB borrowers have estimated costs that lie in between these estimates.

Table 7: Number of Searches and Average Search Costs Across Bins by Committed

Committed (millions)	1-5	5-10	10-25	25-100	100-250	1-5	5-10	10-25	25-100	100-250
	share	share	share	share	share	search cost	search cost	search cost	search cost	search cost
number of searches=1	0.37	0.36	0.34	0.34	0.37	0.80	0.73	0.73	0.68	0.55
	(0.15)	(0.13)	(0.13)	(0.14)	(0.18)	(0.26)	(0.23)	(0.25)	(0.24)	(0.25)
number of searches=2	0.47	0.49	0.51	0.50	0.47	0.34	0.31	0.30	0.28	0.23
	(0.12)	(0.11)	(0.11)	(0.11)	(0.14)	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)
number of searches=3	0.00	0.01	0.00	0.00	0.01	0.20	0.18	0.17	0.16	0.13
	(0.04)	(0.05)	(0.04)	(0.03)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
number of searches=4	0.00	0.00	0.00	0.00	0.00	0.13	0.12	0.11	0.11	0.09
	(0.00)	(0.00)	(0.02)	(0.01)	(0.00)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)
number of searches=n-1	0.00	0.01	0.00	0.00	0.00	0.05	0.04	0.03	0.03	0.04
	(0.01)	(0.03)	(0.02)	(0.03)	(0.00)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
number of searches=n	0.15	0.13	0.13	0.14	0.15	0.04	0.03	0.03 0.03	0.03	
	(0.08)	(0.06)	(0.06)	(0.06)	(0.08)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)

Notes: This table presents summary statistics for the estimation sample of 160,627 loan originations (the same sample as Table 1) for which we can compose bins of loans with similar characteristics. Numbers represent the mean across N bins for each variable (N for 1-5 committed (millions) = 263, 5-10 committed (millions) = 139, 10-25 committed (millions) = 144, 25-100 committed (millions) = 142, and 100-250 committed (millions) = 33). In the search model interest rates are adjusted by subtracting the Federal Funds Rate at the origination date of the loan.

Table 7 shows the estimates when the model is fit separately for the five size buckets. The estimated costs for the smallest loans, for commitments between $1 and $5 million are the highest, though the difference relative to the loans under $100 million are modest. However, the estimates are substantially higher than for the largest category of loans that covers the $100 million to $250 million commitments. For instance, among the borrowers that are assumed to get two loan quotes, the borrowers with the largest loans are estimated to have search costs of at least 23 basis points, while the ones with the smallest loans have a cost of 34 basis points. Of course, given the differences in the size of the loans, the absolute size of the costs would be much higher for the borrowers that

take out the larger loans.

As another way to view the model, we also run regressions that use the estimated switching cost, the deltas, on bin characteristics.

Table 8: Impact of Rating on Search Costs (Δ_1)

	(1) All	(2) Term	(3) Revolver	(4) Fixed	(5) Float
BBB	0.118**	0.221**	0.0947*	0.469	0.0973**
	(0.038)	(0.071)	(0.044)	(0.239)	(0.037)
BB	0.332***	0.483***	0.269***	0.626**	0.330***
	(0.038)	(0.071)	(0.043)	(0.238)	(0.037)
B	0.440***	0.645***	0.347***	0.715**	0.435***
	(0.039)	(0.073)	(0.044)	(0.240)	(0.038)
N	722	312	410	162	560
R^2	0.367	0.451	0.336	0.268	0.417

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regression based on estimation sample in Table 1. Dependent variable is the search cost delta_1. The search cost delta_1 is calculated at the bin-level. The sample in the first column is all loans; in the second column is term loans; and the third is revolver loans; the fourth column are fixed loans; and the fith column are float loans. Standard errors are in parenthesis.

Table 8 shows the coefficients on the ratings (controlling for the loan maturity and sizes). In the first column, when all 722 bins are used in the estimation, the cost for the borrowers who accept the only quote that they get, show rising search costs as credit ratings fall. The B-rated borrowers have about 44 basis points higher costs than the A-rated ones (who are the reference group for the regression). The gradient is even steeper for the term loans that afford the borrowers more discretion in how the funds could be used. In this case, the B-rated firms have switching costs that are 65 basis points higher than A-rated borrowers.

Table 9 shows analagous estimates when the average search cost for each bin is used instead of the search cost for the borrowers that do no search. The patterns are again consistent with the screening and monitoring hypothesis in that the lower rated firms have higher estimated switching costs and the term loans (for a given rated borrower) switching costs are higher than floating rate loans. We also looked within bins to understand if we there were patterns in the distributions of loan pricing were consistent with search costs. Within each bin, we sorted adjusted interest rates

Table 9: Impact of Rating on Search Costs (Δ_{avg})

	(1) All	(2) Term	(3) Revolver	(4) Fixed	(5) Float
BBB	0.302***	0.397***	0.224***	0.854**	0.258***
	(0.064)	(0.100)	(0.065)	(0.309)	(0.067)
BB	0.553***	0.748***	0.401***	0.970**	0.544***
	(0.064)	(0.099)	(0.065)	(0.308)	(0.067)
B	0.632***	0.929***	0.490***	1.009**	0.635***
	(0.066)	(0.103)	(0.067)	(0.311)	(0.069)
N	722	312	410	162	560
R^2	0.913	0.940	0.938	0.907	0.914

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regression based on estimation sample in Table 1 Dependent variable is the search cost delta_all, which is calculated using equation in paper. The search cost delta_all is calculated at the bin-level. The sample in the first column is all loans; in the second column is term loans; and the third is revolver loans; the fourth column are fixed loans; and the fith column are float loans. Standard errors are in parenthesis.

into deciles. We found some patterns consistent with search costs. For example, comparing the highest rate to lowest rate deciles, almost twice as many loans in the lowest rate decile were to borrowers with tickers. Since companies with public equity have financial reporting requirements, it is likely that these companies have lower search costs. Borrowers with CUSIPs, indicating the presence of a public bond, also have lower interest rates. Note that this result is within bins, so this is not a size effect. We show this in Table 10, by regressing adjusted interest rates on bin fixed effects and adding dummy variables indicating the presence of a ticker (column 2) or a CUSIP (column 3). While these coefficients are significant, they do not add much to the fit of the regressions, so the dispersion remains high even after controlling for these proxies.

