The Value of Contingent Liquidity from Banks to Nonbank Financiers*

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[PRELIMINARY. DO NOT CIRCULATE.]

Abstract

I document that 96% of banks' funding to nonbank financiers (NBFs) occurs through credit lines, while NBFs hold about 84% of corporate term loans. NBFs use bank credit lines to manage both investment shocks and liquidity needs, while banks' funding advantage makes them natural insurers for NBFs. I develop a macrofinance model to quantify the value of contingent liquidity. Banks trade off the risk-sharing benefits of "renting" NBF balance sheets through credit line extensions against the costs associated with granting higher credit limits, which influence NBFs' drawdown decisions. Calibrated to U.S. syndicated loan data, the model shows credit lines offer NBFs partial flexibility. By endogenously determining the credit limit, the interconnected economy proves to be more resilient during crises, experiencing smaller increases in the default risk of NBF, milder declines in asset prices (4% vs. 7%), and supporting more safe assets. Policy experiments show that regulating bank off-balance sheet credit lines also reduces NBFs' loan-bearing capacity.

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1 Introduction

Banks and nonbank financiers (NBFs) are connected in our modern financial system. NBFs[1] are a subset of nonbanks that both borrow from banks and lend to corporates in the syndicate loan market[2]. In the U.S., banks provide critical funding to NBFs, about $120 billion quarterly, and 96% of the funding is via revolver/credit lines, a form of contingent liquidity (Figure 2). These same NBFs that borrow from banks also lend extensively in the syndicated loan market, originating about 30% and hold over 84% of corporate term loans on their balance sheets (Figure 3). The role of NBFs in lending and the massive amount of credit lines NBFs get as funding motivate the question: what is the value of contingent liquidity from banks to NBFs?

After the Great Financial Crisis (GFC), regulatory pressures led banks to tighten lending, allowing nonbank financial institutions (NBFIs) to assume riskier loans (Irani et al., 2021; Lee et al., 2023). Initially, this has created segmentation in the financial sector. However, my paper argues that credit lines extended by banks to NBFs, by nature of being options, help complete markets and overcome this segmentation. However, as NBFs expand, concerns arise about their interconnectedness with banks. Do credit lines from banks to NBFs enhance risk-sharing, or can they make the financial system as a whole riskier? While the Basel framework primarily regulates banks, policymakers are increasingly vigilant about the risks transmitted between banks and NBFs (Acharya et al., 2024a).

To measure the real macroeconomic and financial stability impact in a modern financial system as a whole where banks extend credit lines to NBFs, what is crucial but still missing is a macro-finance model capable of offering rich counterfactuals and policy experiments. To address this gap, I develop a general equilibrium model grounded in empirical findings, to quantify the effects of financial interconnectedness and provide a foundation for future regulation. My paper has two

[1]Note the difference between nonbanks and nonbank financiers (NBFs). I use nonbanks to mean all financial institutions that participate in the syndicated loans market but are not commercial banks. Nonbanks include three subtypes, nonbanks that lend to corporates but do not borrow from banks, nonbanks that borrow from banks but do not lend to corporates, and nonbanks that both borrow from banks and lend to corporates. I call the last type nonbank financiers (NBFs), which is the focus of my study. Major NBFs in the U.S. are finance companies, investment funds, institutional investors, as shown in Figure 1.

[2]The syndicated loan market, with an aggregate facility size of 10 trillion per annum (almost half of U.S. GDP), provides large-scale financing to major U.S. corporations and the government.

parts, consisting of both empirical and quantitative modeling. I first document empirical evidence on credit lines from banks to NBFs, focusing on their purpose and usage. Then, I incorporate my empirical findings and institutional details into a model.

In the first (empirical) section of my paper, I present three major findings. An overwhelming majority (96%) of bank funding to nonbank financiers (NBFs) is in the form of credit lines. What makes credit lines so special, and why do NBFs specifically seek them? Credit lines are distinctive because they provide NBFs with flexible funding and protection against liquidity shortages. I use a combination of data from Dealscan, LSEG Loan Connector, and SEC prospectuses to show that NBFs face significant inventory uncertainty and liquidity shortages. On the asset side, as participants rather than lead arrangers in the syndicate loan market, NBFs experience uncertainty in their deal flow because they have less control than banks over when they will be included as participating lenders in syndication packages.[3] I use large language models to analyze NBF prospectuses, showing that protection against inventory uncertainty is the primary reason NBFs seek credit lines (in 80% of all prospectuses). On the liability side, 40% of all prospectuses reveal that NBFs also use credit lines to meet liquidity needs, sometimes as backup support for their commercial paper funding. Therefore, protection against inventory uncertainty and liquidity support are the primary and secondary reasons NBFs seek credit lines from banks. Third, I examine the utilization of these credit lines from banks to NBFs. I find that, over time, NBFs' credit line drawdowns and their demand for credit line options are highly correlated with their lending activities. Cross-sectionally, NBFs with higher lending volatility tend to draw down more and have a greater demand for credit line options.

In the second (model) section of my paper, I map my empirical foundations onto ingredients of my quantitative model, I address the question: What is the real macroeconomic value of contingent liquidity in an interconnected financial system where banks extend credit lines to nonbank financiers. In my model, both banks and NBFs provide debt-financing to non-financial firms by investing in Lucas tree. In addition to lending to firms, banks also provide contingent credit line to NBFs. Credit line is modeled as a long-term option with a short-term drawdown choice. I provide economic

[3]Blickle et al. (2020) also documents that banks frequently act as lead arrangers, which gives them more control over investment timing, amount, covenants, and horizon.

rationale on why the credit line arrangement between banks and NBFs exist. In the paragraph before, I document reasons why NBFs want credit lines. Now I discuss the bank side. Unlike NBFs, only banks have liquidity advantage from convenience yield on consumer deposits and from access to the Fed balance sheet. These accesses amplify banks' comparative liquidity advantage exactly when liquidity is scarce, making banks the natural insurers of NBFs. However, despite liquidity advantage, banks are constrained by regulation. Therefore, banks use their liquidity advantage to route around their regulatory constraints. By extending NBFs credit lines, banks are effectively "renting NBF balance sheets." Banks profit from credit lines while internalizing the risks associated with NBF loan portfolios. This is the *"risk-sharing"* incentive of banks. Additionally, I document that bank credit lines to NBFs frequently bunch at exactly 364-days, and this is because undrawn banks credit lines with less than 1 year of maturity receive only a 20% credit conversion factor, which is a modeled feature in the capital requirement in my model. This is the *"regulatory arbitrage"* benefit for banks in extending credit lines. Therefore, credit lines are desirable for banks due to both "risk-sharing" and "regulatory arbitrage" incentives. Furthermore, I argue that credit line is better than long-term or short-term debt. Compared to long-term debt, credit lines impose funding costs on NBFs only when investment opportunities arise. Compared to short-term debt, credit lines offer a fixed spread, insulating borrowers from the heightened sensitivity of short-term debt rates to market distress. Why are credit lines economically better than both long-term and short-term debt? This is because credit lines are long-term options with short-term drawdowns, which is precisely the value of their *contingent* nature.

I calibrate the model to the entire universe of US syndicated loan market from 1990 to 2023 and targets main economic features of data, including net payout rate, investment volatility, commercial bank debt recovery rate, bank and nonbank default rate, deposit rate, liquidity premium, among many others. The value of contingent liquidity through credit line arrangements is evident when comparing the interconnected versus the segmented economy. In the interconnected economy where banks extend credit lines to NBFs, banks account for the impact of credit limits on NBFs' behavior, leading to disciplined risk-taking and a safer financial system. This dynamic results in a larger

banking sector share of loan origination (54% vs. 22%), higher asset prices (4.09 vs. 3.78), and lower default probabilities (0.28% vs. 3.5%). Furthermore, credit lines enhance welfare by enabling greater deposit creation (0.55 vs. 0.20), directly benefiting households. Finally, the interconnected economy is more resilient during crises, with smaller increases in NBFs' default risk (64% vs. 67%) and less severe asset price declines (4% vs. 7%), highlighting its stability under stress. I also study the transition dynamics of an interconnected economy undergoing a recession,

Finally, my model provides a rigorous framework for evaluating regulatory measures targeting nonbanks and assessing the spillover effects of banking regulations on both on- and off-balance-sheet activities. Future iterations of this paper will incorporate an analysis of quantitative easing in an interconnected financial system.

Literature Review. My paper contributes to the existing literature in three key ways.

Credit Lines. My paper contributes to our current understanding on credit lines (Holmström and Tirole, 1998; Acharya et al., 2014; Greenwald et al., 2023; Choi, 2022). In Acharya et al. (2014), credit line revocation disciplines borrowers. My model features an *endogenously* determined credit limit, enabling banks to internalize the impact of credit line extensions on the drawdown behavior of nonbank financiers (NBFs) and I provide a quantification of this mechanism in a general equilibrium model of the financial system. My modeling demonstrates the *partial* flexibility bank credit lines provide to NBFs, while accounting for NBF default risks. While Greenwald et al. (2023) model credit line limit and rate as exogenous and show that credit lines to large firms crowd out lending to smaller firms and Choi (2022) highlight liquidity insurance for firms, my paper focuses on credit lines to NBFs with fully endogenous credit limit and option fee. I argue that bank credit lines help NBFs hedge inventory uncertainty and offer liquidity support, overcoming two past key credit line modeling challenges by (1) endogenizing credit limits, and (2) capturing realistic, interior credit utilization to improve numerical stability. In this way, my modeling of credit line quantifies not only the option value of contingent liquidity, but also the value of an interconnected financial system. Related to but different from Acharya et al. (2024a,b), which suggest that bank credit lines to nonbanks increase risk for banks, I find that such credit lines enhance stability of the financial system

as a whole. This is precisely because banks internalize NBFs' riskier behavior and default risks when setting credit limits. Consequently, my paper demonstrates that an interconnected financial system where banks extend credit lines to NBFs is safer than a segmented one.

Bank-nonbank Interaction and Macro-finance Models. My paper is related to the literature on the interaction between banks and nonbanks, in both modeling and empirical literature, where I make the following three contributions. *First,* I develop a novel quantitative macro-finance model linking banks and NBFs through credit lines, contributing to the literature on macro-finance models, financial shocks, and regulation (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; Moreira and Savov, 2017; Quarles, 2020; Elenev et al., 2021; Begenau, 2020; Begenau and Landvoigt, 2022; d'Avernas et al., 2023; Elliott et al., 2023; Lee et al., 2023). I provide the first foundational framework to examine bank-NBF interaction via credit lines, quantifying their macroeconomic impacts and the spillover effects of bank regulation on NBFs. *Second, I emphasize collabration over competition between banks and NBFs.* Departing from Jiang (2023), which shows that banks compete with nonbanks by charging higher credit line rates to secure their downstream profits, shows how banks and NBFs collaborate: nonbanks hedge inventory uncertainty, while banks benefit via both channels of "risk-sharing" and "regulatory arbitrage." My findings challenge the competition narrative and quantify how credit lines promote collaboration and macro-financial stability. *Finally,* my paper adds to the growing empirical literature on bank-nonbank interactions, competition, and the rise of nonbanks (Cetorelli et al., 2012; Blickle et al., 2020; Berg et al., 2021; Aldasoro et al., 2022; Gopal and Schnabl, 2022; Berg et al., 2022; Ghosh et al., 2022; Benson et al., 2023; Jiang, 2023; Buchak et al., 2024; Acharya et al., 2024a,b). I provide the first textual evidence on the use of bank credit lines by NBFs to hedge liquidity uncertainty and secure liquidity support.

Structure of the Financial System. Diamond (2020) and Diamond et al. (2023) examine how the financial system provides safe assets, with CLOs enabling more deposits by avoiding mark-to-market pressures. In contrast, I show how the system organizes to extend credit to the real economy. Building on Kashyap et al. (2002), which highlights banks' comparative advantage in contingent funding

due to imperfect correlations between credit line drawdowns and deposit runs, I emphasize banks' incentives for risk-sharing, leveraging nonbank balance sheets, and regulatory arbitrage between credit lines and term loans. Extending capital structure literature (Modigliani and Miller, 1958; Myers, 1984), I argue that the nature of debt matters: contingent debt (credit lines) outperforms both long-term and short-term debt. Unlike long-term debt, credit lines avoid debt overhang and impose costs only when investments arise. Compared to short-term debt, credit lines offer fixed spreads, reducing sensitivity to market distress. Their unique structure as long-term options with short-term drawdowns provides these advantages.

Roadmap. Section 2 documents empirical evidence. Section 3 presents my quantitative macro-finance model. Section 4 presents calibration strategy, internally and externally calibrated parameters and results. Section 5 uses the model to study crisis and transition dynamics, the real macro-economic effects of NBFs and role of frictions. Section 5 also runs several policy experiments on the calibrated model. Section 6 concludes.

2 Empirical Evidence

This Section presents both empirical and narrative evidence highlighting the relationship between banks and nonbank financiers (NBFs) and their roles within the syndicated loan market.

2.1 Data

I use four data sources, Dealscan Legacy (1990-2020), LSEG Loan Connector (2020-2023) and Capital IQ, and the SEC prospectuses.

Facility-level Data. I merge Dealscan Legacy and LSEG Loan Connector ("New Dealscan") data, which I refer the merged data as the "Dealscan data." In Dealscan data, a "facility" represents a loan and includes syndicated and bilateral loans, project finance, and other structured lending types. The dataset provides extensive information on facility types (term loans, revolvers/credit lines, etc.),

loan terms, pricing, covenants, participants, and borrower-lender relationships. For my paper, I focus on two financing types: (1) debt financing from financial intermediaries to non-financial corporates—specifically from banks and nonbank financiers (NBFs) to non-financial corporate firms, which I refer to as "corporate loans"; and (2) financing from banks to nonbank financiers, both being financial intermediaries.

Drawdown Data. The motivating evidence shows that most bank funding to nonbank financiers is through credit lines, prompting me to collect additional credit line drawdown data from Capital IQ, which is unavailable in Dealscan Legacy or LSEG Loan Connector. I use the "Roberts Dealscan-Compustat Linking Database" (Chava and Roberts, 2008) to link Dealscan IDs to gvkey IDs and then to Capital IQ IDs, allowing me to calculate the drawdown portion of bank-issued credit lines to nonbank financiers. I first use Legacy DealScan to get total facility amount for every quarter within the start and end quarter (calculated by adding maturity to the start quarter). Then I pivot and aggregate sum to get pivot table such that each row is quarter and each column is NBF ID and each value is total credit line facility amount. In this way, I obtain for each NBF, the total available credit limit for each quarter. Then, using the linked Gvkey IDs, I find the undrawn amount of each NBFs and calculate the drawn portion as $(1 -$ undrawn/total facility amount$)$

Textual Data. To better understand why nonbank financiers (NBFs) seek credit lines from banks, in addition to these three aforementioned databases, I collect textual data from SEC Prospectuses of nonbank financiers (NBFs). I first manually read 95 out of 585 Prospectuses to identify the reasons why NBFs want credit lines. I then label these target sentences that contain information on credit lines from banks to establish ground truths for the supervised machine reading of the remaining documents. I confirm reading consistency with two large language models (LLMs), GPT and Gemini. Given any arbitrary prospectus document, I use LLMs to implement binary classification to determine whether the document indicates evidence of inventory uncertainty (liquidity support) or not (See Algorithm 1).

2.2 Empirical Findings

Using multiple data sources—Dealscan Legacy (1990-2020), LSEG Loan Connector (2020-2023), Capital IQ, and SEC prospectuses—I find that major NBFs in the US syndicated loan markets that both lend to corporates and borrow from banks are primarily finance companies, investment funds, and institutional investors, as shown in Figure 1. I document 371 NBFs that both lend to corporates and borrow from banks, as shown in Figure 1. These NBFs receive 71% of total bank funding to the nonbank sector and originate about 44% of syndicated loan volume from all nonbank lenders.

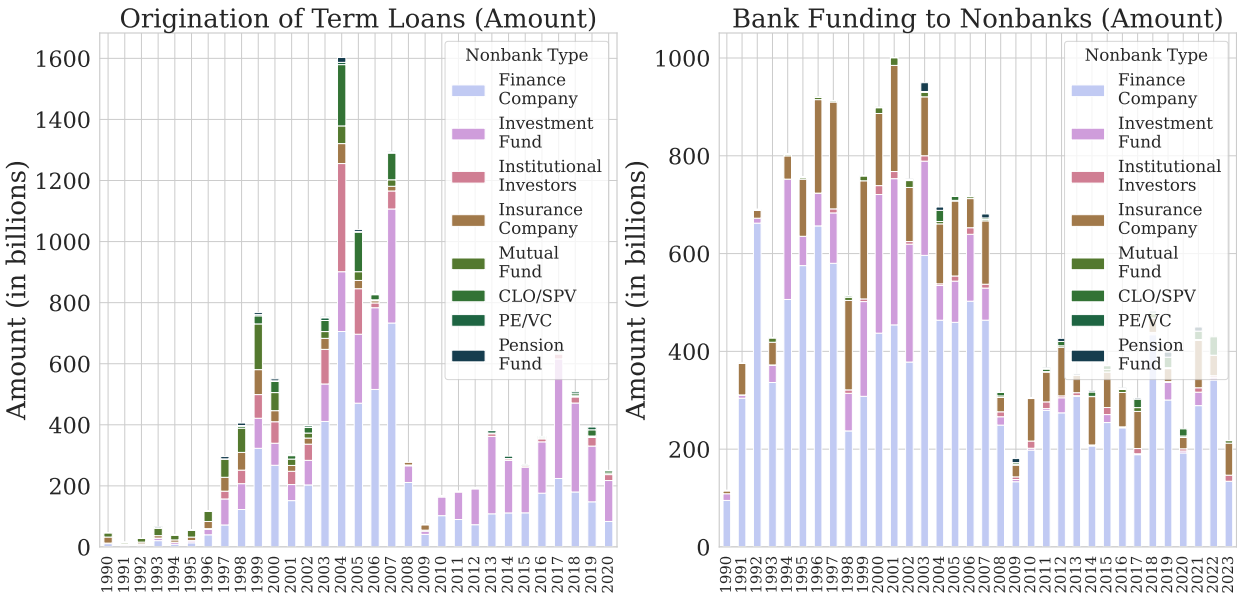


Figure 1: The left panel is nonbank origination of term loans by nonbank type. The right panel is bank funding to nonbanks. NBFs are nonbanks that both borrow from banks and lend to corporates.

In particular, I document three key findings on bank funding to these NBFs:

1. 96% of bank funding to NBFs is in the form of credit lines.

2. NBFs use credit lines from banks to hedge inventory uncertainty on the asset side and to support liquidity on the liability side.

3. NBFs with the highest lending origination volatility exhibit the highest credit line utilization.

The following subsections present these three findings in detail.

2.2.1 Credit Lines from Banks to Nonbank Financiers (NBFs)

Nonbank financiers depend heavily on banks for financing [4]. Notably, 96% of bank funding to NBFs is through credit lines, with less than 4% in term loans and other forms of financing. Why do NBFs want credit lines? As I discuss later in Section 2.2.2 on further empirical details and Section 3 on modeling, credit line contracts with endogenous limits and option fees offer NBFs flexibility, providing partial insurance against inventory uncertainty; additionally, credit lines offer back-up liquidity support.

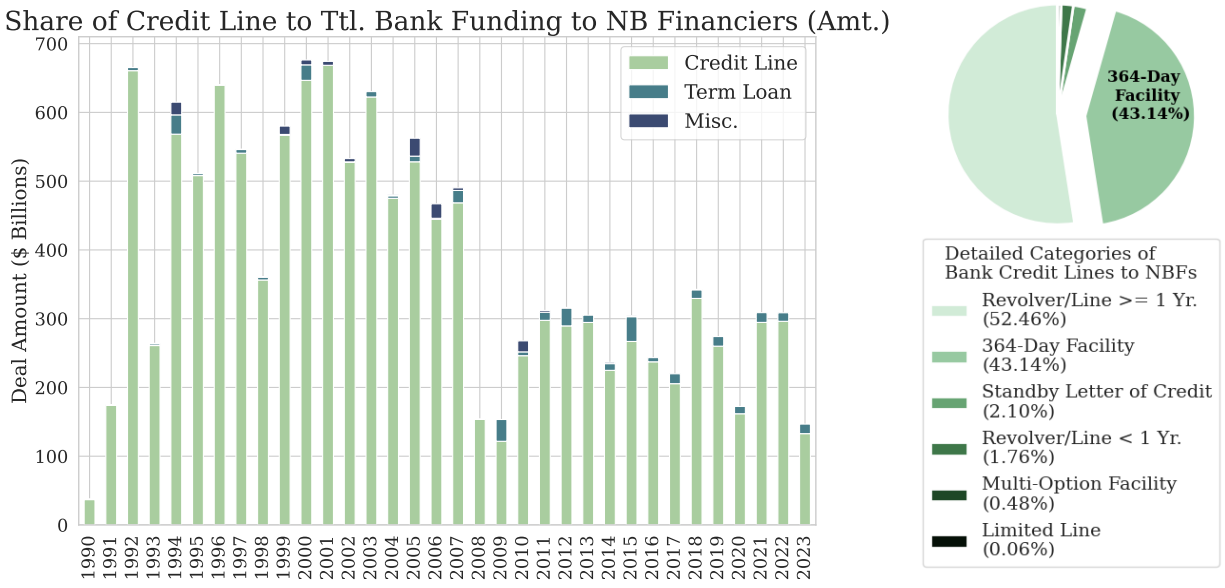


Figure 2: I examine the primary types of bank funding extended to nonbank financiers (NBFs): credit lines, term loans, and miscellaneous types. The left bar chart shows the distribution of these funding types, with credit lines in green, term loans in cyan, and miscellaneous in dark blue. The right pie chart details credit line categories, ranked by prevalence: Revolver/Line < 1 Yr. (52.46%), 364-Day Facility (43.14%), Standby Letter of Credit (2.16%), Revolver/Line < 1 Yr. (1.76%), etc.

