Banks Versus Private Credit:
How Capital Requirements Shape Tailored Lending

Francesco Beraldi* Ali Uppal† Melanie Wallskog‡

September 2026

Abstract

The rise of private credit is typically attributed either to regulatory arbitrage or to a distinctive lending technology. We argue that the key force is their interaction, as capital requirements affect not only how much banks lend but also the contracts they offer. We formalize this insight in a model where banks and private credit funds compete to finance heterogeneous firms with endogenous contract tailoring. Tailoring relaxes borrowing frictions but makes loans harder to distribute. Capital requirements therefore act as a tax on tailored loans, pushing banks to easily distributable loans and widening private credit's comparative advantage in tailored financing for riskier firms. Consistent with the model, more tailored bank loans are less likely to be distributed, while lower-quality firms sort toward private credit and more tailored financing. Exploiting tighter leverage requirements for systemic banks, we show that affected banks reduce hard-to-distribute tailored contract features, while distribution rises. Quantitatively, this channel is important: absent bank capital requirements, private credit lending falls by 25 percent and bank tailoring more than doubles.

*Duke University. Email: francesco.beraldi@duke.edu

†Imperial College London. Email: a.uppal@imperial.ac.uk

‡Duke University. Email: melanie.wallskog@duke.edu

We are grateful to seminar participants at Duke University for their feedback. We thank Radhika Patel, Zhiyao Zhang, and Filipe de Castro Ribeiro Ferreira for their excellent research assistance. We thank Chuck Fang for providing a Compustat crosswalk and David Robinson and Melanie Wallskog for providing private credit data.

1 Introduction

The rapid expansion of private credit has attracted significant attention across financial markets, policymakers, and academia. Efforts to understand the forces behind this growth have increasingly centered on two leading explanations. One emphasizes bank regulation: capital requirements and other constraints push lending toward less regulated intermediaries (Irani et al., 2021; Begenau and Landvoigt, 2022; Davydiuk, Marchuk, and Rosen, 2024; Erel and Inozemtsev, 2025). The other emphasizes lending technology: private credit funds appear particularly well suited to providing flexible, customized, and state-contingent financing (Jang, 2025; Jang, Kim, and Sufi, 2025). These explanations are typically considered separately, with regulation determining where credit is intermediated and lending technology shaping the form of financing that borrowers receive.

We argue that this dichotomy is incomplete because regulation itself can shape intermediaries' comparative advantage in different lending technologies. Borrowers and private equity sponsors often point to highly tailored structures—such as Payment-in-Kind (PIK) provisions and bundled debt-equity claims—as a reason for choosing private credit over syndicated bank markets.[1] But these same features make loans harder to standardize and distribute. Because retaining loans consumes scarce bank balance-sheet capacity, capital requirements disproportionately raise the cost of tailored, hard-to-distribute lending. They therefore act like a tax on tailoring, pushing banks toward more standardized contracts and widening private credit funds' comparative advantage in tailored lending. The effect of bank regulation on private credit therefore depends critically on the lending technologies of competing intermediaries, making the *interaction* between the two explanations central to understanding its growth.

We formalize this interaction in a simple model in which banks and private credit funds compete to finance heterogeneous firms, and both can offer contracts with an endogenous degree of tailoring. The model allows for primitive differences in lending technology across intermediaries, but does not assume that tailored lending is unique to private credit or that banks specialize ex ante in standardized loans. Instead, equilibrium specialization reflects the interaction of technology and balance-sheet structure. Tailoring mitigates borrower financing frictions by making repayment more contingent on firm performance, but also makes loans more difficult to standardize and distribute. At the same time, retaining loans uses scarce bank balance-sheet capacity, while distribution allows banks to economize on costly equity. Private credit funds are less constrained by bank-style capital requirements and therefore face this trade-off to a lesser degree. Tighter capital requirements consequently change the relative attractiveness of different lending technologies: banks shift toward more standardized, distributable contracts,

[1] Borrowers and private equity sponsors often report choosing private credit not only for speed and certainty of execution, but also for highly tailored structures that are difficult to arrange through syndicated bank debt. For industry-facing examples, see https://www.institutionalinvestor.com/article/2bswsphkclc75samrsikg/portfolio/private-equity-funds-fuel-growth-in-private-credit and https://www.chronograph.pe/unpacking-the-structural-drivers-of-private-credit-growth/.

while private credit's comparative advantage in tailored lending widens. Therefore, a tightening of capital requirements acts like a tax on tailored lending. The model thus highlights why neither leading explanation is sufficient on its own. Primitive differences in lending technology shape comparative advantage, but capital requirements amplify those differences by disproportionately raising banks' cost of providing hard-to-distribute, tailored contracts. Conversely, the effect of bank regulation on private credit depends on the lending technologies in which competing intermediaries specialize. The bank–private credit boundary is therefore jointly determined by regulation and lending technology.