6.2 Aggregating borrower switching costs to banks

Because there are not previous estimates of switching costs, there is not an established benchmark against which our estimates can be compared. One way to judge them is to use them to deduce the deadweight loss that would be created if a bank were to fail.

We model a bank failure as an exogenous event that forces all firms associated with a bank to search again for new loans, i.e., we are not allowing borrowers to find alternative financing outside of the bin in response to a bank failure. In the base case, we consider the failed bank to be "small" in

Table 10: Regression of Interest Rate on TKR and Cusip

	(1)	(2)	(3)	(4)
	Interest Rate - FFR	Interest Rate - FFR	Interest Rate - FFR	Interest Rate - FFR
CUSIP Present		-0.226***		0.009
		(0.008)		(0.012)
TKR Present			-0.330***	-0.336***
			(0.008)	(0.012)
Observations	160,627	160,627	160,627	160,627
Number of Bins	722	722	722	722
R-Squared	0.248	0.252	0.255	0.255
RMSE	0.998	0.996	0.993	0.993
Mean(p90 - p10 Residuals Within Bin)	2.441	2.437	2.429	2.429
p10(p90 - p10 Residuals Within Bin)	1.495	1.517	1.500	1.497
p25(p90 - p10 Residuals Within Bin)	1.925	1.915	1.904	1.908
p50(p90 - p10 Residuals Within Bin)	2.295	2.288	2.275	2.275
p75(p90 - p10 Residuals Within Bin)	2.825	2.840	2.820	2.820
p90(p90 - p10 Residuals Within Bin)	3.414	3.440	3.404	3.404
Mean(p75 - p25 Residuals Within Bin)	1.238	1.231	1.227	1.227
p10(p75 - p25 Residuals Within Bin)	0.680	0.692	0.696	0.700
p25(p75 - p25 Residuals Within Bin)	0.956	0.940	0.940	0.940
p50(p75 - p25 Residuals Within Bin)	1.184	1.187	1.178	1.176
p75(p75 - p25 Residuals Within Bin)	1.496	1.482	1.475	1.476
p90(p75 - p25 Residuals Within Bin)	1.777	1.788	1.777	1.777
Bin FE	Y	Y	Y	Y

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Regressions of loan interest rate (adjusted by subtracting the FFR) on a bin fixed effect in column (1), adding a dummy for Cusip in column (2), adding a dummy for TKR in column (3), and finally both dummies in column (4). The sample is the same as Table 1. Variables are defined in the same as Table 12. Each bin has a set of residuals, for each bin we subtract the 10th percentile residual from the 90th and the 25th percentile residual from the 75th. We then report the mean, 10th, 25th, 50th, 75th, and 90th percentile of the bin p90-p10 and p75-p25 residuals within a bin

the sense that when a bank fails, it does not affect the marginal cost of lending of other institutions, and the bank's failure induces another bank to enter the market, so the equilibrium number of competitors is unaffected. In the previous section, we were only talking about how we estimate parameters within a bin, so we suppressed the bin subscript to simplify the notation. Since we now want to examine the variation across bins, indexed by b, we need to add this subscript to our notation. Thus, for any bin b, N_b is the number of banks in the bin, q_{ib} is the fraction of borrowers searching i times. The equilibrium interest-rate distribution will continue to be optimal given the distribution of search costs, so our estimates of q_{ib} and Δ_{ib} describe the properties of the new equilibrium. The impact of the failure, then, is to force the bank's borrowers to incur a search cost in order to continue borrowing.

Let L_{jb} be the average value of loans issued by bank j to all its borrowers in bin b. We can write the average lower bound search costs incurred by borrowers from that bank who, in equilibrium, search i times by $i\Delta_{ib}L_{jb}$. In general, we can write the average lower bound for the search costs for borrowers searching i times as

$$C_{jb} = \sum_{i=1}^{N_b-1} i q_{ib} L_{jb} \Delta_{ib}, \qquad ((7))$$

where C_{jb} and L_{jb} are the average cost and loan amount in a bin. We sum C_{jb} across all bins to compute the total cost $\left(TC_j \equiv \sum_b C_{jb}\right)$. Since L_{jb} will tend to be larger for large banks, total costs will also tend to increase with bank size. It therefore makes sense to express these costs as a share of a bank's total lending in all bins. If we denote a bank's total lending in all bins in the estimation sample by TL_j, we can write the bankruptcy cost, expressed as a share of total lending by $SC_j = TC_j/TL_j$. Thus, the variables we want to know are TC_j and SC_j. Since these vary by bank, while we calculate the result at the individual bank level, we cannot report individual estimates due to data confidentiality concerns, but we can report the mean and standard deviation of the costs across banks in the sample.

Table 11 shows the distribution of the switching costs across the 36 banks. For the median bank, the costs are estimated to be 11 percent of the loan amounts. There is substantial heterogeneity across the banks, with the one at the 5th percentile of distribution having costs of only 2 percent of loans and the bank at the 95th percentile having costs of 47%.

Table 11: Bank Failure Counterfactual and Distribution of Switching Costs

	median	mean	p5	p95	standard deviation
TC (millions)	1758.62	2298.60	141.37	6133.96	1917.12
TL (millions)	20223.10	46052.70	300.31	160984.68	73924.12
SC	0.11	0.17	0.02	0.47	0.15

Notes: Results from an equation in the paper. The sample is made up of 92,906 loans. The sample is only made up of firms who renewed their loans in the sample of Table 1 TC (as defined in the text) is short for total cost in millions, this is calculated for each bank in the sample. TL is short for total lending in millions, this is calculated for each bank by summing its loans over the sample. There are 36 unique banks represented in the sample.

7 Robustness and generalizability

The results depend critically on the loans within a single bin being of similar risk. In addition to the exploration in Sections 4.1 and 4.4, where we experimented with many observable variables to understand if they explained the variation in rates, we restricted the sample in various ways to see whether eliminating variation in different ways leads to different inferences about the switching costs. For example, one alternative that we considered was to study only fixed-rate loans so that any variation that might be due to reference rates would be removed. In another alternative, we limited the sample to include only loans originated between 2012:Q3 and December of 2015. During that whole period, the Fed's policy rate was at its effective lower bound. In both these more limited samples, the estimated switching costs were quite similar to the ones derived from the full sample.