A detailed examination of bank-issued credit lines to NBFs shows that 43.14% of these credit lines are 364-day facilities. Why do they bunch at exactly 364 days? Regulatory influences play a role. According to item 599 in the Minimum Capital Requirements by Basel Committee on Banking Supervision (2020), any committed retail credit line has a credit conversion factor (CCF) of 90%. Item 83 further specifies that commitments with original maturities up to one year have a CCF

[4]Appendix Figure B.1 shows the 1-year moving average of quarterly bank funding to nonbanks. NBFs rely heavily on banks, but not vice versa, consistent with Acharya et al. (2024a).

of 20%, while those over one year incur a CCF of 50%. This difference incentivizes banks to set credit lines at 364 days to optimize risk-weighted capital costs, a practice indicative of regulatory arbitrage. Even without regulation, banks prefer to share risks with NBFs. The regulatory treatment of credit lines vis-á-vis that of term loans adds an additional arbitrage incentive. Both channels, *"risk-sharing"* and *"regulatory arbitrage,"* are explored in the quantitative model in Section 3.

2.2.2 Credit Lines to Hedge Inventory Uncertainty and to Gain Liquidity Support

Why do NBFs want these credit lines from banks? I use textual data from SEC prospectuses to document narrative evidence of inventory uncertainty (asset-side) and liquidity issues (liability-side) faced by NBFs.

First, let's look at the asset-side problems faced by NBFs. Inventory uncertainty arises from volatile NBF investment opportunities, given their role as participants (Blickle et al., 2020) rather than lead arrangers in the syndicated loan market. Through a combination of manual analysis and advanced large language models (LLM), I identify indicators of inventory uncertainty in over 80% of NBFs' SEC prospectuses. I first manually review 95 of 585 SEC prospectuses spanning 371 NBFs. Documents containing phrases like "we will use the credit lines to fund our origination and purchase of a diverse pool of loans" indicate the need for credit line flexibility in response to inventory uncertainties. A sample of these sentences is included in the Empirical Appendix B. Given that prospectuses are often hundreds of pages long, I leverage advancements in Large Language Models (LLMs). I first "educate" the model on inventory uncertainty by manually labeling 95 documents to establish "ground truth." Then, for any prospectus document, I use an LLM to classify whether it indicates inventory uncertainty (Algorithm 1). Specifically, I implement the LLM in a few-shot manner (Wei et al., 2022), using the prompt shown in Figure B.9. Keywords include: "revolving," "line of credit," "facility," and "credit agreement."

This narrative evidence is analyzed alongside empirical data from Dealscan and the LSEG Loan Connector on the pool of loans originated by NBFs, shown in Figure 3. I find that NBFs originate and hold a higher share of sub-A term loans than banks.

Algorithm 1 Inventory Uncertainty Classification Using Large Language Models (LLMs)

Require: Documents $D = \{d_1, d_2, \ldots, d_n\}$, Keywords $\mathcal{K}$, LLM θ
Ensure: Inventory Uncertainty classification for each company's document

for document $d \in D$ **do**
  for keyword $k \in \mathcal{K}$ **do**
    if k in any sentence s of d **then**
      Extract surrounding sentences $S_{\text{set}} = \{s_{-2}, s_{-1}, s, s_{+1}, s_{+2}\}$
      if $\theta(S_{\text{set}}) =$ YES **then**
        Mark company as YES for inventory uncertainty
        break from keyword loop
      end if
    end if
  end for
  if no match or all classified NO **then**
    Mark company as NO for inventory uncertainty
  end if
end for

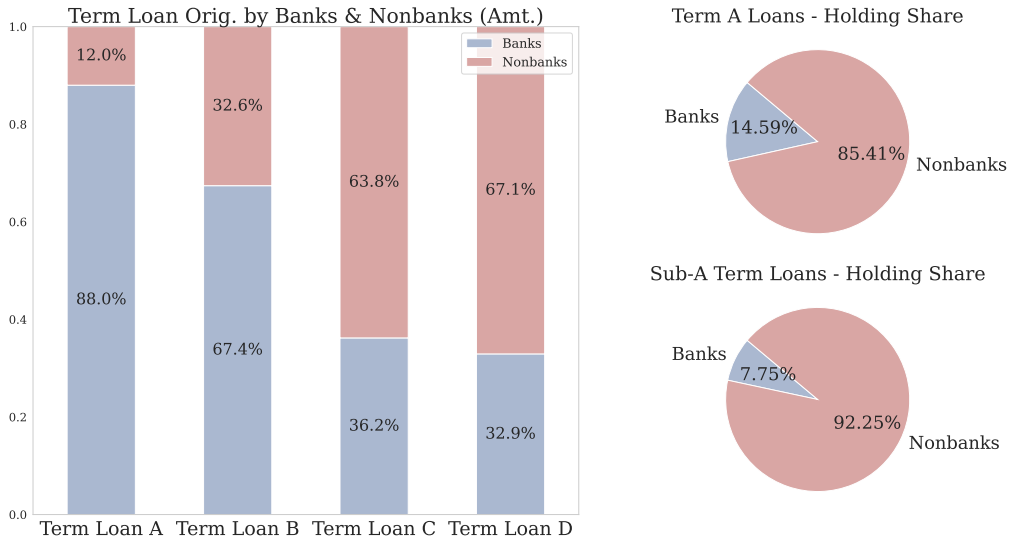


Figure 3: The left panel shows the share split between banks and nonbanks at origination. The right panel uses regression coefficients from Blickle et al. (2020) to approximate the holding-level split from origination.

Corporate term loans on Dealscan are categorized as Term Loans A, B, C, and so on. Banks typically *lead-arrange* these syndicated loans, while NBFs are more often *participating lenders* (Blickle et al., 2020). Term A loans are generally smaller, with lower interest rates, regular amortizing structures, and shorter maturities (under seven years), targeting banks. In contrast, Term B, C, and D loans (I subsequently call these "sub-A term loans") which are primarily aimed at nonbanks, are larger, feature higher interest rates, have bullet payment in the end, and longer maturities (six to ten years). Although covenants within syndication packages are mostly uniform, distinctions can emerge when banks or nonbanks are sole lenders, or when nonbanks originate more sub-A loans. Nonbank loans generally show greater variability in covenant metrics, allowing higher thresholds for debt-to-EBITDA, debt-to-equity, and debt-to-net-worth ratios, as shown in Appendix Figure B.5. Dealscan provides origination-level data only, while Blickle et al. (2020) supplements this with lead-arranger (bank) holding-level data from the Shared National Credit (SNC) database. They estimate that banks sell a significant portion of these loans to nonbanks within 10 days of origination. Since I do not have SNC data, I use regression coefficients from Blickle et al. (2020) tp calculate that banks retain just 14.59% of Term A loans, with nonbanks holding 85.41%. For sub-A term loans, banks retain 8.1%, and nonbanks hold 91.9%, suggesting that nonbanks retain riskier term loans on their balance sheets, highlighting the asset-side volatility they face.

The preceding analyses highlight inventory uncertainty faced by NBFs on the asset side. Now, we turn to liability-side challenges. Unlike banks, NBFs lack liquidity advantages; they cannot issue consumer deposits or access the Federal Reserve balance sheet as Lender of Last Resort (LOLR). A manual review of NBF SEC prospectuses reveals statements like "we use credit lines as backup support for our commercial papers," indicating NBFs' need for additional liquidity support beyond their commercial paper funding, which is prone to runs. Using machine learning on NBF SEC filings, I find that about 40% mention credit lines for liquidity support, partially aligning with Blickle et al. (2020), who attribute nonbank lending volatility to funding instability. The following figures display results from GPT and Gemini models, with a word cloud indicating credit line usage for inventory hedging in the appendix. Model predictions are consistent.

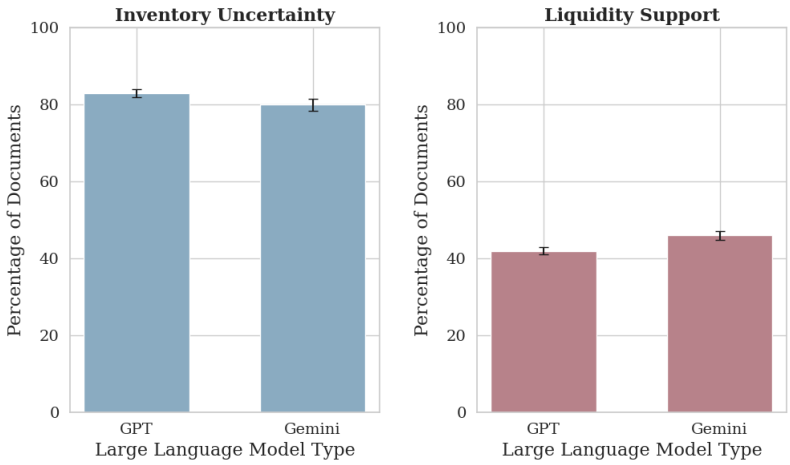


Figure 4: The top (bottom) panel shows the percentage of documents indicating credit line usage for inventory hedging (liquidity support).

2.2.3 Credit Line Drawdown and Pricing

In addition, I examine the credit line utilization patterns of nonbank financiers (NBFs).

First, a time series analysis reveals a strong correlation between available (undrawn) credit lines and lending activity (see Figure 5). In particular, the availability of credit lines appears to precede lending. This suggests that NBFs secure credit lines as a precautionary measure, positioning themselves to capitalize on future investment opportunities.

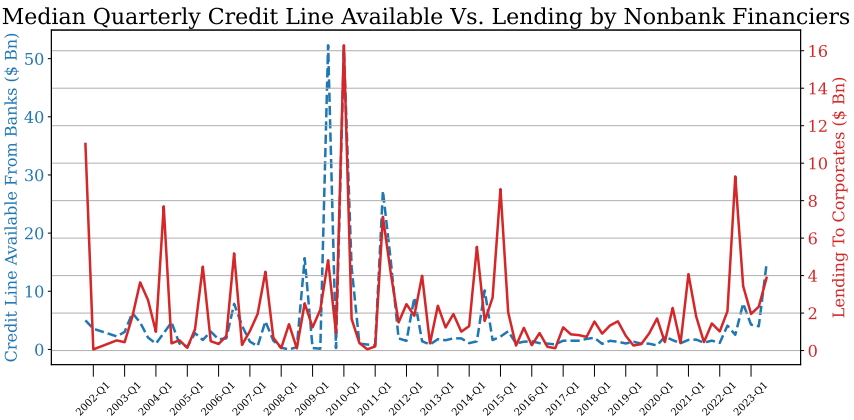


Figure 5: Quarterly credit line available (undrawn) of the median nonbank financier (NBF) is plotted in blue dotted line. Quarterly lending by the median NBF is plotted in the red line. This graph plots the median NBF. The Empirical Appendix B shows the total credit line utilization patterns. The patterns are similar, but the median is less affected by extreme values.

Second, a cross-sectional analysis reveals that NBFs that lend more and have higher lending uncertainty also draw down more.

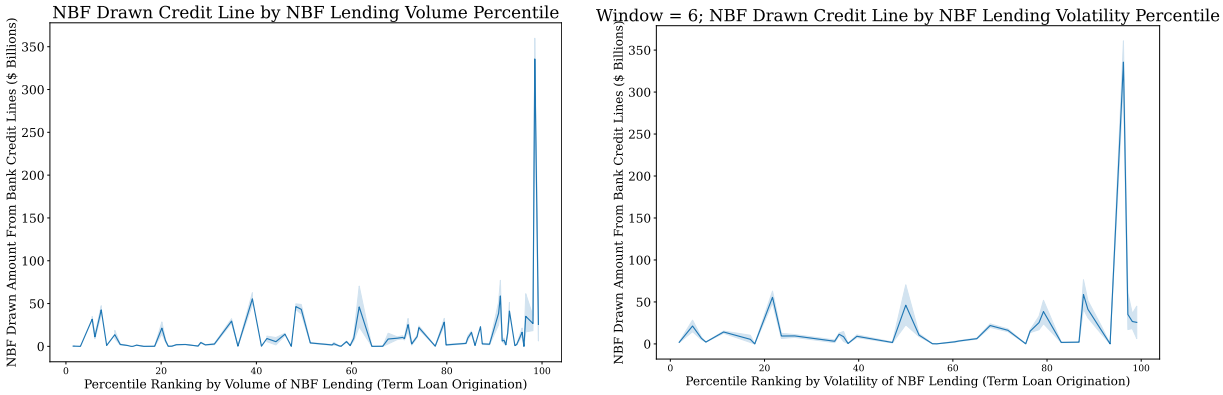


Figure 6: The left panel ranks NBFs by their lending volume. Top lenders in terms of lending volume draw down the most. The right panel ranks NBFs by their lending uncertainty. NBFs that have high lending volatility draw down the most.

NBFs incur an all-in-drawn spread when drawing down credit lines and an all-in-undrawn spread otherwise. The all-in-drawn spread includes an upfront option premium per committed dollar, a fixed spread, and a risk-free base rate, typically LIBOR/SOFR. Other fees may include annual and utilization fees. My credit line model reflects these institutional features, with credit line limits and option fees set endogenously in Section 3.

This section provides the empirical underpinning for my quantitative model, which I now present in Section 3.

3 Quantitative Model

I develop a quantitative macro-finance model with banks, nonbank financiers (NBFs), the government, and households, focusing on credit lines between banks and NBFs as a key mechanism for liquidity and risk-sharing in a connected financial system.

In my model, financial intermediaries transform liabilities into corporate loans, represented as Lucas trees. Banks have a unique liquidity advantage due to access to consumer deposits and Federal Reserve support as a lender of last resort (LOLR), allowing them to fund below market

rates. This advantage enables banks to invest in Lucas trees and extend contingent liquidity to NBFs, which face inventory uncertainty from unpredictable deal flows. Banks, with their liquidity edge, act as natural insurers for NBF inventory risks, despite being constrained by capital requirements that segment them from NBFs. This segmentation motivates banks to "rent" NBF balance sheets by extending credit lines, which function as options to enable risk-sharing.

A key innovation in my model is the endogenous treatment of credit line arrangements, with banks considering how additional credit limits affect NBFs' drawdowns and the credit line option premium.

The following sections first outline the model's preferences, technology, and timing. I then delve into the specific problems of NBFs and banks, with a focus on the credit line arrangement that link their balance sheets. Lastly, I describe the roles of the government and households and present the equilibrium market-clearing conditions that close the model.

3.1 Preferences, Technology and Timing

Preferences. Households have Epstein-Zin preferences given by:

$$U_t^H = \left\{ (1-\beta_H) \left(u_t^H\right)^{1-1/\nu_H} + \beta_H \left(\mathrm{E}t \left[\left(U_{t+1}^H\right)^{1-\sigma_H} \right] \right)^{\frac{1-1/\nu_H}{1-\sigma_H}} \right\}^{\frac{1}{1-1/\nu_H}}. \tag{3.1}$$

Households derive utility from both consumption and liquidity benefits from holding bank deposits and investing in commercial paper, where $u_t^H = \left(C_t^H\right)^{1-\varsigma} \left(\left(D_{t+1}^H\right)^{\theta} \left(B_{t+1}^H\right)^{1-\theta} \right)^{\varsigma}$.

Technology. Financial intermediaries, including banks and nonbank financiers (NBFs), invest in assets modeled as debt claims on Lucas trees. Each tree i is indexed by its value A_t^i at time t, exposed to aggregate shocks Z_t and idiosyncratic shocks z_t^i, such that: $A_t^i = \exp(Z_t + z_t^i)$, where the shock processes are $Z_t = \rho Z_{t-1} + (1-\rho)\mu + \sigma\varepsilon_t$, $z_t^i = \sigma^i \varepsilon_t^i$, and ε_t, ε_t^i are uncorrelated standard normal innovations. Define $G(A_t^i \mid Z_t)$ as the density of A_t^i conditional on Z_t. Loans A_t^i are perpetuity

bonds with geometric coupon payments $\{1, \delta^A, (\delta^A)^2, \ldots\}$, where δ^A determines duration. The loan price is p_t^i, and intermediaries extending loans of face value A_t^i receive $p_t^i A_t^i$.

A corporate borrower owing FA_t^i at time t either repays $F + \delta p_t^i$ if $A_t^i \geq F$ or defaults if $A_t^i < F$. In default, the bank recovers $(1 - \chi)A_t^i$, where χ represents bankruptcy costs. For diversified portfolios, idiosyncratic shocks are averaged out, leaving systematic shocks as primary drivers of defaults. By the strong law of large numbers:

$$\mathscr{R}_t^A = \int_F^\infty \left(F + \delta^A p_t\right) dG(A_t^i \mid Z_t) + (1 - \chi) \int_{-\infty}^F A_t^i dG(A_t^i \mid Z_t).$$

Timing. The timing of agents' decisions at the beginning of period t is as follows:

1. Aggregate shocks are realized. Both banks and nonbank financiers (NBFs) choose investment in Lucas tree. Banks choose deposits. Banks and NBFs negotiate on credit line arrangement, which includes credit limit, credit line fixed spread, and credit line option premium (upfront fee). The credit line contract is specified in detail in Section 3.2.

2. Idiosyncratic inventory uncertainty shocks are realized. NBFs drawdown on the pre-negotiated credit line subject to the fixed all-in-drawn spread on top of floating risk-free rate.

3. Idiosyncratic profit shocks for NBFs are realized. NBFs decide whether to go bankrupt or not. The government liquidates bankrupt NBFs.

4. Agents solve consumption and portfolio choice problems for next period. Markets clear. Households consume.

3.2 Credit Line Contract between Banks and Nonbank Financiers (NBFs)

Real-world credit line contracts are agreements between lenders (typically banks) and borrowers that allow the borrower to draw funds up to a specified limit. The establishment of the credit line limit is dependent on the borrower's creditworthiness at the time the credit line is negotiated. The lender

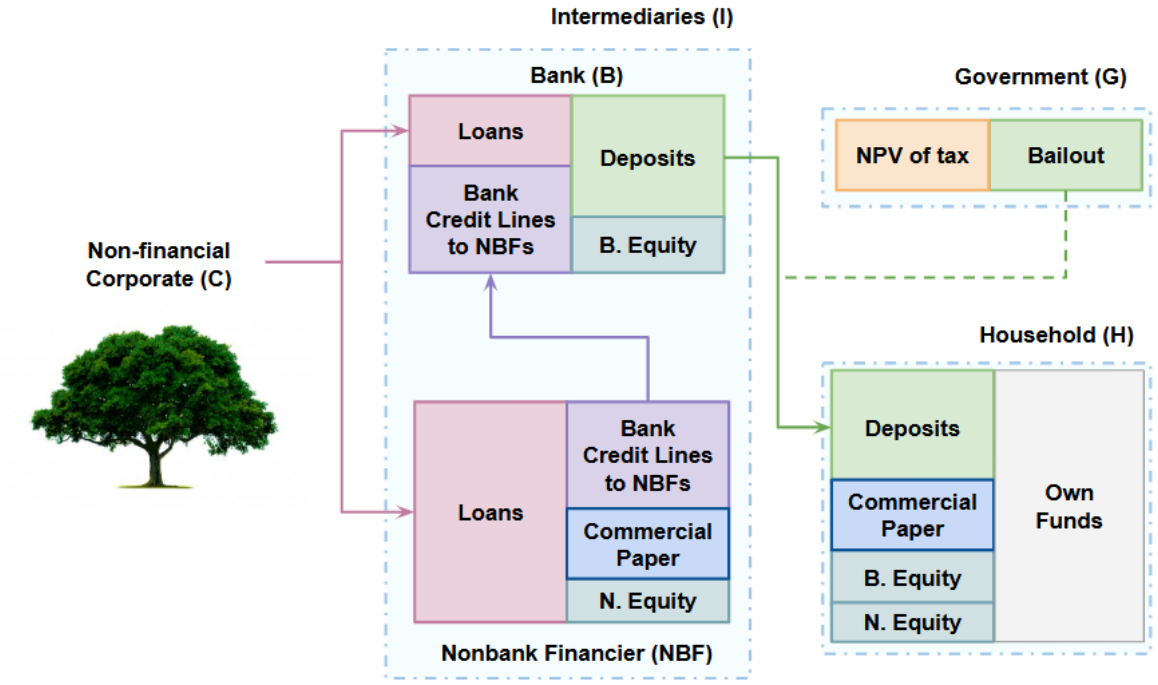


Figure 7: Model Overview

charges an upfront fee[5] to open the credit line, which can be seen as an option fee that the borrower pays in order to access the credit line. For any drawn credit, the borrower pays a fixed spread on top of the floating risk-free rate. The floating risk-free rate reflects market macro conditions, which was typically LiBOR before 2021 and switched to SOFR after 2021.

