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Cyclicality of Nonbank Lending vs. Bank Lending Examined via the Substitution of Bonds for Loans

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Abstract

We study fluctuations in loan supply by revisiting Becker and Ivashina (2014) and analyze the substitution between bonds and loans by disaggregating loans into bank and nonbank loans. We confirm the finding of Becker and Ivashina (2014) that, when aggregate credit conditions tighten, credit issuance shifts from loans to bonds. However, we find that this shift is driven by a reduction in nonbank loan issuance rather than bank loan issuance. Thus, we infer that the cyclical switch from loan to bond issuance is driven by nonbank rather than bank credit supply.

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Cyclicality of Nonbank Lending vs. Bank Lending Examined via the Substitution of Bonds for Loans

1. Introduction

Understanding the credit cycle is crucial because of its role as a "financial accelerator", in which financial frictions amplify temporary economic shocks, prolonging their negative impacts on the business cycle (Bernanke et al., 1998). In the context of credit supply, the current literature presents conflicting views regarding the drivers of credit cyclicality. Becker and Ivashina (2014) discuss empirical evidence that emphasizes significant cyclicality in bank lending. They observe that in periods of bank credit tightening, firms tend to substitute bank loans with bonds, arguing that this observed shift indicates a more pronounced cyclicality in bank loan supply. Conversely, Fleckenstein et al. (2025) argue that bank lending is relatively more stable, in particular because banks benefit from government guarantees and regulation that moderates fluctuations in credit supply. Indeed, they highlight that the comparatively higher cyclicality of nonbank lending is partly due to nonbanks' lack of access to similar protection. These incompatible views present an unresolved tension that requires further empirical examination.

1.1. Research question

Accordingly, this thesis tackles the following question: Is the cyclicality of the credit supply, analyzed through the substitution between loans and bonds, driven by nonbanks or banks? To investigate this, we revisit and confirm whether Becker and Ivashina's (2014) findings on the substitution between loans and bonds hold in a period up to 2010 and an extended timeframe up to 2020. Then, we further parse loans into bank loans and nonbank loans, allowing for separate testing of each category's credit supply cyclicality. Our results indicate distinct cyclical behaviors between banks and nonbanks. Bank lending remains relatively stable, exhibiting mostly minimal and insignificant, or even countercyclical, relationships with credit availability indicators, whereas nonbanks display heightened cyclicality.

1.2. Overview of approach

To answer our research question, we perform regressions on a quarterly panel dataset, which includes U.S. non-financial firm-level data from 1997Q4 to 2020Q2. The debt substitution mechanism is captured through a binary dependent variable, which indicates whether a firm issues a bond or a loan in each quarter, with the latter being further split into bank loans and nonbank loans. The dependent variable is regressed against seven main independent variables in seven distinct regressions. These independent variables act as proxies for aggregate credit conditions. Five of the variables are taken from Becker and Ivashina (2014), namely: i) tightening in lending standards, ii) aggregate lending growth, iii) loan allowances to total loans ratio, iv) a bank stock-index, and v) a monetary policy shock variable, which is only included when replicating Becker and Ivashina (2014). In addition to said variables, we include two new variables, namely: vi) the VIX index and vii) the Excess Bond Premium (EBP), from Gilchrist and Zakrajšek (2012), measuring the difference between corporate bond spreads and expected credit losses.

When controlling for positive demand for credit, the dependent variable ultimately captures an isolated shift in credit supply indicated by a loan-to-bond substitution. Therefore, we filter for firms with positive demand for debt. Additionally, we control for firm-level compositional changes that may influence a firm's financing decision. For the latter, we include a total of seven control variables from Becker and Ivashina (2014); the main four comprise i) the log of the previous quarter’s assets; ii) the log of the previous quarter’s property, plant, and equipment; iii) the return on assets (ROA); and iv) the leverage ratio. An additional three are included only in our initial replication sample. These include v) the previous quarter's market-to-book ratio; vi) the one-year lagged stock price return; and vii) a variable indicating whether firms paid dividends in a given quarter. Crucially, to identify loan-to-bond substitutions, we exclude firm-quarters with simultaneous bond and loan issuances and restrict the sample to firms that have issued a bond within the past five years, thereby eliminating non-switchers and firms with no access to the bond market.

Using our filtered panel dataset, we perform regressions over four distinct samples. Sample 1 replicates the benchmark regressions of Becker and Ivashina (2014) by regressing the loan-to-bond dummy variable against the main independent variable and control variables, between 1997Q4 and 2010Q4, to confirm whether our results align. In this sample, we include an additional independent variable from Becker and Ivashina (2014), measuring monetary policy shocks as the difference between the Fed Funds Rate and the Taylor Rule (Taylor, 1993). Furthermore, we include three additional control variables from the replicated paper, as discussed above. These modifications ensure a fair comparison between Becker and Ivashina's (2014) sample and ours. Importantly, our data is limited to a minimum date of 1997Q2, which is reduced to 1997Q4 after filtering, so we cannot exactly replicate the 1990-2010 range. Sample 2 builds on the first sample by extending the time series from 1997Q4 to 2020Q2, through which we confirm whether the relationship examined in the replicated paper holds out of sample. Crucially, if this is not the case, attempting to explain the loan-to-bond substitution through banks and nonbanks would be futile. The third and fourth samples, spanning from 1997Q4 to 2020Q2, address our primary research question of whether the cyclicality of the credit supply, as identified through the substitution between bonds and loans, is driven by nonbanks or banks. Specifically, Sample 3 tests a dummy dependent variable indicating the substitution of bank loans for bonds. If the regression coefficients are smaller and/or less significant than those in our Sample 2 regressions, this would imply that bank lending is less influential in driving credit supply cyclicality. Conversely, Sample 4 uses a dummy variable indicating a nonbank loan to bond substitution. If the coefficients are larger and/or more significant compared to Sample 2, this would indicate that nonbank loans are indeed the primary driver of credit supply cyclicality. Additionally, we interact each of the main independent variables with a nonbank-loan usage indicator, separating the effects on firms that never used nonbank loans in the sample from those that did. We do so to explore whether firms that depend on nonbank lending exhibit amplified sensitivity to credit availability.

1.3. Summary of findings

Our results highlight several important findings. First, we confirm that the loan-to-bond substitution mechanism remains robust out of sample. By separating bank and nonbank loans, we find that loan substitution is not equally driven by bank and nonbank lenders. Second, bank lending exhibits relative stability across the credit cycle, showing limited responsiveness to changes in credit market conditions. In contrast, nonbank lending appears significantly more cyclical. Third, we document significant firm-level heterogeneity: only firms with prior reliance on nonbank loans respond strongly to deteriorating credit conditions, while firms reliant on banks do not adjust their debt choice as strongly. These findings help resolve conflicting views in the existing literature.

1.4. Related literature

The tension in the literature that our research addresses, regarding credit supply cyclicality, centers on distinguishing between bank credit and nonbank credit. In their baseline results, Becker and Ivashina (2014) compare term loans to bonds, without distinguishing between bank and nonbank loans. As a result, they interpret cyclical fluctuations in the loan market as driven by banks while neglecting nonbank loans. This perspective of bank credit cyclicality is validated by the fact that in the Global Financial Crisis (GFC), banks increased assets, dollar for dollar with debt, holding their equity "sticky", making bank leverage highly procyclical, and leading firms to increase bond issuance as a result of lower bank lending (Adrian et al., 2012). Nevertheless, the syndicated loan market encompasses both banks and nonbank lenders, and it is worth noting the latter's increasing presence, with the share of outstanding syndicated loans from nonbanks rising to 46% in 2022, compared to 22% and 43% in 2001 and 2007, respectively (Fleckenstein et al., 2025).

Consequently, the opposing view in the literature, detailed in Fleckenstein et al. (2025), emphasizes the relative stability of bank lending, which is attributed primarily to stable government support during economic downturns. Instead, they document significant cyclicality in nonbank lending, noting its heightened sensitivity to shifts in aggregate credit supply proxied through the EBP (Gilchrist and Zakrajšek, 2012). This finding is supported by Adrian et al. (2013), who highlight nonbanks' susceptibility to investor-driven liquidity runs due to the absence of government-backed liquidity and credit backstops. Similarly, Irani et al. (2021) identify greater cyclicality in nonbank lending, particularly evident during the Global Financial Crisis when nonbanks withdrew lending.

Our main contribution to the literature is to resolve the identified tension by explicitly distinguishing bank and nonbank lending cyclicality within the syndicated loan market. Initially, our thesis confirms the robustness of Becker and Ivashina's (2014) baseline regression results within an extended timeframe. Subsequently, we investigate the cyclicality of bank and nonbank loans separately. Interaction regressions provide additional empirical evidence highlighting that firms dependent on nonbank financing are more sensitive to credit frictions. Therefore, this thesis advances the current literature by distinguishing between the roles and cyclicality patterns of banks and nonbanks, reconciling previously conflicting findings in the literature, and enhancing our broader understanding of lending dynamics. Finally, our research expands the set of indicators as proxies for economic-wide credit supply by adding the VIX index and the EBP from Gilchrist and Zakrajšek (2012), thereby strengthening the robustness of the original methodology and capturing nuances from these new indicators.

The remainder of the thesis is structured as follows: Section 2 provides an overview of the data; Section 3 outlines the methodology; Section 4 presents the empirical results; and Section 5 concludes.

2. Data

The regressions are run on four sample variations, based on a quarterly panel dataset of firm-level accounting data sourced from Compustat, which is filtered to include only U.S. non-financial firms. In parallel, we retrieve two debt data sets: a quarterly loan panel data set from DealScan, spanning the time range of 1982Q2 to 2020Q3, and a bond data set from Thomson One Banker, which covers the period from 1997Q1 to 2023Q3. To match the loan data from DealScan with the Compustat data, we use the latest DealScan-Compustat link file provided by Chava and Roberts (2008). Similarly, we link the Compustat file with Thomson One Banker using the link file provided by Fang (2024). In our final linked dataset, for each firm and respective quarter (firm-quarter), we indicate whether a bond, loan, bank loan, or nonbank loan exists in the debt datasets via four Boolean variables. We classify bank loans as Term Loan As, Other Loans, or Capex Facilities, and we categorize nonbank loans as Term Loan B-Ks. This classification logic is used by practitioners (see, e.g., S&P Global Ratings, 2020) and in prior literature (Fleckenstein et al., 2025; Ivashina and Sun, 2011). Next, we filter firm-quarters with no debt issuance. By design, the resulting sample only includes firm-quarters with positive demand for debt from 1997Q1 to 2020Q3, as shown by the dotted lines in Figure 1.

