The Value of Contingent Liquidity from Banks to Nonbank Financiers*

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[PRELIMINARY]

Abstract

I document that 96% of banks' funding to nonbank financiers (NBFs) occurs through credit lines. 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, and creating more safe assets. Policy counterfactuals 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 about 70% 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. First, 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. Second, 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.

However, even if credit lines are privately desirable by both banks and NBFs, credit lines do transfer risks from the balance sheet of NBFs to banks. This risk transfer becomes particularly pronounced in adverse economic conditions, when credit lines are heavily drawn upon to meet NBFs' short-term obligations. In the partial equilibrium, the credit lines banks extend to NBFs transfer risks from NBFs to banks. However, the general equilibrium implications for this financial arrangement between banks and NBFs is unclear. What happens to aggregate asset prices? How about the overall

[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.

safe asset the finanical system is able to create and sustain? How do bank regulation spillover to NBFs through credit lines? How do bank regulations spill over to NBFs via credit lines, and what regulatory approach is appropriate for managing off-balance, undrawn credit lines? Addressing these questions necessitates the development of a quantitative macro-finance model.

In the second (model) section of my paper, I develop a novel quantitative macro-finance model that maps the empirical foundations outlined earlier into its core components. My model quantifies the real macroeconomic value of contingent liquidity in a financial system where banks extend credit lines to nonbank financiers (NBFs). Moreover, using the model to conduct policy counterfactuals, I examne how bank regulations spill over to NBFs and the impact of regulating off-balance-sheet items, such as undrawn credit lines. 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 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 NBF 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 NBFs 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 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 NBFs 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 Global Company Key (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 Global Company Key (GVKEY) IDs, I find the undrawn amount of each NBFs and calculate the drawn portion as $(1 - \text{undrawn/total facility amount})$

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.

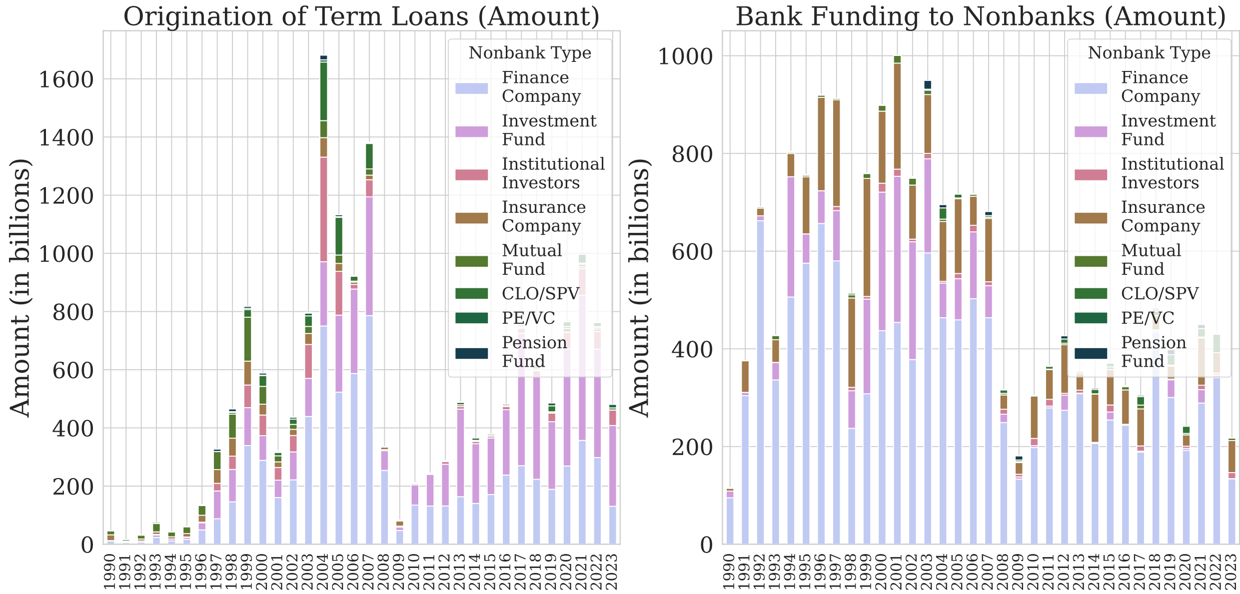

Figure 1: The left panel is nonbank origination of term loans by nonbank type. The right panel is bank funding to nonbanks. NBFs are nonbanks that both borrow from banks and lend to corporates.

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,

[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).

providing partial insurance against inventory uncertainty; additionally, credit lines offer back-up liquidity support.

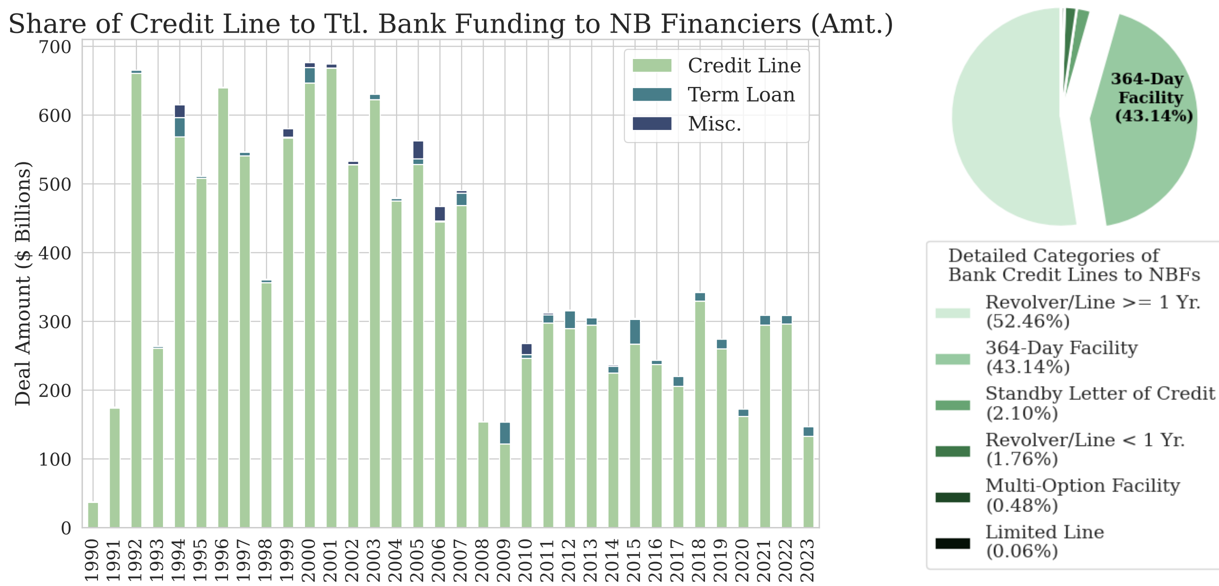

Figure 2: I examine the primary types of bank funding extended to nonbank financiers (NBFs): credit lines, term loans, and miscellaneous types. The left bar chart shows the distribution of these funding types, with credit lines in green, term loans in cyan, and miscellaneous in dark blue. The right pie 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 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

Nonbank financiers (NBFs) seek credit lines from banks primarily to manage inventory uncertainty on the asset side and liquidity risk on the liability side. Using textual analysis of SEC prospectuses, I document narrative evidence of the use of credit lines in the face of these challenges. I find that 80% of prospectuses provide evidence consistent with NBFs using credit lines as flexible funding sources to navigate uncertainty in investment demand. Furthermore, 40% of the prospectuses indicate that credit lines serve as liquidity backstops, particularly as backup funding for NBFs' commercial paper programs. Results are robust to different large language models.

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 two 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).

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.

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

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

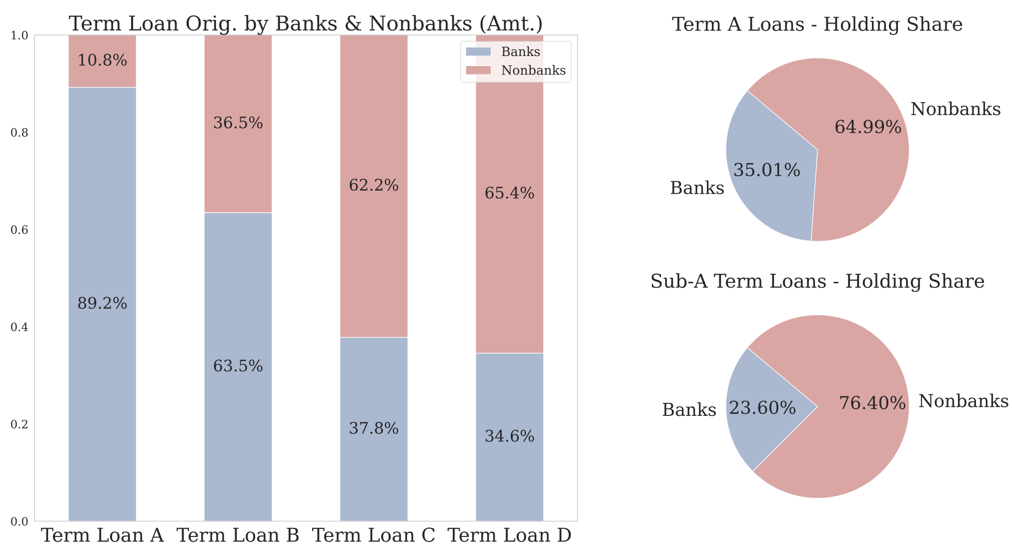

Figure 3: The left panel shows the share split between banks and nonbanks at origination. The right panel approximates the holding-level share during the entire loan duration using estimates from Blickle et al. (2020).

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 "our primary credit facility is available for short-term liquidity requirements and backs[5] our commercial paper facility," "The revolving credit facilities are committed and provide 100% back-stop support[6] for our commercial paper program," "we use credit lines as backup support[7] for our commercial papers," indicating

[5]By saying that the primary credit facility "backs" the commercial paper facility, the NBF is indicating that it has a revolving line of credit (or another form of committed funding) that can be drawn upon if needed to repay the commercial paper. This acts as a safety net, ensuring that the NBF can meet its short-term obligations even if it faces challenges in rolling over or refinancing its commercial paper in the market.

[6]"Back-stop" in this context means that the revolving credit facilities serve as a guaranteed fallback or safety net for the commercial paper program. If the NBF is unable to issue or roll over commercial paper (due to market conditions or lack of investor demand), it can fully rely on the revolving credit facility to obtain the necessary funds. This ensures that the NBF can meet its short-term obligations, preventing liquidity shortages. The revolving credit facilities act as a guaranteed backup funding source that covers the entire commercial paper program if needed. This gives investors confidence that there is no risk of default due to a lack of liquidity.

[7]"Backup support" refers to a secondary or reserve source of funding that can be accessed when needed to ensure that obligations are met. In this case, the revolving credit facility serves as a financial safety net for the operating

NBFs' need for additional liquidity support[8] beyond their commercial paper funding, which is prone to runs. I first manually label sentences in the training sample that indicate inventory uncertainty and liquidity support, and use t-SNE embedding on the training sample to show that there is significant difference in meaning between sentences that indicate inventory uncertainty vs that indicating liquidity support. Then, 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.

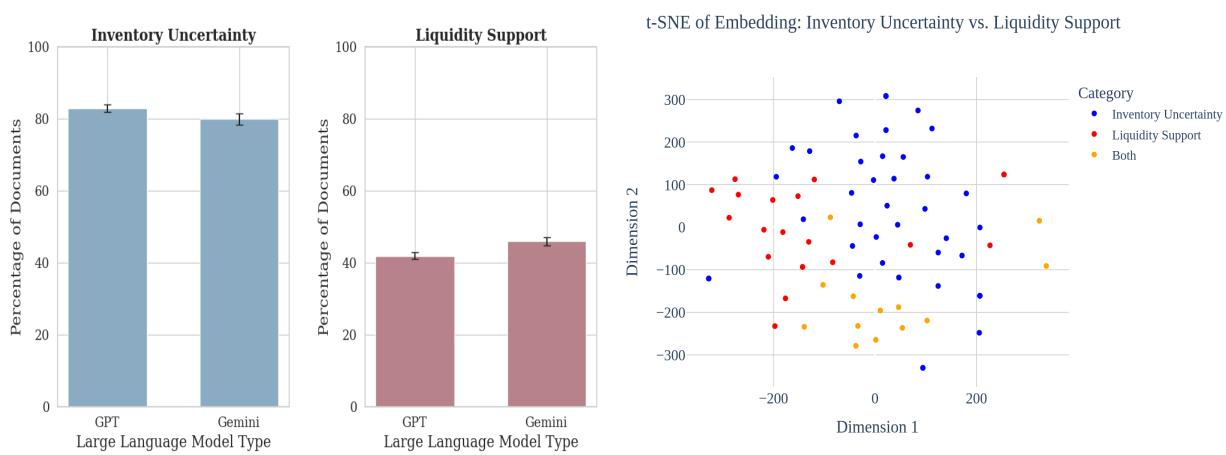

Figure 4: percentage of documents indicating credit line usage for inventory hedging and liquidity support. The embedding graph shows the difference in meaning between sentences that indicate inventory uncertainty vs that indicating liquidity support. The blue dots represent sentences indicating inventory uncertainty. The red dots represent sentences indicating liquidity support. The red and blue dots cluster at different spaces, indicating differences in meaning across these two groups of sentences.