One limitation of the analysis is that we only have a comprehensive sample for the largest banks. Since smaller banks tend to lend to smaller borrowers and using more soft information, the switching costs of those borrowers may be even higher.

8 Conclusion

The cost for a borrower to switch banks is a central determinant of whether a contraction in lending translates into effects on the real economy. Without estimates of these costs, one cannot judge how various events like bank failures, bank mergers, regulatory changes, and monetary policy-induced changes in bank funding costs will play out. We believe this is the first paper to

directly estimate these costs by combining a new methodology with comprehensive data on loan pricing and borrower risk. While our estimates of the switching wedges are calculated for banks and their business customers, the patterns suggest they are tied to screening and monitoring costs. If this is correct, then non-bank lenders would likely face the same considerations in extending credit as banks. If this conjecture could be corroborated, it suggests that there could be externalities from non-bank failures in terms of credit provision.

We cannot rule out that switching costs arise from managerial inattention or laziness. For example, costs of this inattention or laziness would be higher for larger loans and thus be consistent with the patterns we find. If managers are rational, they are endogenously trading off the use of their time to search for a bank loan with other productive endeavors. In this case, forcing these managers to incur those search costs would remain a cost to the economy. However, if managers face severe principal-agent issues leading them to wrongly weight searching for a new banks relative to other uses of their time, or if they are irrationally uninformed, these estimates may represent an upper bound of the potential welfare costs of bank failure.

Given that these are the first estimates of switching wedges in the literature, we have identified several areas for future research. First is to consider the debates over market power in banking by extracting markups from the estimates and examining if the estimated wedges differ depending on the degree of competition. Second is to measure the impact on loan pricing and credit availability after the onset of COVID. Understanding fixed costs offers a method to calculate the likely impact on borrowers and their lenders for loan pricing and credit availability following these shocks. A key subject of interest is understanding the extent of business cycle variation in the switching costs and the ability of firms to replace lost loans. One suspects that when macroeconomic uncertainty is higher, monitoring is more costly and screening is more challenging, in which case wedges would be expected to rise. Finally, if technological change reduces search costs, these numbers could change accordingly.

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9 Appendix

The tables and figures other than Table 12 show how our key estimates for the full sample compare to other samples. The mapping between these tables and the ones in the text are as follows:

Table 1: Loan Characteristics Estimation Sample

- This should be cross-referenced with Table 16: Loan Characteristics Estimation Sample (Regime 1)

Column (1-2) of Table 2: Bin Level Regression

- This should be cross-referenced with columns (1-2) of Table 13: Bond Regression

Table 3: Average Loan Characteristics Across Bins

- This should be cross-referenced with multiple tables. For column (1) of Table 3 refer to column (1) (ZLB), of Table 15: Loan Characteristics and Search Cost By Regime. For column (2-5) of Table 3, refer to Table 17: Loan Characteristics and Search Costs by Rating (Regime 1) . For the remaining columns (6-10) refer to Table 18 : Loan Characteristics and Search Cost by Committed (Regime 1)

Table 4: Interest Rates and Expected Loss

- This table should be cross-referenced with Table 19: Interest Rates and Expected Loss (Regime 1)

Table 5: Number of Searches and Average Search Cost Across Bins.

- This should be cross-referenced with column(1) of Table 15: Loan Characteristics and Search Cost By Regime.

Table 6: Number of Searches and Average Search Costs Across Bins by Rating.

- This should be cross-referenced with Table 17 : Loan Characteristics and Search Costs by Rating (Regime 1).

Table 7: Number of Searches and Average Search Costs Across Bins by Committed.

- This should be cross-referenced with Table 18 Loan Characteristics and Search Costs (Regime 1).

Figure 2: Impact of Loan Characteristics on Adjusted Interest Rates.

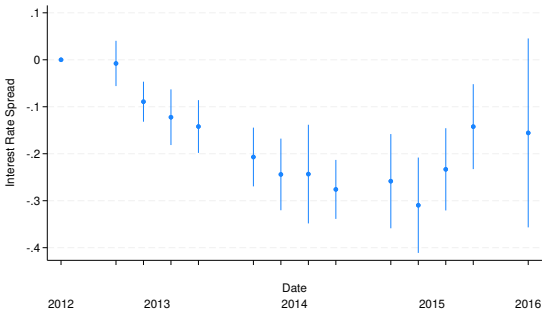
- This should by cross-referenced with Figure 5: Impact of Loan Characteristics on Adjusted Interest Rates (Regime 1).

Table 12: Robustness Regression Variables

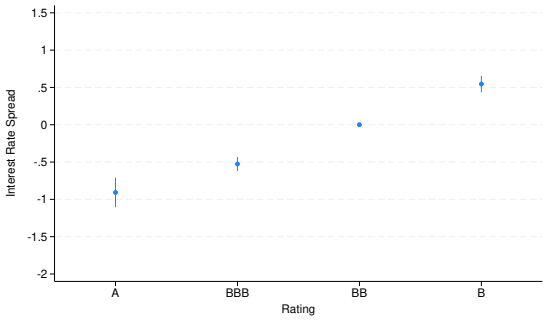
	(1)							
	mean	sd	p5	p25	p50	p75	p95	count
Interest Rate - FFR	2.63	1.15	1.08	1.78	2.50	3.25	4.66	160,627
Relationship Length	9.29	11.54	0.00	0.00	5.00	14.00	37.00	160,627
Relationship Length (Normalized)	2.40	2.23	0.00	0.00	2.25	3.95	6.18	160,627
Leverage	0.61	69.47	0.00	0.18	0.34	0.51	0.81	130,495
Short-Term Debt (millions)	205.53	24,119.96	0.00	0.00	0.04	3.12	72.93	136,117
Current Maturities of Long-Term Debt (millions)	132.47	11,601.18	0.00	0.00	0.21	3.00	81.09	137,055
Long-Term Debt (billions)	1.29	62.34	0.00	0.00	0.00	0.11	2.76	138,073
Total Assets, Currtent (billions)	5.95	489.46	0.00	0.01	0.04	0.48	7.26	138,682
Log Sales (millions)	3.84	4.18	-2.91	2.79	4.14	6.09	8.66	138,697
Net Sales, Current (millions)	2,786.91	93,817.84	0.05	16.14	62.65	438.19	5,765.00	138,855
Expected Loss	0.35	0.74	0.02	0.08	0.18	0.39	1.16	90,221
Interest Coverage	-311.61	278701.17	-3.17	2.20	6.10	17.48	124.41	111,887
Operating Income (millions)	383.44	22,539.35	-1.93	0.56	3.35	35.27	603.00	118,457
Interest Expense (millions)	61.81	2,670.03	0.00	0.06	0.38	6.07	130.31	137,642
Ticker (=1 if present)	0.13	0.34	0.00	0.00	0.00	0.00	1.00	160,627
Cusip (=1 if present)	0.14	0.34	0.00	0.00	0.00	0.00	1.00	160,627
Lien Position (4 FEs)	1.34	0.75	1.00	1.00	1.00	1.00	3.00	158,944
Security Type (7 FEs)	3.35	1.59	1.00	2.00	4.00	4.00	6.00	160,081
Interest Rate Index (7 FEs)	2.76	2.20	1.00	1.00	2.00	5.00	7.00	160,605
Observations	160627							