2.1. Replication data comparison

Given that we revisit Becker and Ivashina's (2014) benchmark regressions, it is important to compare their dataset with ours for consistency. Our sample of U.S. non-financial firms from 1997Q1 to 2020Q3 yields 5,867 unique firms and 30,904 firm-quarters, which compares to 4,000 firms and 21,053 firm-quarters in the time horizon from 1990Q2 to 2010Q4, as reported in Becker and Ivashina (2014). Table 1 provides a more detailed breakdown of the firm-quarter observations between the two samples: both have similar proportions of bonds and loans, with approximately 2/3 of the firm-quarters containing bond issuances, 2/5 loan receipts, 2/10 nonbank loan receipts, and 3/10 bank loan receipts.

Comparing the loan and bond principals in our sample to the figures reported by Becker and Ivashina (2014), we find that bond principals have a mean of $414 million and a median of $256 million in our sample. These figures are 1.75 times and 1.46 times, respectively, greater than the mean of $236 million and median of $175 million reported in Becker and Ivashina (2014) (see Table 2). Similarly, the loan amounts in our sample are also larger. We obtain a mean loan principal amount of $645 million and a median amount of $250 million, compared to a mean of $356 million and a median of $100 million in Becker and Ivashina (2014). Within the loan sample, the average principal amount of nonbank loans is 1.80 times higher at $641 million than that of bank loans, which is $357 million. This finding is in line with Fleckenstein et al. (2025), who also note relatively higher average credit volumes for nonbanks. This points to a higher concentration of debt deployment per firm among nonbank lenders compared to bank lenders. The nonbank lenders in our sample face a greater risk of firm default than the bank lenders in absolute terms, as the former have a greater amount of principal at risk per firm. Default risk is also found to be a significant driver of credit cyclicality: "Intuitively, when default risk is high, insured bank liabilities become more attractive and banks lend more. As default risk falls, nonbank liabilities become more attractive and nonbanks lend more"

(Fleckenstein et al., 2025). This gives rise to an identification challenge, as we aim to analyze cyclicality in the supply of bank and nonbank lending in isolation from credit risk. However, including firm-level control variables correlated with credit risk, such as Log (Assets), Log (PP&E), ROA, and Leverage, should reduce the influence of credit risk to a meaningful extent.

2.2. Definition of regressors

The sample described above is used as a base for each of the four sample variations discussed in the Methodology section. In each sample, a binary dependent variable captures a firm's financing choice between bonds and loans within a given quarter during which that firm has a positive demand for debt. The dependent variable is regressed on seven independent variables in seven distinct regressions. The independent variables considered are proxies for aggregate credit conditions. Five of the independent variables are from Becker and Ivashina (2014), namely, i) the tightening in lending standards measured by the Senior Loan Officer Opinion Survey (SLOOS); ii) the aggregate lending growth, computed as a four-quarter growth in the total of corporate bonds, commercial paper, bank loans, and other loans; iii) the loan allowances ratio, as the weighted average of U.S. banks' loan allowances vs. total loans; iv) a bank stock-index[1]; and v) a monetary policy shock variable, computed as the difference between the Fed Funds Rate and the Taylor Rule (Taylor, 1993). We contribute two additional independent variables to the regression analysis: vi) the VIX index, as a measure of market uncertainty; and vii) the EBP, from Gilchrist and Zakrajšek (2012), which measures the difference between

[1] We compute the bank stock-index as a market capitalization-weighted index of the stock price performance of 16 banks that are consistent with the bank sample considered by Becker and Ivashina (2014). These include: Bank of America Corp, Bank of New York Mellon Corp, Citigroup Inc, Comerica Inc, Fifth Third Bancorp, JPMorgan Chase & Co, KeyCorp, National City Corp, PNC Financial Group Inc, Regions Financial Corp, SunTrust Banks Inc, Truist Financial Corp, Toronto Dominion Bank, US Bancorp, Wells Fargo & Co, and Wachovia Corp. We also note that National City Corp was acquired by PNC Financial Services Group on 24/10/2008; SunTrust Banks Inc merged with BB&T to form Truist Financial Corp on 06/12/2019; and Wachovia Corp was acquired by Wells Fargo & Co on 31/12/2008.

corporate bond spreads and expected credit losses. Only for Sample 1, in which we replicate Becker and Ivashina's (2014) benchmark regressions, do we include the monetary policy variable to remain consistent with their regression specification. This variable is a reduced-form residual lacking a structural foundation, which makes it vulnerable to endogeneity and measurement error. As Coibion (2012) highlights, such ad hoc measures may not accurately isolate exogenous monetary policy shocks. Notably, we also exclude the ratio of non-performing loans to total loans variable included in Becker and Ivashina (2014) due to limited data availability. Regarding data sources, the EBP, the VIX index, the loan allowances ratio, the bank stock index, and the monetary policy variable were obtained from Bloomberg L.P. (2025), whilst the tightening in lending standards and aggregate lending growth variables were obtained from the Federal Reserve Bank of St. Louis (2025).

The seven independent variables can be categorized as either positively or negatively correlated with worsening credit conditions. Figure 2 illustrates the five positively correlated variables – namely, the VIX index, EBP, loan allowances ratio, tightening in lending standards, and monetary policy – from 1997 to 2020, in terms of their Z-scores. The grey bars indicate the Dot-com bubble, the GFC, and the COVID-19 crisis. In times of economic uncertainty and credit cycle downturns, credit availability is assumed to tighten. This can be demonstrated, for example, through the VIX spiking, as volatility increases in uncertain market environments. Notably, the VIX and EBP are the most reactive measures, with more acute spikes, compared to the other variables. This can be explained by the former two being forward-looking, market-based measures that reflect information and expectations in real time. Accordingly, the VIX and EBP are also among the most volatile variables considered. Given their visible positive correlation with "bad times", one should expect these independent variables to have negative coefficients in our regressions. That is to say, an increase in these variables is expected to increase the probability of loans being substituted with bonds.

Figure 3 shows the two variables that are expected to be negatively correlated with worsening credit conditions, namely the bank stock-index and aggregate lending growth, from 1997 to 2020, in terms of their Z-scores. During recessions, both readings drop. The bank stock-index appears to be more reactive, which is to be expected given it is a market-based measure and the banks' stock prices incorporate expected future profits into the current price. Given their past development, one should expect both variables to post a positive coefficient in our regressions. That is to say, an increase in these two variables is expected to decrease the probability of loans being substituted with bonds.

Before regressing the debt-choice variable on our independent variables, firm-demand for debt must be ensured. Accordingly, we filter out all firm-quarters during which no bond or loan issuance is recorded. This allows us to interpret a loan-for-bond substitution as an isolated shift in credit supply, whilst holding demand for debt fixed. Additionally, we control for firm-level compositional changes that could affect the perceived riskiness of a borrowing firm and/or influence financing demand. This is achieved by including four time-varying firm-level control variables, consistent with Becker and Ivashina (2014). The data used to compute the control variables is sourced from Compustat. The control variables include i) the log of the previous quarter's assets; ii) the log of the previous quarter's property, plant, and equipment, as a measure for collateral value; iii) the return on assets (ROA), computed as EBITDA over the previous quarter's total assets; and iv) the leverage ratio of long-term debt to total assets (lagged one quarter). An additional three control variables are included only in our replication sample (Sample 1) from 1997 to 2010, namely, i) the previous quarter's market-to-book ratio; ii) the one-year lagged stock price return[2]; and iii) a dummy variable indicating whether a firm paid a dividend in a given quarter. These control variables are typically only observable for public

[2] This measure is computed by subtracting the five-quarter lagged log stock price from the one-quarter lagged log stock price.

companies. Since not all firms in the Compustat sample are publicly listed, we exclude said variables from our set of control variables in Samples 2-4 to reduce the loss of observations due to missing variable values.

2.3. Definition of filters

We apply seven filters between our starting Compustat sample and our regression sample. The first three filters exclude: i) financial firms (SIC codes from 6000 to 6999); ii) non-U.S. firms; and iii) firm-quarters where no debt issuance was recorded. Fourth, we restrict the sample to firms that have issued a bond within the past five years, thereby eliminating non-switchers or firms with no access to the bond market, and reducing our coefficient biases. Fifth, in order to consider only loan-to-bond substitutions, we exclude quarters in which a firm issues both a bond and a loan. Sixth, we filter for missing regressor values. Seventh, we filter for data within the range of 1997Q2 to 2020Q3, which results in a final sample spanning from 1997Q4 to 2020Q2. Notably, after all the filters are applied, the minimum date is 1997Q4, which is later than 1997Q2, and the maximum date is 2020Q2, which is earlier than 2020Q3. This is due to the sixth filter. The waterfall diagram in Figure 4 illustrates the evolution of Sample 2 by filter, starting from U.S. non-financial firms with a positive demand for debt, and ending with 11,202 firm-quarter observations. Sample 3 additionally excludes nonbank debt, resulting in 10,077 observations. Similarly, Sample 4 excludes bank debt, resulting in 9,896 firm-quarters. Finally, Sample 1 is the most constrained, as we apply a date filter ranging from 1997Q1 to 2010Q4 and must account for more regressor variables with missing data. This results in a total of 5,035 observations.

As shown in Table 3, 80.6% of the observations in Sample 2 record bond issuances; 9.4% record only bank loan receipts; 7.7% record only nonbank loan receipts; and 2.3% record both bank and nonbank loan receipts in the same quarter. We should note that there is an overlap of bank and nonbank lending, as was also noted in Fleckenstein et al. (2025).