2.2.3 Credit Line Drawdown and Pricing

In addition, I examine the credit line utilization patterns of nonbank financiers (NBFs). There is a strong correlation between available (undrawn) credit lines and lending activity (see Figure 5). In

partnership's commercial paper program. If market conditions make it difficult to roll over (refinance) the commercial paper, or if investors hesitate to buy it, the NBF needs an alternative source of funds to repay the maturing debt. The revolving credit facility acts as this alternative source, ensuring that the NBF has access to cash if commercial paper issuance becomes challenging.

[8] See Appendix B.2 for more examples

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.

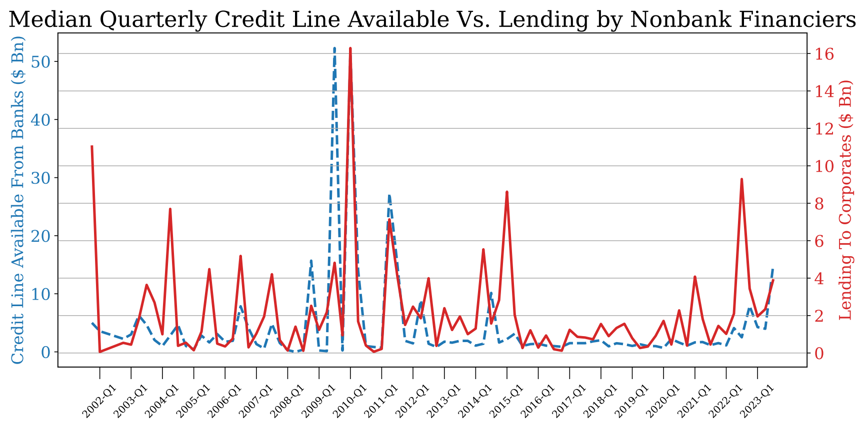

Figure 5: Quarterly credit line available (undrawn) of the median nonbank financier (NBF) is plotted in blue dotted line. Quarterly lending by the median NBF is plotted in the red line. This graph plots the median NBF. The Empirical Appendix B shows the total credit line utilization patterns. The patterns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

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, 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: $A_t^i = \exp(Z_t + z_t^i - \zeta d_t)$, 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. The variable d_t is a dummy that indicates whether the economy is in a disaster state. Specifically, $d_t = 1$ signifies that the economy is experiencing a disaster, while $d_t = 0$ indicates otherwise. The process follows a two-state Markov chain with the transition matrix:

$$\Pi_d = \begin{pmatrix} 1-\pi_d & \pi_d \\ 1-\pi_s & \pi_s \end{pmatrix},$$

where π_d represents the probability of transitioning into a disaster state, and π_s denotes the probability of remaining in that state. Define $G(A_t^i \mid Z_t, d_t)$ as the density of A_t^i conditional on Z_t and d_t. Loan payments decline geometrically at rate $\delta \in (0, 1)$. F is the interest payment that the lender receives on the corporate loan. A fixed fraction $1 - \delta$ of the outstanding notional is repaid in the next period. After the amortization, the remaining fraction δ of the original notional is still outstanding. This remaining portion is not paid off immediately but continues as a loan asset. Its value at time $t + 1$ is given by the market price q_{t+1}. Multiplying these gives the mark-to-market value of the remaining loan balance.

A corporate borrower owing A_t^i at time t either repays $F + (1 - \delta) + \delta q_t^i$ if $A_t^i \geq F + (1 - \delta)$ or defaults if $A_t^i < F + (1 - \delta)$. 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:

$$\mathscr{R}_t^A = \int_{F+(1-\delta)}^{\infty} (F + (1-\delta) + \delta q_t)\, dG(A_t^i \mid Z_t, d_t) + (1-\chi) \int_{-\infty}^{F+(1-\delta)} A_t^i dG(A_t^i \mid Z_t, d_t).$$

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.

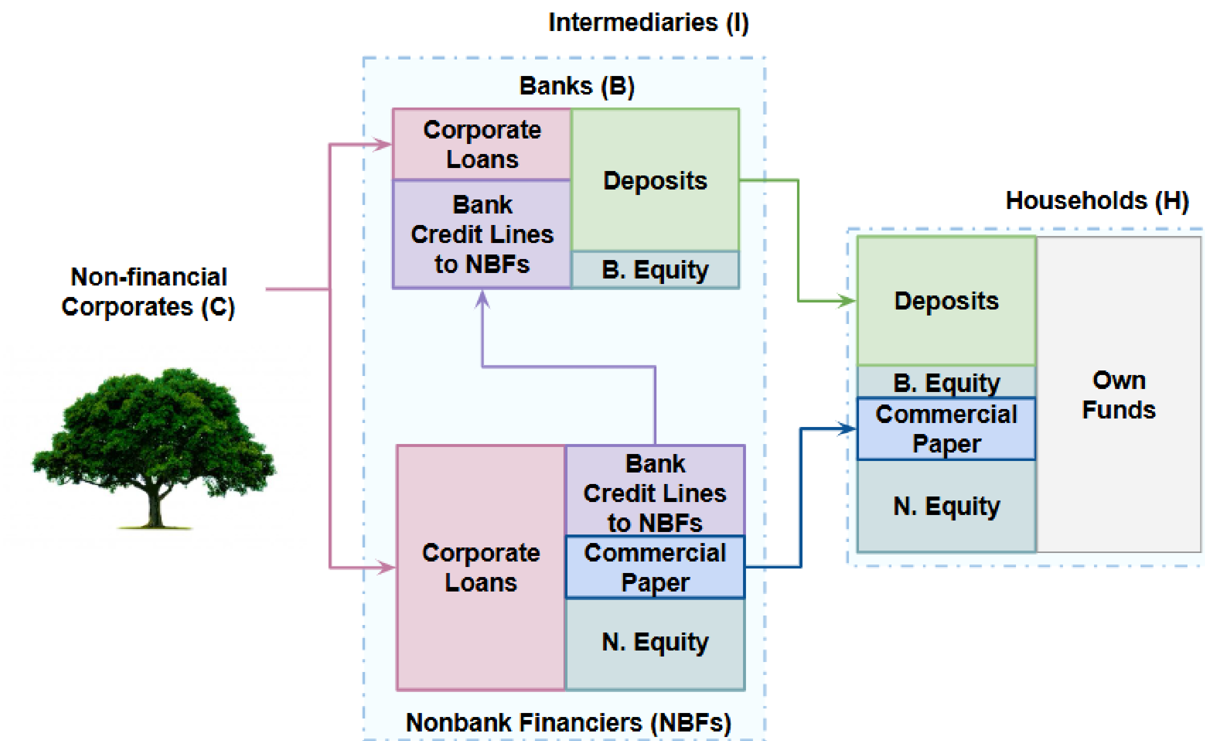

Figure 6: Model Overview

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 charges an upfront fee[9] 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

[9]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.

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 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.[10] 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. Contrasting with banks that finance long-term loans A_t^B with deposits, NBFs fund their long-term loans A_t^N using commercial paper, a relatively stable investment vehicle. However, inventory uncertainty shocks ι_t expose NBFs to sporadic investment opportunities, which are inherently less stable. To accommodate this variability, NBFs rely on credit lines that provide flexible financing. The upfront fee for these credit lines serves as an option premium, effectively capturing the cost of funding flexibility. When faced with inventory uncertainty, it is more efficient to finance investments with flexible credit rather than committing to inflexible long-term loans or short-term loans with floating spreads that are sensitive to market fluctuations. 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 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.

[10] 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).

Finally, I summarize the economic mechanisms in Section 3.7.

3.3 Nonbank Financiers (NBFs)

I consider the problem of a representative nonbank financiers (NBFs) subject to idiosyncratic default shocks, with detail of assumptions that achieve aggregation explained below. Nonbank financiers (NBFs) invest in Lucas trees. Every period, they choose investment a^N_{t+1}, credit line limit L_{t+1} from which they can draw down if needed, commercial paper b^N_{t+1} and equity issuance e^N_{t+1} 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. In addition, a large portion of sub-A term loans (term B, C, D, E, etc. loans) are also sold to NBFs by banks after 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^{rf}_t, i.e., NBFs pay $R^C_t = r^{rf}_t + s$ per unit of drawn credit.

In addition to using credit lines to meet sporadic investment demands, nonbank financiers can also draw from credit lines when there are negative shocks in the economy. These are states of the world where the required rate of return on commercial paper borrowing is high. Specifically, this is evidenced by textual analysis in section 2. Total commercial paper left outstanding $\tilde{B}_t$ after partially repurchasing it with credit-line funds: $\tilde{B}_t = B_t\left[1-\theta\Lambda\left(c_t(L_t)\right)\right]$ where B_t is the original amount of CP outstanding, $\Lambda:[0,1]\to[0,1]$ is an increasing function with $\Lambda(0)=0$ and $\Lambda(1)=1$. onbank 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. Taking stock, a representative nonbank financier's net worth N_t^N evolves as follows:

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

where the first term is payoff of nonbank financier's investments. Whether the investments are funded by credit line or by commercial paper, they both have the same payoff $\mathscr{R}_t^A$. The second term is nonbank financier's repayment of credit line drawdowns. The third term captures the outstanding commercial paper debt.

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 loans A_{t+1}^N and to purchase the option of accessing bank credit line facilities L_{t+1}, which result in the budget constraint shown 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 payoff on credit lines is given by

$$\mathscr{R}^L_{t+1}(L_{t+1}) = \underbrace{\left(1 - F^N_{\epsilon,t+1}\right) R^C_{t+1}}_{\text{non-defaulting NBFs pay back credit lines}} + \underbrace{F^N_{\epsilon,t+1} RV^N_{t+1} + \frac{F^N_{\epsilon,t+1}\epsilon^{N,-}_{t+1}}{c_{t+1}(L_{t+1}) + B^N_{t+1}}}_{\text{defaulting NBFs recovery value on bank credit lines}} . \tag{3.9}$$

As explained before, NBFs are subject to profit shocks ϵ^N_t, with probability $F^N_{\epsilon,t+1}$ of defaulting. The non-defaulting NBFs pay back the drawn credit at rate R^C_{t+1}, while the defaulting NBFs use their investment proceeds to repay the draw credit. The recovery value if NBFs default is

$$RV^N_{t+1} = (1 - \zeta^N) \cdot \frac{\mathscr{R}^A_{t+1}\left(A^N_{t+1} + c_{t+1}(L_{t+1})\right)}{c_{t+1}(L_{t+1}) + B^N_{t+1}} . \tag{3.10}$$

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

Bank's inside equity E^B_{t+1} 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 on credit lines than on term loans.[11] 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

$$E^B_{t+1} \geq \xi^E \left(\mathscr{R}^A_t A^B_{t+1} + \omega^{C,E}\mathscr{R}^L_{t+1} c_{t+1}(L_{t+1}) + \omega^{U,E}\left(L_{t+1} - c_{t+1}(L_{t+1})\right)\right)$$

Since banks are funded by debt and equity, writing this in terms of the maximum leverage that banks can take results in[12]

$$D_{t+1} \leq \xi \left(\mathscr{R}^A_t A^B_{t+1} + \omega^C \mathscr{R}^L_{t+1} c_{t+1} + \omega^U \left(L_{t+1} - c_{t+1}\right)\right)$$

[11]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.