The model delivers a set of predictions for contract design, lender choice, and borrower sorting. First, more tailored loans are harder to distribute, so banks retain relatively more tailored contracts and distribute more standardized ones. Second, lower-quality firms, those with low profitability and high volatility, choose more tailored contracts. Intuitively, these firms benefit more from shifting repayment toward the state-contingent component of the contract, thereby reducing the bankruptcy costs associated with non-contingent debt. As a consequence, they sort toward financing options that can provide tailoring more cheaply, which in the empirically relevant case means private credit and, to a lesser extent, retained bank lending. Finally, capital requirements act as a tax on tailored bank lending. By raising the cost of retaining loans on bank balance sheets, they alter banks' effective lending technology, pushing banks toward more standardized, distributable contracts and widening private credit's comparative advantage in serving borrowers with greater demand for customized financing.

We take these predictions to the data using syndicated bank lending from DealScan and investments by publicly traded Business Development Companies (BDCs). We construct a measure of contractual state contingency based on features that make lenders' exposure, payment timing, or payoff depend on borrower outcomes. The cross-sectional evidence closely matches the model's key margins. Within bank lending, more state-contingent loans are substantially less likely to be distributed: a one-standard-deviation increase in our tailoring measure is associated with a 4.7 percentage point lower probability of distribution. Across intermediaries, conditional on deal size and structure, more state-contingent contracts are substantially more likely to be provided by private credit; a one-standard-deviation increase in the score is associated with an approximately 8 percentage point increase in the probability of a BDC deal. Borrower sorting follows related patterns. Lower-profitability firms are substantially more likely to borrow from private credit, while among bank borrowers greater stock-return volatility predicts both more state-contingent contracts and a lower probability of distribution. Together, these results show that the hold-versus-distribute margin within banks is mirrored by a bank-versus-private-credit margin across intermediaries.

These cross-sectional relationships do not establish that bank balance-sheet constraints cause changes in contract design. We therefore exploit the introduction of the enhanced supplementary leverage ratio (eSLR), which tightened leverage requirements more strongly for G-SIBs than for other large banks. Following the tightening, G-SIB-led deals become substantially less likely to feature pricing grids and financial covenants—contract features that are themselves associated with less distributable lending. The probability that affected loans are distributed also rises, as predicted by the model, although this response is estimated less precisely. These results provide direct support for the model's central comparative static: when bank balance-sheet capacity becomes more costly, banks retreat from hard-to-distribute forms of tailored lending.

We calibrate the model using our empirical stylized facts to discipline the lending technologies of private credit funds and banks, as well as the costs of loan distribution. The quantitative model allows us to separate primitive differences in lending technology from differences that arise endogenously because banks face capital requirements. This distinction is important: a simplified model that abstracts from the interaction of tailoring and distribution costs infers a substantially larger technological disadvantage for banks in tailored lending. Therefore, looking only at the observable contract differences between lenders gives a misleading view of banks' primitive ability to engage in tailored lending. In a counterfactual where we remove bank capital requirements, the market share of private credit drops by 25 percent, suggesting that our mechanism is quantitatively important for the rise of private credit. Furthermore, absent capital requirements and the associated incentive to distribute loans, the degree of tailoring in bank loans more than doubles. Thus, regulation affects not only the allocation of credit across intermediaries, but also the apparent technological specialization of banks and private credit.

We then leverage a second counterfactual to quantify the welfare gains from private credit lending. We find that private credit raises consumption-equivalent welfare by about 0.2%, and that almost the entirety of these gains accrues from the reallocation of borrowers from the banking sector. Although private credit borrowers are observably riskier, our model predicts that most private-credit borrowers could nonetheless obtain bank loans in the absence of private credit funds. The value created by private credit therefore arises primarily not from expanding credit to firms excluded from bank lending, but from providing more tailored contracts to firms that would otherwise borrow from banks on less appropriate terms, therefore reducing equilibrium bankruptcy costs. This result cautions against interpreting borrower risk differences as evidence that banks and private credit funds serve separate markets: they may compete for many of the same firms while differentiating themselves through contract design.

Related Literature. Our paper relates first to the growing literature on private credit and direct lending. Existing work documents the rapid expansion of private debt markets, describes their institutional structure, and studies why firms borrow from nonbanks rather than traditional banks. For example, Chernenko, Erel, and Prilmeier (2022) show that nonbank lenders serve observably riskier middle-market firms, while Ivashina (2025) emphasizes the broader role of private debt in the financial ecosystem and its emergence as an important substitute for bank-intermediated credit. Consistent with recent empirical findings such as Jang, Kim, and Sufi (2025), our framework predicts that private credit funds lend to firms that differ systematically from bank borrowers in their risk profile and, additionally, that they receive substantially more customized contracts. Our contribution is to show that these observed differences need not imply that private credit primarily serves firms excluded from bank lending. In our counterfactual without private credit institutions, the vast majority of fund borrowers could still obtain a bank loan. The value created by private credit instead arises mainly from offering tailored loan solutions to firms that would otherwise borrow from banks, rather than from lending only to firms that cannot access bank credit.