It is also important to note that only a single loan issuance observation is recorded, irrespective of the number of facilities issued by a firm in a given quarter. Nevertheless, it is insightful to examine the distribution of facility types that underpin the firm-quarter debt issuance observations, as illustrated in Table 4. In firm-quarters featuring only bank loan receipts, Term Loans account for 27.53% of issuances, while Term Loan A facilities represent 22.27%. Conversely, nonbank firm-quarters are driven by Term Loan Bs, making up 42.59% of the total loan firm-quarters. The facilities with the most simultaneous bank and nonbank loan issuances were Term Loan Bs, followed by Term Loan As. These figures are consistent with existing literature that documents the predominance of banks as primary holders of Term Loan As, while nonbank entities are predominant holders of Term Loan Bs (Blickle et al., 2020).

2.4. Possible data limitations

While the distinction between banks and nonbanks improves our analysis of the credit cycle, it is important to acknowledge the limitations of this approach. Firstly, the classification of bank and nonbank loans by facility labels (Term Loan A, Other Loans, Capex Facility vs. Term Loan B-K) assumes uniform adherence to industry conventions. Excluding specific debt types, such as securitizations, mezzanine, and unitranche financing, removes important sources of debt capital that vary cyclically. To remedy this, we could extend the definition of bank and nonbank loans to include securitizations, mezzanine financing, and unitranche loans. Second, although firm control variables are included, excluding debt contract details (e.g., covenants and debt maturity) might exclude important demand-side factors, biasing the estimated cyclical effects. An extension of our research could include these debt-specific details as control variables. Third, the filtered loan and bond datasets exhibit, on average, relatively high principal amounts of $645 million and $414 million, respectively, as shown in Table 2. This suggests that smaller firms or transactions are likely underrepresented in our sample, which limits the generalizability of the findings. Similarly, excluding firms that have not issued a bond within the last 5 years excludes new entrants. This biases the sample towards financially stronger firms that are less likely to switch. To make the results more robust, future studies could use a shorter window or filter for firms and transactions below a specific value.

3. Methodology

As stated earlier, we run regressions on four distinct samples. We use the first two samples to replicate the results of Becker and Ivashina (2014) out of sample, confirming their robustness. Samples 3 and 4 are used to distinguish the impact of bank vs. nonbank loan substitution into bonds, challenging the latter paper's conclusion that credit-supply shocks are driven by banks and highlighting whether nonbanks play a significant role.

The identification mechanism works as follows: when the supply of bank or nonbank credit is low, firms issue bonds because, in such a scenario, these are comparatively cheaper and more accessible than loans. The revealed choice of debt serves as a proxy for the variation in the supply of credit when controlling for demand. Nonbank loans are associated with a higher level of risk since nonbank issuers are not subject to the same risk-mitigating regulatory requirements as banks. Consequently, nonbank-financed deals constitute a more volatile proportion of credit, and therefore, nonbank lending can be assumed to be more cyclical than bank lending. However, as mentioned in Section 2, we control for firm-level characteristics that could influence credit demand and credit risk, thus largely isolating the supply-side effects of cyclicality in banks vs. nonbanks.

3.1. Replication

Sample 1. This sample encompasses quarterly time series panel data from 1997Q4 to 2010Q4. This time frame best aligns with the sample period of the benchmark regressions in Becker and Ivashina (2014). These regressions examine the probability of firms taking out a loan rather than a bond, given a positive demand for credit, as a function of credit conditions. Evidently, we are not utilizing the same sample period from 1990 to 2010 as was employed by Becker and Ivashina (2014). Notwithstanding this discrepancy, the sample statistics relating to debt sizes are comparable to those documented by Becker and Ivashina (2014). The mean and median bond principal sizes in our sample exceed their recorded values by factors of 1.22 and 1.00, respectively, while the mean and median loan principal sizes surpass their recorded values by factors of 1.25 and 1.50, respectively. We run OLS regressions with standard errors clustered by quarter to correct for any correlation of residuals within the same quarter. Following Becker and Ivashina (2014), the substitution of bonds for loans is expressed via the following equation:

$$(1) \qquad D_{it} = c_i + \beta B_t + \gamma X_{it} + e_{it}$$

- The dependent variable D_{it} is a binary indicator that equals 1 if firm *i* raises a loan in a given quarter *t* and 0 if firm *i* issues a bond in quarter *t*.
- c_i accounts for firm fixed effects and absorbs time-invariant firm characteristics.
- B_t is a set of time-varying aggregate credit condition proxies indicating either a tightening or expansion of lending among banks and nonbanks.
- X_{it} is a set of time-varying firm-specific control variables.
- β captures how changes in credit supply conditions affect the probability of issuing loans vs. bonds, given a positive firm demand for credit.

Our replication directly tests the core relationship examined by Becker and Ivashina (2014): a contraction in the supply of bank credit causes firms to switch from loans to bonds, holding credit demand constant by conditioning on new debt issuance. In later regressions, however, we differentiate between bank and nonbank credit supply by splitting the initial sample. Therefore, our refined core hypothesis is as follows: a contraction in credit supply causes firms to switch from loans to bonds. Later regressions on Samples 3 and 4 will further examine which type of lender (bank vs. nonbank) plays a greater role in this relationship.

Adding firm-fixed effects removes cross-sectional differences between firms from the study, which might otherwise influence the choice between bonds and loans. The resulting regression specification explains why a given firm's deviation from its mean varies over time. Mathematically, each firm's average value of the dependent variable ($\overline{D}_i$) is subtracted from each firm-quarter's dependent variable observation (D_{it}).

Sample 2. In Sample 2, we test the same relationship as above, but on an extended time horizon from 1997Q4 to 2020Q2. The purpose of these regressions is to test the robustness of the benchmark regressions out-of-sample. Nevertheless, due to the limited minimum date of our bond sample (1997Q4), our sample from 1997 to 2020 is only three years longer than Becker and Ivashina's (2014) sample from 1990 to 2010. Still, we have the added benefit of incorporating several major credit shocks, including the Dot-com crash, the GFC, and the COVID-19 pandemic. Thus, with the regressions in Sample 2, we are testing whether the same credit condition variables that mattered from 1990 to 2010 can still explain firm debt choices over an extended period.

3.2. Differentiating between bank and nonbank loans

Sample 3: In Sample 3, we consider the same time period from 1997Q4 to 2020Q2 as we did in Sample 2, but we exclude nonbank loans from the sample. Thus, we only test for the substitution of bonds for bank loans. For the regressions run on Sample 3, the dummy variable D_{it} equals 1 if firm i raises a bank loan in quarter t and 0 if firm i issues a bond in quarter t. Here, we examine whether the shift from loans to bonds is driven by bank loan supply. If the β coefficients of the regressions run on Sample 3 are smaller in magnitude or less significant than those of the regressions run on Sample 2, this would suggest that nonbanks were partially responsible for the substitution between loans and bonds. Conversely, if the coefficients remain stable and significant, the evidence will support the bank-driven narrative of Becker and Ivashina (2014).

Sample 4. In Sample 4, we again consider the time period from 1997Q4 to 2020Q2, however, this time we exclude bank loans from the sample. Thus, in this sample, the dummy variable D_{it} equals 1 if firm i raises a nonbank loan in quarter t and 0 if firm i issues a bond in quarter t. The regressions in Sample 4 address the core contributions of Fleckenstein et al. (2025), who argue that nonbank lenders (e.g., CLOs and credit funds) are more sensitive to aggregate shocks and that their lending behavior exacerbates the cyclical nature of credit. Suppose the β factors of the independent variables are larger in magnitude or more significant than those of the regressions run on samples 1-3. In that case, this suggests that nonbanks are more relevant in explaining the substitution of loans with bonds. Conversely, if both bank and nonbank loans react similarly to macro conditions, this suggests converging behavior or coordination in lending cycles.

Interaction regressions. To identify the difference in the effect of credit supply shocks on the lending behavior of firms that rely on nonbank lending, compared to those that do not, we run additional regressions, this time interacting the independent variables with an indicator variable indicating whether a given firm *i* uses nonbank loans. We run said regressions on the Sample 2 data from 1997 to 2020. The equation for these regressions is defined below:

$$(2) \qquad D_{it} = c_i + \beta_1 B_t + \beta_2 (B_t \cdot N_i) + \gamma X_{it} + \epsilon_{it}$$

- The dependent variable D_{it} is a binary indicator that equals 1 if firm *i* raises a loan in a given quarter *t* and 0 if firm *i* issues a bond in quarter *t*.
- c_i accounts for firm fixed effects and absorbs time-invariant firm characteristics, including whether a firm has used nonbank loans.
- B_t is a set of time-varying aggregate credit condition proxies indicating either a tightening or expansion of lending among banks and nonbanks.
- N_i is equal to 1 if firm *i* used a nonbank loan at any point in the sample period.
- X_{it} is a set of time-varying firm-specific control variables.
- β_1 captures how changes in credit supply conditions affect the probability of issuing loans vs. bonds for firms that never used nonbank loans, given positive firm demand for credit.
- β_2 captures the difference in effect of changes in credit supply conditions on the probability of issuing loans vs. bonds for firms that have used nonbank loans in the sample compared to those that never used nonbank loans, given positive firm demand for credit.

Applying the interaction term quantifies the firm-level heterogeneity in the reaction to a tightening of the credit supply, testing the hypothesis that firms relying on nonbank lending are more likely to switch to bonds compared to firms relying on bank loans. The coefficient β_1 measures the impact of credit tightening on firms that have never taken out nonbank loans in the sample (N_i = 0). The coefficient β_2 measures the incremental difference in responsiveness to credit supply shocks for nonbank loan-dependent firms (N_i = 1) compared to bank loan-dependent firms. Finding negative and significant β_2 coefficients in regressions with independent variables B_t indicating credit tightening (tightening in lending standards, loan allowances, VIX index, EBP) would suggest that firms that rely on nonbank lending are more likely to switch to bond issuances during economic downturns. This would provide further evidence for the higher cyclicality of nonbank credit compared to bank credit, as suggested by Fleckenstein et al. (2025). The same conclusion can be drawn when finding positive and significant β_2 coefficients in regressions with independent variables B_t indicating credit expansion (aggregate lending growth, bank stock-index).