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

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

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

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_{t+1}^H, nonbank debt B_{t+1}^H to maximize utility U_t^H, subject to household budget constraint:

$$C_t^H+q_t^f D_{t+1}^H+q_t^r B_{t+1}^H\leq W_t^H+Y_t+O_t^H\ , \tag{3.15}$$

where the evolution of household wealth is

$$\begin{aligned} W_t^H=&D_t^H+\mathscr{D}_t^B+\mathscr{D}_t^N\\ &+B_t^H\left[\left(1-F_{\epsilon,t}^N\right)+F_{\epsilon,t}^N\left((1-\zeta^N)\frac{\mathscr{R}_t^A(A_t^N+c_t(L_t))}{B_t^N+c_t(L_t)}\right)+F_{\epsilon,t}^N\frac{\epsilon_t^{N,-}}{B_t^N+c_t(L_t)}\right]. \end{aligned} \tag{3.16}$$

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 $\{e_t^B,A_{t+1}^B,L_{t+1}\}$ for banks, $\{e_t^N,A_{t+1}^N,B_{t+1}^N,c_{t+1},L_{t+1}\}$ for nonbanks, $\{C_t^H,D_{t+1}^H,B_{t+1}^H\}$ for households, and a price vector $\{q_t,q_t^L,q_t^f,q_t^r,R_t^C\}$, 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:

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

$$\text{Non-bank Debt:} \quad B_{t+1}^N = B_{t+1}^H , \tag{3.18}$$

$$\text{Loans:} \quad 1 = A_{t+1}^B + A_{t+1}^N + c_{t+1}(L_{t+1}) , \tag{3.19}$$

$$\text{ARC:} \quad Z_t + Y_t = C_t^H + \Psi^B \left(e_t^B\right) + \Psi^N \left(e_t^N\right) + DWL_t . \tag{3.20}$$

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. Hence, deadweight losses are defined as

$$DWL_t = \zeta^N F_{\epsilon,t}^N \mathscr{R}_{t+1}^A (A_t^N + c_t) , \tag{3.21}$$

The aggregate net dividends paid by the intermediaries are

$$\mathscr{D}_t^N = \phi_0^N N_t^N - e_t^N + \left(1 - F_{\epsilon,t}^N\right) \epsilon_t^{N,+} - F_{\epsilon,t}^N N_t^N , \tag{3.22}$$

$$\mathscr{D}_t^B = \phi_0^B N_t^B - e_t^B . \tag{3.23}$$

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

3.7 Economic Mechanism

This section elucidates the economic mechanism underpinning the credit line model, with detailed derivations provided in the Model Appendix A. Credit lines provide nonbank financiers (NBFs) with partial funding flexibility to seize investment opportunities and liquidity hedging, while banks account for the default risks associated with these nonbanks. NBFs balance the marginal benefits of exploiting investment opportunities and accessing liquidity support from credit lines against the marginal costs—namely, the credit line option premium, the repayment of drawn credit and the elevated NBF default risk. This trade-off is encapsulated in the first-order condition for the NBF credit limit presented in equation (3.24) below.

$$\begin{aligned}&\underbrace{q_t^L}_{\text{premium}} + \underbrace{\mathrm{E}_t\left[\mathcal{M}_{t,t+1}^N R_{t+1}^C \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right]}_{\text{MC of drawn credit}} - \underbrace{\frac{\partial q_t^r}{\partial L_{t+1}} B_{t+1}^N}_{<0,\text{ MC on NBF risk}} \\ &= \underbrace{\mathrm{E}_t\left[\mathcal{M}_{t,t+1}^N \mathscr{R}_{t+1}^A \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right]}_{\text{MB of capturing inv. opp.}} + \underbrace{\mathrm{E}_t\left[\mathcal{M}_{t,t+1}^N \theta B_{t+1}^N \frac{\partial \Lambda_{t+1}}{\partial c_{t+1}} \frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right]}_{\text{MB of liquidity support}} \qquad (3.24)\end{aligned}$$

The first term on the right-hand side represents the marginal benefit of capturing investment opportunities. A higher credit limit increases the potential for drawdowns (i.e., $\partial c_{t+1}\left(L_{t+1}\right)/\partial L_{t+1} > 0$), which enables NBFs to more effectively manage inventory uncertainties. The second term reflects the marginal benefit of liquidity support, where drawing on credit lines assists in repaying commercial paper obligations. Because Λ_{t+1} is increasing and concave in c_{t+1}, the marginal benefit of liquidity support declines as more credit is drawn. This feature mirrors the utilization fee structure on credit lines, which discourages fully exhausting the credit limit by making further drawdowns increasingly costly. The third term $\frac{\partial q_t^r}{\partial L_{t+1}} B_{t+1}^N$ captures the impact of increasing the credit limit on the overall creditworthiness of the NBF. A higher requested credit limit diminishes the NBF's perceived creditworthiness, thereby lowering the price (or equivalently, increasing the required rate of return) on its commercial paper. The complete derivation of this derivative is provided in Appendix section A.3.4 under the paragraph "Derivative of q_t^r with respect to L_{t+1}." Quantitatively, this term is negative, reflecting that as the credit limit increases, the cost associated with lower creditworthiness becomes more pronounced as NBF commercial paper funding becomes more expensive.

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 (3.25). Specifically, banks consider the effect of increasing the credit line limit on NBF drawdown behavior, reflected in the partial derivative in equation 3.26.

$$\underbrace{\mathrm{E}_t\left[\mathcal{M}^B_{t,t+1}\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right]}_{\text{NBF risk-taking cost}} = \underbrace{q^L_t + \frac{\partial q^L_t}{\partial L_{t+1}}L_{t+1}}_{\text{option premium}} + \underbrace{\mathrm{E}_t\left[\mathcal{M}^B_{t,t+1}\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\mathscr{R}^L_{t+1}\right]}_{\text{MB of risk-sharing}}$$
$$+ \underbrace{\tilde{\lambda}^B_t \min_{\mathcal{S}_{t+1}|\mathcal{S}_t} \xi\left(\omega^C\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}} + \omega^U\left(1-\frac{\partial c_{t+1}(L_{t+1})}{\partial L_{t+1}}\right)\right)}_{\text{collateral benefit}}, \tag{3.25}$$

where

$$\frac{\partial c_t(L_t)}{\partial L_t} = \frac{\partial}{\partial L_t}\left(\int_0^{L_t}\iota_t dF(\iota_t) + \int_{L_t}^{\infty} L_t dF(\iota_t)\right) = 1 - F(L_t)\,. \tag{3.26}$$

Importantly in my model, 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, the credit limit affects the price (option premium) q^L_t on these credit lines, as reflected in the partial derivative $\frac{\partial q^L_t}{\partial L_{t+1}}$ taken from the NBF side in (3.24),

$$\frac{\partial q^L_t}{\partial L_{t+1}} = \mathrm{E}_t\Bigg[\mathcal{M}^N_{t,t+1}\Bigg[-\left(\mathscr{R}^A_{t+1} - R^C_{t+1} + \theta B^N_{t+1}\frac{\partial \Lambda_{t+1}}{\partial c_{t+1}}\right)f(L_{t+1})$$
$$+ (1-F(L_{t+1}))\theta B^N_{t+1}\frac{\partial^2\Lambda_{t+1}}{\partial c^2_{t+1}}\Bigg]\Bigg]. \tag{3.27}$$

$\frac{\partial q^L_t}{\partial L_{t+1}}$ is quantitatively negative. The greater the credit limit offered by banks, the lower the price and thus the higher the expected returns on these credit lines. The intuition behind is that banks

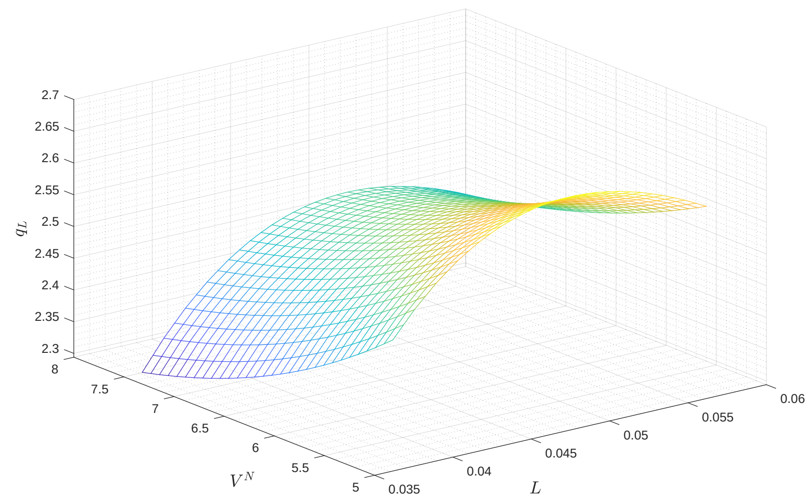

Figure 7: The credit line surface is constructed by approximating the option premium (upfront fee) in the calibrated model with more details in the following calibration section 4. The graph is plotted from bank's first-order condition with respect to credit limit in (3.25).

hold a monopolistic position in extending credit lines, as is empirically true that credit lines are usually extended by banks than other financial entities. As explained before, this is because of banks' liquidity advantage in accessing cheap deposits.

To see the credit line option fee graphically, Figure 7 illustrates the average credit line fees faced by NBFs, represented as a surface that defines the menu of available credit line contracts. 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. From $L_{t+1} = 0.035$ to 0.05, q_t^L is increasing in credit limit. This is because as banks increase credit limit, NBF default risk increases and therefore banks need to be compensated for a higher upfront premium. However, since banks internalize the impact of increased credit limits on pricing of each dollar committed, the partial derivative $\frac{\partial q_t^L}{\partial L_{t+1}}$ kicks in, as shown in equation (3.25), which tilts the surface slightly downwards after 0.05. On the right-hand side, we also see that option premium q_L decreases in NBF net worth V^N. When the NBF net worth is low, the default risk is high. These are states of the world where NBF is highly likely to draw down from credit lines to pay back commercial paper. Therefore, banks need to be compensated more on the premium when NBF net worth is low. This demonstrates that banks account for the default risk of the NBF sector in their pricing, with higher default risk resulting in higher upfront fees. Altogether, credit lines give NBFs partial flexibility while banks take into account an additional unit of credit limit extension on NBF risk-taking decisions and their default probabilities.

4 Calibration

I calibrate the model to U.S. syndicated loan data from 1990 to 2023, with each model period corresponding to one year. There are two groups of parameters, the externally calibrated and the internally calibrated. Externally calibrated parameters (Table 1) are calculated directly from data or sourced from existing literature. Internally calibrated parameters (Table 2) are chosen to align the model with targeted moments observed in the data. In the subsections below, I discuss these parameters for credit risk, financial intermediation, preferences, and regulation[13], presenting externally calibrated parameters first, followed by internally calibrated ones. Additional institutional details are provided in Calibration Appendix C.

4.1 Credit Risk

I calculate the probability of transitioning into a disaster, π_d from the expected annual rare disaster probability. I characterize the disaster threshold as 2.5 standard deviations above the mean expected default probability from Moody's expected default frequency weighted by total assets within one year for non-financial corporations in the US. π_s denotes the probability of remaining in that state. 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 param-

[13]The regulation section includes only externally calibrated parameters estimated from institutional details.

Table 1: Pre-Set Parameters

Parameter	Description	Value	Source
		Credit Risk	
π^d	Annual prob. of disaster	3.97%	Exp. ann. disaster prob. (Moody's)
π^s	Annual prob. of staying in disaster	33%	Exp. disaster length 1 year
		Financial Intermediation	
s	Credit line spread	88 bps	Dealscan Legacy and LSEG Loan-Connector, Appendix C.1
δ	Corporate loan average life	0.928	FRED, Bloomberg, Appendix C.2
ϕ_0^B	Target bank dividend	0.068	Elenev et al. (2021)
ϕ_0^N	Target nonbank dividend	0.072	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

eter 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 $\rho = 0.95$ and $\sigma = 2\%$ are chosen to match the persistence (autocorrelation of order (1)) of the average corporate default rate, which is 0.7, and the volatility of the corporate default rate, which is 0.5%, in the data. Moreover, I use the loan repayment F to target the average corporate default rate. I calculate this target from Moody's average expected default frequency (EDF) within one year of non-financial corporations in the US, weighted by total assets, which is 0.7%. An alternative for corporate loan default rate is to use Elenev et al. (2021)'s target [14] of corporate loan default. However, Elenev et al. (2021) only have the corporate loan default rate for loans on bank balance sheet. Since my paper includes both bank and nonbank loans, I use Moody's EDF instead. The deadweight losses on defaulting loans χ

[14] A brief description of their target calculation is as follows: The first dataset is sourced from the Federal Reserve Board of Governors, provides delinquency and charge-off rates for Commercial and Industrial loans as well as Commercial Real Estate loans issued by U.S. Commercial Banks from 1991 to 2015, with an average delinquency rate of 3.1%. The second dataset from Standard & Poor's reports default rates on publicly-rated corporate bonds spanning 1981 to 2014, with an average default rate of 1.5%—0.1% for investment-grade bonds and 4.1% for high-yield bonds. The results of the model align between these two figures.