Our analysis also connects to recent empirical work on how private credit lending technology differs from bank lending. Recent evidence suggests that direct lenders rely on intensive monitoring, covenant-based control, and relationship-style lending, and that borrowers value the flexibility and customization offered by these arrangements. Jang (2025) and Block et al. (2024) provide evidence on these distinctive lending technologies and on how private debt funds position themselves relative to banks and syndicated lending markets. Robinson and Wallskog (2025), Davydiuk et al. (2024), and Rintamäki and Steffen (2025) highlight how private credit funds frequently incorporate non-standard features—namely equity investments and PIK interest—in their contracts. We build on this literature by treating tailoring as an equilibrium object: rather than taking contractual differences as given, we study how intermediary balance-sheet structure, securitization capacity, and regulation jointly shape the degree of contractual tailoring that emerges in equilibrium.

More broadly, the paper speaks to work on the interaction between bank regulation and non-bank credit supply. A growing literature shows that tighter constraints on banks can shift credit intermediation toward private credit vehicles, including BDCs, and can reshape the transmission of shocks through bank–nonbank funding chains. Chernenko, Ialenti, and Scharfstein (2025) show that private credit funds are substantially less leveraged than banks, arguing against the view that private credit growth is driven simply by higher leverage outside the banking system. Our mechanism is consistent with this evidence, but shows that bank leverage regulation can still be an important driver of private credit growth. In our framework, funds optimally rely more on equity than banks, while tighter bank leverage constraints make it more costly for banks to retain loans on balance sheet and push them toward securitizing more standardized loans. This creates room for private credit lenders to expand precisely in the provision of more tailored loan contracts. In this sense, our paper complements the existing empirical literature by clarifying how differences in intermediary balance-sheet structure and regulation shape not just credit quantities, but also firm sorting and contract design.

Our paper also relates the literature on distribution and securitization. A long-standing theory literature studies how adverse selection and moral hazard shape the securitization of loans and other assets by banks (Gorton and Pennacchi, 1995; DeMarzo and Duffie, 1999; DeMarzo, 2005; Parlour and Plantin, 2008). Our framework departs from this literature in two ways. First, we introduce direct lending from investment funds, which emerges partly to circumvent frictions in the securitization market when banks are constrained. Second, we focus on the loan contract design choice. Indeed, papers in this literature study the optimal retention choice taking as given the underlying asset to be sold. Instead, we focus on how the funding model of the lender affects the incentives to design loan contracts. On the empirical side, several papers study how loan contract design varies with loan distribution and institutional ownership (Drucker and Puri, 2009; Bozanic, Loumioti, and Vasvari, 2018; Becker and Ivashina, 2016; **?**). These findings resonate with our empirical results and theoretical mechanism, showing that loan distribution is typically associated with more standardized (albeit tighter) covenants, reduced use of maintenance covenants that require active monitoring and creditor coordination, and that cov-lite loans exhibit greater secondary-market liquidity. We extend these results in two ways. First, we show that the hold-versus-sell margin is mirrored by a bank-versus-private credit margin dictated by firms' lender choice: private credit, which more often holds to maturity, originates more bespoke and complex contracts than banks. We also show that contract tailoring correlates with borrower characteristics, with riskier firms obtaining more tailored loans within lender type and sorting towards lenders that offer more tailored loans.

Finally, our paper connects to broader theories of financial intermediation that emphasize how lenders' funding structures and lending technologies shape their comparative advantage across borrowers and contract types (Diamond and Rajan, 2000; Boot and Thakor, 2000; Kashyap, Rajan, and Stein, 2002). In particular, Kashyap, Rajan, and Stein (2002) highlight how banks' balance-sheet structure gives them a distinctive funding advantage, while Boot and Thakor (2000) emphasize how intermediaries can differentiate themselves through lending technologies and the provision of more relationship-oriented financing. We bring these perspectives to a setting with competing banks and private credit funds, and show how differences in funding structure and regulation jointly determine firm sorting and equilibrium contract tailoring.

Outline. The rest of the paper is organized as follows. Section 2 presents the model and our key analytical testable predictions. Section 3 describes the institutional setting and the data used. Section 4 and 5 validate the model predictions in the cross-section and in the event-study setup. Section 6 provides the model estimation and quantitative results. Section 7 concludes.