3.3. Possible methodological limitations

As outlined in the Data section, the methodology has several key assumptions and evaluation points that should be considered. First, the regressions assume the substitutability of bonds and loans, as well as bank loans and nonbank loans. Second, nonbank lending is also assumed to be homogeneous, whereas nonbank lenders differ significantly in risk profiles and cyclicality. For example, CLO lenders have their positions marked more frequently than private credit funds. Future research could disaggregate nonbank lending further to distinguish between CLOs, hedge funds, private credit, mutual funds, insurance companies, pension funds, broker-dealers, and finance companies, as per Irani et al. (2021). Finally, the interaction variable N_i in the interaction regressions may exclude temporal shifts in firm-lender relationships and evolving lending behavior, as it compares historic lending behavior. A potential remediation could be to use a rolling variable with a five-year window.

4. Results

4.1. Replication results

Tables 5 and 6 present the results of regressions performed on Sample 1. Table 6 shows the results of the same regressions as in Table 5 but run on Z-score normalized data. Sample 1, spanning from 1997 to 2010, is the most similar to the sample from 1990 to 2010 on which Becker and Ivashina (2014) run their regressions. Column 1 shows the regression results with the net percentage of loan officers reporting a tightening of credit standards as the independent variable. Opposed to Becker and Ivashina (2014), we do not find a significant relationship between tightening in lending standards and the probability of a firm receiving a loan conditional on securing debt financing. Column 2 presents the results of the regression with aggregate lending growth as the main independent variable. We find that a one standard deviation increase in aggregate lending growth increases the probability of a firm receiving a loan by 3.4 percentage points with a 1% significance level. This result is broadly in line with Becker and Ivashina (2014), who find a 2.4 percentage point increase at a 1% significance level. Column 3 presents our regression results, with loan allowances as the main independent variable. Here, our results are also in line with Becker and Ivashina (2014). We find a one standard deviation increase in loan allowances to decrease the probability of a firm receiving a loan by 3.4 percentage points with a 1% significance level, while Becker and Ivashina (2014) find a 3.6 percentage point decrease with a 1% significance level. In column 4, we show the regression results for the forward-looking bank stock-index as the main independent variable. We find similar results to Becker and Ivashina (2014), with a one standard deviation increase in the bank stock-index predicted to increase the probability of a firm receiving a loan by 2.7

percentage points with a 1% significance level according to our regression, while Becker and Ivashina (2014) find a 3.1 percentage point increase with a 1% significance level. For unexpected tightening in monetary policy as the main independent variable (column 5), we find no significant relationship with the probability of a firm receiving a loan. In contrast, Becker and Ivashina (2014) find that a one standard deviation increase in this measure leads to a 2.7 percentage point decrease in the fraction of banks receiving a loan with a 1% significance level. In addition to the independent variables considered by Becker and Ivashina (2014), we follow Fleckenstein et al. (2025) and include the VIX index and the EBP as further measures of tightening credit conditions. We indeed find a negative relationship between the VIX index and the probability of a firm receiving a loan, conditional on the firm receiving debt financing. According to our results, a one standard deviation increase in the VIX index decreases the likelihood of a firm receiving a loan by 1.8 percentage points at a 5% significance level. For the EBP, however, we find no statistically significant relationship in Sample 1.

Having run regressions on Sample 1 (1997-2010), we extend the timeframe to 1997-2020 for Sample 2, as shown in Table 7. This enables us to ascertain whether the relationships between the measures considered in Sample 1 and the probability of a firm receiving a loan, given positive demand for credit, remain intact within an extended timeframe encompassing the post-GFC years.

Like in the regressions run on Sample 1, the measure for tightening in lending standards does not show a statistically significant effect on the probability of a firm receiving a loan. The coefficients of the measures capturing aggregate lending growth and loan allowances retain their 1% significance levels and exhibit similar coefficient magnitudes compared to Sample 1. In Sample 2, the bank stock-index no longer shows a statistically significant relationship with the proportion of firms receiving a loan. In Sample 1, however, we found the relationship to be significant at the 1% level. This suggests that the bank stock-index has less explanatory power post-GFC. The VIX index continues to demonstrate a negative relationship with the fraction of firms receiving a loan in Sample 2, which retains the same 5% significance level as in Sample 1. Like in Sample 1, we find no statistically significant effect for the EBP.

The results of the regressions run on Samples 1 and 2 confirm that lending conditions play a significant role in explaining the substitution between bonds and loans, with aggregate lending growth, loan allowances, and the VIX index all exhibiting a statistically significant relationship in the expected direction in both samples.

However, these regressions do not address the question of whether the substitution from loans to bonds is driven by a contraction in bank lending, as suggested by Becker and Ivashina (2014). In fact, Fleckenstein et al. (2025) suggest that bank lending is relatively stable compared to nonbank lending as banks receive substantial government support in “bad times”. To address this tension, we first split Sample 2 into a sample considering only bank loans (Sample 3) and a sample considering only nonbank loans (Sample 4).

4.2. Results when differentiating between bank and nonbank loans

Figure 5 shows the share of observations of bank and nonbank loan receipts relative to total debt receipt observations (including bonds), plotted against the VIX index, whilst holding the demand for debt fixed. As can be observed in this figure, nonbank loans do in fact appear to be more cyclical than bank loans. The regression results in Tables 8 and 9 quantify the difference in cyclicality between bank loans and nonbank loans.

Table 8 shows our regression results for Sample 3, considering only bank loan receipts. As can be seen in Table 8, the probability of a firm receiving a bank loan is not significantly affected in the expected direction by most measures of lending conditions. It is no surprise that aggregate lending growth and loan allowances continue to have a statistically significant effect in the expected direction. As aggregate lending growth is a realized measure of lending[3] supply rather than a market-wide sentiment measure, such as the VIX index, it is to be expected that the proportion of firms receiving a bank loan is relatively high when lending supply is high, given that bank loans, as reflected in our sample (see Table 3), still make up a significant proportion of loan supply. Loan allowances, being a bank accounting measure, are a direct proxy for bank credit supply conditions.

However, the forward-looking VIX index and EBP, which capture market-wide sentiment, do not indicate that credit conditions have an adverse impact on bank lending. We find no statistically significant effect for the VIX index, while for the EBP, we find a positive coefficient that is significant at the 10% level. A one standard deviation increase in the EBP is predicted to increase the probability of a firm receiving a bank loan by 0.65 percentage points, even suggesting a slight countercyclicality of bank loan supply.

For Sample 4, containing only observations of nonbank loan receipts, we find strong evidence of nonbank lending being more cyclical than bank lending. As presented in Table 9, all measures of lending conditions exhibit statistically significant effects in the expected direction. Notably, the EBP – a risk aversion indicator reflecting sentiment in the credit market – exhibits a negative relationship with the probability of a firm receiving a nonbank loan, which is significant at the 1% level. By contrast, this relationship is slightly positive for bank lending. The significant effects of the bank-specific measures, loan allowances, and bank stock-index may indicate that banks reduce the origination of nonbank loans in bad times due to pipeline risk, i.e., the risk of banks being unable to sell all the nonbank loans they originate (Bruche et al., 2020).

[3] Aggregate lending growth is computed as the four-quarter growth in the total of corporate bonds, commercial paper, bank loans, and other loans.

To quantify the difference in cyclicality of bank lending vs. nonbank lending, we interact the previously examined measures of credit conditions with the indicator variable N_i, which equals 1 if a firm ever used a nonbank loan in the sample and 0 otherwise. The rationale is that firms relying on nonbank lending ($N_i = 1$) should be more prone to substitute loans for bonds in times of deteriorating credit conditions. The results of the interaction regressions are shown in Table 10.

For aggregate lending growth and loan allowances, we find that the coefficients of both the main effects and the interaction terms are statistically significant at the 1% level. This suggests that these measures significantly impact the lending behavior of firms that have and have not used nonbank loans in the sample. Regarding aggregate lending growth, we find that, conditional on positive demand for credit, firms that have used nonbank loans are 4.0 percentage points more likely to receive a loan than firms that have never used nonbank loans, given a one-standard-deviation increase in aggregate lending growth. For loan allowances, we find that firms that have used nonbank loans are 5.9 percentage points less likely to receive a loan than firms that have never used nonbank loans, given a one standard deviation increase in loan allowances. For tightening in lending standards, the bank stock-index, the VIX index, and the EBP, we find no statistically significant main effect. This suggests that firms in the sample that never used nonbank loans do not change their lending behavior in a statistically significant way in response to the examined credit supply shocks. By contrast, firms that have used nonbank loans are significantly more likely to substitute bonds for loans in response to tightening in lending standards, a decrease in the bank stock-index and increases in the VIX index and EBP.

In summary, our findings provide strong evidence that the cyclicality of credit supply is mainly driven by nonbank lenders, as evident in the comparison of regression results between Samples 3 and 4. Furthermore, we observe an elevated degree of sensitivity among firms reliant on nonbank lending with respect to the substitution of loans for bonds during periods of deteriorating credit conditions, as evidenced by the outcomes of our interaction regressions.

5. Conclusion

This thesis revisits the substitution mechanism detailed by Becker and Ivashina (2014) and extends their analysis through to 2020, and importantly, distinguishes loan supply from nonbanks and banks to reflect the evolving composition of lenders. Accordingly, we aim to determine whether the cyclicality of the credit supply, analyzed through the substitution between bonds and loans, is driven by traditional banks or the increasingly influential nonbank lending sector. Our main finding is that the cyclicality of credit supply, measured by the substitution of loans for bonds while holding demand fixed, is mainly driven by nonbank lenders, whereby firms reliant on nonbank credit are more sensitive to credit conditions and switch to bonds more frequently when credit becomes scarce. In light of these findings, we can reject the interpretation of Becker and Ivashina (2014) that a contraction in the supply of bank credit mainly causes firms to replace loans with bonds. In fact, our findings suggest that the supply of nonbank credit has greater explanatory power over the probability of firms receiving a loan. Apart from the central result, we document three additional findings: first, the loan-to-bond substitution mechanism remains robust in an extended sample of 1997-2020; second, bank lending shows relative stability and limited responsiveness to the VIX index and the EBP; and third, firm-level heterogeneity matters greatly, as only firms with a history of nonbank borrowing exhibit strong reactions to tightening credit conditions. These results lend weight to the emerging view in the nonbanking literature, namely Fleckenstein et al. (2025), that government-supported banks are relatively more stable than nonbank intermediaries. For policymakers, our findings underscore the need to monitor nonbank activity to manage the credit cycle and related business cycle fluctuations via the “financial accelerator” mechanism.