Table 2: Calibrated Parameters

Par	Description	Value	Target	Model	Data
			Credit Risk		
ρ	Persistence of Lucas tree dividends	0.95	AC(1) corp. default rate	0.7	0.7
σ	Volatility of Lucas tree dividends	2%	Volatility of corporate default rate	0.6%	0.5%
χ	Losses on defaulting loans	0.62	Corporate loan loss given default (Elenev et al., 2021)	51%	51%
σ^i	Volatility of idiosyncratic shocks	0.07	Moody's EDF within 1 yr for US non-financial firms	0.7%	0.7%
ζ	Disaster multiple	0.1	Corporate default conditional on disaster	2%	2%
			Financial Intermediation		
μ_ι	Mean of inventory uncertainty shocks	0.065	NBF loan share	43%	43%
σ_ι	Dispersion of inventory uncertainty	0.055	Credit line utilization ratio	82%	81%
ϕ_1^B	Bank equity issu. cost	6	Bank equity issu. ratio	1.0%	1.0%
ϕ_1^N	NBF equity issu. cost	2	NBF equity issu. ratio	2.3%	4.5%
ζ^N	NBF loss given default	0.83	Unsecured and Subordinated debt recovery (Moody's)	37%	38%
$\sigma_{\epsilon,N}$	Cross-sect. dispersion ϵ_t^N	1.48	Nonbank bond default rate	0.1%	0.2%
			Preferences		
β_H	Time discount factor	0.99	Risk-free rate	1%	1%
ς	elasticity of substitution btw. dep. and cons.	0.0065	Deposit rate	0.3%	0.3%
θ	elasticity of substitution btw. dep. and CP	0.9	liquidity premium (total, dep. and CP)	0.8%	0.4%

are set to match corporate loan severities of 51.9% as in Elenev et al. (2021).

4.2 Financial Intermediation

Credit line spread. I calculate from Dealscan and LSEG LoanConnector the average fixed spread [15] of credit lines from banks to nonbank financiers (NBFs). The unconditional facility-amount weighted average spread on top of the risk-free rate is 63 basis points. The unconditional unweighted average spread is 88 bps. 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.

Corporate loan average life. In my model, all corporate loans are modeled as geometrically declining perpetuities, where the borrower promises payments of δ^{t-1} over time, for all $t \in \mathbb{N}^{+}$. To align the model with real-world data, I construct an aggregate bond index using investment-grade and high-yield bonds from Bank of America Merril Lynch (BofAML) and Barclays Capital (BarCap) from 1997 to 2023, weighting them by market value to calculate key characteristics like weighted-average maturity (WAM) and weighted-average coupon (WAC). I then compare the price of a standard bond with WAM = 10 years and WAC = 5.93% to a theoretical bond model, calibrating the decay rate $\delta = 0.928$ to match the observed duration of corporate loans. For details, see Calibration Appendix C.2. The implied average duration of corporate loans in the model is 7.01 years.

Target dividends. I use the bank target dividend parameter from Elenev et al. (2021), set at 6.8% of bank net worth. For nonbank financiers (NBFs), I am able to match a subset, 193 out of 371 firms in the Dealscan data to their Global Company Keys (GVKEYs) using the Roberts Dealscan-Compustat Linking Database (Chava and Roberts, 2008). I construct a time series of total annual dividends relative to book equity for these NBFs and find an average dividend payout ratio of 7.2%, slightly higher than that of banks but not significantly so. This result is expected, as my sample includes only those NBFs with identifiable GVKEYs and available dividend data in

[15] In Dealscan and LSEG LoanConnector, "all-in-drawn spread" refers to the spread on top of risk-free rate. See, Dealscan dictionary. 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, as explained inIvashina (2005).

Compustat. I do not use data from Damodaran (2024) since my sample contains few insurance firms, which tend to have higher payout ratios.

Inventory uncertainty. The inventory uncertainty shocks are distributed log-normally with mean μ_ι and time-varying standard deviation $\sigma_{\iota,t}$. I use the mean μ_ι to determine the target NBF loan share, which equals 40%. Then, I use σ_ι to target a credit line utilization ratio of 80%.

Equity funding. The equity issuance costs for banks and nonbank financiers (NBFs) are used to target their equity issuance ratios in the data, calculated as equity issuance divided by book equity. Drawing on calculations from Elenev et al. (2021), banks, on average, distributed 6.8% of their book equity annually as dividends and share repurchases between 1974 and 2018. Additionally, the financial sector's payout ratio, defined as dividends plus share repurchases minus equity issuances divided by book equity, is reported as 5.75% in Elenev et al. (2021). The difference between these two figures yields the bank equity issuance ratio, calculated to be 1.05%. I use bank equity issuance cost parameter $\phi_1^B = 7$ to match the bank equity issuance ratio. I calculate from CRSP the equity issuance ratio of NBF to be 4.5%. I use NBF equity issuance cost parameter $\phi_1^N = 5$ to match the NBF equity issuance ratio.

Default. I set the loss given default on nonbank loans to 0.25 to align with Moody's estimated recovery rate of 38.2% for unsecured and subordinated debt, following Begenau and Landvoigt (2022). To match the average leverage of nonbank financiers (NBFs), I use the cross-sectional dispersion of NBF profitability shocks, ϵ_t^N. The target NBF leverage is calculated using Compustat - Financial Ratios data. Among the 371 firms in the Dealscan database, I successfully match 123 GVKEYs to Compustat - Financial Ratios data from 1990-01-01 to 2023-12-31. I then compute the average leverage ratio, defined as total debt to total assets, across all firms and time, obtaining an estimate of 0.65 for U.S. NBFs. This estimate is consistent with regulatory constraints such as the 1940 Investment Company Act, which limits the maximum debt-to-equity ratio to 2:1 for business development companies. My sample includes not only business development companies but also investment funds, institutional investors, and other financial entities. Given the broad range of NBFs in my sample, a leverage ratio of 0.65 remains broadly aligned with NBF leverage levels.

4.3 Preferences

Household risk aversion and inter-temporal elasticity of substitution are set to 1 for log utility. 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 internally calibrated $\varsigma = 0.005$ to generate an economy-wide liquidity premium[16] of 0.21%, which matches the liquidity premium on risk-free assets in Van Binsbergen et al. (2022). The bank deposit elasticity θ governs the liquidity advantage of bank deposits vis-á-vis that of commercial paper, which are used to calibrate and average deposit rate of 0.31%, matching that in the data. Following Begenau et al. (2024),I calculate the transaction deposit rate by subtracting the interest expense on domestic time deposits from the total interest expenses on domestic deposits. This difference is then divided by the beginning-of-period balance of transaction deposit accounts, excluding time deposit accounts.

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 credid line, we need to separate the undrawn credit line of maturity less than 1 year, versus those that are more than 1 year. Undrawn commitments with less than 1 year of maturity receive conversion factor 20%, and those more than 1 year receive 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

[16]The model counterpart of economy-wide liquidity premium is a weighted average of convenience yield on deposits and on commercial paper.

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 conduct policy counterfactuals that study 1) the spillover effects of bank regulations on NBFs 2) the effects of off-balance sheet regulation on undrawn credit lines.

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 is the model described in section 3, in which banks provide contingent liquidity by extending credit lines to nonbank financiers (NBFs). I refer to this as the *interconnected* economy. To assess the value of this contingent liquidity, I consider a counterfactual scenario in which the credit line connection between banks and NBFs is removed, termed the *segmented* economy. Note that the total investment share is normalized to 1, comprising the investments of banks, NBFs, and additional opportunities arising from inventory uncertainty shocks. NBFs can only seize these extra opportunities up to their credit line limits, so comparing the ergodic means of the two economies reveals the benefits of contingent liquidity.

First, the interconnected economy sustains higher asset prices and creates more safe assets on average (as indicated by the unconditional mean). This occurs because banks, when optimally setting credit limits, consider the impact of an additional unit of credit on NBFs' drawdown choices—thereby disciplining their risk-taking behavior and investment share. In the absence of bank credit lines, NBFs engage in less constrained risk-taking. Notably, the interconnected economy exhibits a larger banking sector, with 55% of the loan pool funded by deposits compared to just 32% in the segmented economy. The presence of credit lines, all else equal, makes the economy less volatile and allows banks to hold a larger *ex ante* share of aggregate risk, as reflected in higher asset prices (6.46 vs. 5.75) and lower default probabilities (0.12% vs. 0.31%). These higher asset prices, in turn, enable banks to create more safe assets.

Table 3: Interconnected Vs. Segmented Financial System

	Interconnected (Baseline)		*Segmented*	
	Unconditional	*Fin. Rec.*	*Unconditional*	*Fin. Rec.*
		Banks		
Investment	0.55	0.53	0.32	0.31
Deposits	0.56	0.54	0.29	0.28
Credit line limit	0.046	0.045	–	–
		Nonbank Financiers (NBFs)		
Investment	0.45	0.47	0.68	0.69
Commercial paper	1.15	1.16	1.15	1.09
Credit line utilization	82%	83%	–	–
Default probability	0.12%	0.23%	0.31%	0.52%
		Pricing		
Risk-free rate	0.99%	3.20%	0.99%	3.56%
Convenience yield on deposits	0.72%	0.69%	0.90%	1.07%
Commercial paper spread	0.92%	1.49%	2.59%	3.68%
Asset price	6.46	5.90	5.75	5.25
		Welfare		
Household welfare	0.65	0.64	0.55	0.54

Second, the interconnected economy enhances welfare. By facilitating the creation of a greater quantity of safe assets—such as deposits—credit lines directly benefit households. For example, deposit creation rises to 0.56 in the interconnected economy compared to only 0.29 in the segmented economy, leading to a marked improvement in household welfare.

Third, the interconnected economy is more resilient during financial crises. Under equivalent uncertainty and disaster shock levels, the default probability for NBFs is 0.23% in the interconnected economy, compared to 0.52% in the segmented economy. Additionally, asset prices decline more sharply in the segmented economy than in the interconnected one.

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.

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 0.3% 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 ompared 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 compared to the steady state, signaling a rebound in this sector.

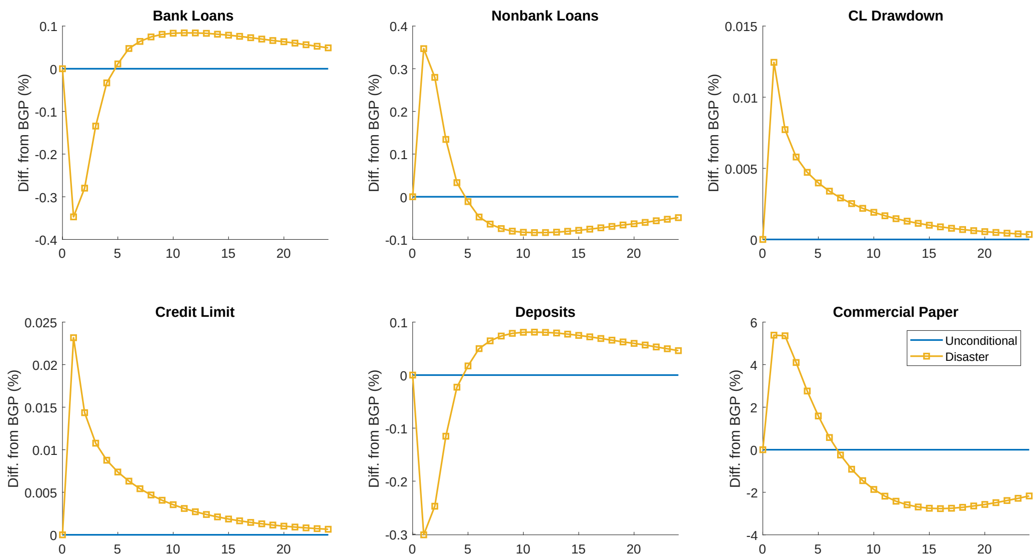

Figure 8: intermediaries balance sheets variables in financial crisis. Blue: no shock. Yellow: recession.

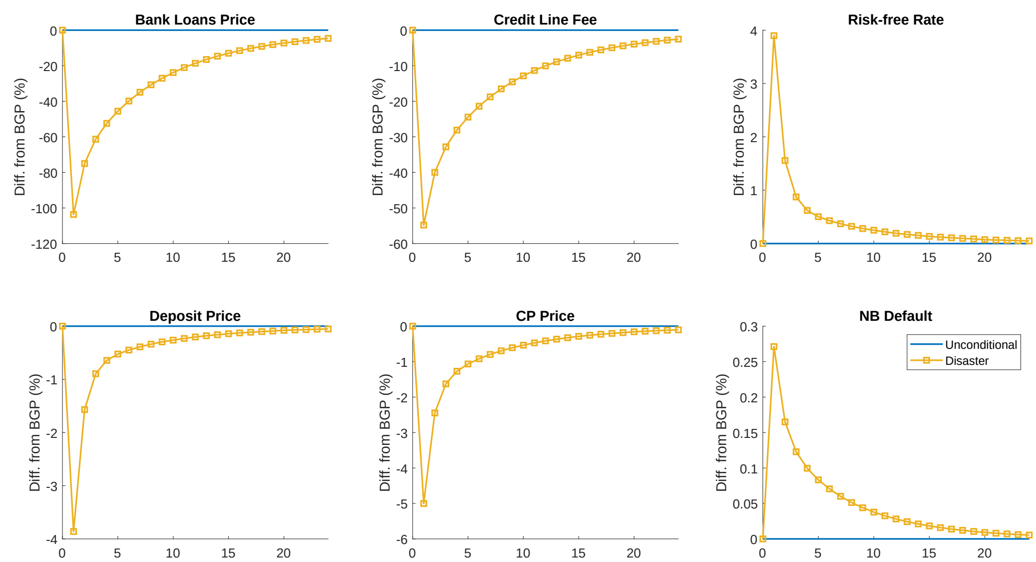

Figure 9: asset prices in financial crisis. Blue: no shock. Yellow: recession.