Notes: The above table presents summary statistics for variables used in the robustness regressions. Interest rates have been adjusted by the FFR at the origination date of the loan. Length of relationship is a measure constructed from the difference in number of quarters between the current loan origination and the earliest observed loan in that bank-firm pair. The variable is then normalized by the mean in each quarter. Leverage is constructed as (short term debt + current maturities of long-term debt + long term debt) / total assets current. Log of net sales is constructed as log((current net sales+1)/1000). Interest coverage is constructed as operating income / interest expense. Expected loss share is constructed as 100*((Probability of Default /100) * Loss Given Default * Exposure at Default)/committed. Ticker (cusip) dummy =1 if Y-14 borrower has a ticker (cusip), =0 otherwise. Lien position is a dummy variable based on integer code for 4 different positions. Indicate using integer code if the credit facility is First Lien Senior (=1), Second Lien (=2), Senior Unsecured (=3), or Contractually Subordinated (=4). Collateral type is a dummy variable based on integer code for 7 security types. If security is provided by collateral other than or in addition to Real Estate, indicate the predominant security type. =0 if Real Estate only, =1 if Cash and Marketable Securities, =2 if Accounts Receivable and Inventory, =3 if Fixed Assets excluding Real Estate, =4 if Blanket Lien, =5 if Other, =6 if Unsecured. MSA fixed effect is replaced by state if missing. Naics-3 is a fixed effect for industry. Interest rate index is a dummy variable based on integer code for 7 indexes, =1 if LIBOR, =2 if PRIME or Base, =3 if Treasury Index, =4 if Other, =5 if not applicable (Fixed or entirely fee based), =6 if Mixed, =7 if SOFR.

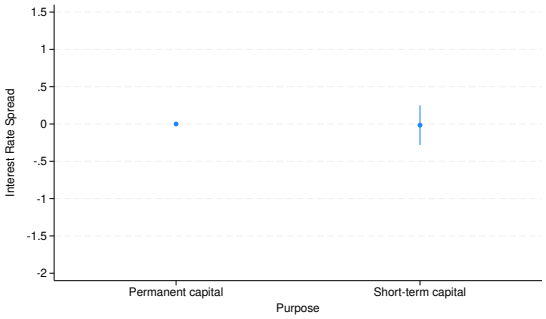
Figure 5: Impact of Loan Characteristics on Adjusted Interest Rates (Regime 1: 2012Q4-2015Q4)



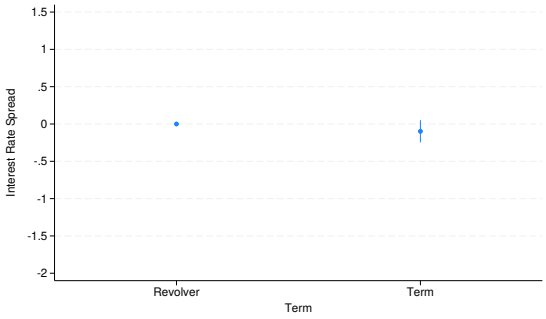
(a) Loan Origination Date Fixed Effect



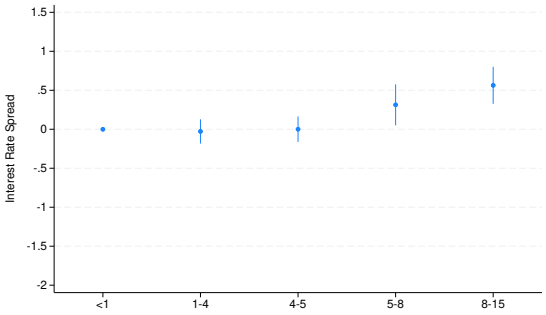
(b) Loan Rating Fixed Effects



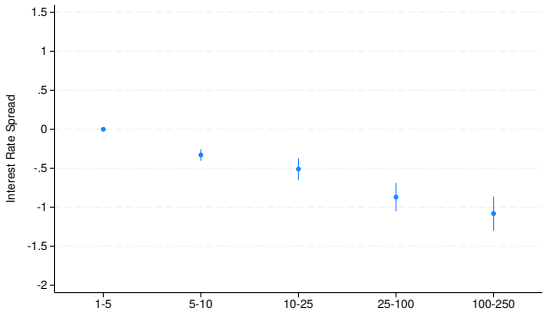
(c) Loan Purpose Fixed Effects



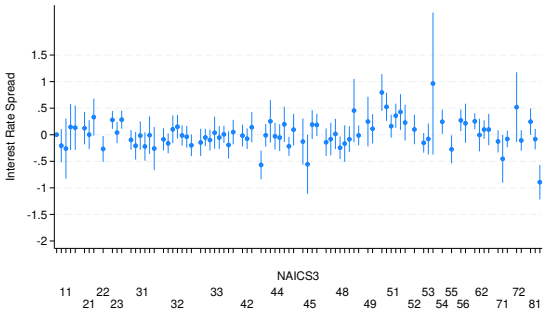
(d) Term Loan vs. Revolver Fixed Effects



(e) Maturity Fixed Effect (years)



(f) Committed Loan Size Fixed Effect (millions)



(g) NAICS Fixed Effect

Notes: These charts show the coefficients of a regression of the adjusted interest rates (at the origination date of the loan) on various fixed effects. These controls include binary variables equal to one for categories of internal risk rating and fixed effects for the dollar amount of loan commitment, maturity in years, loan type, loan purpose, quarter of origination, and North American Industrial Classification System (NAICS) 3-digit industry. The sample is the estimation sample of 66,829 originations (the same sample as Table 1) from 2012:Q4 to 2015:Q4. Blue bars represent 95% confidence intervals. Y axis in pp.