2 Theory

The regulatory and lending-technology explanations for private credit are often treated as distinct. The first emphasizes that tighter bank regulation shifts lending toward less regulated intermediaries, while the second emphasizes that private credit funds have a comparative advantage in providing more customized forms of financing. We show in a simple model that, once tailored loans are more costly to distribute and banks face balance-sheet constraints, these two explanations interact in economically meaningful ways: bank regulation changes the relative attractiveness of different lending technologies.

The key ingredient is that tailoring and loan distribution are linked. Tailored contracts can mitigate borrower financing frictions by making repayment more contingent on firm performance, but these same features make loans more difficult to standardize and distribute. This matters particularly for banks. Retaining loans uses scarce balance-sheet capacity, while distributing them allows banks to economize on costly equity. Private credit funds, by contrast, are less constrained by bank-style capital requirements and are therefore better able to retain loans whose contractual features make them costly to distribute. As a result, differences in intermediary balance-sheet structure affect not only how much each lender is willing to finance, but also the types of contracts it can competitively offer.

2.1 Environment

We study a two-date economy where banks and private credit funds compete to finance heterogeneous firms with contracts that feature an endogenous degree of tailoring. There is a unit mass of firms, initially fully owned by entrepreneurs. To operate, firms must make an initial investment of one dollar, which entrepreneurs fully finance from the financial sector. A continuum of banks and investment funds perfectly compete to finance firms. These two types of intermediaries have access to the same investment opportunities. They can buy safe assets from the government, which yield a return r^f, and can originate loans. Loans can also be traded on a secondary market, allowing banks to distribute exposures rather than retain them on balance sheet.

Firms. Each firm is endowed with a project that has expected output $\bar{y}$ and volatility σ, which are heterogeneous across firms. Specifically, for each firm, output y is log-normally distributed: $y = \tilde{\omega}\bar{y}$, with $ln\tilde{\omega} \sim N(\mu, \sigma^2)$. We set $\mu = -\frac{1}{2}\sigma^2$, so that $\mathbb{E}[\tilde{\omega}] = 1$ for all firms, and expected output is governed by $\bar{y}$.

Lending contracts. Loan contracts between lenders and firms are defined by a pair $C = (R, x)$. The first component of the contract, R, is the non-contingent repayment promised by the borrower, and corresponds to the vanilla component of a traditional loan. The second component of the contract, x captures the complex and customized state-contingent features often embedded in credit contracts by direct lenders, and to a more limited degree by banks. For tractability, we model the contingent component x as the portion of the firm's equity which the entrepreneur pledges to the lender. This gives the lender a payoff that varies with the borrower's realized performance and provides a parsimonious way to model contractual state contingency. This modelling approach has a direct empirical analogue, as private credit deals often feature an equity kicker alongside a traditional loan. However, R and x need not necessarily be two separate components of the deal, as their combination could reflect a unique loan embedded with state-contingencies (such as PIK, credit lines, pricing grids, or covenants), which may make the loan's payoff potentially vary with borrowers' non-default state.

If realized output falls below the promised repayment, the firm defaults. In default, the entrepreneur receives zero and the lender recovers a fraction $1-\delta$ of realized output. Otherwise, the entrepreneur retains a fraction $1-x$ of residual output, while the lender receives the promised repayment together with its contingent claim. Payoffs are therefore

$$\text{Entrepreneur:} \quad \pi(y, C) = \begin{cases} 0 & \text{if } y < R \\ (1-x)(y-R) & \text{if } y \geq R \end{cases}$$

$$\text{Lender:} \quad f(y, C) = \begin{cases} (1-\delta)y & \text{if } y < R \\ R + x(y-R) & \text{if } y \geq R \end{cases}$$

Entrepreneurs choose the lending contract C among those offered by lenders. Because there is perfect competition among lenders, including within lender type, the entrepreneur's problem can be written as the maximization of their expected cash-flows π subject to delivering zero-profits in expectation to the lender. We describe the funding and cost structure of lenders next, and we will subsequently turn to the entrepreneur's problem in Section 2.4.

Lenders. Both banks and private credit funds can originate loans of the type $C = (R, x)$ defined above. Banks and funds primitive lending technologies are summarized by their origination cost $C_o^k(x)$, which can potentially be different across the two lender types $k \in \{b, f\}$. Distributing a loan on the secondary market also involves a cost $C_s(x)$. Such costs depend on the extent to which loans are tailored, capturing the idea that tailored loans are more costly both to originate and to subsequently distribute.

Banks and private credit funds differ in their liability structure. Funds are modeled as unconstrained intermediaries that can raise equity from households frictionlessly, and therefore act as a veil for households. Instead, banks face higher balance sheet costs due to a combination of capital requirements and costly external equity. Specifically, we assume that banks can raise equity from households, but incur an additional cost λ_e per dollar raised. They can also finance themselves by borrowing at the risk-free rate,[2] subject to a regulatory leverage constraint requiring that the loans on their balance sheet do not exceed a multiple ϕ of their equity. This reduced-form asymmetry captures the institutional differences highlighted in the introduction: banks rely much more heavily on debt financing and face regulatory capital requirements, whereas private credit funds operate with substantially lower leverage. The combination of costly bank equity and the leverage constraint creates an incentive for banks to free up balance-sheet capacity by distributing loans.