Asset Pricing. Figure 9 illustrates the behavior of asset prices during a crisis. As corporate assets lose value, the price of bank loans declines 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 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 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.

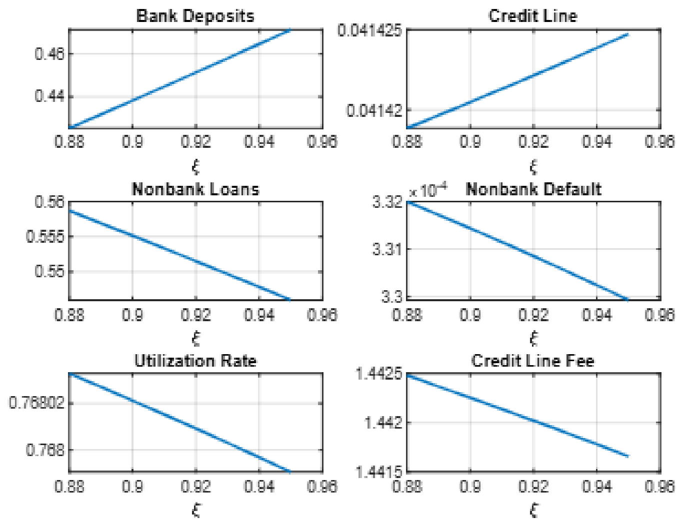

Figure 10: Spillover Effect of Bank Capital Regulation on Nonbank Loan Origination, B

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 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.

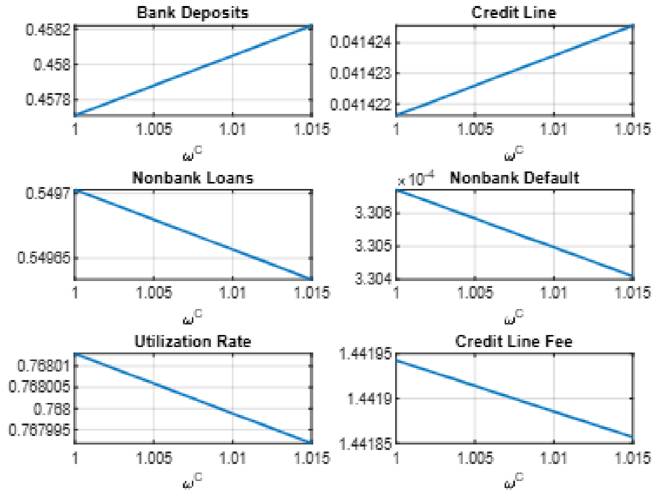

Figure 11: Effect of Regulation of Drawn Credit from Bank Credit Lines to Nonbank Financiers (NBFs).

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.

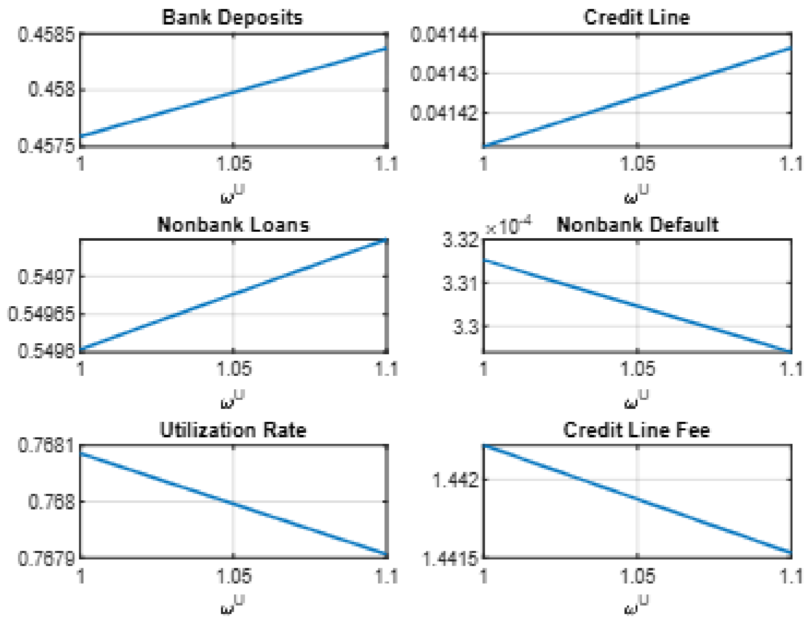

Figure 12: Effect of Regulation Off-balance sheet Undrawn Credit Lines.

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 nonbank financier. 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

$$V_t^N\left(\epsilon_{i,t},\iota_{i,t},\mathcal{S}_t\right)=\max_{a^N_{i,t+1},b^N_{i,t+1},l^N_{i,t+1},e^N_{t,i}}\phi_0^N n_t^N-e^N_{t,i}+\epsilon_{i,t}+\mathrm{E}_t\left[\mathcal{M}_{t,t+1}\max\left\{V^N_{t+1}\left(\epsilon_{i,t},\iota_{i,t+1,}\mathcal{S}_{t+1}\right),0\right\}\right]$$

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

$$\tilde{V}_t^N\left(\iota_{i,t},\mathcal{S}_t\right)=\max_{a^N_{i,t+1},b^N_{i,t+1},l^N_{i,t+1},e^N_{t,i}}\phi_0^N n_t^N-e^N_{t,i}+\mathrm{E}_t\left[\mathcal{M}_{t,t+1}\max\left\{\tilde{V}^N\left(\iota_{i,t+1},\mathcal{S}_{t+1}\right)+\epsilon_{i,t+1},0\right\}\right],$$

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 Using Credit Lines To Manage Inventory Uncertainty

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

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

A.1.3 Using Credit Lines as Liquidity Support

Commercial paper left outstanding $\tilde{B}_t$ after partially repurchasing it with credit-line funds: $\tilde{B}_t = B_t \left[1 - \theta\Lambda\left(c_t(L_t)\right)\right]$ where B_t is the original amount of CP outstanding, $\Lambda : [0,1] \to [0,1]$ is an increasing function with $\Lambda(0) = 0$ and $\Lambda(1) = 1$.

This formulation means the fraction of CP bought back is $\Lambda\big(c_t(L_t)\big)$. A simple example is: $\Lambda(x) \ = \ x^\alpha, \quad$ where $\ 0 < \alpha < 1$, which grows from 0 to 1 as $x \in [0,1]$ increases, but does so at a diminishing rate for $0 < \alpha < 1$. This curvature encourages an interior solution rather than an extreme (full or zero) drawdown of the credit line.

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

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

A.1.4 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

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

and nonbank no-shorting constraint

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

and nonbank credit line limit

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

where

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

A.1.5 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_{t+1}^N is

$$\left(q_t - \frac{\partial q_t^r}{\partial A_{t+1}^N}\right) \nu_t^N = \mu_t^N + \mathrm{E}\left[\mathcal{M}_{t,t+1} \tilde{V}_{N,t+1}^N \left(1 - F_{\epsilon,t+1}^N\right) \mathscr{R}_{t+1}^A\right] \,,$$

Nonbank Debt. The FOC for loans B_{t+1}^N is

$$\left(q_t^r + \frac{\partial q_t^r}{\partial B_{t+1}^N}\right) \nu_t^N = \mathrm{E}\left[\mathcal{M}_{t,t+1} \tilde{V}_{N,t+1}^N \left(1 - F_{\epsilon,t+1}^N\right) \left(1 - \theta \Lambda\left(c_{t+1}(L_{t+1})\right)\right)\right] \,,$$

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

$$\left(q_t^L - \frac{\partial q_t^r}{\partial L_{t+1}} B_{t+1}^N\right) \nu_t^N = \mu_{t,L}^N + \mathrm{E}_t\left[\mathcal{M}_{t,t+1} \tilde{V}_{N,t+1}^N \left(1 - F_{\epsilon,t+1}^N\right) \left(\mathscr{R}_{t+1}^A - R_{t+1}^C + \theta B_{t+1} \frac{\partial \Lambda_{t+1}}{\partial c_{t+1}}\right) \frac{\partial c_{t+1}}{\partial L_{t+1}}\right] .$$

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.2 Banks

A.2.1 Optimization Problem

Bank net worth is given by

$$N_t^B = \mathscr{R}_t^A A_t^B - D_t + \mathscr{R}_t^L c_t(L_t) - c_t(L_t) \,, \tag{A.6}$$

where

$$\mathscr{R}_{t+1}^L(L_{t+1}) = \left(1 - F_{\epsilon,t+1}^N\right) R_{t+1}^C + F_{\epsilon,t+1}^N RV_{t+1}^N + \frac{F_{\epsilon,t+1}^N \epsilon_{t+1}^{N,-}}{\tilde{B}_{t+1}^N + c_{t+1}(L_{t+1})} \,, \tag{A.7}$$

where the recovery value of nonbank default is

$$RV_{t+1}^N = (1 - \zeta^N) \cdot \frac{\mathscr{R}_{t+1}^A \left(A_{t+1}^N + c_{t+1}(L_{t+1})\right)}{\tilde{B}_{t+1}^N + c_{t+1}(L_{t+1})} \,. \tag{A.8}$$

Bank's problem is characterized recursively as

$$V_t^B\left(\mathcal{S}_t\right)=\max_{A_{t+1}^B, D_{t+1}, L_{t+1}, e_t^B} \phi_0^B N_t^B-e_t^B+\mathrm{E}_t\left[\mathcal{M}_{t,t+1} V_{t+1}^B\left(\mathcal{S}_{t+1}\right)\right] \ , \tag{A.9}$$

subject to bank budget constraint

$$q_t A_{t+1}^B-q_t^f D_{t+1} \leq (1-\phi_0^B) N_t^B+q_t^L L_{t+1}+e_t^B-\Psi^B\left(e_t^B\right) \ , \tag{A.10}$$

bank capital requirement,

$$D_{t+1} \leq \min_{\mathcal{S}_{t+1}|\mathcal{S}_t}\Big(\xi\big(\left[Z_{t+1}+q_{t+1}\right] A_{t+1}^B+\omega^C c_{t+1}(L_{t+1})+\omega^U\left(L_{t+1}-c_{t+1}(L_{t+1})\right)\big)\Big), \tag{A.11}$$

no-shorting constraint on bank loans to firms,

$$0 \leq A_{t+1}^B \, , \tag{A.12}$$

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

$$E_{t+1}^B \geq \xi^E\left(\mathscr{R}_{t+1}^A A_{t+1}^B+\omega^{C,E} \mathscr{R}_{t+1}^L c_{t+1}(L_{t+1})+\omega^{U,E}\left(L_{t+1}-c_{t+1}(L_{t+1})\right)\right)$$

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

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

A.2.3 First-Order Conditions

Attach Lagrange multipliers λ_t^B to the capital requirement (A.11), μ_t^B to the no-shorting constraint on bank loans (A.12) and ν_t^B to the budget constraint (A.10). 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

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

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

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

A.2.4 Partial Derivatives

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

$$\frac{\partial q_t^L}{\partial L_{t+1}} = \mathrm{E}_t\left[\mathcal{M}_{t,t+1}^N \left[-\left(\mathscr{R}_{t+1}^A - R_{t+1}^C + \theta B_{t+1}^N \frac{\partial \Lambda_{t+1}}{\partial c_{t+1}}\right) f(L_{t+1}) + (1 - F(L_{t+1}))\theta B_{t+1}^N \frac{\partial^2 \Lambda_{t+1}}{\partial c_{t+1}^2}\right]\right] \,.$$

where $\frac{\partial^2 \Lambda_{t+1}}{\partial c_{t+1}^2} = \alpha(\alpha - 1)c_{t+1}^{\alpha-2}$.