For researchers, our findings highlight the importance of distinguishing between lender types when examining credit supply. Our study broadens the scope of credit supply research by incorporating a differentiation between banks and nonbanks into the bond-for-loan substitution mechanism. Future research could investigate which regulatory frameworks are most effective in managing nonbank cyclicality.

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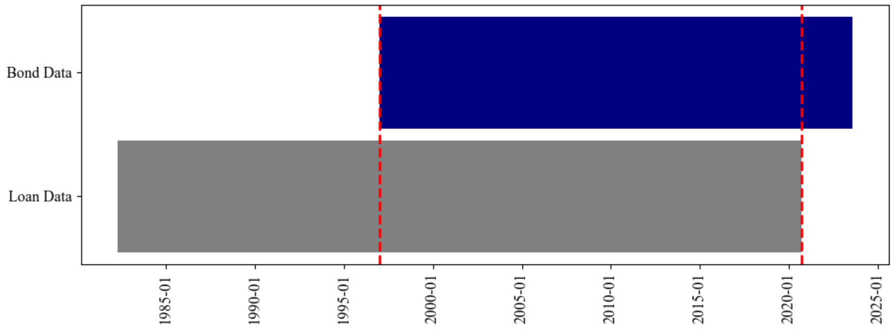
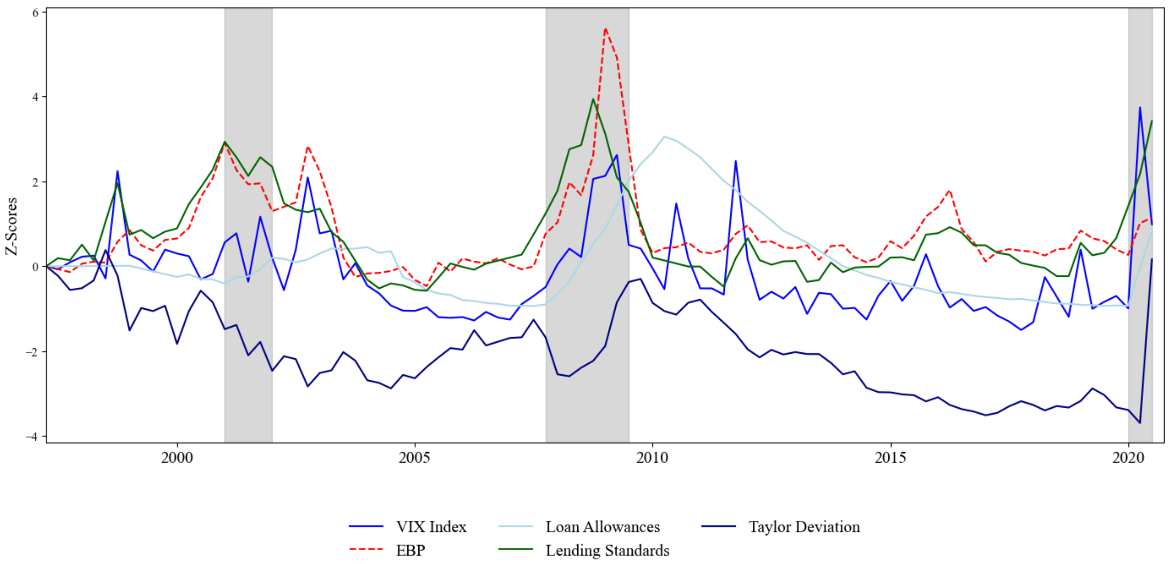
Figures

Figure 1: Sample date range



Note: This figure shows the overlapping date ranges of bond data from Thomson One Banker and loan data from DealScan, when matched with our sample of U.S. non-financial firms with positive demand for debt. The resulting range is 02/01/1997 to 10/09/2020 (1997Q1-2020Q3). To match the loan data from DealScan with the Compustat data, we use the latest DealScan-Compustat link file provided by Chava and Roberts (2008). Similarly, we link the Compustat file with Thomson One Banker by using Fang (2024).

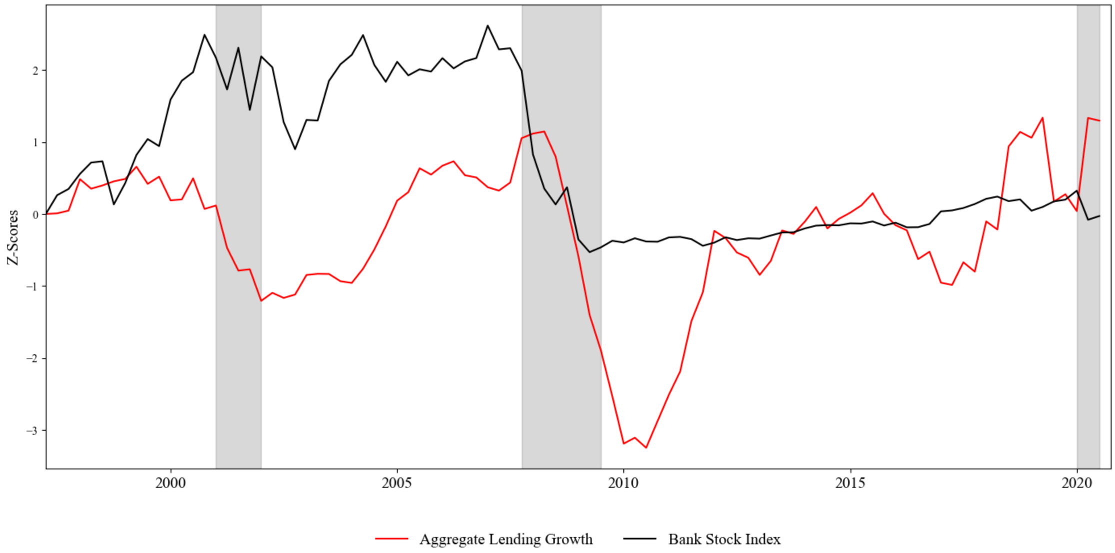
Figure 2: Independent variables with positive correlation to economic downturns



Note: This figure shows five Z-score normalized independent variables, with a date range of 1997Q1-2020Q3. The independent variable sample is before filters are applied. The VIX index, Loan Allowances, and Taylor Deviation are sourced from Bloomberg L.P. (2025). Specifically, the Loan Allowances ratio is the quarterly weighted average of bank loan allowances to total loans ratio of 16 U.S. banks[4]. The Taylor Deviation is defined as the difference between the Fed Funds Rate and the Taylor Rule (Taylor, 1993). The EBP is from Gilchrist and Zakrajšek (2012). The Lending Standards variable comes from the Federal Reserve Bank of St. Louis (2025). The grey bars indicate the Dot-com bubble (2001Q1-2001Q4), the GFC (2007Q4-2009Q2), and the COVID-19 crisis (2020Q1-2020Q2).

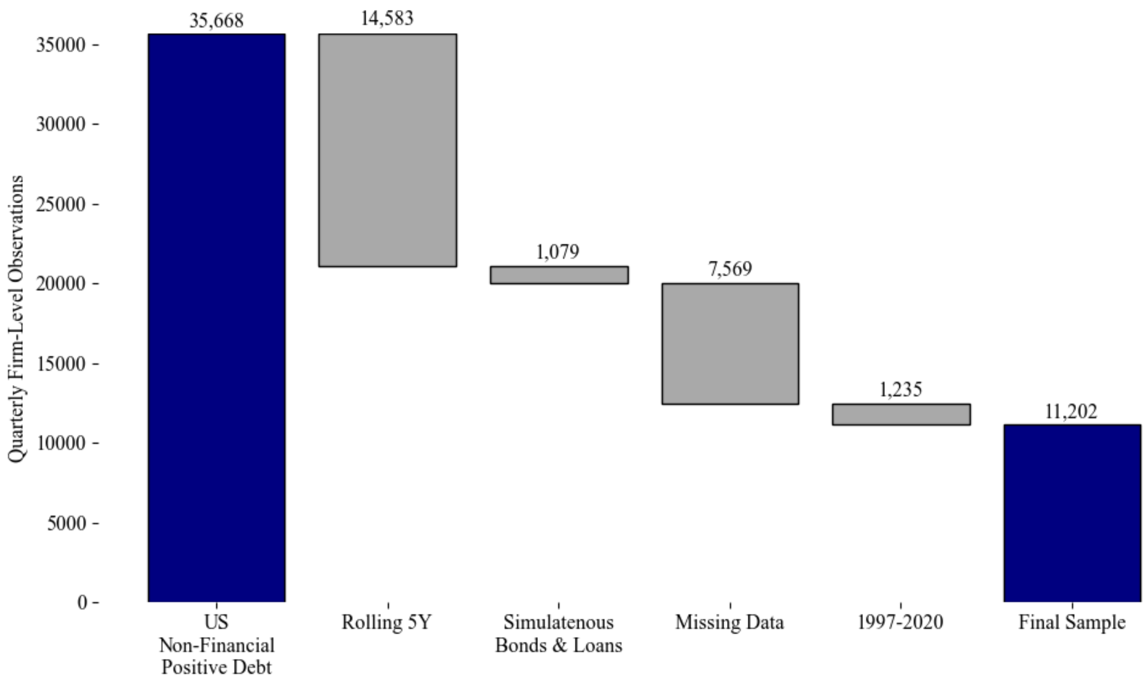
[4] Bank of America Corp, Bank of New York Mellon Corp, Citigroup Inc, Comerica Inc, Fifth Third Bancorp, JPMorgan Chase & Co, KeyCorp, National City Corp, PNC Financial Group Inc, Regions Financial Corp, SunTrust Banks Inc, Truist Financial Corp, Toronto Dominion Bank, US Bancorp, Wells Fargo & Co, and Wachovia Corp.