Table 13: Bond Regression

	Interest Rate Spread				
	(1)	(2)	(3)	(4)	(5)
Log Offering				0.013	0.012
				(0.043)	(0.043)
Maturity (Years)					0.007**
					(0.002)
Observations	7,231	7,231	6,797	6,797	6,797
Number of Bins	272	272	264	264	264
R-Squared	0.770	0.798	0.815	0.815	0.815
Adj. R-Squared	0.761	0.789	0.804	0.804	0.804
RMSE	0.743	0.698	0.672	0.672	0.671
Mean(p90 - p10 Residuals Within Bin)	1.400	1.334	1.278	1.278	1.273
p10(p90 - p10 Residuals Within Bin)	0.300	0.425	0.402	0.403	0.390
p25(p90 - p10 Residuals Within Bin)	0.590	0.600	0.618	0.618	0.607
p50(p90 - p10 Residuals Within Bin)	0.935	0.877	0.861	0.862	0.856
p75(p90 - p10 Residuals Within Bin)	1.650	1.473	1.400	1.399	1.398
p90(p90 - p10 Residuals Within Bin)	3.230	2.981	2.658	2.658	2.659
Bin FE	Y	Y	Y	Y	Y
Quarter FE	N	Y	Y	Y	Y
Industry FE	N	N	Y	Y	Y

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: The dependent variable is the difference between the offering yield and a comparable U.S. Treasury security. Each observation is a different bond.

Table 14: Loan Characteristics and Search Cost By Maturity

Maturity (years)	0-1	1-4	4-5	5-8	8-15
min(interest rate)	1.28	1.30	1.41	1.63	2.08
	(0.71)	(0.72)	(0.64)	(0.61)	(0.69)
max(interest rate)	7.78	7.84	7.83	7.55	6.88
	(3.01)	(2.75)	(2.46)	(2.33)	(1.57)
min(interest rate - FFR)	0.50	0.54	0.58	0.68	0.89
	(0.53)	(0.48)	(0.77)	(0.92)	(0.96)
max(interest rate - FFR)	6.18	6.31	6.35	6.29	5.52
	(2.35)	(2.20)	(2.05)	(2.21)	(0.64)
median range(interest rate)	6.32	6.31	6.39	5.71	4.18
mean range(interest rate)	6.50	6.54	6.42	5.93	4.80
	(2.70)	(2.50)	(2.26)	(2.21)	(1.37)
median interquartile range(interest rate)	1.29	1.41	1.41	1.24	1.20
mean interquartile range(interest rate)	1.39	1.45	1.55	1.42	1.37
	(0.49)	(0.47)	(0.70)	(0.64)	(0.64)
median p90-p10 range(interest rate)	2.58	2.78	2.65	2.55	2.27
mean p90-p10 range(interest rate)	2.89	2.98	3.05	2.91	2.67
	(1.12)	(0.97)	(1.31)	(1.19)	(1.18)
median range(interest rate - FFR)	5.27	5.41	5.47	5.14	4.65
mean range(interest rate - FFR)	5.68	5.77	5.77	5.61	4.64
	(2.30)	(2.21)	(2.09)	(2.26)	(0.93)
median interquartile range(interest rate - FFR)	1.17	1.24	1.18	1.10	1.11
mean interquartile range(interest rate - FFR)	1.23	1.27	1.23	1.22	1.19
	(0.44)	(0.40)	(0.54)	(0.52)	(0.52)
median p90-p10 range(interest rate - FFR)	2.21	2.41	2.34	2.26	2.23
mean p90-p10 range(interest rate - FFR)	2.39	2.45	2.46	2.52	2.46
	(0.87)	(0.71)	(0.97)	(1.01)	(0.97)
search cost	-2.41	-5.36	-104.80	-0.35	-0.45
	(19.48)	(76.89)	(1202.25)	(1.70)	(2.15)
number of banks	12.35	13.43	13.43	12.37	11.30
	(4.32)	(4.88)	(5.32)	(4.53)	(4.35)
number of loans	339.01	231.66	196.86	99.69	109.30
	(665.19)	(284.63)	(240.83)	(113.90)	(90.15)
interest rate	3.98	3.90	3.86	3.91	4.11
	(1.68)	(1.71)	(1.58)	(1.26)	(0.93)
maturity (years)	0.75	2.70	4.91	6.39	10.54
	(0.12)	(0.31)	(0.07)	(0.42)	(0.50)
loan size (millions)	13.61	26.69	29.36	13.71	2.03
	(16.34)	(36.59)	(43.18)	(19.83)	(0.23)