A.3 Households

A.3.1 The Optimization Problem

The problem of the representative household is

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

subject to

$$
\begin{aligned}
u_t^H &= \left(C_t^H\right)^{1-\varsigma}\left(\left(D_{t+1}^H\right)^{\theta}\left(B_{t+1}^H\right)^{1-\theta}\right)^{\varsigma} \\
C_t^H &= W_t^H + Y_t - q_t^f D_{t+1}^H - q_t^r B_{t+1}^H + O_t^H \qquad \text{(A.13)} \\
W_t^H &= D_t^H + \mathscr{D}_t^B + \mathscr{D}_t^N \\
&\quad + B_t^H\left[\left(1 - F_{\epsilon,t}^N\right) + F_{\epsilon,t}^N\left((1-\zeta^N)\frac{\mathscr{R}_t^A(A_t^N + c_t(L_t))}{B_t^N + c_t(L_t)]}\right) + F_{\epsilon,t}^N\frac{\epsilon_t^{N,-}}{B_t^N + c_t(L_t)}\right] \qquad \text{(A.14)}
\end{aligned}
$$

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

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

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

$$
\begin{aligned}
&\left(V_t^H\right)^{1/\nu_H}(1-\beta_H)\frac{\left(u_t^H\right)^{1-1/\nu_H}}{C_t^H}\left((1-\varsigma)\,q_t^r - (1-\theta)\,\varsigma\frac{C_t^H}{B_{t+1}^H}\right) \\
&= \left(V_t^H\right)^{1/\nu_H}\beta_H\left(CE_t^H\right)^{\sigma_H - 1/\nu_H}\mathrm{E}\Bigg\{\left(V_{t+1}^H\right)^{-\sigma_H}V_{W,t+1}^H\Bigg[1 - F_{\epsilon,t+1}^N \\
&\qquad + F_{\epsilon,t+1}^N\left((1-\zeta^N)\frac{\mathscr{R}_{t+1}^A(A_{t+1}^N + c_{t+1}(L_{t+1}))}{B_{t+1}^N + c_{t+1}(L_{t+1})}\right) \\
&\qquad + \frac{F_{\epsilon,t}^N\epsilon_t^{N,-}}{B_{t+1}^N + c_{t+1}(L_{t+1})}\Bigg]\Bigg\}.
\end{aligned}
$$

A.3.3 Marginal Values of State Variables and SDF

The marginal value of saver wealth is

$$V_{W,t+1}^{H}=\left(V_{t+1}^{H}\right)^{\frac{1}{\nu_H}}\left(1-\beta_H\right)\frac{\left(u_{t+1}^{H}\right)^{1-1/\nu_H}}{C_{t+1}^{H}}(1-\varsigma)$$

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

$$\mathcal{M}_{t,t+1}=\beta_H\left(\frac{C_{t+1}^{H}}{C_t}\right)^{-1}\left(\frac{u_{t+1}^{H}}{u_t^{H}}\right)^{1-1/\nu_H}\left(\frac{V_{t+1}^{H}}{CE_t^{H}}\right)^{1/\nu_H-\sigma_H}$$

A.3.4 Derivatives of q_t^r.

Household choose their commercial paper at the non-banks, taking into account the risks associated with non-bank debt. In the Euler equation of the price of the nonbank debt, define

$$\mathcal{A}_{t+1}^{H}\equiv(1-\zeta^N)\frac{\mathscr{R}_{t+1}^{A}(A_{t+1}^{N}+c_{t+1}(L_{t+1}))}{\tilde{B}_{t+1}^{N}+c_{t+1}(L_{t+1})}\,,$$

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

We can now write

$$q_t^r=\mathrm{E}_t\left\{\mathcal{M}_{t,t+1}\left[1+\left(\mathcal{A}_{t+1}^{H}-1\right)F_{\epsilon,t+1}^{N}+\mathcal{B}_{t+1}^{H}\right]\right\}+\frac{(1-\theta)\,\varsigma C_t^{H}}{(1-\varsigma)B_{t+1}^{H}}$$

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

$$\frac{\partial q_t^r}{\partial A_{t+1}^{N}}=\mathrm{E}_t\left\{\mathcal{M}_{t,t+1}\left[\left(\mathcal{A}_{t+1}^{H}-1\right)\frac{\partial F_{\epsilon,t+1}^{N}}{\partial A_{t+1}^{N}}+\frac{\partial\mathcal{A}_{t+1}^{H}}{\partial A_{t+1}^{N}}F_{\epsilon,t+1}^{N}+\frac{\partial\mathcal{B}_{t+1}^{H}}{\partial A_{t+1}^{N}}\right]\right\}\tag{A.15}$$

First, the derivative of $\mathcal{A}_{t+1}^{H}$ with respect to A_{t+1}^{N} is:

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

Then, I take derivative of $F_{\epsilon,t+1}^{N}$ with respect to A_{t+1}^{N}.

$$\frac{\partial F_{\epsilon,t+1}^{N}}{A_{t+1}^{N}}=-f_{\epsilon,t+1}^{N}(-\tilde{V}_{t+1}^{N})\frac{\partial\tilde{V}_{t+1}^{N}}{\partial N_{t+1}^{N}}\frac{\partial N_{t+1}^{N}}{\partial A_{t+1}^{N}}=-f_{\epsilon,t+1}^{N}(-\tilde{V}_{t+1}^{N})\left(\phi_0^N+\frac{1-\phi_0^N}{1-\phi_1^N e_{t+1}^{N}}\right)\mathscr{R}_{t+1}^{A}.$$

Lastly,

$$\frac{\partial \mathcal{B}_{t+1}^{B}}{\partial A_{t+1}^{N}}=\frac{f_{\epsilon,t+1}^{N}(-\tilde{V}_{t+1}^{N})\left(\phi_0^N+\frac{1-\phi_0^N}{1-\phi_1^N e_{t+1}^N}\right)\mathscr{R}_{t+1}^{A}\tilde{V}_{t+1}^{N}}{B_{t+1}^{N}+c_{t+1}(L_{t+1})}\,.$$

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

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

$$\frac{\partial q_t^r}{\partial B_{t+1}^N}=\mathrm{E}_t\left\{\mathcal{M}_{t,t+1}\left[\left(\mathcal{A}_{t+1}^{H}-1\right)\frac{\partial F_{\epsilon,t+1}^{N}}{\partial B_{t+1}^{N}}+\frac{\partial \mathcal{A}_{t+1}^{H}}{\partial B_{t+1}^{N}}F_{\epsilon,t+1}^{N}+\frac{\partial \mathcal{B}_{t+1}^{H}}{\partial B_{t+1}^{N}}\right]\right\} \tag{A.16}$$

First, I take the derivative of $\mathcal{A}_{t+1}^H$ with respect to B_{t+1}^N:

$$\frac{\partial \mathcal{A}_{t+1}^{H}}{\partial B_{t+1}^{N}}=-(1-\zeta^N)\frac{\mathscr{R}_{t+1}^{A}(A_{t+1}^{N}+c_{t+1}(L_{t+1}))}{\left(\tilde{B}_{t+1}^{N}+c_{t+1}(L_{t+1})\right)^2}\left[1-\theta\Lambda(c_{t+1}(L_{t+1}))\right]\,.$$

Then, I take derivative of $F_{\epsilon,t+1}^N$ with respect to B_{t+1}^N:

$$\begin{aligned}\frac{\partial F_{\epsilon,t+1}^{N}}{\partial B_{t+1}^{N}}=&f_{\epsilon,t+1}^{N}(-\tilde{V}_{t+1}^{N})\frac{\partial\left(-\tilde{V}_{t+1}^{N}\right)}{\partial N_{t+1}^{N}}\frac{\partial N_{t+1}^{N}}{\partial \tilde{B}_{t+1}^{N}}\frac{\partial \tilde{B}_{t+1}^{N}}{\partial B_{t+1}^{N}}\\=&f_{\epsilon,t+1}^{N}(-\tilde{V}_{t+1}^{N})\left(\phi_0^N+\frac{1-\phi_0^N}{1-\phi_1^N e_{t+1}^N}\right)\left[1-\theta\Lambda(c_{t+1}(L_{t+1}))\right].\end{aligned}$$

At last, we take the derivative of $\mathcal{B}_{t+1}^H$ with respect to B_{t+1}^N.

$$\frac{\partial \mathcal{B}_{t+1}^{H}}{\partial B_{t+1}^{N}}=\frac{\left(\tilde{B}_{t+1}^{N}+c_{t+1}(L_{t+1})\right)\frac{\partial\left(\epsilon_{t+1}^{N,-}F_{\epsilon,t+1}\right)}{\partial B_{t+1}^{N}}-\left[1-\theta\Lambda\left(c_{t+1}\left(L_{t+1}\right)\right)\right]\left(\epsilon_{t+1}^{N,-}F_{\epsilon,t+1}\right)}{\left(\tilde{B}_{t+1}^{N}+c_{t+1}(L_{t+1})\right)^2}\,.$$

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

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

$$\frac{\partial q_t^r}{\partial L_{t+1}}=\mathrm{E}_t\left\{\mathcal{M}_{t,t+1}\left[\left(\mathcal{A}_{t+1}^{H}-1\right)\frac{\partial F_{\epsilon,t+1}^{N}}{\partial L_{t+1}}+\frac{\partial \mathcal{A}_{t+1}^{H}}{\partial L_{t+1}}F_{\epsilon,t+1}^{N}+\frac{\partial \mathcal{B}_{t+1}^{H}}{\partial L_{t+1}}\right]\right\} \tag{A.17}$$

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

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

where $\frac{\partial \tilde{B}^N_{t+1}}{\partial L_{t+1}} = -\theta B_{t+1} \frac{\partial \Lambda_{t+1}}{\partial c_{t+1}} \frac{\partial c_{t+1}}{\partial L_{t+1}}$. Then, I take derivative of $F^N_{\epsilon,t+1}$ with respect to L_{t+1}:

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

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

$$\frac{\partial \mathcal{B}^H_{t+1}}{\partial L_{t+1}} = \frac{\frac{\partial \left(\epsilon^{N,-}_{t+1} F_{\epsilon,t+1}\right)}{\partial L_{t+1}} \left(\tilde{B}^N_{t+1} + c_{t+1}\left(L_{t+1}\right)\right) - \epsilon^{N,-}_{t+1} F_{\epsilon,t+1} \left(\frac{\partial \tilde{B}^N_{t+1}}{\partial L_{t+1}} + \frac{\partial c_{t+1}}{\partial L_{t+1}} \right)}{\left(\tilde{B}^N_{t+1} + c_{t+1}\left(L_{t+1}\right)\right)^2}.$$

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

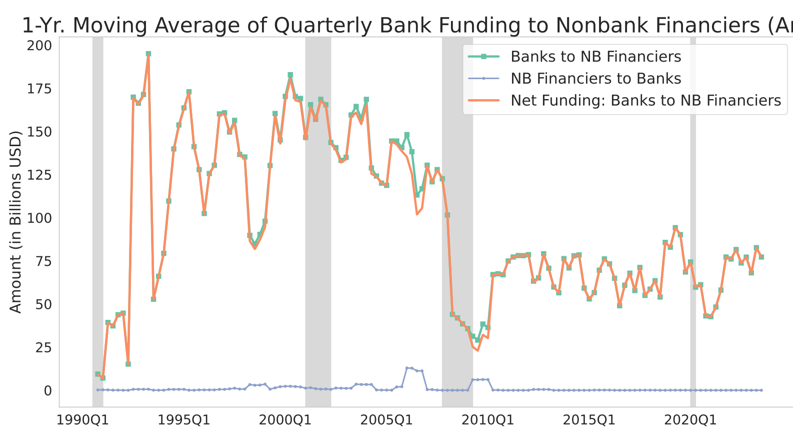


Figure B.1: This figure plots the 1-year moving average of quarterly bank funding (amount in billions USD) to NBFs that lend to corporates, combining Legacy Dealscan and LSEG LoanConnector facility-level data. Green squared line is bank funding to NBFs. Blue dot line is NBF funding to banks. Orange is 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.

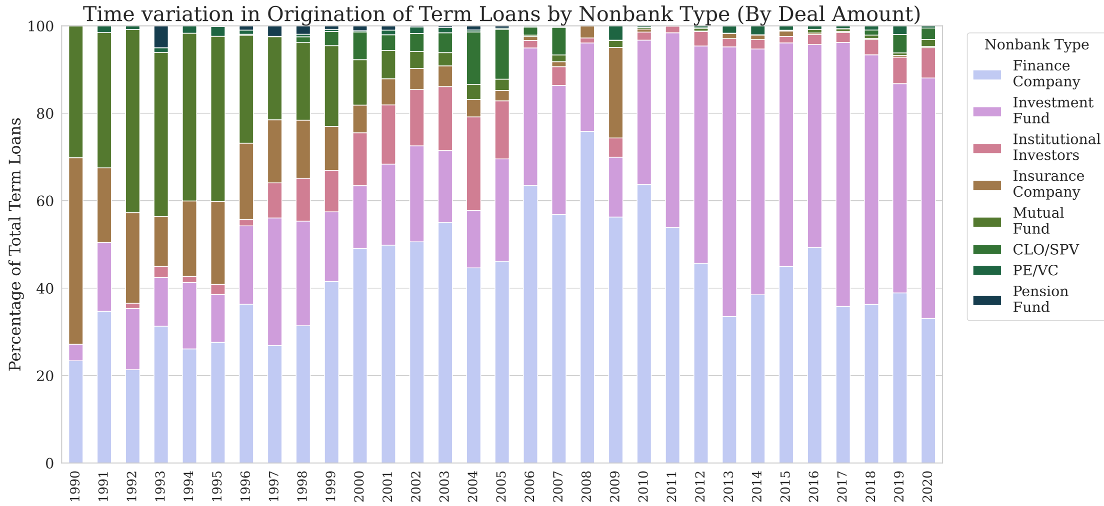


Figure B.2: Time variation in origination of term loans by nonbank type. Finance companies contribute about 45.6% of total term loans generated by all NBFs, followed by investment fund (43.8%).