Figure 3: Independent variables with negative correlation to economic downturns



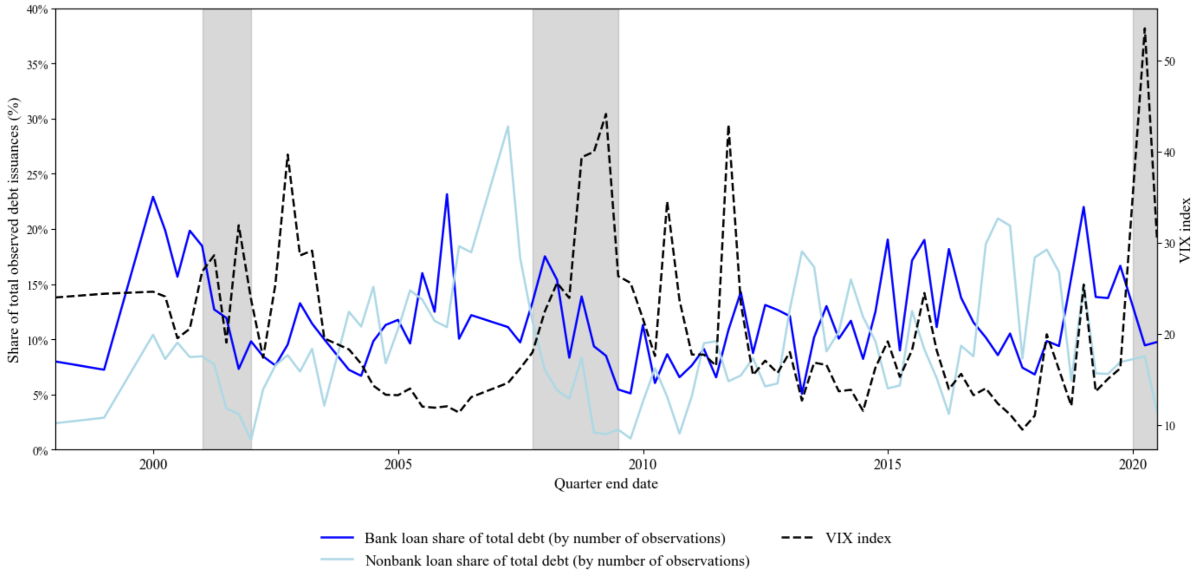
Note: This figure shows two Z-score normalized independent variables, with a date range of 1997Q1-2020Q3. The independent variable sample is before filters are applied. The bank stock-index is computed as the quarterly weighted average stock price of the 16 U.S. banks (see description of Figure 2), taken from Bloomberg L.P. (2025). The aggregate lending growth is the four-quarter total growth of corporate bonds, commercial paper, bank loans, and other loans from the U.S. Flow of Funds Accounts, sourced from the Federal Reserve Bank of St. Louis (2025). The grey bars indicate the Dot-com bubble (2001Q1-2001Q4), the GFC (2007Q4-2009Q2), and the COVID-19 crisis (2020Q1-2020Q2).

Figure 4: Filters waterfall of main sample (1997Q4 – 2020Q2)



Note: This figure shows the filtering evolution for Sample 2. We initially filter for US non-financial firms with positive debt, regardless of the date range. The final sample is filtered by date between 1997Q1 and 2020Q3, which results in a final date range of 1997Q4 to 2020Q2. This is driven by missing regressor values, resulting in a final date range being shorter than the 1997Q1 to 2020Q3 filter.

Figure 5: Shares of bank and nonbank loans of total debt vs. VIX index



Note: This figure shows the share of observations of bank and nonbank loan receipts relative to total debt receipt observations, from 1997Q4 to 2020Q2, plotted against the VIX index, whilst controlling for debt demand by excluding firm-quarters with non-positive demand and with simultaneous loan and bond issuances. Debt is defined as the total of bonds, bank loans, and nonbank loans. The VIX index is sourced from Bloomberg L.P. (2025). The loan data is taken from DealScan, and we use the latest DealScan-Compustat link file provided by Chava and Roberts (2008) to match our loan data to our firm-quarter sample from Compustat. Similarly, we link the Compustat file with Thomson One Banker by using Fang (2024). The grey bars indicate the Dot-com bubble (2001Q1-2001Q4), the GFC (2007Q4-2009Q2), and the COVID-19 crisis (2020Q1-2020Q2).

Tables

Table 1: U.S. non-financial firm-quarter observations – counts and percentages

Panel A: Firm-quarter count

Label	1997–2020	Becker & Ivashina 1990–2010
With new debt	30,904	21,053
With new bond debt	19,953	13,237
With new loan debt	12,429	9,458
With new nonbank loan debt	5,574	N/A
With new bank loan debt	8,472	N/A

Panel B: Firm-quarter percentages

Label	1997–2020	Becker & Ivashina 1990–2010
With new debt	100.0%	100.0%
With new bond debt	64.6%	62.9%
With new loan debt	40.2%	44.9%
With new nonbank loan debt	18.0%	N/A
With new bank loan debt	27.4%	N/A

Note: This table shows the count (Panel A) and percentage count (Panel B) of firm-quarters, using three filters to ensure consistency when comparing with Becker & Ivashina (2014). These filters are: firm-quarters of non-financial firms, U.S. firms, and positive demand for debt. The date range spans from 1997Q1 to 2020Q3. We classify bank loans as Term Loan As, Other Loans, or Capex Facilities, and we categorize nonbank loans as Term Loan B-Ks. Debt is defined as the total of bonds, bank loans, and nonbank loans.

Table 2: U.S. non-financial firm-quarter statistics – mean and median (000s USD)

Type	Metric	1997–2020	Becker_Ivashina 1990–2010
Bond	Mean	413,714	236,000
Bond	Median	255,690	175,000
Loan	Mean	645,114	356,000
Loan	Median	250,000	100,000
Bank Loan	Mean	357,165	N/A
Bank Loan	Median	100,000	N/A
Nonbank Loan	Mean	641,382	N/A
Nonbank Loan	Median	330,000	N/A

Note: This table presents sample statistics of bonds and loans matched with the Compustat sample from 1997Q1 to 2020Q3, using three filters to ensure consistency when comparing with Becker & Ivashina (2014). These filters are: firm-quarters of non-financial firms, U.S. firms, and positive demand for debt. The date range spans from 1997Q1 to 2020Q3. We classify bank loans as Term Loan As, Other Loans, or Capex Facilities, and we categorize nonbank loans as Term Loan B-Ks.

Table 3: Composition of Sample 2 by type of debt

Type of Debt	**Number of Observations**	**Fraction of Observations**
Bank loan only	1047	9.35%
Nonbank loan only	866	7.73%
Both bank and nonbank only	259	2.31%
Bonds	9030	80.61%
Total	**11202**	**100.00%**

Note: This table shows the firm-quarter count by debt type, after applying all filters for Sample 2, with a date range spanning from 1997Q4 to 2020Q2. We classify bank loans as Term Loan As, Other Loans, or Capex Facilities, and we categorize nonbank loans as Term Loan B-Ks.

Table 4: Firm-quarter counts by facility, for Sample 2

Loan Type	**# Bank Only Quarters**	**# Nonbank Only Quarters**	**# Both Bank & Nonbank Quarters**	**% of Total Firm-Quarters**
Term Loan	610	0	81	27.53%
Term Loan A	379	0	180	22.27%
Other Loan	80	0	9	3.55%
CAPEX Facility	2	0	0	0.08%
Term Loan B	0	813	256	42.59%
Term Loan C	0	46	32	3.11%
Term Loan D–K	0	22	0	0.88%
Total	**1071**	**881**	**558**	**100.00%**

Note: This table shows the firm-quarter count by facility, after applying all filters for Sample 2, with a date range spanning from 1997Q4 to 2020Q2. Multiple facilities in each firm-quarter are counted as one. Therefore, this breakdown of facilities results in 2,510 firm-quarters, which is larger than the 11,202 observations in Table 3. The total quarters column refers to the total number of firm-quarters that include loans.

Table 5: Replication of Becker and Ivashina's (2014) baseline regressions (1997-2010)

Dependent variable	D_{it} = 1 if firm *i* receives a loan and D_{it} = 0 if firm *i* issues a bond in quarter *t*						
Mean, D_{it}	0.172 (1)	0.172 (2)	0.172 (3)	0.172 (4)	0.172 (5)	0.172 (6)	0.172 (7)
Tightening in lending standards	-0.0153						
	(0.0316)						
Aggregate lending growth		0.3430***					
		(0.0871)					
Loan allowances			-4.1624***				
			(0.9965)				
Bank stock-index				0.3887***			
				(0.1112)			
Monetary policy					-0.8128		
					(0.6107)		
VIX index						-0.2321**	
						(0.0950)	
Excess bond premium							-0.1070
							(0.0758)
Log (Assets)	-0.0032	-0.0213	-0.0198	-0.0109	-0.0048	-0.0064	-0.0032
	(0.0312)	(0.0301)	(0.0305)	(0.0305)	(0.0309)	(0.0304)	(0.0309)
Log (PP&E)	0.0120	0.0448	0.0514	0.0401	0.0174	0.0163	0.0128
	(0.0395)	(0.0387)	(0.0400)	(0.0386)	(0.0383)	(0.0385)	(0.0390)
ROA	-0.1906	-0.2655	-0.2304	-0.1931	-0.1797	-0.2307	-0.2120
	(0.2354)	(0.2382)	(0.2339)	(0.2272)	(0.2351)	(0.2278)	(0.2345)
Market-to-book	0.0034	-0.0022	-0.0016	0.0010	0.0035	0.0020	0.0031
	(0.0075)	(0.0062)	(0.0062)	(0.0067)	(0.0072)	(0.0067)	(0.0072)
Lagged return	-0.0202	-0.0180	-0.0178	-0.0220*	-0.0204	-0.0237*	-0.0223*
	(0.0129)	(0.0126)	(0.0125)	(0.0125)	(0.0126)	(0.0130)	(0.0129)
Leverage	0.0532	0.0611	0.0632	0.0599	0.0553	0.0562	0.0552
	(0.0490)	(0.0483)	(0.0489)	(0.0493)	(0.0485)	(0.0492)	(0.0492)
Dividend payer	-0.0302	-0.0376	-0.0337	-0.0288	-0.0293	-0.0319	-0.0308
	(0.0269)	(0.0267)	(0.0271)	(0.0273)	(0.0268)	(0.0269)	(0.0268)
Firm fixed effects (obs.)	Yes (1298)	Yes (1298)	Yes (1298)	Yes (1298)	Yes (1298)	Yes (1298)	Yes (1298)
Clusters(quarter)	44	44	44	44	44	44	44
R-squared	0.47	0.48	0.48	0.47	0.47	0.47	0.47
Observations	5035	5035	5035	5035	5035	5035	5035