Timing. At time t_0, firms choose which lender to borrow from, and which contract C to select among those offered. Firms to which no lender can profitably lend are unable to raise funds and do not operate. At time t_1, firm's output y is realized, and payoffs are determined depending on the original contract C, alongside the possibility of default.

[2] We do not explicitly model bank deposits, but we can think of banks' ability to borrow large sums at the risk-free rate as stemming from their deposit market power. Giving banks the ability to borrow at below the risk-free rate would break the zero-profit environment that we are focusing on.

2.2 Intermediaries, Loan Pricing, and Distribution

The economy features perfect competition both across and within lender types. Therefore, the relevant contracts for the borrowers are those summarized by the zero-profit condition of the lender. We start by displaying such condition for private credit funds, which is immediate. Then, we characterize the closely related price of loans on the secondary market, which will be a useful input in the bank's own zero-profit condition. Finally, we address the bank's zero-profit condition, which requires more care as it results from the interaction of balance sheet and distribution costs, and the bank's own internal optimal distribution policy.

Private credit funds. We first show the zero-profit loan pricing schedule offered to firm i by private credit funds. This is, more generally, the zero-profit condition of a financially unconstrained lender with origination cost $C_o^f(x)$.

$$1 + C_o^f(x) = \beta \mathbb{E}^i [f(y, C)] . \tag{1}$$

The expected payoff of the loan depends on the identity of firm i because firms differ in their expected output and risk. The set of contracts that can be offered at zero profit is therefore firm-specific.

Equation (1) pins down the contracts C that make private credit lenders break-even. That is, it pins down the combinations of lending rate R and tailoring x which the firm can choose from. In particular, private credit lenders offer loan contracts C so that the expected loan payoff is set equal to one unit, which is the amount advanced to operate the firm, plus the loan origination costs.

Secondary market. Before turning to banks, we specify the price at which they can distribute an originated loan. Competitive, unconstrained investors price a contract according to its discounted expected payoff. The secondary-market price of contract C extended to firm i is therefore

$$q^i(C) = \beta \mathbb{E}^i [f(y, C)] \tag{2}$$

Notice that the secondary market price $q^i(C)$ is closely related to Equation (1). This is not a coincidence, as it comes from the assumption that both private credit lenders and secondary-market investors, such as CLOs, are financially unconstrained and perfectly competitive. This also shows that it is without loss of generality to abstract from distribution in private credit funds: because funds face no balance sheet costs, they would never be willing to pay a distribution cost to raise $q^i(C)$ for their loans. This will be different for banks, as we outline next.

Banks. Differently from private credit funds, we assume that banks face capital requirements, so that their maximum leverage takes the value of ϕ. Therefore, for each dollar of balance-sheet lending, banks must raise $1/\phi$ dollars of equity, which we assume to incur an equity issuance cost of λ_e. Therefore, each dollar of balance-sheet lending entails an additional λ_e/ϕ financing cost. Notice that both leverage regulation and costly equity are necessary for banks to be balance-sheet constrained. While we assumed that funds are unconstrained for simplicity, one could also more generally model them as an intermediary with either lighter leverage regulation or cheaper access to external equity.

To avoid incurring the balance-sheet cost λ_e/ϕ, banks can choose to distribute the loans they originate. Selling a loan enables banks to recover an amount $q^i(C)$, as pinned down in Equation (2), net of the resale cost $C_s(x)$.

In Appendix B.1, we write down the full bank's problem described above, showing that it is scale-free and thus consistent with zero-profit and perfect competition. There, we show that our bank setup delivers the following zero-profit condition for bank lending, given a distribution choice z:

$$\underbrace{1 + (1-z)\frac{\lambda_e}{\phi}}_{\text{cost of funds}} + \underbrace{C_o^b(x)}_{\text{origination cost}} + \underbrace{zC_s(x)}_{\text{distribution cost}} = \beta\mathbb{E}^i\left[f(y,C)\right]. \tag{3}$$

Starting from the equation above, the next proposition characterizes banks' optimal loan distribution policy as a function on one hand of the characteristics of the loan, and more specifically its degree of tailoring x, and on the other hand of the bank's own balance sheet capacity, as captured by its marginal balance sheet cost λ_e/ϕ.