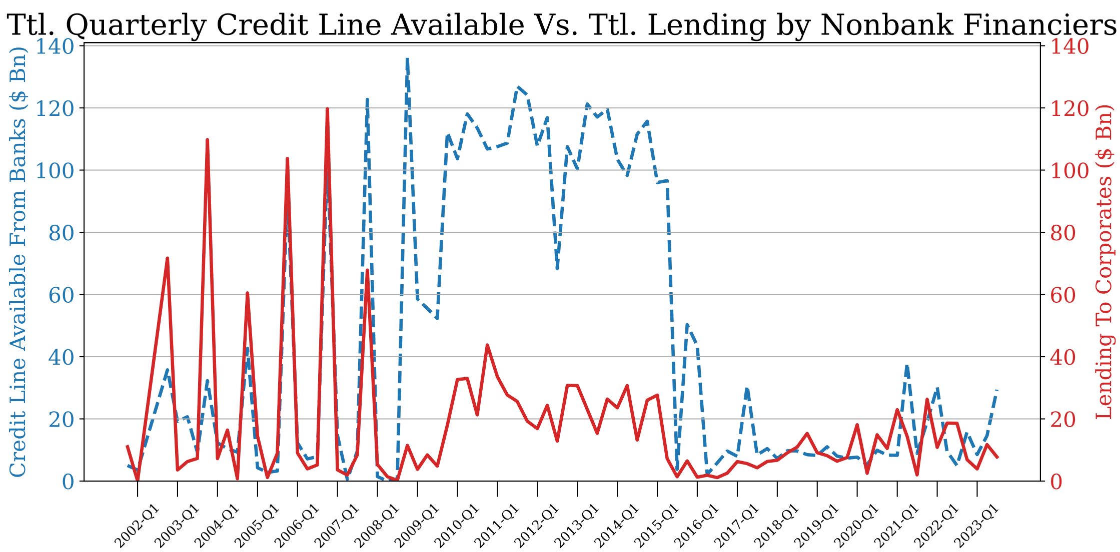
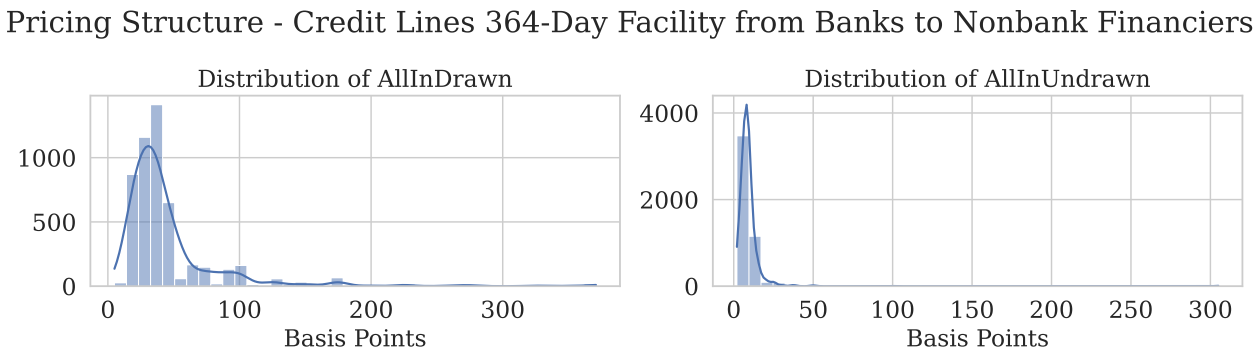


Figure B.3: Total quarterly credit line available (undrawn) to nonbank financiers (NBFs) is plotted in blue dotted line. Total quarterly lending by NBFs is plotted in the red line.



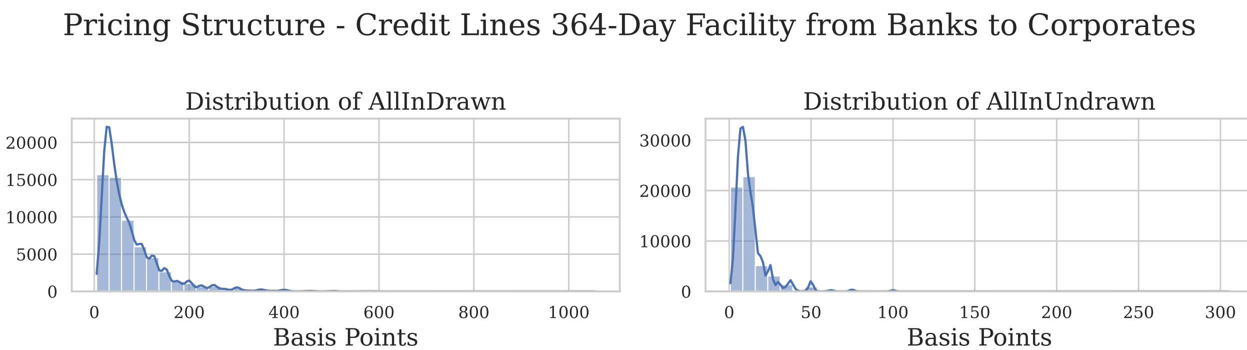


Figure B.4: Comparing credit lines 364-day facility from banks to NBFs Vs. that from banks to corporates. Adjusting for maturity differences, the required rate of return for all-in-drawn spread is 63 bps lower for credit lines from banks to NBFs than for credit lines from banks to corporates. Specifically, 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.

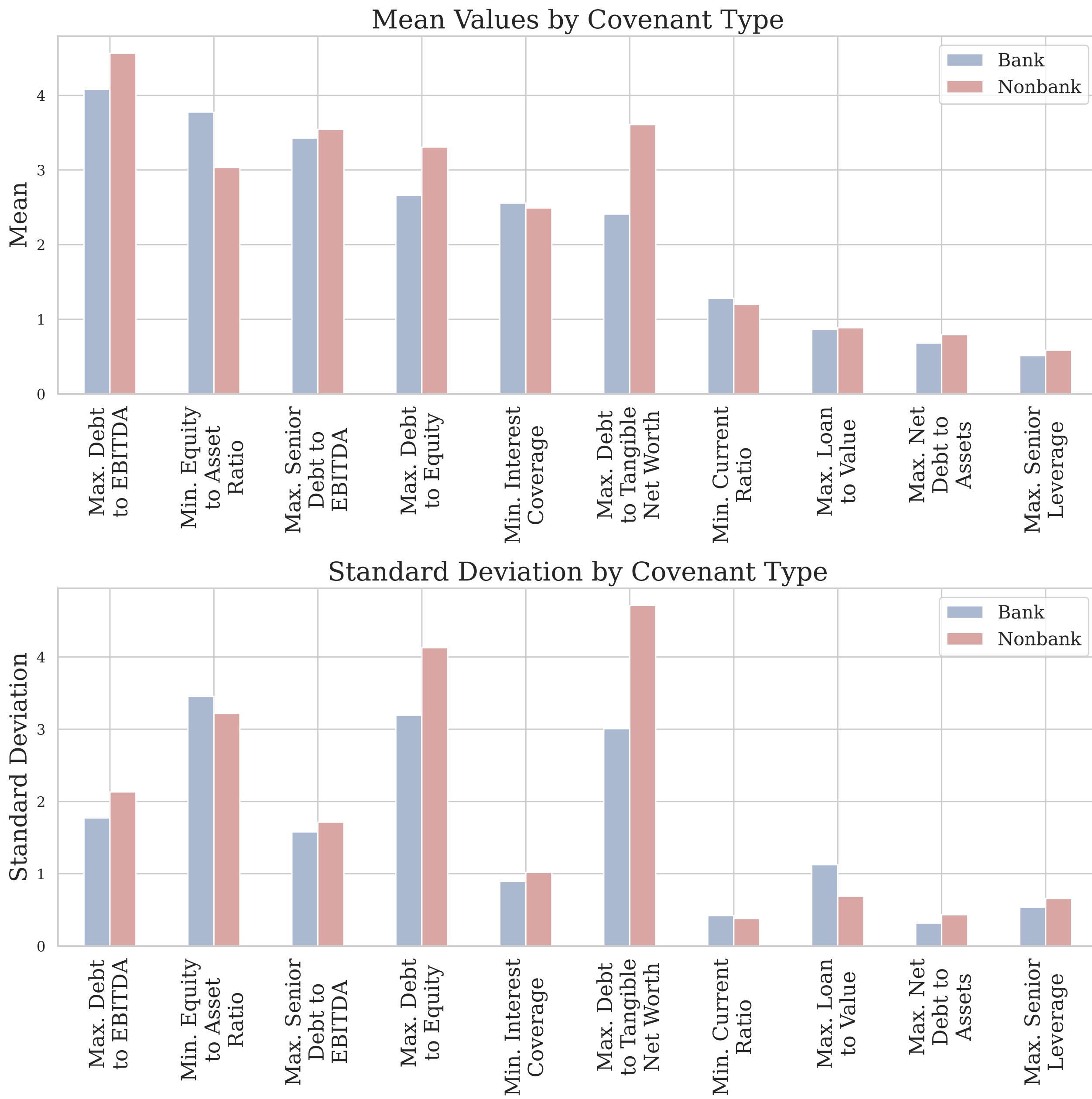
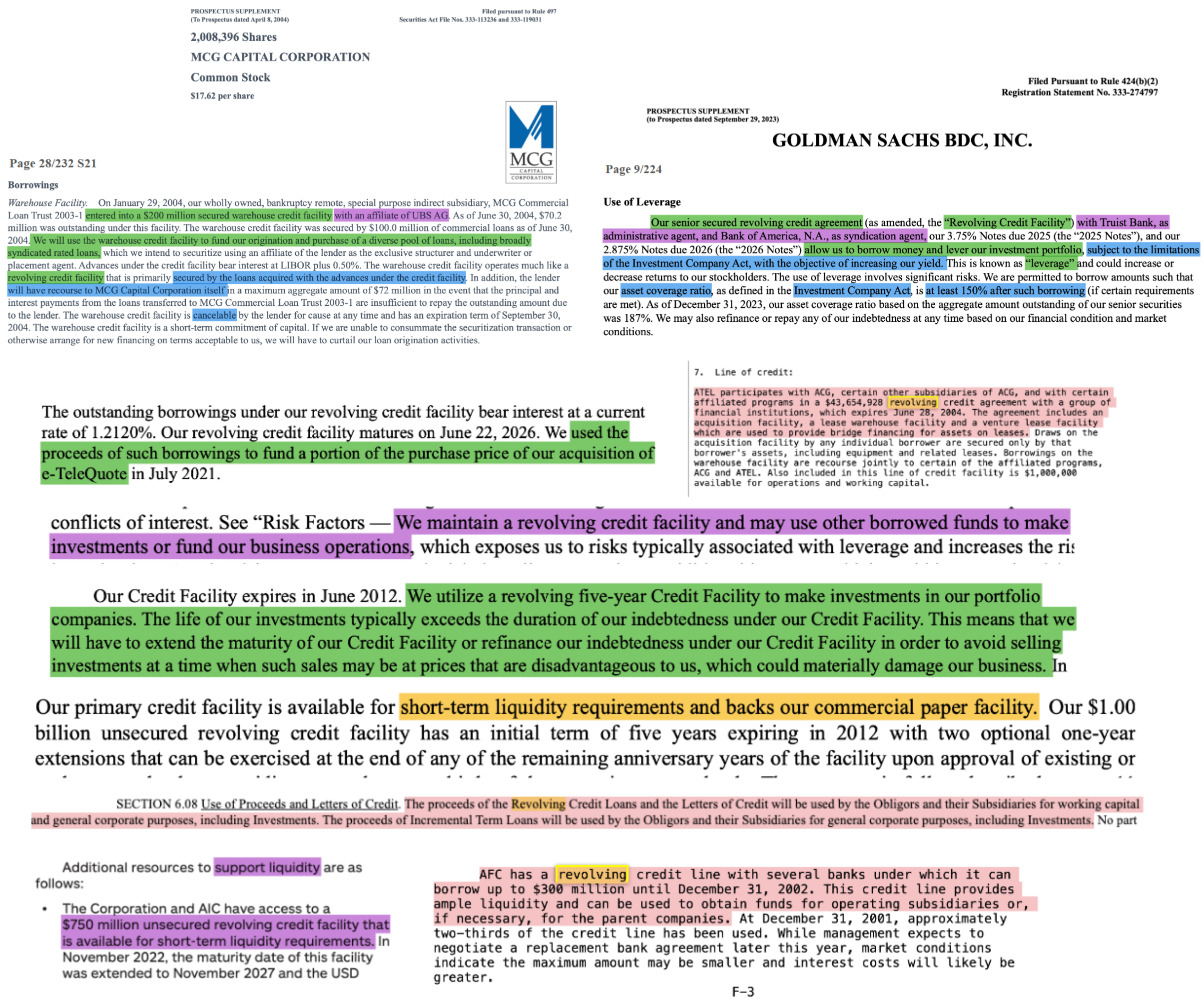