Maturity (years)	0-1	1-4	4-5	5-8	8-15	0-1	1-4	4-5	5-8	8-15
	share	share	share	share	share	search cost	search cost	search cost	search cost	search cost
number of searches=1	0.37	0.35	0.33	0.39	0.47	0.75	0.74	0.73	0.74	0.65
	(0.15)	(0.12)	(0.14)	(0.16)	(0.15)	(0.26)	(0.25)	(0.24)	(0.28)	(0.15)
number of searches=2	0.46	0.50	0.51	0.45	0.39	0.32	0.31	0.30	0.32	0.30
	(0.12)	(0.09)	(0.12)	(0.14)	(0.13)	(0.10)	(0.10)	(0.11)	(0.13)	(0.08)
number of searches=3	0.01	0.00	0.00	0.01	0.02	0.18	0.18	0.17	0.19	0.18
	(0.06)	(0.01)	(0.04)	(0.05)	(0.07)	(0.06)	(0.06)	(0.07)	(0.08)	(0.06)
number of searches=4	0.00	0.00	0.00	0.00	0.00	0.12	0.12	0.11	0.13	0.13
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.05)	(0.06)	(0.04)
number of searches=n-1	0.00	0.00	0.00	0.01	0.00	0.04	0.04	0.04	0.05	0.06
	(0.01)	(0.03)	(0.02)	(0.04)	(0.00)	(0.04)	(0.03)	(0.03)	(0.04)	(0.05)
number of searches=n	0.15	0.14	0.14	0.13	0.12	0.04	0.03	0.03	0.04	0.05
	(0.08)	(0.07)	(0.06)	(0.07)	(0.07)	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)

Notes: This table presents summary statistics for the estimation sample of 160,627 loan originations (the same sample as Table 1) for which we can compose bins of loans with similar characteristics. Numbers represent the mean across N bins for each variable (N for 0-1 maturity (years) = 153, 1-4 maturity (years) = 224, 4-5 maturity (years) = 230, 5-8 maturity (years) = 94, and 8-15 maturity (years) = 20). The minimum (maximum) interest rate is therefore an average of the minimum (maximum) interest rate across N bins for each maturity range. For observered characteristics we first calculclate the average of a variable within a bin and then average the means accross bins within the same matrurity (in years) range (some interest rate statistics such as the bin range, bin interquartile range, and bin 90th-10th percentile are also display the median accross bins). Observable variables reported in the table are averages across bins by maturity (in years) for the following variables the lowest interest rate, highest interest rate, mean interest rate, number of banks, number of loan originations, mean maturity (years), and mean committed amount (millions). The rest of the variables are estimated in a search model. In the search model interest rates are adjusted by subtracting the Federal Funds Rate at the origination date of the loan. The variables estimated are unit cost, the portion of firms searching n times for a new bank quote, and different search costs.

Table 15: Loan Characteristics and Search Cost By Regime

Regime	ZLB	RATE HIKE	COVID ZLB	RATE HIKE
min(interest rate)	0.97	1.52	1.07	2.16
	(0.46)	(0.48)	(0.43)	(0.72)
max(interest rate)	7.13	7.46	5.94	10.64
	(2.52)	(1.81)	(1.81)	(2.13)
min(interest rate - FFR)	0.72	0.62	0.82	0.07
	(0.46)	(0.35)	(0.43)	(1.10)
max(interest rate - FFR)	6.88	6.02	5.69	6.11
	(2.52)	(1.82)	(1.81)	(2.04)
median range(interest rate)	5.81	5.75	4.44	8.14
mean range(interest rate)	6.16	5.94	4.87	8.48
	(2.50)	(1.77)	(1.77)	(2.19)
median interquartile range(interest rate)	1.16	1.34	1.19	1.91
mean interquartile range(interest rate)	1.28	1.40	1.23	2.04
	(0.52)	(0.38)	(0.45)	(0.63)
median p90-p10 range(interest rate)	2.30	2.60	2.34	4.41
mean p90-p10 range(interest rate)	2.51	2.75	2.45	4.41
	(1.01)	(0.75)	(0.81)	(0.87)
median range(interest rate - FFR)	5.81	5.28	4.44	5.75
mean range(interest rate - FFR)	6.16	5.40	4.87	6.04
	(2.50)	(1.77)	(1.77)	(2.18)
median interquartile range(interest rate - FFR)	1.16	1.13	1.19	1.30
mean interquartile range(interest rate - FFR)	1.28	1.16	1.23	1.30
	(0.52)	(0.48)	(0.45)	(0.39)
median p90-p10 range(interest rate - FFR)	2.30	2.18	2.34	2.51
mean p90-p10 range(interest rate - FFR)	2.51	2.30	2.45	2.55
	(1.01)	(0.83)	(0.81)	(0.76)
search cost	-30.47	-85.16	0.09	-113.28
	(471.69)	(1140.45)	(0.62)	(1365.90)
number of banks	12.65	14.47	12.03	12.29
	(4.70)	(5.73)	(3.71)	(4.24)
number of loans	277.30	236.53	124.69	193.60
	(494.91)	(373.33)	(152.39)	(273.85)
interest rate	2.94	3.83	2.76	6.52
	(0.80)	(0.65)	(0.69)	(0.86)
maturity (years)	3.73	3.95	3.56	3.50
	(2.26)	(2.59)	(2.16)	(2.17)
loan size (millions)	16.65	20.48	24.15	32.72
	(22.91)	(30.03)	(34.80)	(49.19)

Rating	ZLB	RATE HIKE	COVID ZLB	RATE HIKE	ZLB	RATE HIKE	COVID ZLB	RATE HIKE
	share	share	share	share	search cost	search cost	search cost	search cost
number of searches=1	0.34	0.35	0.35	0.41	0.78	0.69	0.64	0.80
	(0.14)	(0.14)	(0.13)	(0.16)	(0.28)	(0.21)	(0.21)	(0.26)
number of searches=2	0.50	0.49	0.48	0.45	0.32	0.29	0.27	0.36
	(0.12)	(0.11)	(0.11)	(0.13)	(0.11)	(0.08)	(0.09)	(0.13)
number of searches=3	0.00	0.00	0.00	0.01	0.18	0.17	0.15	0.21
	(0.04)	(0.02)	(0.03)	(0.06)	(0.06)	(0.05)	(0.05)	(0.09)
number of searches=4	0.00	0.00	0.00	0.00	0.12	0.11	0.10	0.14
	(0.00)	(0.02)	(0.00)	(0.00)	(0.04)	(0.03)	(0.04)	(0.07)
number of searches=n-1	0.00	0.00	0.01	0.00	0.04	0.03	0.03	0.05
	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)
number of searches=n	0.15	0.14	0.13	0.13	0.03	0.03	0.03	0.04
	(0.06)	(0.06)	(0.09)	(0.06)	(0.02)	(0.02)	(0.02)	(0.03)