To reflect these real-world properties, I model the credit line contract between banks and NBFs in the following way. A credit line contract between banks and NBFs is characterized by a triple of $\{L_t, q_t^L, s^C\}$. L_t is the credit limit. Banks and NBFs negotiate on the credit limit. When deciding on the credit limit to extend to NBFs, banks internalize the effect of an additional unit of credit limit extended on the drawdown behavior of NBFs. q_t^L is the premium that NBFs pay to banks in order to establish a credit line that gives NBFs the right but not the obligation to drawdown when they face inventory uncertainty shocks described in Section 3.3. The option premium (upfront fee) of the credit line changes with respect to the credit limit NBFs requested. Banks operate as monopolists in providing credit lines to NBFs and internalize the effect of credit limit extension on the option

[5]Other typical fees associated with credit lines include an annual fee, which is required for banks to maintain the credit line, and a utilization fee if the drawn portion exceeds a high threshold. See Ivashina (2005) for details.

premium they collect from NBFs. s^C is the fixed-spread on credit line on top of the floating risk-free rate determined by r_t^{rf}, which NBFs pay when they drawdown from the credit line. s^C is determined at the time the credit line contract is established, and is kept the same at the time of the drawdown.

Differing from existing literature, my credit line modeling emphasizes the option feature of the credit line contract. By its nature as an option, credit lines help complete markets by allowing for better risk-sharing between banks and NBFs. Importantly, unlike the past literature (Greenwald et al., 2023), my model features endogenous credit limits and endogenous credit line option premiums (upfront fees). When determining the credit limit to extend to NBFs, banks account for how an additional unit of credit limit influences NBFs' drawdown behavior. By optimally setting both the credit limit, banks take into account corporate credit risks and mitigate the risk of moral hazard, effectively discouraging NBFs from "gambling" with these credit lines. Third, my credit line modeling features an interior drawdown choice, which differs from past literature's bang-bang solution of either fully utilizing the credit line or not (Greenwald et al., 2023; Choi, 2022). The interior feature allows me to achieve both realism and numerical stability. Lastly, my credit line modeling also reflects regulation. In the Basel framework, credit lines are preferentially treated vis-à-vis term loans.[6] While banks and NBFs already want to risk-share in the absence of regulatory preferential treatment of credit lines, banks additionally take into account the collateral benefits of extending credit lines. This is because credit lines require less equity buffer compared to term loans, and therefore, all else equal, allow banks to back more deposits.

Finally, my model of credit lines between banks and nonbank financiers (NBFs) reflects the real-world flexibility that allows NBFs to better capture investment opportunities, based on the narrative evidence I have documented on NBF inventory uncertainty. This is unexplored in the existing literature. Credit lines are better than short-term and long-term debt because of their very nature as long-term options with short-term drawdown choices. In the model, NBFs trade off the

[6]Basel II Part 2, item 83: "Commitments with an original maturity up to one year and commitments with an original maturity over one year will receive a credit conversion factor (CCF) of 20% and 50%, respectively." Item 599: "Committed retail and non-retail credit lines receive a CCF of 90%." See `https://www.bis.org/publ/bcbs128b.pdf` for the Basel requirement and `https://support.precisionlender.com/hc/en-us/articles/115009834408-Regulatory-Capital-Requirements-for-Line-of-Credit-Products` for an example of using the credit conversion factor (CCF).

marginal benefit of utilizing the credit line to capture additional investment opportunities against the marginal cost of paying the option premium and drawn credit repayment. Banks trade off the marginal profit from renting NBFs' balance sheets and the marginal collateral benefit of the credit line against the marginal cost of credit line investment. The extension of the credit limit takes into account NBF moral hazard risk, and the credit line option premium (upfront fee) efficiently prices in the corporate credit risks. In the following pages, I show how banks and NBFs interact via credit lines in detailing the NBF optimization problem in Section 3.3 and the bank optimization problem in Section 3.4, respectively. Finally, I summarize the economic mechanisms in Section 3.7.

3.3 Nonbank Financiers (NBFs)

Nonbank financiers (NBFs) invest in Lucas trees. Every period, they choose investment a_{t+1}^N, credit line limit L_{t+1} from which they can draw down if needed, commercial paper b_{t+1}^N and equity issuance e_{t+1}^N subject to an equity issuance cost, as well as a drawdown policy to be specified below.

Unlike banks who are lead arrangers in syndicated loan market, NBFs are frequently participants. This exposes NBFs to deal flow uncertainties. On top of that, a large portion of sub-A term loans (term B, C, D, E, etc. loans) are also sold to NBFs by banks post origination. In the model, this is modeled by investment opportunity shocks on NBF portfolio. I denote idiosyncratic inventory shocks as $\iota_{i,t}$, which are independent and identically distributed (i.i.d.) with cumulative distribution function (CDF) $F(\iota_{i,t})$ with support over $[0, \infty]$. NBFs can draw on their credit line facility when investment opportunities arise. Specifically, the inventory uncertainty shock is sustainable if the credit line limit at time t is larger than the the new investment amount commensurate to the shock. Hence, the individual drawdown policy is $c_{t,\iota} = \min(\iota, L_t)$. The aggregate drawdown amount is then

$$c_t(L_t) = \int_0^\infty \min(\iota, L_t) dF(\iota) = \int_0^{L_t} \iota dF(\iota) + \int_{L_t}^\infty L_t dF(\iota)\,. \tag{3.2}$$

NBFs pay back the drawn portion on their credit line. The required rate of return on the drawn

portion of the credit line is a fixed all-in-drawn spread s on top of a floating risk-free rate r_t^{rf}, i.e., NBFs pay $R_t^C = r_t^{rf} + s$ per unit of drawn credit. Denote the net worth of NBFs by N_t^N, then we can write the evolution of N_t^N as follows:

$$N_t^N = \mathscr{R}_t^A[A_t^N + c_t(L_t)] - R_t^C c_t(L_t) - B_t^N \,. \tag{3.3}$$

Nonbank financiers (NBFs) experience idiosyncratic profit shocks ϵ_t^N, which occur at the time of dividend payouts. These shocks are i.i.d. across NBFs and time, with $\mathrm{E}\left(\epsilon_t^N\right) = 0$ and cumulative distribution function F_ϵ. The idiosyncratic shocks capture the heterogeneity in NBF portfolios, such as variations in credit quality across loan portfolios (Elenev et al., 2021). This assumption ensures a consistent fraction $F_{\epsilon,t}$ of NBFs default. The shocks impact only the dividend payout and have no effect on the future net worth of NBFs. Three key assumptions are sufficient to achieve aggregation to a representative NBF. These are: (i) the NBF's objective function is linear with respect to idiosyncratic profit shocks, (ii) idiosyncratic profit shocks affect only the contemporaneous payout without impacting net worth, and (iii) defaulting NBFs are replaced by new NBFs with equity levels matching those of non-defaulting NBFs. Appendix A.1.1 has more details on model aggregation properties. NBFs distribute a fraction ϕ_0^N of their book equity as target dividends each period, but they can deviate by issuing equity e_t^N, incurring a convex cost $\Psi^N\left(e_t^N\right)$. The budget constraint specifies that NBFs utilize resources from their remaining net worth after dividend payments $(1-\phi_0^N)N_t^N$, equity issuance e_t^N (accounting for issuance costs $\Psi^N\left(e_t^N\right)$), and commercial paper borrowing B_{t+1}^N to fund investments in the Lucas tree A_{t+1}^N and to purchase the option of accessing bank credit line facilities L_{t+1}, as shown below in (3.5).

I now state the problem of the representative NBF.

$$V\left(\mathcal{S}_t^N, N_t^N\right) = \max_{A_{t+1}^N, L_{t+1}, e_t^I, B_{t+1}^N} \phi_0^N N_t^N - e_t^N + \epsilon_t^N + \mathrm{E}_t\left[\mathcal{M}_{t,t+1} \max\{V_{t+1}^N\left(\mathcal{S}_{t+1}^N, N_{t+1}^N\right), 0\}\right] \,, \tag{3.4}$$

subject to NBF budget constraint

$$q_t A_{t+1}^N + q_t^L L_{t+1} \leq (1 - \phi_0^N) N_t^N + e_t^N - \Psi^N \left(e_t^N\right) + q_t^r B_{t+1}^N \,, \tag{3.5}$$

and nonbank no-shorting constraint

$$0 \leq A_{t+1}^N \,, \tag{3.6}$$

and nonbank credit line limit

$$0 \leq L_{t+1} \,, \tag{3.7}$$

where NBF equity issuance cost has the form $\Psi^N \left(e_t^N\right) = \frac{\phi_1^N}{2} \left(e_t^N\right)^2$. The NBF's objective is to maximize its objective function (3.4) subject to the budget constraint (3.5) and non-negativity constraints (3.6)-(3.7).

3.4 Banks

Banks also provide debt financing to the corproate sector by investing in Lucas trees. Importantly, banks are different from nonbank financiers (NBFs) in three ways:

1. Banks are subject to occasionally-binding capital requirements. There are no capital requirements on NBFs.

2. Banks have access to short-term household deposits.

3. Banks have access to the Fed (government) balance sheet as lender of last resort (LORR).

The economic implications of these differences are as follows.

First, capital regulation on banks implies market segmentation, creating a motive for constrained banks to "rent" the balance sheet of unconstrained NBFs by extending credit lines to NBFs. Credit lines give NBFs the right but not the obligation to drawdown when needed. In this way, the option

nature of credit line provides insurance to NBFs, allows for better risk-sharing between banks and NBFs, and thereby help complete markets.

Second, only banks have access to consumer deposits, on which they earn a convenience yield as specified in Section 3.5 on the modeling of the household sector. Convenience yield on deposits allows banks to fund themselves below market risk-free rates. This gives banks a liquidity advantage, allowing banks to extend cheaper credit and making them natural insurers of NBFs. This explains my facility-level empirical fact using Dealscan Legacy and LSEG LoanConnector data (See Appendix Figure B.1) that NBFs are heavily reliant on banks for banking, but not vice versa, which is consistent what Acharya et al. (2024a) find in the "From Whom to Whom" US financial accounts data.

Third, only banks have access to the Fed balance sheet. NBFs do not. Having access to LORR amplifies bank's liquidity advantage exactly when liquidity is most scarce.

Banks invest in corporate Lucas trees A_t^B and extend credit lines L_t to NBFs. Whenever NBFs draw down c_t from bank credit lines, banks satisfy the requisite drawdown request. Banks are funded by short-term deposits D_t subject to capital requirements, where there are different capital risk-weights attached to bank corporate loans versus that to bank credit lines, using ω^C for drawn and ω^U for undrawn credit, to be specified below in detail. Similar to NBFs, banks distribute a fraction ϕ_0^B of their book equity as target dividends each period, but they can deviate by issuing equity e_t^B, incurring a convex cost $\Psi^B\left(e_t^B\right)$. Bank net worth is given by

$$N_t^B = \mathscr{R}_t^A A_t^B - D_t + \mathscr{R}_t^L c_t(L_t) - c_t(L_t)\,, \tag{3.8}$$

The return on credit line is given by

$$\mathscr{R}_{t+1}^L(L_{t+1}) = \underbrace{\left(1 - F_{\epsilon,t+1}^N\right) R_{t+1}^C}_{\text{non-defaulting NBFs pay back credit lines}} + \underbrace{F_{\epsilon,t+1}^N RV_{t+1}^N + \frac{F_{\epsilon,t+1}^N \epsilon_{t+1}^{N,-}}{c_{t+1}(L_{t+1}) + B_{t+1}^N}}_{\text{defaulting NBFs recovery value on bank credit lines}}\,. \tag{3.9}$$

As explained before, NBFs are subject to profit shocks ϵ_t^N, with probability $F_{\epsilon,t+1}^N$ of defaulting. The non-defaulting NBFs pay back the drawn credit at rate R_{t+1}^C, while the defaulting NBFs use their

investment proceeds to repay the draw credit. The recovery value if NBFs default is

$$RV_{t+1}^{N} = (1-\zeta^{N}) \cdot \frac{\mathscr{R}_{t+1}^{A}\left(A_{t+1}^{N} + c_{t+1}(L_{t+1})\right)}{c_{t+1}(L_{t+1}) + B_{t+1}^{N}}\,. \tag{3.10}$$

Bank capital requirement (3.13) reflects Basel-type risk-weighted capital requirement.

Bank's inside equity E_{t+1}^{B} has to be greater than a portion ξ^{E} of bank assets coming from corporate loans and drawn credit on their credit line facilities. In the baseline, I follow a $\xi^{E} = 7\%$ capital requirement. The current Basel framework has lower effective capital risk weight [7] on credit lines than on term loans. In particular, drawn credit receives a 90% conversion factor undrawn credit receives a 20% conversion factor if maturity is less than a year but 50% if maturity is more than a year. This means

$$E_{t+1}^{B} \geq \xi^{E}\left([Z_{t+1}+q_{t+1}]A_{t+1}^{B} + \omega^{C,E}c_{t+1}(L_{t+1}) + \omega^{U,E}\left(L_{t+1} - c_{t+1}(L_{t+1})\right)\right)$$

Since banks are funded by debt and equity, writing this in terms of the maximum leverage that banks can take results in[8]

$$D_{t} \leq \xi\left([Z_{t+1}+q_{t+1}]A_{t+1}^{B} + \omega^{C}c_{t+1} + \omega^{U}\left(L_{t+1} - c_{t+1}\right)\right)$$

where I denote $\xi \coloneqq 1-\xi^{E}$, $\omega^{C} \coloneqq \left(1-\xi^{E}\omega^{C,E}\right)/\xi$, $\omega^{U} \coloneqq \left(1-\xi^{E}\omega^{U,E}\right)/\xi$. This requirement has to be satisfied in the worst possible aggregate state, and hence the $\min$ operator in (3.13) down below. The undrawn $\omega^{U,E}$ risk weight takes into account the relative portion of credit lines from banks to NBFs that are less than one year (364-Day Facility and Revolver/Line < 1 Yr.) versus those over than one year (Revolver/Line > 1 Yr.) in maturity, as shown in the detailed credit line categories in Figure 2 in Empirical Section 2. Detailed calculations on policy parameters are in the Calibration Section 4. Finally, the budget constraint (3.12) states that banks use net-worth net of

[7] This is explained in detail in the Empirical Section 2. See Basel requirement and example of using the credit conversion factor (CCF) in the risk-weight capital requirement calculation.

[8] See Appendix A.2 for detailed derivations in writing the capital requirements in terms of maximum deposits banks can issue.

dividend payments $(1-\phi_0^B)N_t^B$, credit upfront fee collected from NBFs $q_t^L L_{t+1}$, equity issuance net of issuance cost $e_t^B - \Psi^B(e_t^B)$ and deposits from households D_{t+1} to fund the investment in corporate Lucas tree A_{t+1}^B.

I now characterize the bank's problem recursively as

$$V_t^B\left(\mathcal{S}_t\right) = \max_{A_{t+1}^B, D_{t+1}, L_{t+1}, e_t^B} \phi_0^B N_t^B - e_t^B + \mathrm{E}_t\left[\mathcal{M}_{t,t+1} V_{t+1}^B\left(\mathcal{S}_{t+1}\right)\right] , \tag{3.11}$$

subject to bank budget constraint

$$q_t A_{t+1}^B - q_t^f D_{t+1} \leq (1-\phi_0^B)N_t^B + q_t^L L_{t+1} + e_t^B - \Psi^B\left(e_t^B\right) , \tag{3.12}$$

bank capital requirement

$$D_{t+1} \leq \min_{\mathcal{S}_{t+1}|\mathcal{S}_t} \Big(\xi\big(\left[Z_{t+1} + q_{t+1}\right] A_{t+1}^B + \omega^C(\mathscr{R}_{t+1}^L c_{t+1}(L_{t+1}))) + \omega^U\left(L_{t+1} - c_{t+1}(L_{t+1})\right)\big)\Big) , \tag{3.13}$$

no-shorting constraint on bank loans to firms

$$0 \leq A_{t+1}^B , \tag{3.14}$$

where equity issuance cost has the form

$$\Psi^B\left(e_t^B\right) = \frac{\phi_1^B}{2}\left(e_t^B\right)^2 .$$

3.5 Households

Households own the equity of banks and non-banks, and receive aggregate dividends $\mathscr{D}_t^B$, $\mathscr{D}_t^N$. Households can invest in and derive liquidity benefits from one-period deposits and commercial paper that trade at price q_t^f and q_t^r respectively. Households choose consumption C_t^H, deposits at

banks D^H_{t+1}, nonbank debt B^H_{t+1} to maximize utility U^H_t, subject to household budget constraint:

$$C^H_t + q^f_t D^H_{t+1} + q^r_t B^H_{t+1} \leq W^H_t + Y_t + O^H_t \ , \tag{3.15}$$

where the evolution of household wealth is

$$\begin{aligned} W^H_t =& D^H_t + \mathscr{D}^B_t + \mathscr{D}^N_t \\ &+ B^H_t \left[\left(1 - F^N_{\epsilon,t}\right) + F^N_{\epsilon,t} \left((1-\zeta^N) \frac{\mathscr{R}^A_t (A^N_t + c_t(L_t))}{B^N_t + c_t(L_t)]} \right) + F^N_{\epsilon,t} \frac{\epsilon^{N,-}_t}{B^N_t + c_t(L_t)} \right] . \end{aligned} \tag{3.16}$$

3.6 Equilibrium

Given a sequence of aggregate shocks$\{Z_t\}$, and a government policy $\Theta_t = \{\xi, \omega^C, \omega^U\}$, a competitive equilibrium is an allocation $\{e^B_t, A^B_{t+1}, L_{t+1}\}$ for banks, $\{e^N_t, A^N_{t+1}, B^N_{t+1}, c_{t+1}, L_{t+1}\}$ for nonbanks, $\{C^H_t, D^H_{t+1}, B^H_{t+1}\}$ for households, and a price vector $\{q_t, q^L_t, q^f_t, q^r_t, R^C_t\}$, such that given the prices, households maximize life-time utility, banks and nonbanks maximize shareholder value, the government satisfies its budget constraint, and markets clear. The market-clearing conditions are:

$$\text{Deposits:} \quad D_{t+1} = D^H_{t+1} \ , \tag{3.17}$$

$$\text{Non-bank Debt:} \quad B^N_{t+1} = B^H_{t+1} \ , \tag{3.18}$$

$$\text{Loans:} \quad 1 = A^B_{t+1} + A^N_{t+1} + c_{t+1}(L_{t+1}) \ , \tag{3.19}$$

$$\text{ARC:} \quad Z_t + Y_t = C^H_t + \Psi^B\left(e^B_t\right) + \Psi^N\left(e^N_t\right) + DWL_t \ . \tag{3.20}$$

The last equation is the economy's resource constraint. It states that total output equals the sum of aggregate consumption including equity issuance costs and deadweight losses. During the bankruptcy processes, ζ^N are losses given default (in proportion to total assets) of nonbanks. When non-banks default, a a fraction η^N is deadweight loss to society. Hence, deadweight losses are

defined as

$$DWL_t = \zeta^N \eta^N F^N_{\epsilon,t} \mathscr{R}^A_{t+1}(A^N_t + c_t)\,, \tag{3.21}$$

and the bankruptcy proceedings rebated to households are

$$O^H_t = \zeta^N \left(1 - \eta^N\right) F^N_{\epsilon,t} \mathscr{R}^A_{t+1}(A^N_t + c_t)\,. \tag{3.22}$$

The aggregate net dividends paid by the intermediaries are

$$\mathscr{D}^N_t = \phi^N_0 N^N_t - e^N_t + \left(1 - F^N_{\epsilon,t}\right) \epsilon^{N,+}_t - F^N_{\epsilon,t} N^N_t\,, \tag{3.23}$$

$$\mathscr{D}^B_t = \phi^B_0 N^B_t - e^B_t\,. \tag{3.24}$$

where $\epsilon^{N,+}_t = \mathrm{E}_\epsilon\left(\epsilon \mid \epsilon \geq -\tilde{V}^N\left(\mathcal{S}^N_t\right)\right)$ are the expected idiosyncratic profit shocks conditional on not defaulting.