Figure B.5: This figure presents the mean and standard deviations of covenant metrics, distinguishing between loans extended by banks and those extended by nonbanks. While covenants within a syndication package are largely uniform across lenders, differences arise in cases where banks or nonbanks are 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



PROSPECTUS SUPPLEMENT
(To Prospectus dated April 8, 2004)

Filed pursuant to Rule 497
Securities Act File Nos. 333-113236 and 333-119031

2,008,396 Shares

MCG CAPITAL CORPORATION

Common Stock

$17.62 per share

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Borrowings

Warehouse Facility. On January 29, 2004, our wholly owned, bankruptcy remote, special purpose indirect subsidiary, MCG Commercial Loan Trust 2003-1 entered into a $200 million secured warehouse credit facility with an affiliate of UBS AG. As of June 30, 2004, $70.2 million was outstanding under this facility. The warehouse credit facility was secured by $100.0 million of commercial loans as of June 30, 2004. We will use the warehouse credit facility to fund our origination and purchase of a diverse pool of loans, including broadly syndicated rated loans, which we intend to securitize using an affiliate of the lender as the exclusive structurer and underwriter or placement agent. Advances under the credit facility bear interest at LIBOR plus 0.50%. The warehouse credit facility operates much like a revolving credit facility that is primarily secured by the loans acquired with the advances under the credit facility. In addition, the lender will have recourse to MCG Capital Corporation itself in a maximum aggregate amount of $72 million in the event that the principal and interest payments from the loans transferred to MCG Commercial Loan Trust 2003-1 are insufficient to repay the outstanding amount due to the lender. The warehouse credit facility is cancelable by the lender for cause at any time and has an expiration term of September 30, 2004. The warehouse credit facility is a short-term commitment of capital. If we are unable to consummate the securitization transaction or otherwise arrange for new financing on terms acceptable to us, we will have to curtail our loan origination activities.

Filed Pursuant to Rule 424(b)(2)
Registration Statement No. 333-274797

PROSPECTUS SUPPLEMENT
(to Prospectus dated September 29, 2023)

GOLDMAN SACHS BDC, INC.

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Use of Leverage

Our senior secured revolving credit agreement (as amended, the "Revolving Credit Facility") with Truist Bank, as administrative agent, and Bank of America, N.A., as syndication agent, our 3.75% Notes due 2025 (the "2025 Notes"), and our 2.875% Notes due 2026 (the "2026 Notes") allow us to borrow money and lever our investment portfolio, subject to the limitations of the Investment Company Act, with the objective of increasing our yield. This is known as "leverage" and could increase or decrease returns to our stockholders. The use of leverage involves significant risks. We are permitted to borrow amounts such that our asset coverage ratio, as defined in the Investment Company Act, is at least 150% after such borrowing (if certain requirements are met). As of December 31, 2023, our asset coverage ratio based on the aggregate amount outstanding of our senior securities was 187%. We may also refinance or repay any of our indebtedness at any time based on our financial condition and market conditions.

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.

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7.  Line of credit:

ATEL participates with ACG, certain other subsidiaries of ACG, and with certain
affiliated programs in a $43,654,928 revolving credit agreement with a group of
financial institutions, which expires June 28, 2004. The agreement includes an
acquisition facility, a lease warehouse facility and a venture lease facility
which are used to provide bridge financing for assets on leases. Draws on the
acquisition facility by any individual borrower are secured only by that
borrower's assets, including equipment and related leases. Borrowings on the
warehouse facility are recourse jointly to certain of the affiliated programs,
ACG and ATEL. Also included in this line of credit facility is $1,000,000
available for operations and working capital.
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conflicts of interest. See "Risk Factors — We maintain a revolving credit facility and may use other borrowed funds to make investments or fund our business operations, which exposes us to risks typically associated with leverage and increases the ris

Our Credit Facility expires in June 2012. We utilize a revolving five-year Credit Facility to make investments in our portfolio companies. The life of our investments typically exceeds the duration of our indebtedness under our Credit Facility. This means that we will have to extend the maturity of our Credit Facility or refinance our indebtedness under our Credit Facility in order to avoid selling investments at a time when such sales may be at prices that are disadvantageous to us, which could materially damage our business. In

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

SECTION 6.08 Use of Proceeds and Letters of Credit. The proceeds of the Revolving Credit Loans and the Letters of Credit will be used by the Obligors and their Subsidiaries for working capital and general corporate purposes, including Investments. The proceeds of Incremental Term Loans will be used by the Obligors and their Subsidiaries for general corporate purposes, including Investments. No part

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

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    AFC has a revolving credit line with several banks under which it can
borrow up to $300 million until December 31, 2002. This credit line provides
ample liquidity and can be used to obtain funds for operating subsidiaries or,
if necessary, for the parent companies. At December 31, 2001, approximately
two-thirds of the credit line has been used. While management expects to
negotiate a replacement bank agreement later this year, market conditions
indicate the maximum amount may be smaller and interest costs will likely be
greater.
                                    F-3
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Figure B.6: These are samples of Prospectuses screenshots that I use large language models to textually analyze.

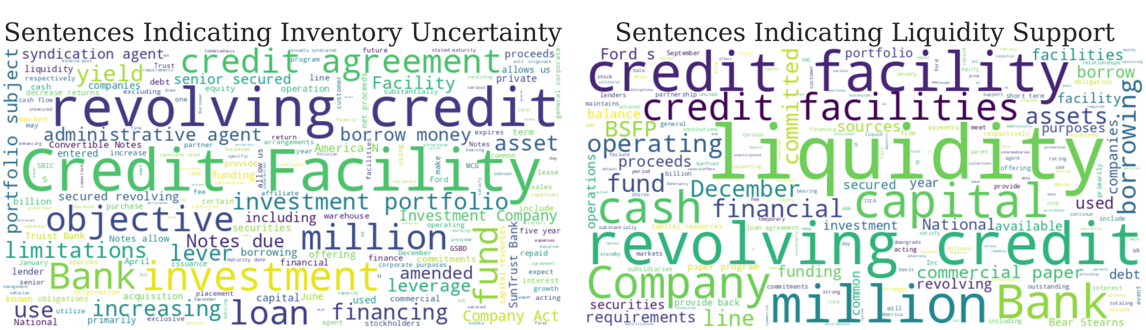

Figure B.7: The two word clouds are sentences that indicate inventory uncertainty (left) and liquidity support (right).

C Calibration Appendix

C.1 Credit Line Spread

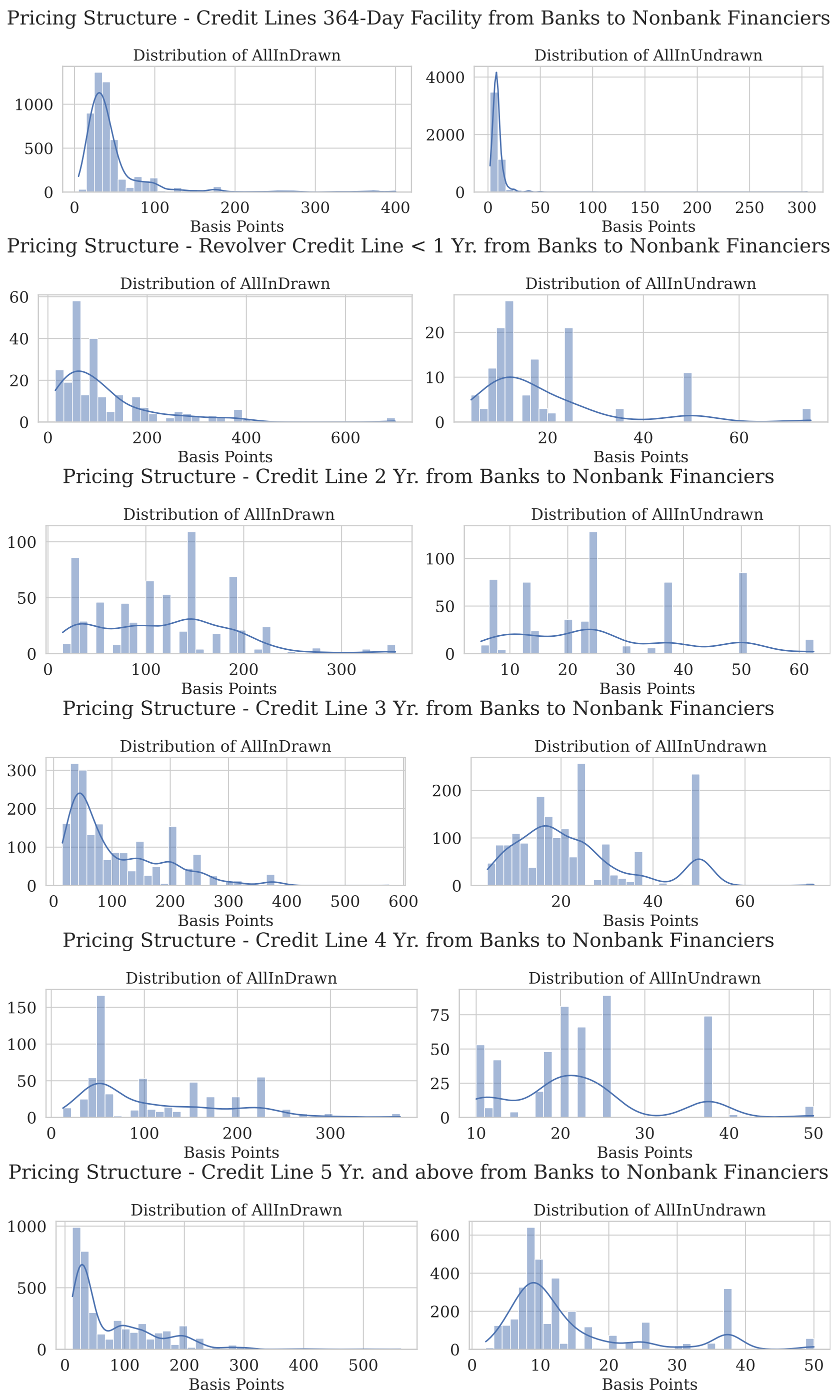

Figure C.1: This figure plots the all-in-drawn and all-in-undrawn spread in Dealscan and LSEG LoanConnector for credit lines from banks to nonbank financiers, categorized in maturities of exactly 364 days, less than 1 year, exactly 2 years, 3 years, 4 years, and 5 years and above.

C.2 Corporate loan average life

I model corporate bonds as geometrically declining perpetuities with no explicit principal repayment. Each bond pays 1 at $t+1$, δ at $t+2$, δ^2 at $t+3$, and so on. Firms must hold capital to collateralize these bonds, with the face value defined as $\frac{\theta}{1-\delta}$, where θ represents the fraction of total repayments treated as principal. The procedure described above closely follows Elenev et al. (2021), but I extend the period to 2023. In syndicated loan markets, term loans vary in structure. Term A loans are typically regularly amortized, while Term B, C, and D loans often feature balloon payments at maturity. However, as a broad classification, these loans can generally be grouped based on their investment-grade or high-yield status. Therefore, I adopt Elenev et al. (2021)'s strategy To align the model with real-world corporate loans, I use investment-grade and high-yield indices from Bank of America Merril Lynch (BofAML) and Barclays Capital (BarCap) (1997–2023), incorporating data on market values, durations, weighted average maturity (WAM), and weighted-average coupons (WAC). Details on the data collection are provided here:

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: Bloomberg Barclays Aggregate Bond Index includes both investment-grade and high-yield securities (codes LUACTRUU and LF98STAT for investment-grade and high-yield corporate bonds). 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.

Real-world bonds have finite maturity, a principal repayment, and vintage effects, which the model does not explicitly include. With the data, I make the following calculations:

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

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

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

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

2. I then calculate the weighted average coupons (WAC) and weighted-average maturity (WAM) for the aggregate bond index. I find its mean WAC c of 5.93% [17] and WAM T of 10 years over our time period, similar to Elenev et al. (2021).

[17] Elenev et al. (2021) finds WAC of 5.5%. There is a slight difference due to my extension of the data time fame

3. Next, I 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." I add the time series of OAS to the constant maturity treasury rate corresponding to that period's WAM to get a time series of yields r_t .

I construct a plain vanilla bond with WAC = 5.93% and WAM = 10 years and compare its price:

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

with the bond price in the model derived as:

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

I calibrate δ and X (units of model bonds needed per real-world bond) by minimizing pricing errors across historical yields:

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

I estimate $\delta = 0.928$ and $X = 13.0059$. 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 years, matching observed duration. To approximate principal, I compare the geometric bond to a duration-matched zero-coupon bond. 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 $F_B = \frac{\theta_B}{1-\delta_B} = 8.67$

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

I estimate $\delta = 0.928$ and $X = 13.0059$. 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 7.01 years.

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

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