Note: Following Becker and Ivashina (2014), all observations in the sample correspond to a new issuance of loan or bond debt. Any observations for which a firm has not issued a bond within the last five years are excluded. The table shows the results of OLS regressions for a period spanning from 1997Q4 to 2010Q4. The coefficients displayed relate to aggregate measures of credit conditions. We follow Becker and Ivashina (2014) in the computation of these measures. Data pertaining to the tightening of lending standards is derived from the Federal Senior Loan Officer Opinion Survey on Bank Lending Practices. This series represents the net percentage of domestic respondents who report tightening standards for commercial and industrial loans to large and medium-sized enterprises. Aggregate lending growth is the four-quarter total growth of corporate bonds, commercial paper, bank loans, and other loans from the U.S. Flow of Funds Accounts. Loan allowances (which are calculated as a percentage of total loans) were obtained from Call Reports for large banks. We compute the bank stock index as a market capitalization-weighted index of the stock price performance of 16 U.S. banks (see description of Figure 2). Monetary policy is computed as the difference between the federal funds rate and the Taylor rule target level. In addition to the measures considered by Becker and Ivashina (2014), we also consider the VIX index and Excess Bond Premium. Errors are clustered by quarter and are heteroskedasticity-robust. $*p < .1$; $**p < .05$; $***p < .01$.

Table 6: Replication of Becker and Ivashina's (2014) benchmark regressions (1997-2010) with Z-score normalized data

Dependent variable	D_{it} = 1 if firm *i* receives a loan and D_{it} = 0 if firm *i* issues a bond in quarter *t*						
Mean, D_{it}	0.172 (1)	0.172 (2)	0.172 (3)	0.172 (4)	0.172 (5)	0.172 (6)	0.172 (7)
Tightening in lending standards	-0.0041						
	(0.0086)						
Aggregate lending growth		0.0341***					
		(0.0086)					
Loan allowances			-0.0344***				
			(0.0082)				
Bank stock-index				0.0270***			
				(0.0077)			
Monetary policy					-0.0113		
					(0.0085)		
VIX index						-0.0183**	
						(0.0075)	
Excess bond premium							-0.0092
							(0.0065)
Log (Assets)	-0.0055	-0.0367	-0.0342	-0.0188	-0.0082	-0.0110	-0.0055
	(0.0538)	(0.0518)	(0.0526)	(0.0526)	(0.0533)	(0.0525)	(0.0533)
Log (PP&E)	0.0238	0.0887	0.1018	0.0793	0.0345	0.0322	0.0254
	(0.0782)	(0.0766)	(0.0791)	(0.0764)	(0.0759)	(0.0762)	(0.0771)
ROA	-0.0080	-0.0112	-0.0097	-0.0081	-0.0076	-0.0097	-0.0089
	(0.0099)	(0.0100)	(0.0099)	(0.0096)	(0.0099)	(0.0096)	(0.0099)
Market-to-book	0.0044	-0.0029	-0.0021	0.0013	0.0046	0.0026	0.0041
	(0.0098)	(0.0081)	(0.0081)	(0.0087)	(0.0094)	(0.0088)	(0.0094)
Lagged return	-0.0147	-0.0130	-0.0130	-0.0159*	-0.0148	-0.0172*	-0.0162*
	(0.0094)	(0.0092)	(0.0091)	(0.0091)	(0.0092)	(0.0095)	(0.0094)
Leverage	0.0137	0.0157	0.0163	0.0154	0.0142	0.0145	0.0142
	(0.0126)	(0.0124)	(0.0126)	(0.0127)	(0.0125)	(0.0127)	(0.0127)
Dividend payer	-0.0148	-0.0185	-0.0165	-0.0141	-0.0144	-0.0156	-0.0151
	(0.0132)	(0.0131)	(0.0133)	(0.0134)	(0.0132)	(0.0132)	(0.0131)
Firm fixed effects (obs.)	Yes (1298)	Yes (1298)	Yes (1298)	Yes (1298)	Yes (1298)	Yes (1298)	Yes (1298)
Clusters(quarter)	44	44	44	44	44	44	44
R-squared	0.47	0.48	0.48	0.47	0.47	0.47	0.47
Observations	5035	5035	5035	5035	5035	5035	5035

Note: Following Becker and Ivashina (2014), all observations in the sample correspond to a new issuance of loan or bond debt. Any observations for which a firm has not issued a bond within the last five years are excluded. The table shows the results of OLS regressions for a period spanning from 1997Q4 to 2010Q4. The coefficients displayed relate to aggregate measures of credit conditions. We follow Becker and Ivashina (2014) in the computation of these measures. Data pertaining to the tightening of lending standards is derived from the Federal Senior Loan Officer Opinion Survey on Bank Lending Practices. This series represents the net percentage of domestic respondents who report tightening standards for commercial and industrial loans to large and medium-sized enterprises. Aggregate lending growth is the four-quarter total growth of corporate bonds, commercial paper, bank loans, and other loans from the U.S. Flow of Funds Accounts. Loan allowances (which are calculated as a percentage of total loans) were obtained from Call Reports for large banks. We compute the bank stock index as a market capitalization-weighted index of the stock price performance of 16 U.S. banks (see description of Figure 2). Monetary policy is computed as the difference between the federal funds rate and the Taylor rule target level. In addition to the measures considered by Becker and Ivashina (2014), we also consider the VIX index and Excess Bond Premium. Errors are clustered by quarter and are heteroskedasticity-robust. $*p < .1$; $**p < .05$; $***p < .01$.

Table 7: Extended baseline regressions (1997-2020) with Z-score normalized data

Dependent variable	D_{it} = 1 if firm *i* receives a loan and D_{it} = 0 if firm *i* issues a bond in quarter *t*					
Mean, D_{it}	0.194 (1)	0.194 (2)	0.194 (3)	0.194 (4)	0.194 (5)	0.194 (6)
Tightening in lending standards	-0.0060					
	(0.0047)					
Aggregate lending growth		0.0269***				
		(0.0051)				
Loan allowances			-0.0323***			
			(0.0039)			
Bank stock-index				0.0105		
				(0.0078)		
VIX index					-0.0115**	
					(0.0049)	
Excess bond premium						-0.0054
						(0.0042)
Log (Assets)	-0.0582**	-0.0717**	-0.0744**	-0.0552*	-0.0611**	-0.0586**
	(0.0289)	(0.0292)	(0.0292)	(0.0292)	(0.0290)	(0.0290)
Log (PP&E)	0.0641*	0.0731**	0.0795**	0.0797**	0.0675**	0.0648*
	(0.0331)	(0.0329)	(0.0329)	(0.0345)	(0.0329)	(0.0331)
ROA	-0.0042	-0.0033	-0.0039	-0.0036	-0.0047	-0.0040
	(0.0046)	(0.0050)	(0.0045)	(0.0046)	(0.0047)	(0.0047)
Leverage	0.0014	-0.0017	-0.0024	0.0022	0.0013	0.0012
	(0.0070)	(0.0072)	(0.0069)	(0.0073)	(0.0070)	(0.0071)
Firm fixed effects (obs.)	Yes (2057)	Yes (2057)	Yes (2057)	Yes (2057)	Yes (2057)	Yes (2057)
Clusters(quarter)	81	81	81	81	81	81
R-squared	0.42	0.42	0.42	0.42	0.42	0.42
Observations	11202	11202	11202	11202	11202	11202

Note: Following Becker and Ivashina (2014), all observations in the sample correspond to a new issuance of loan or bond debt. Any observations for which a firm has not issued a bond within the last five years are excluded. The table shows the results of OLS regressions for a period spanning from 1997Q4 to 2020Q2. The coefficients displayed relate to aggregate measures of credit conditions. We follow Becker and Ivashina (2014) in the computation of these measures. Data pertaining to the tightening of lending standards is derived from the Federal Senior Loan Officer Opinion Survey on Bank Lending Practices. This series represents the net percentage of domestic respondents who report tightening standards for commercial and industrial loans to large and medium-sized enterprises. Aggregate lending growth is the four-quarter total growth of corporate bonds, commercial paper, bank loans, and other loans from the U.S. Flow of Funds Accounts. Loan allowances (which are calculated as a percentage of total loans) were obtained from Call Reports for large banks. We compute the bank stock index as a market capitalization-weighted index of the stock price performance of 16 U.S. banks (see description of Figure 2). In addition to the measures considered by Becker and Ivashina (2014), we also consider the VIX index and Excess Bond Premium. Errors are clustered by quarter and are heteroskedasticity-robust. $*p < .1$; $**p < .05$; $***p < .01$.