3.7 Economic Mechanism

The detailed derivations of the model are provided in the Model Appendix A. This section explains the economic mechanism underlying my credit line model. Credit lines offer nonbank financiers (NBFs) partial funding flexibility, enabling them to seize investment opportunities as they arise while also taking into account their default risks. NBFs trade off the marginal benefit of capitalizing on investment opportunities by drawing on credit lines against the marginal cost, which includes both the credit line option premium and repayment of drawn credit, as captured by the first-order condition for the NBF credit limit in equation 3.25.

$$\underbrace{\mathrm{E}_t\left[\mathcal{M}^N_{t,t+1}\mathscr{R}^A_{t+1}\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right]}_{\text{MB of capturing inv. opp.}} = \underbrace{q^L_t}_{\text{premium}} + \underbrace{\mathrm{E}_t\left[\mathcal{M}^N_{t,t+1}R^C_{t+1}\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right]}_{\text{MC of drawn credit}}\,. \tag{3.25}$$

Banks collect the option premium (credit line upfront fee) when extending credit lines. Banks weigh the marginal benefit of risk-sharing with NBFs and the collateral benefit derived from regulatory preferential treatment for credit lines vis-á-vis term loan against the marginal cost associated with NBF risk-taking, as shown in the first-order condition in (3.26). Specifically, banks consider the effect of increasing the credit line limit on NBF drawdown behavior, reflected in the partial derivative in equation 3.27.

$$\underbrace{\mathrm{E}_t\left[\mathcal{M}^B_{t,t+1}\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right]}_{\text{NBF risk-taking cost}} = \underbrace{q^L_t + \frac{\partial q^L_t}{\partial L_{t+1}}L_{t+1}}_{\text{option premium}} + \underbrace{\mathrm{E}_t\left[\mathcal{M}^B_{t,t+1}\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\mathscr{R}^L_{t+1}\right]}_{\text{MB of risk-sharing}}$$
$$+ \underbrace{\tilde{\lambda}^B_t \min_{\mathcal{S}_{t+1}|\mathcal{S}_t}\xi\left(\omega^C\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}} + \omega^U\left(1 - \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right)\right)}_{\text{collateral benefit}}, \tag{3.26}$$

where

$$\frac{\partial c_t(L_t)}{\partial L_t} = \frac{\partial}{\partial L_t}\left(\int_0^{L_t}\iota_t dF(\iota_t) + \int_{L_t}^{\infty}L_t dF(\iota_t)\right) = 1 - F(L_t)\,. \tag{3.27}$$

In this framework, NBFs' drawdown behavior c_{t+1} depends on the credit line limit L_{t+1} set by banks. The derivative of the NBFs' drawdown choice c_{t+1} with respect to the credit limit L_{t+1} reflects how an additional unit of credit line limit affects granted by banks affect the drawdown behavior of NBFs. Importantly, banks account for the effect of extending an additional unit of credit limit on NBF credit line extension, effectively acting as an endogenous deterring mechanism that restrains the maximum credit limit banks are willing to commit to *ex ante*.

Additionally, banks consider how extending the credit limit affects the price—and thus the expected return—on these credit lines, as reflected in the partial derivative $\frac{\partial q^L_t}{\partial L_{t+1}}$ from the NBF side in (3.25),

$$\frac{\partial q^L_t}{\partial L_{t+1}} = -\mathrm{E}_t\left[\mathcal{M}^N_{t,t+1}\left(\mathscr{R}^A_{t+1} - R^C_{t+1}\right)f\left(L_{t+1}\right)\right], \tag{3.28}$$

where $f_{t+1} = -\partial/\partial L_{t+1}\left(\partial c_{t+1}(L_{t+1})/L_{t+1}\right)$. Here, $\partial q_t^L/\partial L_{t+1}$ is negative, assuming banks hold a monopolistic position in extending credit lines. The greater the credit limit offered by banks, the lower the price and thus the higher the expected returns on these credit lines. Consequently, banks internalize the impact of increased credit limits on the pricing of each dollar committed, driven by the change in NBFs' response to incremental credit line extensions.

4 Calibration

I calibrate the model to the universe of US syndicated loan data from 1990 to 2023. A period is a year. In the subsequent subsections on credit risk[9], financial intermediation, preferences, and regulation[10], I separately discuss the parameters listed in Table 1 (externally calibrated) and Table 2 (internally calibrated). Externally calibrated parameters are derived directly from data or sourced from existing literature. Internally calibrated parameters are selected to jointly align the model with targeted moments observed in the data. Further institutional details are provided in Calibration Appendix C.

4.1 Credit Risk

4.1.1 Internally Calibrated Paramters

Aggregate shocks to the borrowers collateral values, denoted as Z_t, follow an autoregressive process of order 1, AR(1). This process is characterized by a persistence parameter ρ and a volatility parameter σ. Z_t is treated as an exogenous state variable. I employ the method outlined in Rouwenhorst (1995) for discretizing Z_t into a five-state Markov chain. The parameters $\rho = 0.9$ and $\sigma = 2\%$ are chosen to match the persistence (autocorrelation of order (1)) of the average corporate default rate, which is 0.85, and the volatility of the corporate default rate, which is 4.12%, in the data. Moreover, I use the loan repayment F to calibrate the average corporate default rate which is 2.09%. The

[9]The section on credit risk only has internally calibrated parameters to match model moments with that of the data

[10]The section on regulation only has externally calibrated parameters directly estimated from relevant empirical an institutional details.

Table 1: Pre-Set Parameters

Parameter	Description	Value	Source
		Financial Intermediation	
s	Credit line spread	88 bps	Dealscan Legacy and LSEG Loan-Connector, Appendix C.1
δ	Corporate loan average life	0.898	Dealscan Legacy and LSEG Loan-Connector, Appendix C.2
η_N	DWL (nonbanks) / total loss	1	No HH rebate
ϕ_0^B	Target bank dividend	0.068	Elenev et al. (2021)
ϕ_0^N	Target nonbank dividend	0.073	Avg. NBF dividend
		Preferences	
σ_H	Households risk aversion	1	Log utility
ν_H	Households IES	1	Log utility
		Regulation	
ξ	Max. bank leverage	0.93	Basel II reg. capital charge
ω^C	Drawn portion adjustment	1.007	Basel CCF details in Appendix C.3
ω^U	Undrawn portion adjustment	1.047	Basel CCF details in Appendix C.3

deadweight losses on defaulting loans χ are set to match corporate loan severities of 51.9%. Finally, I use the volatility of idiosyncratic shocks σ^i to target the average corporate default conditional on a crisis.

4.2 Financial Intermediation

4.2.1 Externally Calibrated Parameters

Credit line Spread. I calculate from Dealscan and LSEG LoanConnector the average fixed spread[11] on top of the risk-free rate. The credit lines from banks to NBFs have different maturities. The average fixed spread on top of the risk-free rate is 88 basis points. Appendix Figure C.1 has detailed credit line all-in-drawn and all-in-undrawn spread (in Dealscan and LSEG language) for credit lines of different maturities.

[11] In Dealscan and LSEG LoanConnector, all-in-drawn spread, is the spread on top of risk-free rate. See, Dealscan dictionary. Although we traditionally think of all-in-drawn spread as the total rate which includes the upfront fee, the LiBOR/SOFR risk-free base rate, fixed spread, and annual fee, etc, which is the convention in Ivashina (2005).

Table 2: Calibrated Parameters

Par	Description	Value	Target	Model	Data
			Credit Risk		
ρ	Persistence of borrower collateral	0.9	AC(1) corp. default rate	0.9	0.85
σ	Volatility of borrower collateral	2%	Volatility of corp. default rate	5%	4.12%
F	Loan Repayment	0.56	Avg. corporate default rate	2.09%	1.7%
χ	Losses on defaulting loans	0.8	Corporate loan severities	51.9%	51.9%
σ^i	Volatility of idios. shocks	0.07	Avg. corporate default conditional on crisis	2.9%	2.56%
			Financial Intermediation		
μ_ι	Mean of inventory uncertainty shocks	0.068	Avg. credit line utilization rate	80%	80%
σ_ι	Standard deviation of inventory uncertainty shocks	0.055	Volatility of credit line utilization rate	6.8%	6.2%
ϕ_1^B	Bank equity issuance cost	7	Bank equity issuance ratio	1.05%	1.05%
ϕ_1^N	NBF equity issuance cost	5	NBF equity issuance ratio	5.8%	4.5%
ζ^N	Loss given default (nonbanks)	0.8	Unsecured and Subordinated debt recovery (Moody's)	35%	38.2%
$\sigma_{\epsilon,N}$	Cross-sect. dispersion ϵ_t^N	1.4%	Nonbank bond default rate (Begenau and Landvoigt, 2022)	0.28%	0.28%
			Preferences		
β_H	Time discount factor	0.99	Risk-free rate	0.99%	1%
ς	elasticity of substitution between dep. and consumption	0.005	Liquidity premium	0.21%	0.21%
θ	elasticity of substitution between dep. and CP	0.9	Comm. paper conv. yield	0.1%	0.1%

Duration of Corporate Loans. In my model, all corporate loans are modeled as geometric bonds. The borrower promises to pay $\{\delta^{t-1}\}$ at time $t = 1, 2, 3, ...$ I gathered data from FRED and Bloomberg databases. From FRED, I obtained time series data on option-adjusted spreads (OAS) for high-yield and investment-grade bonds using Bank of America Merrill Lynch indices. The Bloomberg Barclays Aggregate Bond Index provided data on corporate loans and bonds, including market values, durations, maturities, and coupon rates from January 1997 to September 2023. I combined Barclays' investment-grade and high-yield portfolios to create an aggregate bond index, calculating the Fraction of High Yield, which informed the maturity and coupon rate of the index. This calculation yielded a mean WAC of 5.93% and a WAM of 10 years. I then adjusted the OAS series for both bond types with the Fraction of High Yield and added them to the constant maturity treasury rate to derive bond yields r_t. For the calibration process, I constructed a plain vanilla corporate bond $P^c(r_t)$ and a geometric bond $P^G(r_t)$ with parameter δ. The objective was to determine the quantity of geometric bonds needed to hedge interest rate shifts. My results showed $\delta_B = 0.928$ for bank loans. For nonbank loans, I calculated the WAM as 4.461 years using Dealscan data and estimated $\delta_N = 0.805$. I take a volume weighted average to calculate the coupon payment and principal fraction for the entire Dealscan loan pool. See Calibration Appendix C.2 for details.

Bankruptcies losses. In my model, I incorporate findings from Bennett and Unal (2015), the average loss severity for banks taken over by the FDIC — the portion of assets that is unrecoverable — is approximately 36.2%. Without a good reference on nonbank financier's dead-weight loss to society in their defaults, I apply the same baseline loss given default for nonbanks, $\eta_N = 36.2\%$. This approach reflects the dynamics of fire sales, where not all losses represent societal losses, but only a fraction.

Target Dividends. I use bank target dividend parameter in Elenev et al. (2021) at 6.8% of bank net worth. I am able to match 193 out of the total 371 nonbank financiers (NBFs) and find their gvkey through the Roberts Dealscan-Compustat Linking Database (Chava and Roberts, 2008). I construct construct time series of total dividend divided by book equity of each NBF and report the

average dividend payout ratio to be 6.9%, which is slightly above banks but not much[12]. This is to be expected because I am only able to match those NBFs that has Gvkey can be found on Compustat.

4.2.2 Internally Calibrated Parameters

Investments and Funding. As I explain in the drawdown data paragraph inside Section 2, I target drawn ratio of 80% using the mean of inventory uncertainty shocks that nonbank financiers (NBFs) face. As I explain in the model Section 3, credit lines allows NBFs to drawdown whenever investment opportunities arise. I use the standard deviation of inventory uncertainty shocks to calibrate the volatility of NBF drawdown portion. Bank and NBF equity issuance costs are used to match bank and NBF equity issuance ratio, which is calculated by dividing equity issuance by book equity.

Default. I use loss given default of 0.25 on nonbank loans to target the Moody's unsecured and subordinated debt recovery rate, which is 38.2% in the data, following Begenau and Landvoigt (2022). I use the cross-sectional dispersion of nonbank profitability shocks ϵ_t^N to match the nonbank bond default rate, which is also used in Begenau and Landvoigt (2022) as their S-bank bond default rate target, 0.28%.

4.3 Preferences

4.3.1 Externally Calibrated Parameters

I externally calibrate household risk aversion and inter-temporal elasticity of substitution to 1 for log utility.

4.3.2 Internally Calibrated Parameters

The time discount factor $\beta_H = 0.991$ is internally calibrated to target the risk free interest rate, which is around 1% in the data, and 0.99% generated by the model. The liquidity elasticity parameter is

[12]Damodaran (2024) show higher dividend payout ratio for both banks and financial services (nonbank and insurances). I do not use Damodaran (2024) because my sample do not have a lot of insurance companies as NBFs.

internally calibrated $\varsigma = 0.005$ to generate a liquidity premium on bank deposits of 0.21% following Van Binsbergen et al. (2022). The bank deposit elasticity θ governs the liquidity advantage of commercial paper, which equals 0.1% both in the model and in the data and it is lower then the one on safe bank deposits.

4.4 Regulation

I externally calibrate the maximum bank leverage $\xi = 0/93$ to fit a 7% capital requirement. In Section 3.4, I have derived expressions for ξ, ω^C and ω^U, with details in Model Appendix A.2.2. Note that for the capital weight on the undrawn, we need to separate the undrawn credit line of maturity less than 1 year, versus those that are more than 1 year. Undrawn commitment with less than 1 year of maturity receives conversion factor 20%, and those more than 1 year receives conversion factor 50%. According to Figure 2, we know that 364-day facility and revolver/line < 1 year altogether account for $43.14\% + 1.76\% = 44.9\%$ of all credit lines from banks to nonbank financiers (NBFs). Revolver/Line > 1 Yr account for 52.46% and the rest account for 2.64% and I count them as >1 year of maturity. Therefore, I calculate $\omega^C = \left(1 - \xi^E \omega^{C,E}\right)/\xi = (1 - 0.07 * 0.90)/0.93 = 1.007$, $\omega^U = \left(1 - \xi^E \omega^{U,E}\right)/\xi = (1 - 0.07 * (20\% * 44.9\% + 50\% * 55.1\%))/0.93 = 1.047$. Details are in Calibration Appendix C.3.

5 Results

This section presents three set of results of the calibrated model. To highlight on the value of contingent liquidity between banks and nonbank financiers (NBFs), my first main result examines the impact of shutting down credit lines from banks to nonbank financiers (NBFs), comparing the baseline interconnected financial system to a segmented system in which banks are not linked to NBFs. Second, I study how the dynamics of a financial crisis, focusing on key financial balance sheet variables and asset prices. Finally, I explore policy experiments that demonstrate the spillover effects of bank regulations on NBFs when banks extend credit lines to them.

5.1 Interconnected Vs. Segmented Financial Systems

I report unconditional means from a long simulation of the model (50,000 years), as well as averages conditional on being a in a bad state (high credit risk, i.e. Z_t below average).

The baseline economy reflects the model presented in the main text in Section 3, where banks extend contingent liquidity in the form of credit lines to nonbank financiers (NBFs). I call the baseline economy the "Interconnected" economy. To understand the value of contingent liquidity between banks and NBFs, I study the counterfactual world where there is no such link by shutting down the credit line from banks to NBFs. I call the counterfactual economy the "Segmented" economy.

Table 3: Interconnected Vs. Segmented Financial System

	Interconnected (Baseline)		*Segmented*	
	Unconditional	*Fin. Rec.*	*Unconditional*	*Fin. Rec.*
		Banks		
Investment	0.54	0.53	0.22	0.23
Deposits	0.55	0.54	0.20	0.21
Credit line limit	0.05	0.051	–	–
		Nonbank Financiers (NBFs)		
Investment	0.42	0.43	0.78	0.77
Commercial paper	1.19	1.21	2.16	2.14
Credit line utilization	80%	81%	–	–
Default probability	0.28%	0.46%	3.5%	5.83%
		Pricing		
Deposit rate	0.21%	0.23%	0.15%	0.17%
Risk-free rate	0.99%	1.30%	1%	1.3%
Commercial paper rate	1.02%	1.27%	1.6%	2%
Asset price	4.09	3.93	3.78	3.5
		Welfare		
Household welfare	1.17	1.15	1.09	1.08

Note that total share of investment is 1. This consists of bank's share of investment, nonbank financier's (NBF's) share of investment, and the additional investment opportunities that arise from inventory uncertainty shocks. NBFs are only able to seize investment opportunities up to their credit

line limit. The actual additional investment by NBFs is their drawdown on the credit line, which si credit line limit times the credit line utilization.

The value of contingent liquidity provided by credit line arrangements becomes evident when comparing the interconnected and segmented economies at their ergodic means.

First, the interconnected economy is safer on average (in the sense of comparing "Unconditional Mean"), precisely because when deciding the credit limit, banks take into account the effect of an additional unit of credit limit extension on the drawndown choice of NBFs, and hence NBFs' risk-taking behavior and the share of their investment is disciplined by bank credit lines. Without bank credit lines, NBFs' risk-taking less bridled. In particular, we observe that the interconnected economy displays a larger banking sector originating 54% of the loan pool funded by deposits compared to a segmented economy in which the origination share drops to 22%. This is because the presence of credit lines, everything else equal, makes the economy safe allowing the banking sector to hold ex-ante a large share of aggregate risk, as we can see from higher asset prices (4.09 versus 3.78) and lower default probabilities (0.28% versus 3.5%). The fact that asset prices are higher in the interconnected economy makes banks better able to back safe assets, which lead me to the second value of contingent liquidity.

Second, the interconnected economy enhances welfare. Credit lines enable banks to manufacture a greater quantity of safe assets, such as deposits, which directly benefits households. For example, deposit creation rises to 0.55 in the interconnected economy compared to just 0.20 in the segmented economy, resulting in a marked improvement in household welfare.

Third, the interconnected economy is more resilient during financial crises. Comparing the unconditional mean with the financial recession mean, we observe that NBFs' default risk rises by 64% in the interconnected economy, whereas it increases by 67% in the segmented economy under equivalent aggregate risk levels. Additionally, asset prices decline more sharply in the segmented economy (7%) than in the interconnected economy (4%).

5.2 Impulse Responses of the Macro-economy to Crises

Next, I present impulse-response graphs to analyze the behavior of macroeconomic variables conditional on the state of the economy. The analysis begins in year 0 , where collateral values are set at their average state ($Z_t = 0$), and the four endogenous state variables are initialized at their respective ergodic averages. In period 1, I introduce a shock where Z_t declines by two standard deviations (depicted by the yellow line). From period 2 onward, the exogenous state variable evolves according to its stochastic laws of motion. For comparison, I also include a series where no shock occurs in period 1, and the exogenous state variable follows a mean-reverting process (shown by the blue line). To estimate the dynamics, I simulate 50,000 sample paths over a 25-year horizon and calculate the average behavior across these paths.

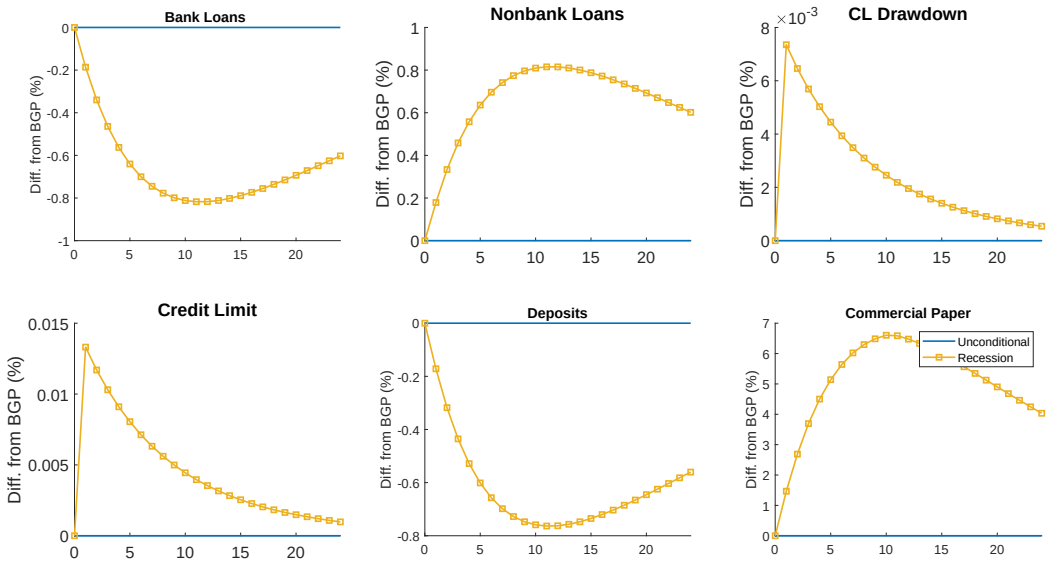


Figure 8: intermediaries balance sheets variables in financial crisis. Blue: no shock. Yellow: recession.

Intermediary Balance Sheets. Figure 8 compares the baseline economy without shock with the economy in financial recessions. The yellow line shows the impulse response during crisis. In a recession, bank deposits decrease by 0.77% compared to the steady state. The decrease in deposits strip banks of a vital source of inexpensive funding, thereby increasing bank funding costs.

Therefore, the contraction in bank funding leads to a reduction in bank lending to non-financial firms and NBFs. As illustrated in the top panel of Figure 8, bank loans to firms experience immediate declines upon the onset of a crisis by 0.82% compared to the steady state. However, the regulatory environment favors credit lines over corporate loans, which makes credit lines a less direct form of credit exposure for banks. Consequently, banks substitute away from directly investing in corporate loans towards investing in credit lines to NBFs. This boost in bank funding to NBFs helps revive NBFs' lending to firms. NBFs draw down more from their balance sheet during crisis, which is consistent with the data. During the recovery period, nonbank loans increase by 0.81% compared to the steady state, signaling a rebound in this sector.