Proposition 1 (Optimal loan distribution). *Assume that distribution costs are strictly increasing in loan tailoring: $C_s'(x) > 0$. Then, for a given contract C, the bank optimally distributes the loan whenever the cost of distribution is below the balance-sheet cost of retention:*

$$z(C) = \begin{cases} 1 & \text{if} \quad x \le C_s^{-1}(\lambda_e/\phi) \\ 0 & \text{if} \quad x > C_s^{-1}(\lambda_e/\phi) \end{cases} \tag{4}$$

That is, banks distribute sufficiently standardized loans and retain sufficiently tailored loans. The cutoff $C_s^{-1}(\lambda_e/\phi)$ increases with the shadow cost of bank balance-sheet capacity, so tighter capital requirements expand the set of loans that banks choose to distribute. Substituting the optimal distribution decision into the bank's zero-profit condition gives

$$1 + C_o^b(x) + \min\{\frac{\lambda_e}{\phi}, C_s(x)\} = \beta E^i\left[f(y,C)\right] \tag{5}$$

Proof: *See Appendix B.1.1.*

Equation (5) captures the central interaction between bank regulation and lending technology. Standardized loans, for which $C_s(x)$ is low, can be distributed without using scarce bank balance-sheet capacity. More tailored loans are costly to distribute and are therefore more likely to be retained. A tightening of capital requirements raises ψ, increasing the cost of contracts that rely on bank balance sheets while leaving the cost of already-distributed loans unchanged. Because the loans that rely on bank balance sheets are endogenously the more tailored loans, a regulation that formally applies to all retained assets acts disproportionately on tailored lending. Capital requirements therefore affect not only how much banks lend, but also the types of contracts they can competitively offer.

Notice that if either the cost of bank equity vanishes ($\lambda_e \to 0$) or the leverage constraint becomes arbitrarily loose, $\phi \to \infty$, then $\psi \to 0$. Provided distribution is costly, the bank optimally retains its loans and Equation (5) collapses to $1 + C_o^b(x) = \beta \mathbb{E}^i[f(y, C)]$, which mirrors the zero-profit conditions of private credit funds and differs from it only because of possible differences in the origination technology C_o among banks and funds.

Generic cost function. For the remainder of the analysis, it is useful to represent retained and distributed bank lending as two separate financing options. This representation is equivalent to the bank's internal distribution choice characterized above, but makes the comparison with private credit and the resulting borrower sorting more transparent.

In particular, combining the zero-profit condition for funds in Equation (1) and the one for banks resulting from their optimal distribution policy in Proposition 1, we can write a generic zero profit condition for any of the three financing options k as follows:

$$1 + C^k(x) = \beta \, \mathbb{E}^i[f(y, C)] \,. \tag{6}$$

Thus, conditional on a contract $C = (R, x)$, the three financing options differ only in the intermediation cost $C^k(x)$ required to provide that contract, which takes the following values for the three lenders:

$$\begin{aligned} C^f(x) &\equiv C_o^f(x), \\ C^{br}(x) &\equiv C_o^b(x) + \psi, \\ C^{bd}(x) &\equiv C_o^b(x) + C_s(x), \end{aligned} \tag{7}$$

where recall that $\psi \equiv \lambda_e/\phi$ is the balance-sheet cost of retaining a bank loan.

In the next subsection, we impose functional forms for the origination and distribution costs C_o^f, C_o^b, and C_s. This will allow us to characterize analytically the optimal contract choice and the solution of the problem, and will facilitate the mapping of the model to the data in the calibration exercise in Section 6.

2.3 A Tractable Cost Specification

In this section, we introduce a functional form for the origination costs C_o^f, C_o^b and the distribution costs C_s that will allows us to derive analytical characterizations for the borrower's optimal contract choice, their sorting across lenders, and the effects of capital requirements.

As a first step, it is useful to define a few objects that are normalized by $\bar{y}$, firm's expected output. Let $\omega = R/\bar{y}$ the normalized vanilla loan payoff. Notice that ω is the threshold such that for any realization $\tilde{\omega} < \omega$ the firm is in default. The total payoff for equity-holders, which include the entrepreneur and possibly a lender-shareholder, is $y - R = (\tilde{\omega} - \omega)\bar{y}$ if $\tilde{\omega} > \omega$, and zero otherwise. We can then compactly denote the expected payoff of equity, normalized by $\bar{y}$, as follows:

$$Y(\omega) \equiv \mathbb{E}[(\tilde{\omega} - \omega)\mathbf{1}\{\tilde{\omega} \geq \omega\}]$$

From this point onward, throughout the rest of the paper, we assume that origination and distribution costs are affine in the value of the tailored component. In particular, origination costs depend on the primitive technological parameters $\{\tau_o^k, \tau_x^k\}$ as follows:

$$C_o^k(x) = \tau_o^k + \tau_x^k \bar{y} Y(\omega) x, \quad k \in \{f, b\}$$

while distribution costs are:

$$C_s(x) = \eta \bar{y} Y(\omega) x$$

As we later discuss in more detail with the support of Table 1, the lack of an intercept term in $C_s(x)$ is without loss of generality for both the theoretical results and the estimation.