Table 8: Bank loan vs. bond regressions (1997-2020) with Z-score normalized data

Dependent variable	D_{it} = 1 if firm *i* receives a bank loan and D_{it} = 0 if firm *i* issues a bond in quarter *t*					
Mean, D_{it}	0.104 (1)	0.104 (2)	0.104 (3)	0.104 (4)	0.104 (5)	0.104 (6)
Tightening in lending standards	0.0066					
	(0.0041)					
Aggregate lending growth		0.0163***				
		(0.0036)				
Loan allowances			-0.0154***			
			(0.0033)			
Bank stock-index				-0.0018		
				(0.0056)		
VIX index					-0.0004	
					(0.0030)	
Excess bond premium						0.0065*
						(0.0036)
Log (Assets)	-0.0706***	-0.0799***	-0.0794***	-0.0708***	-0.0706***	-0.0700**
	(0.0274)	(0.0274)	(0.0272)	(0.0272)	(0.0272)	(0.0274)
Log (PP&E)	0.0830***	0.0858***	0.0883***	0.0779**	0.0805***	0.0824***
	(0.0293)	(0.0291)	(0.0294)	(0.0306)	(0.0296)	(0.0294)
ROA	-0.0031	-0.0035	-0.0038	-0.0037	-0.0037	-0.0031
	(0.0042)	(0.0044)	(0.0043)	(0.0042)	(0.0043)	(0.0042)
Leverage	-0.0144**	-0.0160***	-0.0159***	-0.0144**	-0.0142**	-0.0141**
	(0.0058)	(0.0058)	(0.0056)	(0.0058)	(0.0057)	(0.0057)
Firm fixed effects (obs.)	Yes (1956)	Yes (1956)	Yes (1956)	Yes (1956)	Yes (1956)	Yes (1956)
Clusters(quarter)	81	81	81	81	81	81
R-squared	0.36	0.36	0.36	0.36	0.36	0.36
Observations	10077	10077	10077	10077	10077	10077

Note: Following Becker and Ivashina (2014), all observations in the sample correspond to a new issuance of bank loan or bond debt. We classify bank loans as Term Loan As, Other Loans, or Capex Facilities, and we categorize nonbank loans as Term Loan B-Ks. Any observations for which a firm has not issued a bond within the last five years are excluded. The table shows the results of OLS regressions for a period spanning from 1997Q4 to 2020Q2. The coefficients displayed relate to aggregate measures of credit conditions. We follow Becker and Ivashina (2014) in the computation of these measures. Data pertaining to the tightening of lending standards is derived from the Federal Senior Loan Officer Opinion Survey on Bank Lending Practices. This series represents the net percentage of domestic respondents who report tightening standards for commercial and industrial loans to large and medium-sized enterprises. Aggregate lending growth is the four-quarter total growth of corporate bonds, commercial paper, bank loans, and other loans from the U.S. Flow of Funds Accounts. Loan allowances (which are calculated as a percentage of total loans) were obtained from Call Reports for large banks. We compute the bank stock index as a market capitalization-weighted index of the stock price performance of 16 U.S. banks (see description of Figure 2). In addition to the measures considered by Becker and Ivashina (2014), we also consider the VIX index and Excess Bond Premium. Errors are clustered by quarter and are heteroskedasticity-robust. $*p < .1$; $**p < .05$; $***p < .01$.

Table 9: Nonbank loan vs. bond regressions (1997-2020) with Z-score normalized data

Dependent variable	D_{it} = 1 if firm *i* receives a nonbank loan and D_{it} = 0 if firm *i* issues a bond in quarter *t*					
Mean, D_{it}	0.088 (1)	0.088 (2)	0.088 (3)	0.088 (4)	0.088 (5)	0.088 (6)
Tightening in lending standards	-0.0136***					
	(0.0033)					
Aggregate lending growth		0.0142***				
		(0.0044)				
Loan allowances			-0.0226***			
			(0.0041)			
Bank stock-index				0.0108*		
				(0.0056)		
VIX index					-0.0123**	
					(0.0052)	
Excess bond premium						-0.0125***
						(0.0041)
Log (Assets)	-0.0175	-0.0254	-0.0294	-0.0146	-0.0210	-0.0187
	(0.0235)	(0.0239)	(0.0236)	(0.0236)	(0.0237)	(0.0237)
Log (PP&E)	0.0261	0.0354	0.0410	0.0459	0.0328	0.0276
	(0.0272)	(0.0281)	(0.0277)	(0.0294)	(0.0274)	(0.0275)
ROA	-0.0027	-0.0012	-0.0015	-0.0014	-0.0025	-0.0024
	(0.0032)	(0.0034)	(0.0032)	(0.0033)	(0.0033)	(0.0034)
Leverage	0.0090	0.0071	0.0063	0.0097	0.0085	0.0084
	(0.0057)	(0.0059)	(0.0057)	(0.0060)	(0.0058)	(0.0058)
Firm fixed effects (obs.)	Yes (1925)	Yes (1925)	Yes (1925)	Yes (1925)	Yes (1925)	Yes (1925)
Clusters(quarter)	81	81	81	81	81	81
R-squared	0.48	0.48	0.48	0.48	0.48	0.48
Observations	9896	9896	9896	9896	9896	9896

Note: Following Becker and Ivashina (2014), all observations in the sample correspond to a new issuance of nonbank loan or bond debt. We classify bank loans as Term Loan As, Other Loans, or Capex Facilities, and we categorize nonbank loans as Term Loan B-Ks. Any observations for which a firm has not issued a bond within the last five years are excluded. The table shows the results of OLS regressions for a period spanning from 1997Q4 to 2020Q2. The coefficients displayed relate to aggregate measures of credit conditions. We follow Becker and Ivashina (2014) in the computation of these measures. Data pertaining to the tightening of lending standards is derived from the Federal Senior Loan Officer Opinion Survey on Bank Lending Practices. This series represents the net percentage of domestic respondents who report tightening standards for commercial and industrial loans to large and medium-sized enterprises. Aggregate lending growth is the four-quarter total growth of corporate bonds, commercial paper, bank loans, and other loans from the U.S. Flow of Funds Accounts. Loan allowances (which are calculated as a percentage of total loans) were obtained from Call Reports for large banks. We compute the bank stock index as a market capitalization-weighted index of the stock price performance of 16 U.S. banks (see description of Figure 2). In addition to the measures considered by Becker and Ivashina (2014), we also consider the VIX index and Excess Bond Premium. Errors are clustered by quarter and are heteroskedasticity-robust. $*p < .1$; $**p < .05$; $***p < .01$.

Table 10: Interaction regression results (1997-2020) with Z-score normalized data

Dependent variable	D_{it} = 1 if firm *i* receives a nonbank loan and D_{it} = 0 if firm *i* issues a bond in quarter *t*					
Interaction variable	N_i = 1 if firm *i* has used a nonbank loan at any quarter *t* in the sample and N_i = 0 otherwise					
Mean, D_{it}	0.194 (1)	0.194 (2)	0.194 (3)	0.194 (4)	0.194 (5)	0.194 (6)
Tightening in lending standards	0.00544					
	(0.00386)					
Tightening in lending standards × N_i	-0.03559***					
	(0.00921)					
Aggregate lending growth		0.01346***				
		(0.00348)				
Aggregate lending growth × N_i		0.04000***				
		(0.01287)				
Loan allowances			-0.01176***			
			(0.00343)			
Loan allowances × N_i			-0.05870***			
			(0.01170)			
Bank stock-index				-0.00001		
				(0.00577)		
Bank stock-index × N_i				0.02845*		
				(0.01476)		
VIX index					-0.00049	
					(0.00274)	
VIX index × N_i					-0.03530***	
					(0.01205)	
Excess bond premium						0.00469
						(0.00356)
Excess bond premium × N_i						-0.03176**
						(0.01285)
Log (Assets)	-0.05623*	-0.07221**	-0.07693***	-0.05545*	-0.06143**	-0.05702*
	(0.02922)	(0.02923)	(0.02961)	(0.02926)	(0.02918)	(0.02921)
Log (PP&E)	0.06062*	0.07453**	0.08244**	0.07975**	0.06614**	0.06287*
	(0.03339)	(0.03318)	(0.03363)	(0.03472)	(0.03336)	(0.03344)
ROA	-0.00466	-0.00313	-0.00403	-0.00313	-0.00521	-0.00409
	(0.00469)	(0.00488)	(0.00445)	(0.00452)	(0.00480)	(0.00475)
Leverage	0.00129	-0.00209	-0.00255	0.00213	0.00113	0.00138
	(0.00704)	(0.00708)	(0.00698)	(0.00728)	(0.00697)	(0.00704)
Firm fixed effects (obs.)	Yes (2057)	Yes (2057)	Yes (2057)	Yes (2057)	Yes (2057)	Yes (2057)
Clusters(quarter)	81	81	81	81	81	81
R-squared	0.42	0.42	0.42	0.42	0.42	0.42
Observations	11202	11202	11202	11202	11202	11202

Note: Following Becker and Ivashina (2014), all observations in the sample correspond to a new issuance of loan or bond debt. We classify bank loans as Term Loan As, Other Loans, or Capex Facilities, and we categorize nonbank loans as Term Loan B-Ks. Any observations for which a firm has not issued a bond within the last five years are excluded. The table shows the results of OLS regressions for a period spanning from 1997Q4 to 2020Q2. The coefficients displayed relate to aggregate measures of credit conditions. We follow Becker and Ivashina (2014) in the computation of these measures. Data pertaining to the tightening of lending standards is derived from the Federal Senior Loan Officer Opinion Survey on Bank Lending Practices. This series represents the net percentage of domestic respondents who report tightening standards for commercial and industrial loans to large and medium-sized enterprises. Aggregate lending growth is the four-quarter total growth of corporate bonds, commercial paper, bank loans, and other loans from the U.S. Flow of Funds Accounts. Loan allowances (which are calculated as a percentage of total loans) were obtained from Call Reports for large banks. We compute the bank stock index as a market capitalization-weighted index of the stock price performance of 16 U.S. banks (see description of Figure 2). In addition to the measures considered by Becker and Ivashina (2014), we also consider the VIX index and Excess Bond Premium. Errors are clustered by quarter and are heteroskedasticity-robust. $*p < .1$; $**p < .05$; $***p < .01$.