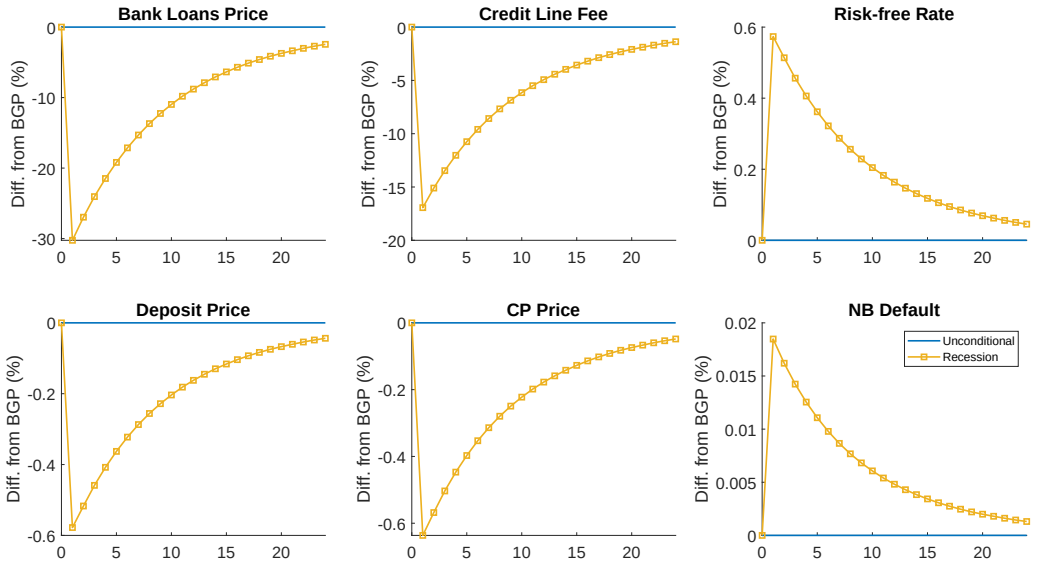


Figure 9: asset prices in financial crisis. Blue: no shock. Yellow: recession.

Asset Pricing. Figure 9 illustrates the behavior of asset prices during a crisis. As corporate assets lose value, the price of bank loans declines by 28.5% compared to the steady state. On the balance sheet side, as shown in Figure 8, banks adjust their allocation by substituting direct loans to the non-financial corporate sector with contingent liquidity in the form of credit lines extended to NBFs. This shift results in an increase in the amount of credit lines. Because banks hold monopolistic power in offering credit lines, an increase in credit limits leads to a lower valuation of each dollar of

credit. This is evident in the decline of the credit line fee by 17.2% compared to the steady state, which represents the cost per dollar of the total credit line limit that NBFs pay for the option to draw funds. Alternatively, this phenomenon can be viewed through the lens of credit line options, where the return on the unused portion of the credit line (not the drawn portion) increases. During a crisis, shareholders (households) of the total economy, including the corporate and intermediary equity, are more constrained and therefore to induce investments in bank deposits, risk-free rate rises by 0.78% compared to that in the steady state to clear the market.

5.3 Policy Experiment

In this Section, I use the calibrated model as a laboratory to conduct policy experiments. Current draft contains two policy experiments, one on the spillover effect of bank capital regulation on nonbank financiers (NBFs), and two on the effect of regulating credit lines from banks to NBFs (both the drawn and the undrawn off-balance sheet items). Future drafts contain more experiments on quantitative easing.

Bank Capital Requirement. I show that tightening bank capital requirements can have non-monotonic effects over the entire policy space. There are two forces. On the one hand, tightening capital requirements reduces bank leverage, lowering total deposits and therefore increases bank funding costs, which makes nonbanks bear a higher loan share of. On the other hand, tightening capital requirements makes deposit more scarce (Begenau, 2020), which increases the convenience yield banks earn on deposits, further emphasize bank's comparative advantage in cred it extension to the real non-financial corporate sector. Now I show results on the policy spillover effects across the entire financial system, including the nonbank sector.

Under the baseline scenario, a 7% bank capital requirement translates to a maximum leverage of 93% for banks. An increase in this requirement from 4% to 12% results in a reduced maximum leverage from 96% to 88% for banks, which is represented in the westward movement in the subsequent figure. Tightened bank capital regulations limit banks' ability to issue deposits. Due to

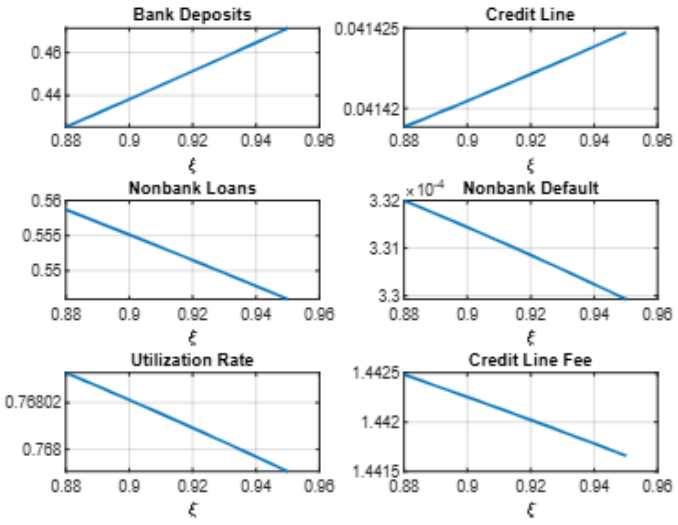


Figure 10: Spillover Effect of Bank Capital Regulation on Nonbank Loan Origination, B

the regulated nature of banks, their deposits remain highly sought after by households. Although this reduction in the supply of bank deposits may lead to an increase in the convenience yield for bank deposits, the increase in convenience yield does not offset the reduction in total deposit supply, at least in the current policy spectrum. As a result, banks have less funding and extend fewer corporate loans, but nonbank loan share rises. Bank credit line to NBFs also decreases, but the utilization rate of credit line increases to make sure that NBFs have enough funding to invest in a larger share of loans in the total economy. Heavier utilization makes NBFs more prone to default. Credit line option fee rises because banks are now more constrained and credit line supply becomes scarce.

Regulation on Credit Lines. I show that preferential treatment on credit lines vis-à-vis term loans increase nonbank financier's (NBF's) loan share.

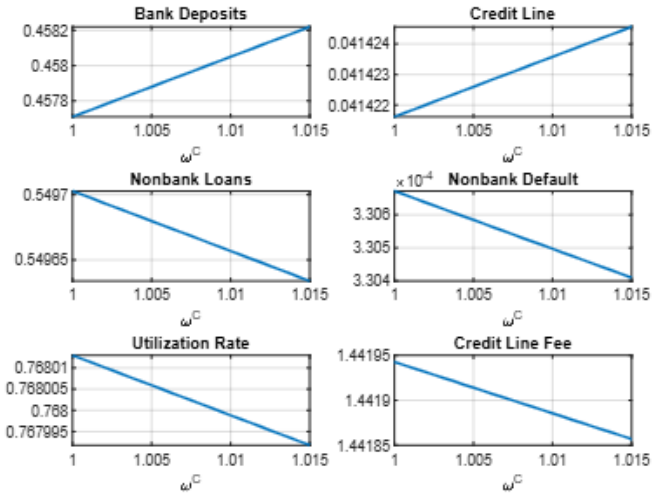


Figure 11: Effect of Regulation of Drawn Credit from Bank Credit Lines to Nonbank Financiers (NBFs).

In my model, ω^C governs how much deposits banks can back per unit of drawn credit from credit line. Suppose ω^C increases, this means a more lax regulatory treatment of credit lines vis-à-vis corporate loans. We can see that with an increase in ω^C, banks tilt away from extending corporate loans towards extending credit lines to NBFs. NBFs get more funding and extend more intermediated credit to firms. NBFs become larger but also more volatile, exposing themselves more to corporate credit risks, thus increasing the failure rate of NBFs.

Next, I show the effect of regulating off-balance sheet undrawn credit lines. ω^U governs collateral benefit of the undrawn credit line. Tightening the off-balance sheet regulation decreases the amount of deposits bank can take, further limiting total credit limit banks extend to NBFs, and decreasing NBF loans.

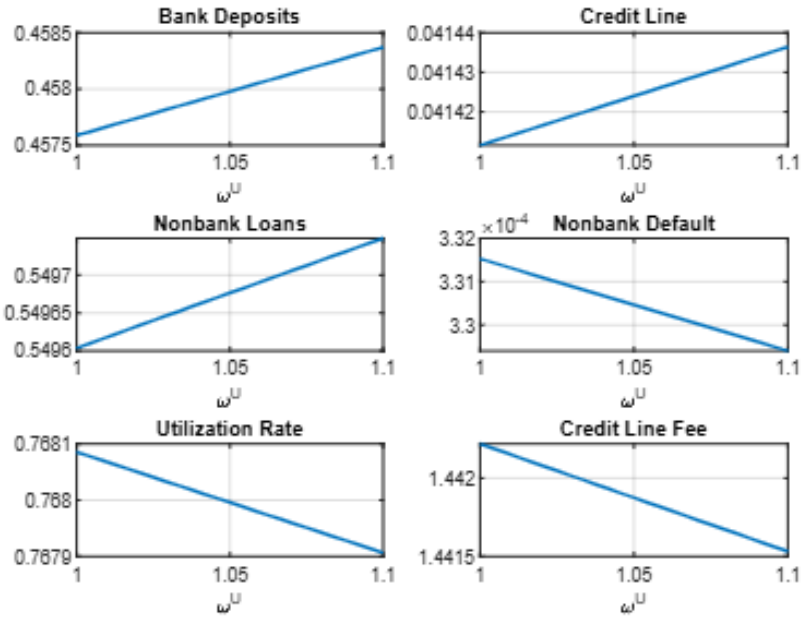


Figure 12: Effect of Regulation Off-balance sheet Undrawn Credit Lines.

6 Conclusion

This paper examines the value of contingent liquidity provided by banks to nonbank financiers (NBFs). In the modern financial system, banks are connected to NBFs primarily through credit line extensions, which account for 96% of these linkages and serve as a key form of contingent liquidity. While this arrangement offers private benefits to both banks and NBFs, it also has significant macroeconomic implications and policy relevance.

In the syndicated loan market, NBFs rely on banks for liquidity support and insurance against inventory uncertainties, while banks leverage their liquidity advantage to act as natural insurers. Banks also benefit from risk-sharing and relaxing their regulatory constraints. Credit lines offer advantages over other funding forms: unlike long-term debt, they impose funding costs only when investment opportunities arise, avoiding the debt overhang problem for NBFs. Compared to short-term debt, credit lines feature fixed spreads that remain favorable during crises, unlike short-term debt rates, which are highly sensitive to market distress. This is precisely because I model credit

lines with endogenous long-term option with short-term drawndown.

To quantify the macroeconomic value of contingent liquidity, I develop a novel macro-finance model calibrated to the universe of the U.S. syndicated loan market. This model enables counterfactual comparisons with a segmented economy where banks and NBFs operate in isolation. I demonstrate that an interconnected economy, where banks extend credit lines to NBFs, is safer, experiences smaller asset price declines during crises, and allows banks to support more deposits. The model provides a rigorous framework for evaluating regulatory measures targeting nonbanks and assessing the spillover effects of banking regulations on both on- and off-balance-sheet activities. Future iterations of this paper will incorporate an analysis of quantitative easing in an interconnected financial system.

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A Model Appendix

A.1 NBFs

A.1.1 Aggregation

Three assumptions are sufficient to obtain aggregation to a representative non-bank. These assumptions are: (i) the intermediary objective is linear in the idiosyncratic profit shock, (ii) idiosyncratic profit shocks only affect the contemporaneous payout (but not net worth), and (iii) defaulting intermediaries are replaced by new intermediaries with equity equal to that of non-defaulting intermediaries.

I can define the optimization problem of the non-defaulting non-banks with profit shock realization $\epsilon_{t,i}$ recursively as

$$V_t^N\left(\epsilon_{i,t},\iota_{i,t},\mathcal{S}_t\right)=\max_{a_{i,t+1}^N,b_{i,t+1}^N,l_{i,t+1}^N,e_{t,i}^N}\phi_0^N n_t^N-e_{t,i}^N+\epsilon_{i,t}+\mathrm{E}_t\left[\mathcal{M}_{t,t+1}\max\left\{V_{t+1}^N\left(\epsilon_{i,t},\iota_{i,t+1},\mathcal{S}_{t+1}\right),0\right\}\right]$$

subject to the no-shorting constraints. Since the objective function is linear (assumption (i)) in the profit shock $\epsilon_{t,i}$, we can equivalently define a value function $\tilde{V}^N\left(\epsilon_{i,t},\iota_{i,t},\mathcal{S}_t\right)=V^N\left(\epsilon_{t,i},\iota_{i,t},\mathcal{S}_t\right)-\epsilon_{t,i}$, and write the objective as

$$\tilde{V}_t^N\left(\iota_{i,t},\mathcal{S}_t\right)=\max_{a_{i,t+1}^N,b_{i,t+1}^N,l_{i,t+1}^N,e_{t,i}^N}\phi_0^N n_t^N-e_{t,i}^N+\mathrm{E}_t\left[\mathcal{M}_{t,t+1}\max\left\{\tilde{V}^N\left(\iota_{i,t+1},\mathcal{S}_{t+1}\right)+\epsilon_{i,t+1},0\right\}\right],$$

subject to the same set of constraints. Conditional on the same state variables $(\mathcal{S}_t)$, the objective functions imply the same optimal choices are independent of the realization of the current profit shock $\epsilon_{t,i}$. Thus we can find a representative non-bank for all non-defaulting non-banks. Additionally, the realization of the idiosyncratic shocks are irrelevant for non-banks that defaulted and replaced, assuming that equity holders (households) endow the replacing non-banks with identical capital N_t^N. Hence, all nonbanks have the same beginning-of-period wealth and we now have the problem of a representative non-bank.

A.1.2 Intermediary sector: inventory uncertainty shocks

Nonbank financiers (NBFs) face inventory uncertainty shocks on their loan portfolio, denoted as $\iota_{i,t}$, which are independent and identically distributed (i.i.d.) with cumulative distribution function (CDF) $F(\iota_{i,t})$ with support over $[0,\infty]$.

NBFs can draw on their credit line facility when investment opportunities arise. Specifically, the inventory uncertainty shock is sustainable if the credit line limit at time t is larger than the the new investment amount commensurate to the shock. The individual drawdown policy is therefore $c_{t,\iota}=\min(\iota,L_t)$. The aggregate drawdown amount is then

$$\begin{aligned}c_t(L_t)&=\int_0^\infty\min(\iota,L_t)dF(\iota)\\&=\int_0^{L_t}\iota dF(\iota)+\int_{L_t}^\infty L_t dF(\iota)\,.\end{aligned}$$

Per unit of drawn credit, NBFs pay the required rate of return

$$R_t^C = \underbrace{s^C}_{\text{fixed spread}} + \underbrace{\frac{1}{\mathrm{E}[\mathcal{M}_{t,t+1}]}}_{\text{risk-free rate}}$$

. Denote the net worth of NBFs by N_t^N, and we can write the evolution of N_t^N as follows:

$$N_t^N = \mathscr{R}_t^A[A_t^N + c_t(L_t)] - R_t^C c_t(L_t) - B_t^N \,.$$

where $\mathscr{R}_t^A = Z_t + q_t$ is the return on non-bank assets modelled as Lucas trees.

A.1.3 Optimization Problem

The recursive problem of a nonbank is:

$$V\left(\mathcal{S}_t^N, N_t^N\right) = \max_{A_{t+1}^N, B_{t+1}^N, L_{t+1}, e_t^I} \phi_0^N N_t^N - e_t^N + \epsilon_t^N + \mathrm{E}_t\left[\mathcal{M}_{t,t+1} \max\{\tilde{V}_{t+1}^N\left(\mathcal{S}_{t+1}^N, N_{t+1}^N\right) + \epsilon_{t+1}^N, 0\}\right] \,, \tag{A.1}$$

subject to nonbank budget constraint

$$q_t A_{t+1}^N + q_t^L L_{t+1} \leq (1-\phi_0^N) N_t^N + e_t^N - \Psi^N\left(e_t^N\right) + q_t^r B_{t+1}^N \,, \tag{A.2}$$

and nonbank no-shorting constraint

$$0 \leq A_{t+1}^N \,, \tag{A.3}$$

and nonbank credit line limit

$$0 \leq L_{t+1} \,, \tag{A.4}$$

where

$$\Psi^N\left(e_t^N\right) = \frac{\phi_1^N}{2}\left(e_t^N\right)^2 \,.$$

A.1.4 First-order Conditions

Attach Lagrange multiplier μ_t^N to the nonbank no-shorting constraint on loans to firms (A.3), and $\mu_{t,L}^N$ for the nonbank credit limit constraint (A.4) and ν_t^N to the budget constraint (A.2).

Equity Issuance. We can differentiate the objective function with respect to e_t^N :

$$\nu_t^N\left(1 - \phi_1^N e_t^N\right) = 1 \,,$$

Nonbank Loans. The FOC for loans A^N_{t+1} is

$$\left(q_t - \frac{\partial q^r_t}{\partial A^N_{t+1}}\right)\nu^N_t = \mu^N_t + \mathrm{E}\left[\mathcal{M}_{t,t+1}\tilde{V}^N_{N,t+1}\left(1 - F^N_{\epsilon,t+1}\right)\mathscr{R}^A_{t+1}\right],$$

Nonbank Debt. The FOC for loans B^N_{t+1} is

$$\left(q^r_t + \frac{\partial q^r_t}{\partial B^N_{t+1}}\right)\nu^N_t = \mathrm{E}\left[\mathcal{M}_{t,t+1}\tilde{V}^N_{N,t+1}\left(1 - F^N_{\epsilon,t+1}\right)\right],$$

Nonbank Credit Limit. The FOC for nonbank credit limit L_{t+1} is

$$\left(q^L_t - \frac{\partial q^r_t}{\partial L_{t+1}}\right)\nu^N_t = \mu^N_{t,L} + \mathrm{E}_t\left[\mathcal{M}_{t,t+1}\tilde{V}^N_{N,t+1}\left(1 - F^N_{\epsilon,t+1}\right)\left(\mathscr{R}^A_{t+1} - R^C_{t+1}\right)\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right].$$

where

$$\begin{aligned}\frac{\partial c_t(L_t)}{\partial L_t} =& \frac{\partial}{\partial L_t}\left(\int_0^{L_t}\iota_t dF(\iota_t) + \int_{L_t}^{\infty} L_t dF(\iota_t)\right)\\ =& f(L_t)L_t - L_t f(L_t) + \int_{L_t}^{\infty} dF(\iota_t)\\ =& 1 - F(L_t)\,.\end{aligned} \tag{A.5}$$

A.1.5 Euler Equations

First take the envelope condition:

$$\tilde{V}^N_{N,t} = \phi^N_0 + \left(1 - \phi^N_0\right)\nu^N_t\,.$$

Combining this with the FOC for equity issuance above to eliminate ν^N_t yields

$$\tilde{V}^N_{N,t} = \phi^N_0 + \frac{1 - \phi^N_0}{1 - \phi^N_1 e^N_t}\,.$$

Define the stochastic discount factor of the intermediary as

$$\mathcal{M}^N_{t,t+1} = \mathcal{M}_{t,t+1}\left(1 - \phi^N_1 e^N_t\right)\left(\phi^N_0 + \frac{1 - \phi^N_0}{1 - \phi^N_1 e^N_{t+1}}\right)\left(1 - F^N_{\epsilon,t+1}\right)$$

I can organize the FOCs as:

$$q_t - \frac{\partial q_t^r}{\partial A_{t+1}^N} B_{t+1}^N = \tilde{\mu}_t^N + \mathrm{E}\left[\mathcal{M}_{t,t+1}^N \mathscr{R}_{t+1}^A\right] \ , \tag{A.6}$$

$$q_t^r + \frac{\partial q_t^r}{\partial B_{t+1}^N} B_{t+1}^N = \mathrm{E}\left[\mathcal{M}_{t,t+1}^N\right] \ , \tag{A.7}$$

$$q_t^L - \frac{\partial q_t^r}{\partial L_{t+1}} B_{t+1}^N = \tilde{\mu}_{t,L}^N + \mathrm{E}_t\left[\mathcal{M}_{t,t+1}^N \left(\mathscr{R}_{t+1}^A - R_{t+1}^C\right)\left(1 - F(L_{t+1})\right)\right] \ . \tag{A.8}$$

where I plug in equation (A.5) and define $\tilde{\mu}_t^N \equiv \mu_t^N / \nu_t^N$ and $\tilde{\mu}_{t,L}^N \equiv \mu_{t,L}^N / \nu_t^N$.