These functional forms assume that originating or distributing a loan entails a fixed cost even for vanilla loans, and an additional cost which increases with loan tailoring x, and which is proportional to the firm's expected equity payoff $\bar{y}Y(\omega)$. This proportionality allows us to derive neater analytical solutions. Economically, it can be interpreted as capturing the fact that the cost of originating or distributing an equity tranche depends on its value, although such proportionality may not be exact in practice.

Importantly, combining these specifications with the expressions derived in (7) allow us to write the zero-profit conditions associated with any financing option k (private credit, bank retained loans, and bank distributed loans), under an identical functional form which only depends on two parameters:

$$C^k(x) = c_o^k + c_x^k \bar{y} Y(\omega) x \tag{8}$$

That is, the entire schedule of loan contracts offered by all types of lenders can be summarized by the two parameters $\{c_o^k, c_x^k\}$, which govern, respectively, the baseline cost to extend a vanilla loan, and the additional cost associated with tailoring. Table 1 clarifies how the three possible financing regimes for a firm are nested in Equation (8).

Table 1: Cost structure across financing regimes. The fundamental origination technology parameters are denoted by τ. Banks' balance sheet retention cost is $\psi = \lambda_e/\phi$. Distribution of tailored loan products incurs a cost η.

Financing regime	c_o^k	c_x^k
Private credit	τ_o^f	τ_x^f
Bank retained	$\tau_o^b + \psi$	τ_x^b
Bank distributed	τ_o^b	$\tau_x^b + \eta$

For private credit, the two parameters simply correspond to the fund's origination costs. A retained bank loan additionally incurs the balance-sheet cost $\psi = \lambda_e/\phi$, but no distribution cost. A distributed bank loan avoids the balance-sheet cost, but incurs the additional tailoring cost η. Thus, distribution can give banks a cost advantage in providing standardized loans while making highly tailored loans comparatively expensive.[3]

As mentioned earlier, the lack of an intercept term in $C_s(x)$ is without loss of generality. Suppose we had an intercept term c_s. Then, the baseline cost for bank distributed loans would read as $\tau_o^b + c_s$. For the theory, this is irrelevant as long as $c_s < \lambda_e/\phi$. If this was not the case, bank distributed loans would be dominated by retained loans. For the estimation and quantitative results, it is easy to see that c_s would not be identified against ψ and τ_o^b.[4]

2.4 Optimal Contract Choice

We now turn to the entrepreneur's problem, using the compact zero-profit conditions derived above. We characterize the entrepreneur's optimal contract C choice conditional on a given financing option k, which can be summarized by a pair of effective cost parameters $\{c_o^k, c_x^k\}$. Throughout, we suppress the lender index k and borrower index i for convenience.

We denote the expected loss from bankruptcy frictions, normalized by expected output $\bar{y}$, by:

$$B(\omega) \equiv \delta\,\mathbb{E}[\tilde{\omega}\,\mathbf{1}\{\tilde{\omega} < \omega\}]\,.$$

We also define the expected payoff of the vanilla component as:

$$L(\omega) \equiv 1 - Y(\omega) - B(\omega).$$

Conditional on a financing option characterized by $\{c_o, c_x\}$, the entrepreneur solves:

[3] Under the functional forms outlined above, we can also more neatly characterize the threshold of tailoring derived in Proposition 1 beyond which banks choose to hold on balance sheet: $x > C_s^{-1}(\lambda_e/\phi) = \frac{\lambda_e/\phi - c_s}{\eta \bar{y} Y(\omega)}$.

[4] Importantly, any combinations of these three parameters which leaves c_o unchanged for the two bank options would deliver the same quantitative results. The implication, however, is that we only recover a lower bound in our estimates for ψ.

$$
\begin{aligned}
&\max_{\omega,x} \quad (1-x)\,\bar{y}\,Y(\omega) \\
\text{s.t.} \quad & (1+c_o) = \beta[\underbrace{1 - Y(\omega) - B(\omega)}_{L(\omega)\text{: vanilla loan payoff}} + \underbrace{(1-c_x)xY(\omega)}_{\text{equity stake net payoff}}]\,\bar{y} \\
& \omega \geq 0, \quad 0 \leq x \leq 1
\end{aligned}
$$

We start by characterizing the optimality conditions for an interior solution, in which the firm borrows with a tailored loan ($x > 0$), which shows that firms optimally trade off tailoring and bankruptcy costs.