Notes: This table presents summary statistics for the estimation sample of 160,627 loan originations (the same sample as Table 1) for which we can compose bins of loans with similar characteristics. Numbers represent the mean across N bins for each variable (N for regime 1 = 241, regime 2 = 210, regime 3 = 121, and 5-8 regime 4 = 150). The minimum (maximum) interest rate is therefore an average of the minimum (maximum) interest rate across N bins for each committed range. For observered characteristics we first calculclate the average of a variable within a bin and then average the means accross bins within the same matrurity (in years) range (some interest rate statistics such as the bin range, bin interquartile range, and bin 90th-10th percentile are also display the median accross bins). Observable variables reported in the table are averages across bins by maturity (in years) for the following variables the lowest interest rate, highest interest rate, mean interest rate, number of banks, number of loan originations, mean maturity (years), and mean committed amount (millions). The rest of the variables are estimated in a search model. In the search model interest rates are adjusted by subtracting the Federal Funds Rate at the origination date of the loan. The variables estimated are unit cost, the portion of firms searching n times for a new bank quote, and different search costs.

Table 16: Loan Characteristics Estimation Sample (Regime 1)

	Share of obs (%)	Share of committed (%)	Mean interest rate (pp.)	Median interest rate (pp.)	Mean spread (pp.)	Median spread (pp.)	Mean utilization (%)	SD interest rate (pp.)
Rating:								
A	1.7	3.0	2.07	1.95	1.75	1.65	63.89	0.91
BBB	28.0	42.4	2.42	2.20	2.04	1.85	65.98	0.98
BB	55.9	45.3	3.09	2.99	2.69	2.54	70.36	1.11
B	14.4	9.3	3.69	3.50	3.34	3.15	73.52	1.36
Committed (millions):								
1-5	55.8	9.4	3.28	3.25	2.83	2.75	73.11	1.11
5-10	12.7	7.1	2.92	2.70	2.59	2.40	70.89	1.22
10-25	15.4	19.5	2.72	2.45	2.40	2.15	68.16	1.21
25-100	15.2	54.8	2.24	2.00	1.94	1.70	57.70	1.00
100-250	0.9	9.2	1.80	1.68	1.53	1.40	46.06	0.64
Maturity (years):								
0-1	34.7	13.6	3.18	3.20	2.91	2.95	63.95	1.06
1-4	32.6	40.3	2.85	2.69	2.51	2.35	67.54	1.20
4-5	25.1	42.5	2.73	2.44	2.29	1.98	73.62	1.24
5-8	6.4	3.3	3.26	3.15	2.45	2.17	87.82	1.28
8-15	1.3	0.2	3.84	3.99	2.18	2.00	96.26	1.09
>15								
Loan type:								
Revolver, short-term capital	23.5	13.5	3.18	3.17	2.88	2.90	60.57	1.05
Revolver, general working capital	49.2	71.6	2.86	2.71	2.51	2.40	60.04	1.18
Term, short-term capital	8.0	2.6	2.82	2.65	2.33	2.05	95.78	1.32
Term, general working capital	19.4	12.2	3.09	2.92	2.50	2.30	93.43	1.26

Notes: This table reports summary statistics for the 66,832 estimation sample of loan originations for 31 stress-tested banks from 2012:Q4 to 2015:Q4 after we have restricted the data. Bins are constructed by splitting by banks' internal risk rating, commitment amount, maturity, loan type, and loan purpose. We drop the revolver loans that were never drawn on over the life of the loan, bins with less than 6 unique banks and bins that have less than 20 loans. The first two columns show the share of originations by number and committed value. The next columns show the mean, median, and standard deviation of the interest rate and interest rate spread for all loan originations in each category calculated as of origination date. Interest rate spreads are calculated based on spreads to 3-month LIBOR, and use forward curves at origination for fixed-rate loans. Mean utilization is the mean of the loans in the category, defined as utilized divided by committed, calculated for each loan over the loan's lifespan in the dataset.

Table 17: Loan Characteristics and Search Costs by Rating (Regime 1)

Rating	A	BBB	BB	B
min(interest rate)	0.64	0.58	0.73	0.96
	(0.36)	(0.34)	(0.44)	(0.60)
max(interest rate)	3.65	5.35	7.79	8.75
	(1.40)	(1.38)	(2.31)	(2.09)
unit cost	-430.71	-0.05	-0.09	-0.18
	(1776.32)	(0.58)	(0.70)	(0.97)
number of banks	8.76	12.49	13.77	12.23
	(2.49)	(4.40)	(5.09)	(4.32)
number of loans	66.59	231.42	414.82	181.53
	(64.85)	(329.39)	(696.82)	(266.80)
interest rate	1.98	2.39	3.09	3.84
	(0.60)	(0.51)	(0.46)	(0.66)
maturity (years)	3.08	3.76	3.85	3.69
	(1.85)	(2.19)	(2.33)	(2.39)
loan size (millions)	28.52	18.80	15.24	11.92
	(37.10)	(26.34)	(19.45)	(14.25)

Rating	A	BBB	BB	B	A	BBB	BB	B
	share	share	share	share	search cost	search cost	search cost	search cost
number of searches=1	0.40	0.34	0.32	0.35	0.42	0.60	0.87	1.02
	(0.19)	(0.14)	(0.13)	(0.13)	(0.18)	(0.15)	(0.23)	(0.24)
number of searches=2	0.41	0.50	0.53	0.49	0.18	0.25	0.35	0.42
	(0.16)	(0.13)	(0.10)	(0.12)	(0.08)	(0.06)	(0.08)	(0.09)
number of searches=3	0.02	0.01	0.00	0.01	0.11	0.14	0.19	0.24
	(0.09)	(0.05)	(0.00)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)
number of searches=4	0.00	0.00	0.00	0.00	0.07	0.09	0.13	0.16
	(0.00)	(0.00)	(0.01)	(0.00)	(0.03)	(0.03)	(0.03)	(0.04)
number of searches=n-1	0.00	0.00	0.00	0.00	0.04	0.03	0.04	0.06
	(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.05)
number of searches=n	0.16	0.15	0.15	0.15	0.03	0.03	0.03	0.05
	(0.10)	(0.06)	(0.06)	(0.08)	(0.02)	(0.02)	(0.02)	(0.03)