A.2 Banks

A.2.1 Optimization Problem

Bank net worth is given by

$$N_t^B = \mathscr{R}_t^A A_t^B - D_t + \mathscr{R}_t^L c_t(L_t) - c_t(L_t) \ , \tag{A.9}$$

where

$$\mathscr{R}_{t+1}^L(L_{t+1}) = \left(1 - F_{\epsilon,t+1}^N\right) R_{t+1}^C + F_{\epsilon,t+1}^N RV_{t+1}^N + \frac{F_{\epsilon,t+1}^N \epsilon_{t+1}^{N,-}}{B_{t+1}^N + c_{t+1}(L_{t+1})} \, , \tag{A.10}$$

where the recovery value of nonbank default is

$$RV_{t+1}^N = (1 - \zeta^N) \cdot \frac{\mathscr{R}_{t+1}^A \left(A_{t+1}^N + c_{t+1}(L_{t+1})\right)}{B_{t+1}^N + c_{t+1}(L_{t+1})} \, . \tag{A.11}$$

Bank's problem is characterized recursively as

$$V_t^B\left(\mathcal{S}_t\right) = \max_{A_{t+1}^B, D_{t+1}, L_{t+1}, e_t^B} \phi_0^B N_t^B - e_t^B + \mathrm{E}_t\left[\mathcal{M}_{t,t+1} V_{t+1}^B\left(\mathcal{S}_{t+1}\right)\right] \ , \tag{A.12}$$

subject to bank budget constraint

$$q_t A_{t+1}^B - q_t^f D_{t+1} \leq (1 - \phi_0^B) N_t^B + q_t^L L_{t+1} + e_t^B - \Psi^B\left(e_t^B\right) \ , \tag{A.13}$$

bank capital requirement,

$$D_{t+1} \leq \min_{\mathcal{S}_{t+1} | \mathcal{S}_t} \left(\xi \big(\left[Z_{t+1} + q_{t+1}\right] A_{t+1}^B + \omega^C c_{t+1}(L_{t+1}) + \omega^U \left(L_{t+1} - c_{t+1}(L_{t+1})\right) \big) \right) , \tag{A.14}$$

no-shorting constraint on bank loans to firms,

$$0 \leq A_{t+1}^B \, , \tag{A.15}$$

where

$$\Psi^B\left(e_t^B\right) = \frac{\phi_1^B}{2}\left(e_t^B\right)^2 \ .$$

A.2.2 Bank Capital Requirements

The current Basel framework has lower effective capital risk weight on credit lines than on term loans. In particular, drawn credit receives a 90% conversion factor undrawn credit receives a 20% conversion factor if maturity is less than a year but 50% if maturity is more than a year. This means

$$E_{t+1}^B \geq \xi^E\left([Z_{t+1}+q_{t+1}]A_{t+1}^B + \omega^{C,E}c_{t+1}(L_{t+1}) + \omega^{U,E}\left(L_{t+1}-c_{t+1}(L_{t+1})\right)\right)$$

For brevity here, I omit parenthesis (L_{t+1}) from $c_{t+1}(L_{t+1})$, but note that c_{t+1} is a function of L_{t+1} as shown in the bank net worth evolution (3.8). Writing the capital requirement in terms of maximum deposits banks can support yields

$$\begin{aligned}
D_t \leq & [Z_{t+1}+q_{t+1}]A_{t+1}^B + L_{t+1} - \xi^E\left([Z_{t+1}+q_{t+1}]A_{t+1}^B + \omega^{C,E}c_{t+1} + \omega^{U,E}\left(L_{t+1}-c_{t+1}\right)\right)\\
= & [Z_{t+1}+q_{t+1}]A_{t+1}^B + c_{t+1} + L_{t+1} - c_{t+1} - \xi^E\left([Z_{t+1}+q_{t+1}]A_{t+1}^B + \omega^{C,E}c_{t+1} + \omega^{U,E}\left(L_{t+1}-c_{t+1}\right)\right)\\
= & (1-\xi^E)[Z_{t+1}+q_{t+1}]A_{t+1}^B + (1-\xi^E\omega^{C,E})c_{t+1} + (1-\xi^E\omega^{U,E})\left(L_{t+1}-c_{t+1}\right)\\
\equiv & \xi\left([Z_{t+1}+q_{t+1}]A_{t+1}^B + \omega^C\mathscr{R}_{t+1}^L c_{t+1} + \omega^U\left(L_{t+1}-c_{t+1}\right)\right)
\end{aligned}$$

A.2.3 First-Order Conditions

Attach Lagrange multipliers λ_t^B to the capital requirement (A.14), μ_t^B to the no-shorting constraint on bank loans (A.15) and ν_t^B to the budget constraint (A.13). Denote $V_{N,t+1}^B = \frac{\partial V_{t+1}^B}{\partial N_{t+1}^B}$.

Equity Issuance. We can differentiate the objective function with respect to e_t^B :

$$\nu_t^B\left(1-\phi_1^B e_t^B\right) = 1\,,$$

Bank loans. The FOC for loans A_{t+1}^B

$$q_t\nu_t^B = \lambda_t^B\xi\min_{\mathcal{S}_{t+1}|\mathcal{S}_t}\left([Z_{t+1}+q_{t+1}]\right) + \mu_t^B + \mathrm{E}\left[\mathcal{M}_{t,t+1}V_{N,t+1}^B\mathscr{R}_{t+1}^A\right]\ ,$$

Deposits. The FOC for deposits D_{t+1}

$$q_t^f\nu_t^B = \lambda_t^B + \mathrm{E}_t\left[\mathcal{M}_{t,t+1}V_{N,t+1}^B\right]\ ,$$

Credit Line Option. The FOC for credit line option L_{t+1} is

$$q_t^L \nu_t^B + \frac{\partial q_t^L}{\partial L_{t+1}} \nu_t^B L_{t+1} + \lambda_t^B \min_{\mathcal{S}_{t+1}|\mathcal{S}_t} \xi \left(\omega^C \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}} + \omega^U \left(1 - \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}} \right) \right)$$
$$= \mathrm{E}_t \left[\mathcal{M}_{t,t+1} V_{N,t+1}^B \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}} \left(1 - \mathscr{R}_{t+1}^L \right) \right] .$$

A.2.4 Euler Equations

First take the envelope condition:

$$V_{N,t}^B = \phi_0^B + \left(1 - \phi_0^B \right) \nu_t^B .$$

Combining this with the FOC for equity issuance above to eliminate ν_t^B yields

$$V_{N,t}^B = \phi_0^B + \frac{1 - \phi_0^B}{1 - \phi_1^B e_t^B} .$$

Define the stochastic discount factor of the intermediary as

$$\mathcal{M}_{t,t+1}^B = \mathcal{M}_{t,t+1} \left(1 - \phi_1^B e_t^B \right) \left(\phi_0^B + \frac{1 - \phi_0^B}{1 - \phi_1^B e_{t+1}^B} \right)$$

I can organize the FOCs as:

$$q_t = \tilde{\lambda}_t^B \xi \min_{\mathcal{S}_{t+1}|\mathcal{S}_t} \left([Z_{t+1} + q_{t+1}] \right) + \tilde{\mu}_t^B + \mathrm{E} \left[\mathcal{M}_{t,t+1}^B \mathscr{R}_{t+1}^A \right] , \tag{A.16}$$

$$q_t^f = \tilde{\lambda}_t^B + \mathrm{E}_t \left[\mathcal{M}_{t,t+1}^B \right] , \tag{A.17}$$

$$q_t^L + \frac{\partial q_t^L}{\partial L_{t+1}} L_{t+1} + \tilde{\lambda}_t^B \min_{\mathcal{S}_{t+1}|\mathcal{S}_t} \xi \left(\omega^C (1 - F(L_{t+1}) + \omega^U F(L_{t+1}) \right)$$
$$= \mathrm{E}_t \left[\mathcal{M}_{t,t+1}^B (1 - F(L_{t+1})) \left(1 - \mathscr{R}_{t+1}^L \right) \right] , \tag{A.18}$$

where we define $\tilde{\mu}_t^B \equiv \mu_t^B / \nu_t^B$ and $\tilde{\lambda}_t^B \equiv \lambda_t^N / \nu_t^B$.

A.2.5 Partial Derivatives

Derivative of q_t^L with respect to L_{t+1}.

$$\frac{\partial q_t^L}{\partial L_{t+1}} = -\mathrm{E}_t \left[\mathcal{M}_{t,t+1}^N \left(\mathscr{R}_{t+1}^A - R_{t+1}^C \right) f(L_{t+1}) \right] .$$

Banks internalize the effect of credit limit extension on the price of credit line through the behavior of nonbank credit line utilization when nonbanks are extended an additional unit of credit line.

A.3 Households

A.3.1 The Optimization Problem

The problem of the representative household is

$$V^H\left(W_t^H, \mathcal{S}_t\right) = \max_{\{C_t^H, D_{t+1}^H, B_{t+1}^H\}} \left\{ \left(1-\beta_H\right)\left(u_t^H\right)^{1-1/\nu_H} + \beta_H \left(\mathrm{E}_t\left[\left(V^H\left(W_{t+1}^H; \mathcal{S}_{t+1}\right)\right)^{1-\sigma_H}\right]\right)^{\frac{1-1/\nu_H}{1-\sigma_H}} \right\}^{\frac{1}{1-1/\nu_H}}$$

subject to

$$\begin{aligned}
u_t^H &= \left(C_t^H\right)^{1-\varsigma}\left(\left(D_{t+1}^H\right)^{\theta}\left(B_{t+1}^H\right)^{1-\theta}\right)^{\varsigma} \\
C_t^H &= W_t^H + Y_t - q_t^f D_{t+1}^H - q_t^r B_{t+1}^H + O_t^H \qquad \text{(A.19)} \\
W_t^H &= D_t^H + \mathscr{D}_t^B + \mathscr{D}_t^N \qquad \text{(A.20)} \\
&\quad + B_t^H \Bigg[\left(1 - F_{\epsilon,t}^N\right) + F_{\epsilon,t}^N \left((1-\zeta^N) \frac{\mathscr{R}_t^A(A_t^N + c_t(L_t))}{B_t^N + c_t(L_t)]} \right) \\
&\qquad + F_{\epsilon,t}^N \frac{\epsilon_t^{N,-}}{B_t^N + c_t(L_t)} \Bigg] \qquad \text{(A.21)}
\end{aligned}$$

Denote the value function and the marginal value of wealth as

$$\begin{aligned}
V_t^H &\equiv V_t^H\left(W_t^H, \mathcal{S}_t\right), \\
V_{W,t}^H &\equiv \frac{\partial V_t^H\left(W_t^H, \mathcal{S}_t\right)}{\partial W_t^H}.
\end{aligned}$$

Denote the certainty equivalent of future utility as

$$CE_t^H = \mathrm{E}_t\left[\left(V_{t+1}^H\right)^{1-\sigma_H}\right]^{\frac{1}{1-\sigma_H}}$$

A.3.2 First-Order Conditions

Deposits. The FOC for bank deposits D_{t+1}^H

$$\begin{aligned}
&\left(V_t^H\right)^{1/\nu_H}\left(1-\beta_H\right)\frac{\left(u_t^H\right)^{1-1/\nu_H}}{C_t^H}\left(\left(1-\varsigma\right)q_t^f - \varsigma\theta\frac{C_t^H}{D_{t+1}^H}\right) \\
&= \left(V_t^H\right)^{1/\nu_H}\beta_H\left(CE_t^H\right)^{\sigma_H - 1/\nu_H}\mathrm{E}\left[\left(V_{t+1}^H\right)^{-\sigma_H} V_{W,t+1}^H\right].
\end{aligned}$$

Non-bank Debt. The FOC for non-bank one-period bonds B^H_{t+1} is

$$\begin{aligned}
&\left(V^H_t\right)^{1/\nu_H}(1-\beta_H)\frac{\left(u^H_t\right)^{1-1/\nu_H}}{C^H_t}\left((1-\varsigma)\,q^r_t-(1-\theta)\,\varsigma\frac{C^H_t}{B^H_{t+1}}\right)\\
&=+\left(V^H_t\right)^{1/\nu_H}\beta_H\left(CE^H_t\right)^{\sigma_H-1/\nu_H}\mathrm{E}\Bigg\{\left(V^H_{t+1}\right)^{-\sigma_H}V^H_{W,t+1}\Bigg[1-F^N_{\epsilon,t+1}\\
&\qquad+F^N_{\epsilon,t+1}\left((1-\zeta^N)\frac{\mathscr{R}^A_{t+1}(A^N_{t+1}+c_{t+1}(L_{t+1}))}{B^N_{t+1}+c_{t+1}(L_{t+1})}\right)\\
&\qquad+\frac{F^N_{\epsilon,t}\epsilon^{N,-}_t}{B^N_{t+1}+c_{t+1}(L_{t+1})}\Bigg]\Bigg\}.
\end{aligned}$$

A.3.3 Marginal Values of State Variables and SDF

The marginal value of saver wealth is

$$V^H_{W,t+1}=\left(V^H_{t+1}\right)^{\frac{1}{\nu_H}}(1-\beta_H)\frac{\left(u^H_{t+1}\right)^{1-1/\nu_H}}{C^H_{t+1}}(1-\varsigma)$$

Define the household stochastic discount factor (SDF) from t to $t+1$ as:

$$\mathcal{M}_{t,t+1}=\beta_H\left(\frac{C^H_{t+1}}{C_t}\right)^{-1}\left(\frac{u^H_{t+1}}{u^H_t}\right)^{1-1/\nu_H}\left(\frac{V^H_{t+1}}{CE^H_t}\right)^{1/\nu_H-\sigma_H}$$

A.3.4 Euler Equations

The Euler equation for bank deposits is :

$$q^f_t=\mathrm{E}_t\left[\mathcal{M}_{t,t+1}\right]+\frac{\theta\varsigma C^H_t}{(1-\varsigma)D^H_{t+1}}, \tag{A.22}$$

$$\begin{aligned}
q^r_t=&\frac{(1-\theta)\,\varsigma C^H_t}{(1-\varsigma)B^H_{t+1}}+\mathrm{E}_t\Bigg\{\mathcal{M}_{t,t+1}\Bigg[1-F^N_{\epsilon,t+1}\\
&+F^N_{\epsilon,t+1}\underbrace{\left((1-\zeta^N)\frac{\mathscr{R}^A_{t+1}(A^N_{t+1}+c_{t+1}(L_{t+1}))}{B^N_{t+1}+c_{t+1}(L_{t+1})}\right)}_{:=\mathcal{A}^H}+\underbrace{\frac{\epsilon^{N,-}_{t+1}F_{\epsilon,t+1}}{B^N_{t+1}+c_{t+1}(L_{t+1})}}_{:=\mathcal{B}^H}\Bigg]\Bigg\}.
\end{aligned} \tag{A.23}$$

A.3.5 Derivatives of q_t^r.

Household choose their commercial paper at the non-banks, taking into account the risks associated with non-bank debt. Let's group some terms in the Euler Equation of the price of the nonbank debt:

$$\begin{aligned} q_t^r &= \mathrm{E}_t\left\{\mathcal{M}_{t,t+1}\left[1 - F^N_{\epsilon,t+1} + F^N_{\epsilon,t+1}\mathcal{A}^H_{t+1} + \mathcal{B}^H_{t+1}\right]\right\} + \frac{(1-\theta)\,\varsigma C_t^H}{(1-\varsigma)B^H_{t+1}} \\ &= \mathrm{E}_t\left\{\mathcal{M}_{t,t+1}\left[1 + \left(\mathcal{A}^H_{t+1} - 1\right)F^N_{\epsilon,t+1} + \mathcal{B}^H_{t+1}\right]\right\} + \frac{(1-\theta)\,\varsigma C_t^H}{(1-\varsigma)B^H_{t+1}} \end{aligned}$$

Derivative of q_t^r with respect to A^N_{t+1}. We would like to evaluate:

$$\frac{\partial q_t^r}{\partial A^N_{t+1}} = \mathrm{E}_t\left\{\mathcal{M}_{t,t+1}\left[\left(\mathcal{A}^H_{t+1} - 1\right)\frac{\partial F^N_{\epsilon,t+1}}{\partial A^N_{t+1}} + \frac{\partial \mathcal{A}^H_{t+1}}{\partial A^N_{t+1}}F^N_{\epsilon,t+1} + \frac{\partial \mathcal{B}^H_{t+1}}{\partial A^N_{t+1}}\right]\right\} \tag{A.24}$$

First, we take the derivative of $\mathcal{A}^H_{t+1}$ with respect to A^N_{t+1}:

$$\frac{\partial \mathcal{A}^H_{t+1}}{\partial A^N_{t+1}} = (1-\zeta^N)\frac{\mathscr{R}^A_{t+1}}{B^N_{t+1} + c_{t+1}(L_{t+1})}\,.$$

Then, we need to take derivative of $F^N_{\epsilon,t+1}$ with respect to A^N_{t+1}. To do so, we first take the derivative of the default threshold $-\tilde{V}^N_{t+1}$ with respect to A^N_{t+1}, then we use Leibniz rule,

$$\frac{\partial F^N_{\epsilon,t+1}}{A^N_{t+1}} = -f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1})\frac{\partial \tilde{V}^N_{t+1}}{\partial N^N_{t+1}}\frac{\partial N^N_{t+1}}{\partial A^N_{t+1}} = -f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1})\left(\phi^N_0 + \frac{1-\phi^N_0}{1-\phi^N_1 e^N_{t+1}}\right)\mathscr{R}^A_{t+1}.$$

At last, we take the derivative of $\mathcal{B}^H_{t+1}$ with respect to A^N_{t+1}.

$$\mathcal{B}^H_{t+1} = \frac{\epsilon^{N,-}_{t+1}F_{\epsilon,t+1}}{B^N_{t+1} + c_{t+1}(L_{t+1})}$$

We can calculate

$$\begin{aligned} \frac{\partial\left(\epsilon^{N,-}_{t+1}F_{\epsilon,t+1}\right)}{\partial A^N_{t+1}} &= \frac{\partial}{\partial A^N_{t+1}}\int_{-\infty}^{-\tilde{V}^N_{t+1}} \epsilon_{t+1} f^N_{\epsilon,t+1}\,d\epsilon \\ &= \frac{\partial(-\tilde{V}^N_{t+1})}{\partial A^N_{t+1}}(-\tilde{V}^N_{t+1})f^N_{\epsilon,t+1} \\ &= \frac{\partial(-\tilde{V}^N_{t+1})}{\partial N^N_{t+1}}\frac{\partial N^N_{t+1}}{\partial A^N_{t+1}}(-\tilde{V}^N_{t+1})f^N_{\epsilon,t+1} \\ &= f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1})\left(\phi^N_0 + \frac{1-\phi^N_0}{1-\phi^N_1 e^N_{t+1}}\right)\mathscr{R}^A_{t+1}\tilde{V}^N_{t+1}\,. \end{aligned}$$

Hence,

$$\frac{\partial \mathcal{B}^B_{t+1}}{\partial A^N_{t+1}} = \frac{f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1})\left(\phi^N_0 + \frac{1-\phi^N_0}{1-\phi^N_1 e^N_{t+1}}\right)\mathscr{R}^A_{t+1}\tilde{V}^N_{t+1}}{B^N_{t+1} + c_{t+1}(L_{t+1})}\,.$$

We can then plug in the expressions to get the explicit form of the derivatives.

Derivative of q^r_t with respect to B^N_{t+1}. We would like to evaluate:

$$\frac{\partial q^r_t}{\partial B^N_{t+1}} = \mathrm{E}_t\left\{\mathcal{M}_{t,t+1}\left[\left(\mathcal{A}^H_{t+1}-1\right)\frac{\partial F^N_{\epsilon,t+1}}{\partial B^N_{t+1}} + \frac{\partial \mathcal{A}^H_{t+1}}{\partial B^N_{t+1}}F^N_{\epsilon,t+1} + \frac{\partial \mathcal{B}^H_{t+1}}{\partial B^N_{t+1}}\right]\right\} \tag{A.25}$$

First, we take the derivative of $\mathcal{A}^H_{t+1}$ with respect to B^N_{t+1}:

$$\frac{\partial \mathcal{A}^H_{t+1}}{\partial B^N_{t+1}} = -(1-\zeta^N)\frac{\mathscr{R}^A_{t+1}(A^N_{t+1} + c_{t+1}(L_{t+1}))}{\left(B^N_{t+1} + c_{t+1}(L_{t+1})\right)^2}\,.$$

Then, we need to take derivative of $F^N_{\epsilon,t+1}$ with respect to B^N_{t+1}. To do so, we first take the derivative of the default threshold $-\tilde{V}^N_{t+1}$ with respect to B^N_{t+1}. Then we use Leibniz rule,

$$\frac{\partial F^N_{\epsilon,t+1}}{\partial B^N_{t+1}} = -f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1})\frac{\partial \tilde{V}^N_{t+1}}{\partial N^N_{t+1}}\frac{\partial N^N_{t+1}}{\partial B^N_{t+1}} = f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1})\left(\phi^N_0 + \frac{1-\phi^N_0}{1-\phi^N_1 e^N_{t+1}}\right).$$

At last, we take the derivative of $\mathcal{B}^H_{t+1}$ with respect to B^N_{t+1}.

$$\mathcal{B}^H_{t+1} = \frac{\epsilon^{N,-}_{t+1}F_{\epsilon,t+1}}{B^N_{t+1} + c_{t+1}(L_{t+1})}$$

We can calculate

$$\begin{aligned}
\frac{\partial\left(\epsilon^{N,-}_{t+1}F_{\epsilon,t+1}\right)}{\partial B^N_{t+1}} &= \frac{\partial}{\partial B^N_{t+1}}\int_{-\infty}^{-\tilde{V}^N_{t+1}} \epsilon_{t+1} f^N_{\epsilon,t+1}\,d\epsilon \\
&= \frac{\partial(-\tilde{V}^N_{t+1})}{\partial B^N_{t+1}}(-\tilde{V}^N_{t+1})f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1}) \\
&= \frac{\partial(-\tilde{V}^N_{t+1})}{\partial N^N_{t+1}}\frac{\partial N^N_{t+1}}{\partial B^N_{t+1}}(-\tilde{V}^N_{t+1})f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1}) \\
&= -f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1})\left(\phi^N_0 + \frac{1-\phi^N_0}{1-\phi^N_1 e^N_{t+1}}\right)\tilde{V}^N_{t+1}\,.
\end{aligned}$$

Hence,

$$\frac{\partial \mathcal{B}^H_{t+1}}{\partial B^N_{t+1}} = \frac{1}{B^N_{t+1} + c_{t+1}(L_{t+1})} \frac{\partial \left(\epsilon^{N,-}_{t+1} F_{\epsilon,t+1}\right)}{\partial B^N_{t+1}} - \frac{\epsilon^{N,-}_{t+1} F_{\epsilon,t+1}}{\left(B^N_{t+1} + c_{t+1}(L_{t+1})\right)^2}$$
$$= \frac{1}{B^N_{t+1} + c_{t+1}(L_{t+1})} \left[-\tilde{V}^N_{t+1} f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1}) \left(\phi^N_0 + \frac{1-\phi^N_0}{1-\phi^N_1 e^N_{t+1}} \right) - \frac{\epsilon^{N,-}_{t+1} F_{\epsilon,t+1}}{B^N_{t+1} + c_{t+1}(L_{t+1})} \right].$$

We can then plug in the expressions to get the explicit form of the derivatives.

Derivative of q^r_t with respect to L_{t+1}. We would like to evaluate:

$$\frac{\partial q^r_t}{\partial L_{t+1}} = \mathrm{E}_t \left\{ \mathcal{M}_{t,t+1} \left[\left(\mathcal{A}^H_{t+1} - 1 \right) \frac{\partial F^N_{\epsilon,t+1}}{\partial L_{t+1}} + \frac{\partial \mathcal{A}^H_{t+1}}{\partial L_{t+1}} F^N_{\epsilon,t+1} + \frac{\partial \mathcal{B}^H_{t+1}}{\partial L_{t+1}} \right] \right\} \tag{A.26}$$

First, we take the derivative of $\mathcal{A}^H_{t+1}$ with respect to L_{t+1}:

$$\frac{\partial \mathcal{A}^H_{t+1}}{\partial L_{t+1}} = (1-\zeta^N) \frac{\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}}{\left(B^N_{t+1} + c_{t+1}(L_{t+1})\right)} \left(\mathscr{R}^A_{t+1} - \frac{\mathscr{R}^A_{t+1}(A^N_{t+1} + c_{t+1}(L_{t+1}))}{\left(B^N_{t+1} + c_{t+1}(L_{t+1})\right)} \right).$$

Then, we need to take derivative of $F^N_{\epsilon,t+1}$ with respect to L_{t+1}. To do so, we first take the derivative of the default threshold $-\tilde{V}^N_{t+1}$ with respect to L^N_{t+1}. Then we use Leibniz rule,

$$\frac{\partial F^N_{\epsilon,t+1}}{\partial L_{t+1}} = -f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1}) \frac{\partial \tilde{V}^N_{t+1}}{\partial N^N_{t+1}} \frac{\partial N^N_{t+1}}{\partial L_{t+1}} = -f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1}) \left(\phi^N_0 + \frac{1-\phi^N_0}{1-\phi^N_1 e^N_{t+1}} \right) \left(\mathscr{R}^A_{t+1} - R^C_{t+1} \right) \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}.$$

At last, we take the derivative of $\mathcal{B}^H_{t+1}$ with respect to B^N_{t+1}.

$$\mathcal{B}^H_{t+1} = \frac{\epsilon^{N,-}_{t+1} F_{\epsilon,t+1}}{B^N_{t+1} + c_{t+1}(L_{t+1})}$$

We can calculate

$$\begin{aligned}
\frac{\partial \left(\epsilon^{N,-}_{t+1} F_{\epsilon,t+1}\right)}{\partial L_{t+1}} &= \frac{\partial}{\partial B^N_{t+1}} \int_{-\infty}^{-\tilde{V}^N_{t+1}} \epsilon_{t+1} f^N_{\epsilon,t+1} d\epsilon \\
&= \frac{\partial(-\tilde{V}^N_{t+1})}{\partial L_{t+1}} (-\tilde{V}^N_{t+1}) f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1}) \\
&= \frac{\partial(-\tilde{V}^N_{t+1})}{\partial N^N_{t+1}} \frac{\partial N^N_{t+1}}{\partial L_{t+1}} (-\tilde{V}^N_{t+1}) f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1}) \\
&= f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1}) \left(\phi^N_0 + \frac{1-\phi^N_0}{1-\phi^N_1 e^N_{t+1}} \right) \left(\mathscr{R}^A_{t+1} - R^C_{t+1} \right) \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}} \tilde{V}^N_{t+1}.
\end{aligned}$$

Hence,

$$\begin{aligned}\frac{\partial \mathcal{B}^H_{t+1}}{\partial L_{t+1}} &= \frac{1}{B^N_{t+1} + c_{t+1}(L_{t+1})} \frac{\partial \left(\epsilon^{N,-}_{t+1} F_{\epsilon,t+1}\right)}{\partial L_{t+1}} - \frac{\epsilon^{N,-}_{t+1} F_{\epsilon,t+1}}{\left(B^N_{t+1} + c_{t+1}(L_{t+1})\right)^2} \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}} \\ &= \frac{1}{B^N_{t+1} + c_{t+1}(L_{t+1})} \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}} \\ &\left[\left(\mathscr{R}^A_{t+1} - R^C_{t+1}\right) \tilde{V}^N_{t+1} f^N_{\epsilon,t+1}(-\tilde{V}^N_{t+1}) \left(\phi^N_0 + \frac{1-\phi^N_0}{1-\phi^N_1 e^N_{t+1}}\right) - \frac{\epsilon^{N,-}_{t+1} F_{\epsilon,t+1}}{B^N_{t+1} + c_{t+1}(L_{t+1})} \right].\end{aligned}$$

We can then plug in the expressions to get the explicit form of the derivatives.

B Empirical Appendix

This section contains additional empirical findings, textual evidence, and large-language model prompting and results that are referenced in the main texts.

B.1 Additional Empirical Findings

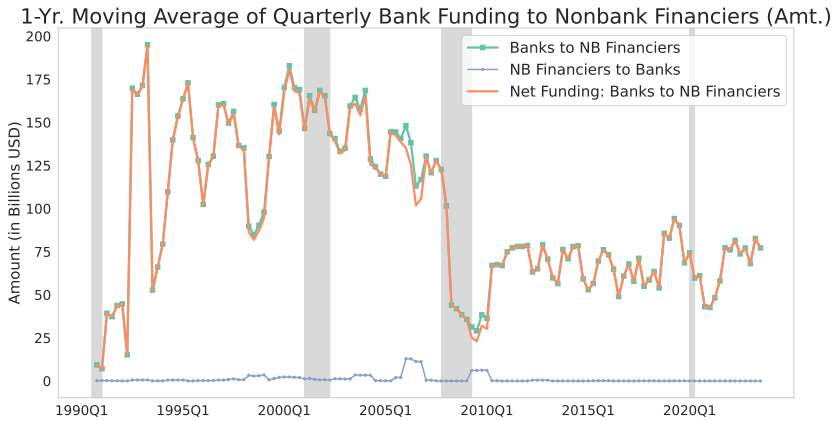


Figure B.1: This figure plots the 1-year moving average of quarterly bank funding (amount in billions USD) to NBFs that lend to corporates, combining Legacy Dealscan and LSEG LoanConnector facility-level data. Green squared line is bank funding to NBFs. Blue dot line is NBF funding to banks. Orange is the net. This figure shows: **NBFs rely heavily on banks for funding, but not vice versa.** My facility-level finding is consistent with what Acharya et al. (2024a) find in the "From Whom to Whom" US financial accounts data.

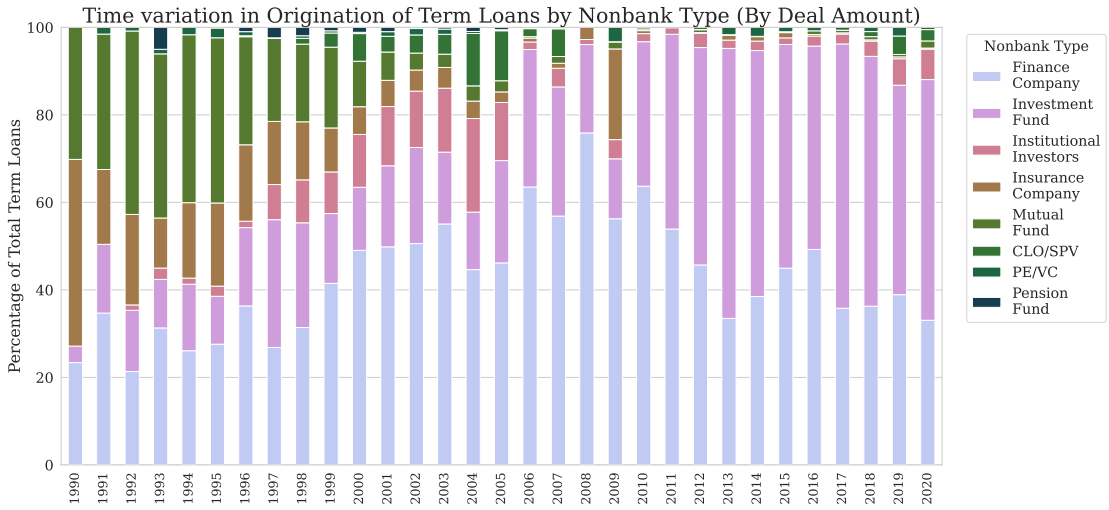


Figure B.2: Time variation in origination of term loans by nonbank type. Finance companies contribute about 45.6% of total term loans generated by all NBFs, followed by investment fund (43.8%).

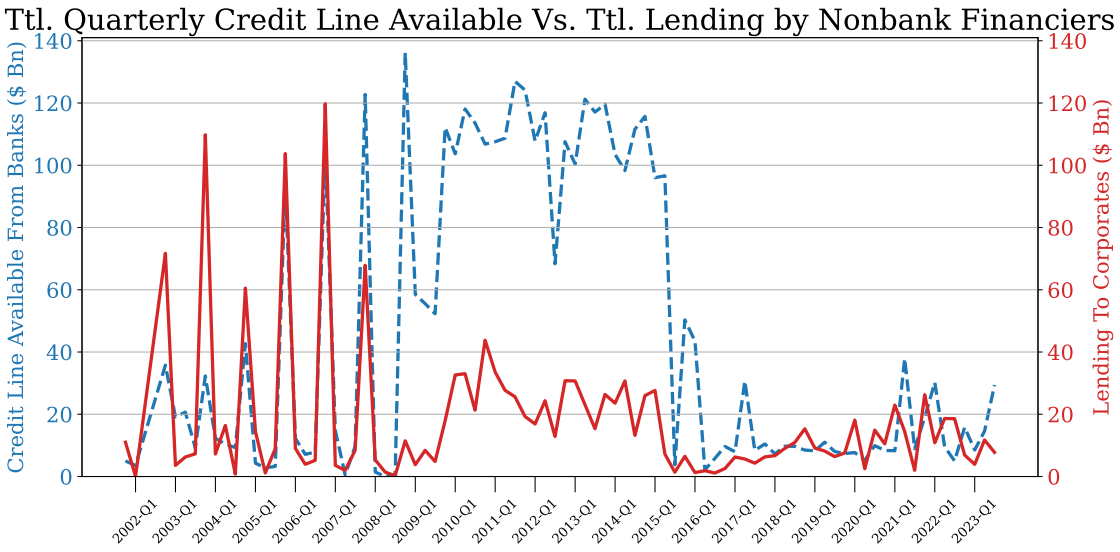


Figure B.3: Total quarterly credit line available (undrawn) to nonbank financiers (NBFs) is plotted in blue dotted line. Total quarterly lending by NBFs is plotted in the red line.

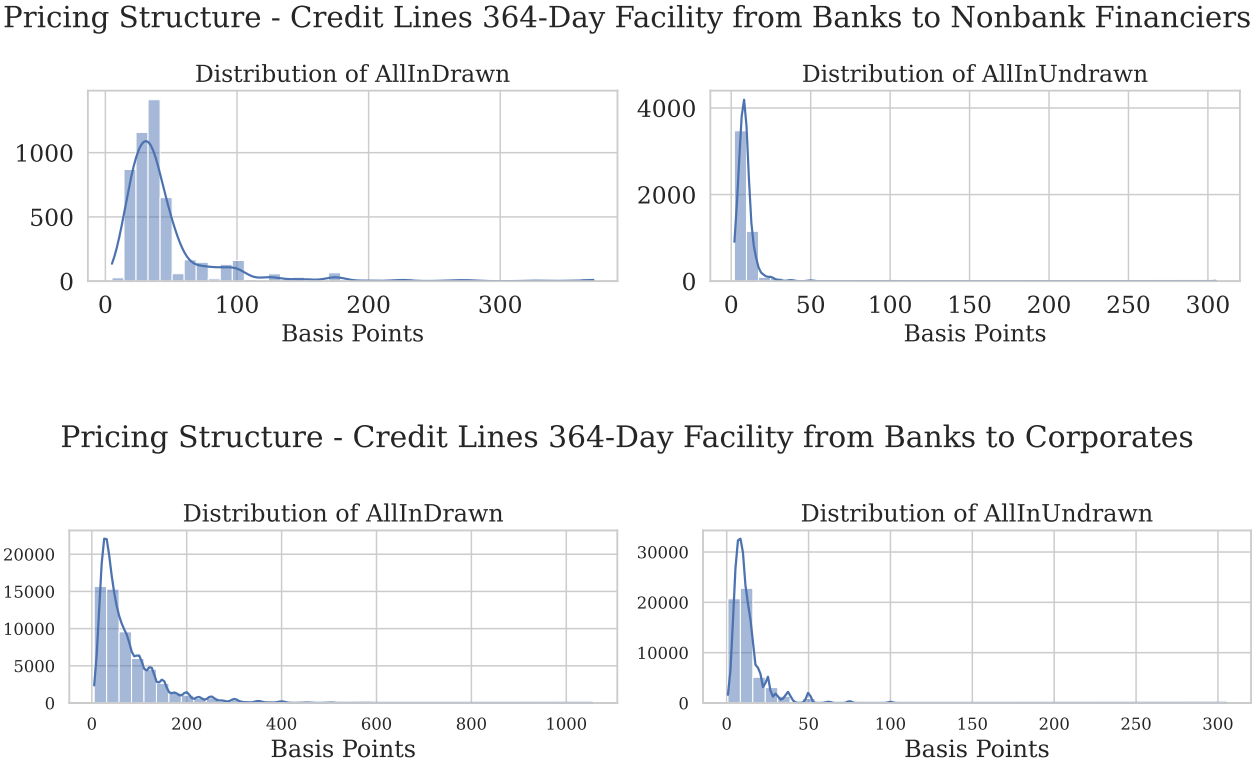


Figure B.4: Comparing credit lines 364-day facility from banks to NBFs Vs. that from banks to corporates. Adjusting for maturity differences, the required rate of return for all-in-drawn spread is 63 bps lower for credit lines from banks to NBFs than for credit lines from banks to corporates. Specifically, we can compare the all-in-drawn spread for the 364-day facility. The mean of the all-in-drawn spread for 364-day facility from banks to NBFs is 46bps, while that for 364-day facility from banks to corporates is 76bps. Difference in pricing of credit lines suggest that banks perceive it as safer to lend to NBFs than directly lending to corporates. As intermediaries, NBFs reduce banks' direct corporate credit risks.

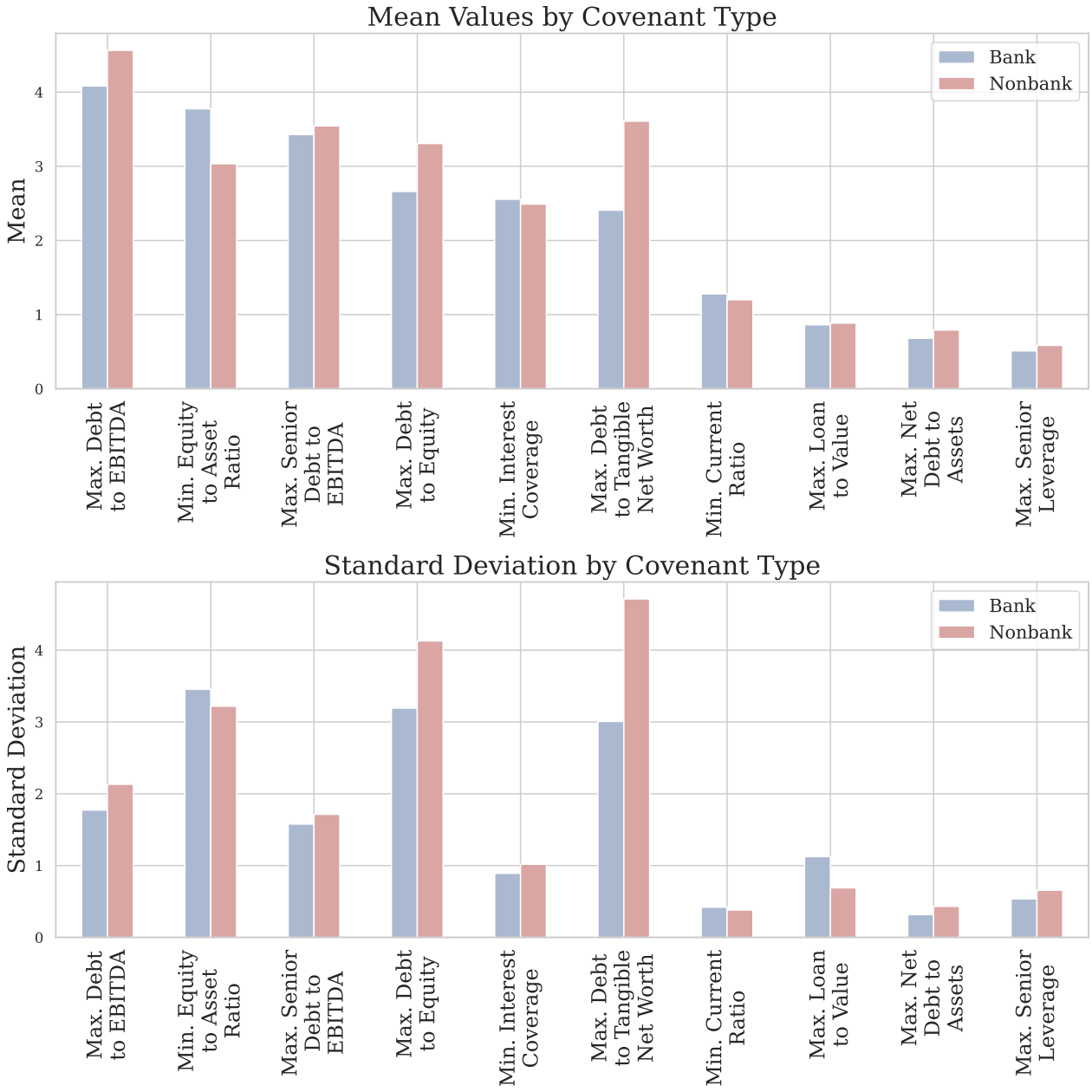


Figure B.5: This figure presents the mean and standard deviations of covenant metrics, distinguishing between loans extended by banks and those extended by nonbanks. While covenants within a syndication package are largely uniform across lenders, differences arise in cases where banks or nonbanks are the sole lenders or when nonbanks are originating more sub-A term loans. These distinctions reveal variations in the average values and variability of loan covenant restrictions. In particular, nonbank loans tend to exhibit slightly greater variability in covenant metrics, permitting higher thresholds for debt-to-EBITDA, debt-to-equity, and debt-to-net-worth ratios.