Notes: This table presents summary statistics for the estimation sample of 66,832 loan originations (the same sample as Table 34) for which we can compose bins of loans with similar characteristics. Numbers represent the mean across N bins for each variable (N for A ratings = 17, BBB ratings = 81, BB ratings = 90, and B ratings = 53). The minimum (maximum) interest rate is therefore an average of the minimum (maximum) interest rate across N bins for each rating. For observered characteristics we first calculclate the average of a variable within a bin and then average the means accross bins within the same matrurity (in years) range. Observable variables reported in the table are averages across bins by maturity (in years) for the following variables the lowest interest rate, highest interest rate, mean interest rate, number of banks, number of loan originations, mean maturity (years), and mean committed amount (millions). The rest of the variables are estimated in a search model. In the search model interest rates are adjusted by subtracting the Federal Funds Rate at the origination date of the loan. The variables estimated are unit cost, the portion of firms searching n times for a new bank quote, and different search costs.

Table 18: Loan Characteristics and Search Costs by Committed Loan Size (Regime 1)

Committed (millions)	1-5	5-10	10-25	25-100	100-250
min(interest rate)	0.89	0.69	0.68	0.46	0.46
	(0.47)	(0.42)	(0.49)	(0.30)	(0.30)
max(interest rate)	7.56	6.76	6.74	6.03	3.81
	(2.57)	(2.21)	(2.52)	(2.38)	(0.38)
unit cost	-77.82	-0.22	-0.19	-0.21	0.14
	(755.41)	(0.76)	(0.81)	(0.61)	(0.35)
number of banks	13.01	12.54	12.69	12.00	11.75
	(4.98)	(4.49)	(4.68)	(4.51)	(4.03)
number of loans	396.83	169.16	202.14	242.17	148.00
	(693.43)	(198.77)	(260.39)	(394.11)	(100.82)
interest rate	3.31	2.98	2.82	2.32	1.74
	(0.69)	(0.74)	(0.78)	(0.64)	(0.33)
maturity (years)	3.94	3.52	3.65	3.59	3.92
	(2.77)	(2.03)	(1.92)	(1.69)	(1.08)
loan size (millions)	2.29	7.54	17.10	47.21	141.03
	(0.32)	(0.38)	(1.03)	(5.30)	(2.93)

Committed (millions)	1-5	5-10	10-25	25-100	100-250	1-5	5-10	10-25	25-100	100-250
	share	share	share	share	share	search cost	search cost	search cost	search cost	search cost
number of searches=1	0.34	0.35	0.33	0.31	0.28	0.85	0.78	0.76	0.68	0.43
	(0.14)	(0.13)	(0.15)	(0.14)	(0.03)	(0.28)	(0.27)	(0.28)	(0.24)	(0.06)
number of searches=2	0.49	0.51	0.50	0.53	0.56	0.35	0.32	0.31	0.27	0.17
	(0.12)	(0.11)	(0.14)	(0.12)	(0.03)	(0.10)	(0.11)	(0.11)	(0.09)	(0.03)
number of searches=3	0.00	0.00	0.01	0.01	0.00	0.20	0.18	0.17	0.15	0.09
	(0.03)	(0.00)	(0.07)	(0.06)	(0.00)	(0.05)	(0.06)	(0.06)	(0.05)	(0.02)
number of searches=4	0.00	0.00	0.00	0.00	0.00	0.13	0.12	0.11	0.10	0.06
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)
number of searches=n-1	0.00	0.00	0.01	0.00	0.00	0.05	0.04	0.04	0.04	0.02
	(0.00)	(0.00)	(0.04)	(0.01)	(0.00)	(0.04)	(0.04)	(0.03)	(0.03)	(0.01)
number of searches=n	0.16	0.13	0.14	0.15	0.16	0.04	0.03	0.03 0.03	0.02	
	(0.07)	(0.06)	(0.07)	(0.07)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)

Notes: This table presents summary statistics for the estimation sample of 66,832 loan originations (the same sample as Table 34) for which we can compose bins of loans with similar characteristics. Numbers represent the mean across N bins for each variable (N for 1-5 committed (millions) = 94, 5-10 committed (millions) = 50, 10-25 committed (millions) = 51, 25-100 committed (millions) = 42, and 100-250 committed (millions) = 4). The minimum (maximum) interest rate is therefore an average of the minimum (maximum) interest rate across N bins for each committed range. For observered characteristics we first calculclate the average of a variable within a bin and then average the means accross bins within the same matrurity (in years) range. Observable variables reported in the table are averages across bins by maturity (in years) for the following variables the lowest interest rate, highest interest rate, mean interest rate, number of banks, number of loan originations, mean maturity (years), and mean committed amount (millions). The rest of the variables are estimated in a search model. In the search model interest rates are adjusted by subtracting the Federal Funds Rate at the origination date of the loan. The variables estimated are unit cost, the portion of firms searching n times for a new bank quote, and different search costs.

Table 19: Interest Rates and Expected Loss (Regime 1)

	(1) Interest Rate	(2) Interest Rate	(3) Interest Rate	(4) Interest Rate Standardized
Expected loss ratio			0.246***	
			(0.016)	
Standardized Expected loss ratio				0.128***
				(0.009)
Bin FE	Yes	Yes	Yes	Yes
Observations	66832	13736	13736	13736
R-Squared	0.262	0.264	0.276	0.276
RMSE	1.024	0.988	0.980	0.858

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Results from regressing interest rates on an indicator variable for each loan bin where bins are based on monetary policy cycle, rating, maturity, size, type, and purpose. The first column estimates the regression for the estimation sample of 66,832 observations (the same sample as Table 34), while Column 2 limits the specication to the sample of 13,736 observations for which the expected loss ratio data is available. The third column adds the expected loss ratio (denoted as the probability of default times loss given default times the exposure given default, divided by the committed size of the loan) as an explanatory variable and the fourth column standardizes both the expected loss ratio and the interest rate to mean 0 and standard deviation 1. The median interest rate and expected loss ratio for column 3 is 2.75 percentage points and 0.18 percentage points, respectively. The standard deviation interest rate and expected loss ratio for column 3 is 1.14 percentage points and 0.59 percentage points, respectively.