B.2 Textual Evidence

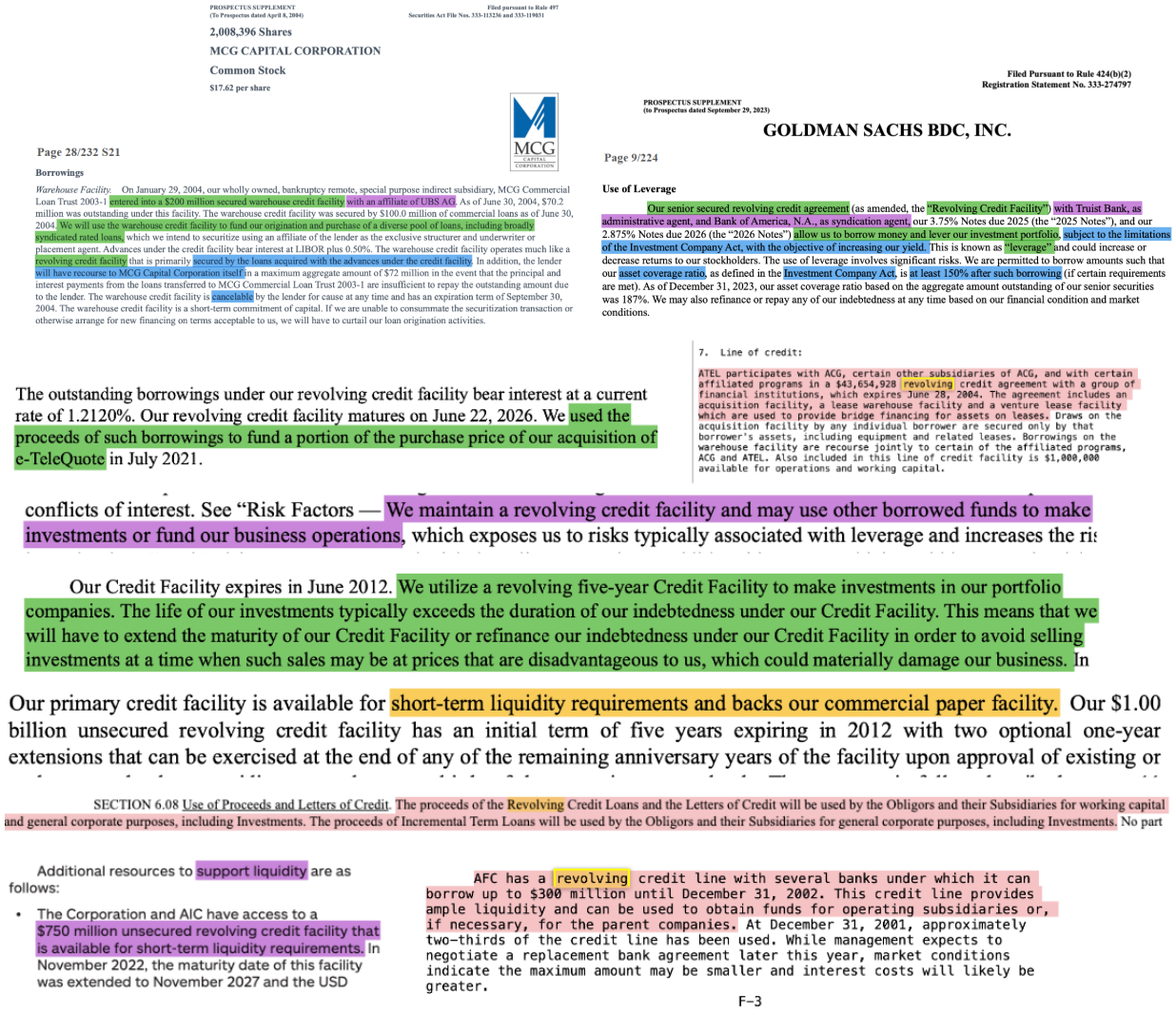


Figure B.6: The screenshots of Prospectuses with highlighted sentences indicate evidence of inventory uncertainty or liquidity support.

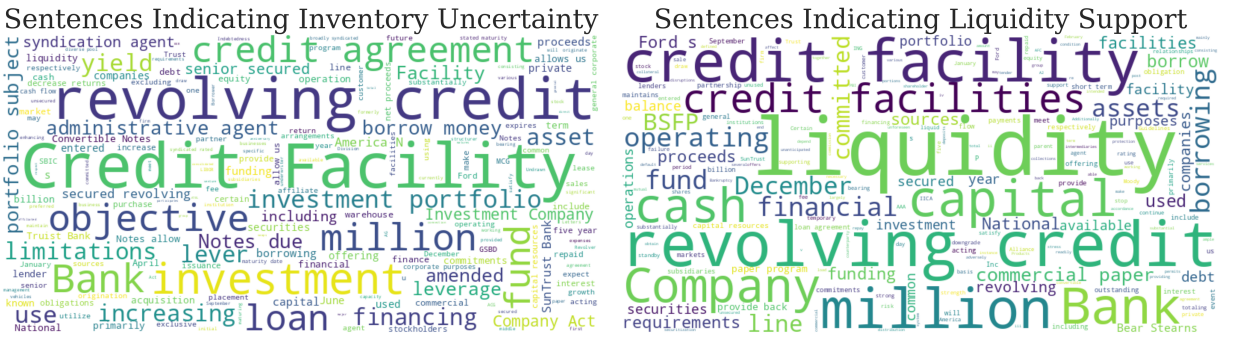


Figure B.7: The two word clouds are sentences that indicate inventory uncertainty (left) and liquidity support (right).

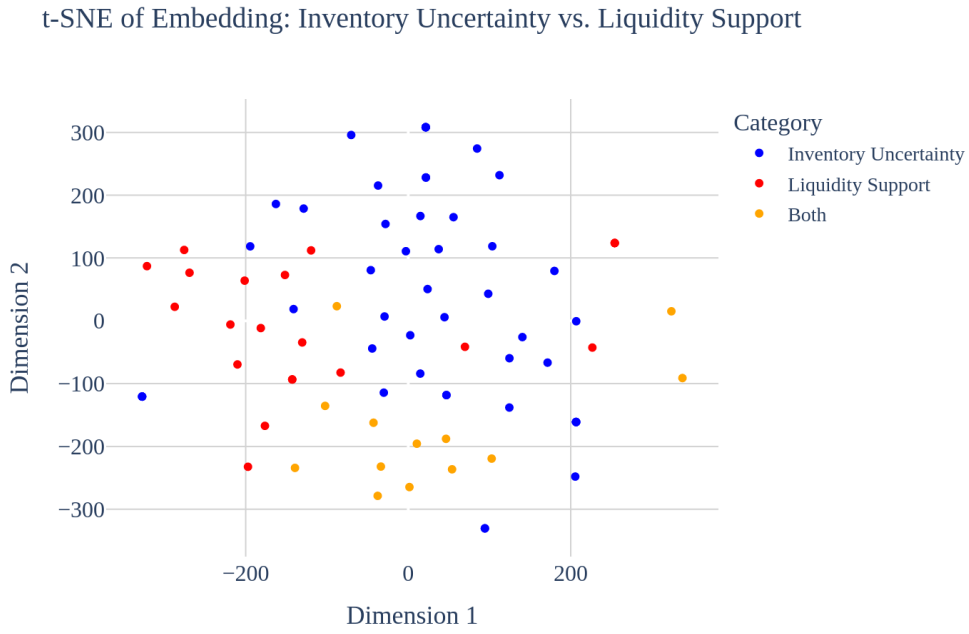


Figure B.8: This embedding graph shows that there is significant difference in meaning between sentences that indicate inventory uncertainty vs that indicating liquidity support.

C Calibration Appendix

C.1 Credit Line Fixed Spread



Figure C.1: This figure plots the all-in-drawn and all-in-undrawn spread in Dealscan and LSEG LoanConnector for credit lines from banks to nonbank financiers, categorized in maturities of exactly 364 days, less than 1 year, exactly 2 years, 3 years, 4 years, and 5 years and above.

C.2 Duration of Corporate Loans

We first collected the following data to calculate the coupon δ_B, δ_N, and principal fraction θ_B, θ_N, for bank and nonbank loans respectively.

1. FRED data: we obtain a time series of option-adjusted spreads (OAS) for both high-yield and investment-grade bonds relative to the Treasury yield curve. These OAS values are sourced from Bank of America Merrill Lynch (BofAML) indices, with codes BAMLH0A0HYM2 and BAMLC0A0CM for high-yield OAS and investment-grade OAS, correspondingly.

2. Bloomberg data: our model's representation of corporate loans and bonds encompasses the entire pool of outstanding corporate loans and bonds. To approximate this pool, we rely on the Bloomberg Barclays Aggregate Bond Index, which includes both investment-grade and high-yield securities. Specifically, we utilize the Barclays indices with codes LUACTRUU and LF98STAT for investment-grade and high-yield corporate bonds, respectively. These indices provide a time series of monthly data, including market values, durations (indicating price sensitivity to interest rate changes), maturity (life days), and coupon rates, spanning from January 1997 to September 2023.

Then, we made the following calculations:

1. We combine Barclays investment grade and high-yield portfolios using market values as the weighting factors to create an aggregate bond index with maturity ahd coupon rate shown below:

$$\text{Fraction of High Yield} = \frac{\text{High Yield Market Value}}{\text{High Yield Market Value} + \text{Investment Grade Market Value}}$$

$$\begin{aligned}\text{Maturity} = {} & \text{Fraction of High Yield} \times \text{Barclays US CORP High Yield Maturity} \\ & + (1 - \text{Fraction of High Yield}) \times \text{Barclays US CORP Investment Grade Duration}\end{aligned}$$

$$\begin{aligned}\text{Coupon} = {} & \text{Fraction of High Yield} \times \text{Barclays US CORP High Yield Coupon} \\ & + (1 - \text{Fraction of High Yield}) \times \text{Barclays US CORP Investment Grade Coupon}\end{aligned}$$

2. We then calculate the weighted average coupons (WAC) and weighted-average maturity (WAM) for the aggregate bond index. We find its mean WAC c of 5.93% and WAM T of 10 years over our time period.

3. Next, we assign weights to the time series of Option-Adjusted Spreads (OAS) for both the high-yield and investment-grade indices, using the previously established "Fraction of High Yield." We add the time series of OAS to the constant maturity treasury rate corresponding to that period's WAM to get a time series of bond yields r_t .

4. Subsequently, we construct a plain vanilla corporate bond, denoted as $P^c(r_t)$, with a semi-annual coupon and maturity equal to the WAC and WAM of the aggregate bond index, and

compute the price for $\$1$ par of this bond for each yield r_t:

$$P^c(r_t) = \sum_{i=1}^{2T} \frac{c/2}{(1+r_t)^{i/2}} + \frac{1}{(1+r_t)^T}$$

5. We then calculate the steady-state price of a geometric bond, denoted as $P^G(r_t)$, with parameter δ as:

$$P^G(r_t) = \frac{1}{(1+r_t)}[1 + \delta P^G(r_t)]$$

Solving for $P^G(r_t)$, we get:

$$P^G(r_t) = \frac{\frac{1}{1+r_t}}{1 - \frac{\delta}{1+r_t}}$$

6. This external calibration process determines the quantity of geometric bonds with a parameter δ, denoted as X, required to hedge against parallel shifts in interest rates for a single unit of the plain vanilla bond P^c, considering a range of historical yields:

$$\min_{\delta, X} \sum_{t=1997.1}^{2023.9} \left[P^c(r_t) - XP^G(r_t; \delta)\right]^2$$

I obtain the following results:

1. I estimate $\delta_B = 0.928$ and $X_B = 13.0059$. This value for δ_B implies a time series of durations $D_t = -\frac{1}{P_t^G}\frac{dP_t^G}{dr_t}$ with a mean of 7.009.

2. I set the "principal" F of one unit of the geometric bond to be some fraction θ of the undiscounted sum of all its cash flows $\frac{\theta}{1-\delta}$, where

$$\theta = \frac{1}{N} \sum_{t=1997.1}^{2023.9} \frac{1}{(1+r_t)^{D_t}}.$$

Therefore, I estimate $\theta_B = 0.624$ and $F_B = \frac{\theta_B}{1-\delta_B} = 8.67$

Calculation for loans originated from NBFs:

1. I calculate WAM for Nonbank loans using dealscan data from January 1997 to September 2023 as following:

$$WAM = \frac{\sum_{i=1}^{n} (\text{ Principal }_i * \text{ Maturity }_i)}{\sum_{i=1}^{n} \text{ Principal}}$$

Where i represents each nonbank loan in the portfolio, and I get WAM T = 4.461 years.

2. It would be ideal it one can observe a time series of coupon rates for the same loan. However, Dealscan data is structured at the facility level and is fixed at the loan origination stage.

Unfortunately, this means I lack a time series of coupon rates. As a result, I rely on the previously calculated WAC c = 5.93% as a substitute.

3. I estimate $\delta_N = 0.805$ and $X_N = 25.3298$. This value for δ_N implies a time series of durations $D_t = -\frac{1}{P_t^G}\frac{dP_t^G}{dr_t}$ with mean equal to 3.744. I estimate $\theta_N = 0.772$.

Finally, I obtain a volume-weighted average of total corporate loan coupon payment

$$\delta = 76.2\%\delta_B + 23.8\%\delta_N = 76.2\% \times 0.928 + 23.8\% \times 0.805 = 0.898$$

and principal fraction

$$\theta = 76.2\%\theta_B + 23.8\%\theta_N = 76.2\% \times 0.624 + 23.8\% \times 0.772 = 0.659$$

C.3 Basel Credit Conversion Factor

The Credit Conversion Factor (CCF) under the Basel framework is a key metric used to assess the credit risk of off-balance sheet exposures, such as letters of credit and guarantees. It calculates the percentage of the off-balance sheet exposure potentially converted into an actual on-balance sheet equivalent exposure. This metric is vital for banks and financial institutions to estimate and manage the risk associated with these exposures. In Basel I and II Part 2: The First Pillar- Minimum Capital Requirements published by Basel Committee on Banking Supervision (2020), item 599 specifies for any committed retail credit line, the credit conversion factor is 90%. According to item 83, "Commitments with an original maturity up to one year and commitments with an original maturity over one year will receive a CCF of 20% and 50%, respectively. However, any commitments that are unconditionally cancellable at any time by the bank without prior notice, or that effectively provide for automatic cancellation due to deterioration in a borrower's creditworthiness, will receive a 0% CCF." Basel III has further refined the regulatory framework for off-balance sheet items. It introduces more risk-sensitive credit conversion factors (CCFs), which are essential for determining the risk-weighted exposure amounts. It includes the implementation of positive CCFs for unconditionally cancellable commitments (UCCs), enhancing the precision of risk assessment. To estimate the relative capital risk weight on credit line, I take a weighted average of CCF based on drawn and undrawn credit lines from banks to NBFs. year. The required regulatory capital in terms of equity is

$$E_{t+1}^B \geq \xi^E \left(\left[Z_{t+1} + q_{t+1} \right] A_{t+1}^B + \omega^{C,E} c_{t+1} \left(L_{t+1} \right) + \omega^{U,E} \left(L_{t+1} - c_{t+1} \left(L_{t+1} \right) \right) \right)$$

Since banks are funded by debt and equity, writing this in terms of the maximum leverage that banks can take results in

$$D_t \leq \xi \left(\left[Z_{t+1} + q_{t+1} \right] A_{t+1}^B + \omega^C c_{t+1} + \omega^U \left(L_{l+1} - c_{t+1} \right) \right)$$

where I denote $\xi := 1 - \xi^E, \omega^C := \left(1 - \xi^E \omega^{C,E}\right)/\xi, \omega^U := \left(1 - \xi^E \omega^{U,E}\right)/\xi$. Therefore, I can calculate,

$$\begin{aligned} &\xi = 1 - 0.07 = 0.93 \\ &\omega^C = \left(1 - \xi^E \omega^{C,E}\right)/\xi = (1 - 0.07 * 0.90)/0.93 = 1.0075 \end{aligned}$$

Note that for the capital weight on the undrawn, we need to separate the undrawn credit line of maturity less than 1 year, versus those that are more than 1 year. Undrawn commitment with less than 1 year of maturity receives conversion factor 20%, and those more than 1 year receives conversion factor 50%. According to Figure 2, we know that 364-day facility and revolver/line < 1 year altogether account for $43.14\% + 1.76\% = 44.9\%$ of all credit lines from banks to nonbank financiers (NBFs). Revolver/Line > 1 Yr account for 52.46% and the rest account for 2.64% and I count them as >1 year of maturity. Therefore, I calculate

$$\begin{aligned}\omega^U &= \left(1 - \xi^E \omega^{U,E}\right)/\xi \\ &= (1 - 0.07 * (20\% * 44.9\% + 50\% * 55.1\%))/0.93 \\ &= 1.047\end{aligned}$$

```
You are a finance analyst and you are looking at the reports of finance companies or investment funds that get
 revolving credit facilities.
Given sentences, you need to predict which whether it indicates "inventory uncertainty": YES or NO.

The definition of "inventory uncertainty": finance companies or investment funds have uncertainties in their
lending.
They do not know how much money they need in order to fund corporates.
Because of this uncertainty, they get revolving credit facilities so that they can draw down from these
revolving credit facilities if they need money to fund corporates.
Generally, if you find verbs like "to fund", "to purchase", "to acquire", "to invest", "to provide financing",
 "to provide bridge financing", or any other words with similar meanings, either in the active voice or the
passive voice like "financing provided through revolving credit facility," the purpose is "inventory
uncertainty".
Also, nouns such as "investments", "acquisitions", etc. are also indicators of "inventory uncertainty."

Again, you should only predict whether it is "inventory uncertainty" and output YES or NO. Nothing else.

## Sample
Content:
The outstanding borrowings under our revolving credit facility bear interest at a current rate of 1.2120%. Our
 revolving credit facility matures on June 22, 2026. We used the proceeds of such borrowings to fund a portion
 of the purchase price of our acquisition of e-TeleQuote in July 2021.
inventory uncertainty? (only reply YES or NO): YES

Content:
Additional resources to support liquidity are as follows:
The Corporation and AIC have access to a $750 million unsecured revolving credit facility that is available
for short-term liquidity requirements. In November 2022, the maturity date of this facility was extended to
November 2027 and the USD
inventory uncertainty? (only reply YES or NO): NO

Content:
Our primary credit facility is available for short-term liquidity requirements and backs our commercial paper
facility. Our $1.00 billion unsecured revolving credit facility has an initial term of five years expiring in
2012 with two optional one-year extensions that can be exercised at the end of any of the remaining
anniversary years of the facility upon approval of existing or replacement lenders providing more than two-
thirds of the commitments to lend.
inventory uncertainty? (only reply YES or NO): NO

Content:
From time to time, we will borrow funds, including under our revolving credit facilities, or issue debt
securities or preferred securities to make additional investments or for other purposes. This is known as "
leverage" and could increase or decrease returns to our stockholders. The use of borrowed funds or the
proceeds of preferred stock offerings to make investments has specific benefits and risks, and all of the
costs of borrowing funds or issuing preferred stock are borne by our stockholders.
inventory uncertainty? (only reply YES or NO): YES

Content:
[CONTENTS]
inventory uncertainty? (only reply YES or NO):
```

Figure B.9: Prompt of inventory uncertainty prediction, where [CONTENTS] should be replaced by the input sentences.

```
You are a finance analyst and you are looking at the reports of finance companies, investment funds,
institutional investors, etc. that get revolving credit facilities.
Given sentences, you need to predict which whether it indicates "liquidity support": YES or NO.

The definition of "liquidity support":  to help satisfy liquidity requirement or provide back-up liquidity or
complement other liquidity facilities,
like the commercial paper program.
When you see words like "available for short-term liquidity requirements," "to meet short-term liquidity needs
," "to meet cash requirements," "to provide back-up liquidity,"
"to back up the commercial paper program," "back-stop support for our commercial paper program," "to satisfy
the current liquidity requirement,"
these are indicators of liquidity support.

Again, you should only predict whether it is "liquidity support" and output YES or NO. Nothing else.

## Sample
Content:
The outstanding borrowings under our revolving credit facility bear interest at a current rate of 1.2120%. Our
 revolving credit facility matures on June 22, 2026. We used the proceeds of such borrowings to fund a portion
 of the purchase price of our acquisition of e-TeleQuote in July 2021.
liquidity support? (only reply YES or NO): NO

Content:
Additional resources to support liquidity are as follows:
    The Corporation and AIC have access to a $750 million unsecured revolving credit facility that is
available for short-term liquidity requirements. In November 2022, the maturity date of this facility was
extended to November 2027 and the USD
liquidity support? (only reply YES or NO): YES

Content:
From time to time, we will borrow funds, including under our revolving credit facilities, or issue debt
securities or preferred securities to make additional investments or for other purposes. This is known as
leverage and could increase or decrease returns to our stockholders. The use of borrowed funds or the proceeds
 of preferred stock offerings to make investments has specific benefits and risks, and all of the costs of
borrowing funds or issuing preferred stock are borne by our stockholders.
liquidity support? (only reply YES or NO): NO

Content:
The maximum potential borrowings under the seasonal line of credit totaled $4,500,000 at October 31, 2003 and
at July 31, 2004. It is used to meet cash requirements during Sea Pines off-season winter months. The seasonal
 line of credit had no outstanding balance at October 31, 2003 or at July 31, 2004, and it expires on November
 1, 2007.
liquidity support? (only reply YES or NO): YES

Content:
[CONTENTS]
liquidity support? (only reply YES or NO):
```

Figure B.10: Prompt of liquidity support prediction, where [CONTENTS] should be replaced by the input sentences.