Proposition 2 (Optimal default threshold). *For an interior solution, the optimal default threshold ω when borrowing from a lender with effective tailoring cost c_x solves:*

$$
\underbrace{c_x\,(-Y'(\omega))}_{\textit{tailoring costs}} = \underbrace{B'(\omega)}_{\textit{bankruptcy costs}} \tag{9}
$$

Proof: *See Appendix B.2.*

To understand Proposition 2, notice that increasing ω, and thus R, shifts the financing mix away from the equity stake and toward the vanilla loan. Its optimal choice therefore optimally trades-off the savings in the tailoring costs associated with a smaller tailored stake, captured by $c_x\,(-Y'(\omega))$, where recall that $Y'(\omega) < 0$, against the higher bankruptcy costs associated with a larger vanilla stake, captured by $B'(\omega)$. When borrowing from a lender with a large tailoring cost c_x, the former costs are particularly high, pushing firms to optimally choose a more vanilla financing mix.

Corollary to Proposition 2: *The optimality condition in Equation (9) characterizing the interior optimum default threshold can be rewritten as:*

$$
\underbrace{\frac{\varphi(q)}{1-\Phi(q)}}_{\text{repayment hazard}} = \frac{c_x}{\delta}\,\sigma \tag{10}
$$

where φ and Φ are the standard normal PDF and CDF, and q is the standardized default threshold: $q \equiv \frac{\ln\omega-\mu}{\sigma} = \frac{\ln\omega+\frac{1}{2}\sigma^2}{\sigma}$.

Proof: *See Appendix B.2.1.*

Equation (10) provides a convenient characterization under log-normality. The inverse Mills ratio $\frac{\varphi(q)}{1-\Phi(q)}$, which we refer to as the repayment hazard, is high when a marginal increase in the vanilla component q substantially reduces the probability of repayment. Hence, when the repayment hazard is high, lowering q can substantially reduce default risk, but doing so requires shifting more of the contract toward the costly tailored component. At the optimum, this marginal benefit of reducing default risk is balanced against the relative cost of tailoring, as captured by the right-hand side of Equation (10). Since the inverse Mills ratio is increasing in q, a higher effective tailoring cost c_x or lower bankruptcy losses δ raises the optimal standardized default threshold q, shifting the optimal contract toward the vanilla component.

The optimal degree of tailoring is then obtained residually from the lender's zero-profit condition, as follows:

$$x(\omega) = \frac{S - L(\omega)}{(1 - c_x)Y(\omega)} \tag{11}$$

where $S \equiv \frac{1+c_o}{\beta \bar{y}}$ is the normalized vanilla origination cost. The numerator captures the financing gap remaining between S and the vanilla loan payoff $L(\omega)$. If any such gap exists, it must be covered by issuing an equity stake $x > 0$, where $(1 - c_x)Y(\omega)$ captures the net value to the lender of a unit of the equity claim.

Equation (11) also determines whether the solution is indeed interior, which occurs when the resulting x lies in $(0, 1)$. Instead, when $S \leq L(\omega)$, the optimal contract features a vanilla loan with $x = 0$, which alone is sufficient to compensate the lender for the amount advanced. Finally, when $x > 1$, that is, $S - L(\omega) > (1 - c_x)Y(\omega)$, the financing gap is so large that no feasible contract can satisfy the lender's zero-profit condition, so that the firm must either exit or borrow elsewhere. Appendix B.1.1 provides the full characterization of these corner cases.

In the next proposition, we show that—when borrowing from a given lender—firms of lower quality, both in terms of lower profitability or higher volatility, choose more tailored lending contracts. To characterize that proposition, it is useful to first state the following assumption, which we refer to as risk regularity.

Assumption 1 (Risk regularity). *Fix a financing option $\{c_o, c_x\}$ and expected output $\bar{y}$. Along the optimal contract, the payoff from the vanilla component of the loan is strictly decreasing in firm volatility:*

$$\frac{\partial L^*(\bar{y}, \sigma)}{\partial \sigma} < 0,$$

where

$$L^*(\bar{y}, \sigma) \equiv L(\omega^*(\bar{y}, \sigma), \sigma)\,.$$

The vanilla loan payoff L depends on σ both directly and indirectly through contract choice, as made explicit in the heavier notation $L(\omega^*(\bar{y}, \sigma), \sigma)$. Assumption 1 therefore requires that the direct negative effect of volatility on the payoff of the vanilla claim is not overturned by the endogenous choice. Appendix B.3.2 shows that $c_x < \delta$ is a simple sufficient condition for Assumption 1. Notice that neither this parametric condition nor Assumption 1 itself are necessary for the results that follow, and the relevant sign condition can be verified numerically and is easily satisfied in our parametrization. We now turn to characterize how optimal tailoring varies with firm quality.

Proposition 3 (Optimal tailoring and firm quality). *Conditional on a financing option $\{c_o, c_x\}$, suppose the optimal contract is interior, $0 < x^* < 1$. Then:*

1. *Optimal tailoring is strictly decreasing in expected output:*

$$\frac{\partial x^*}{\partial \bar{y}} < 0.$$

2. *Under the risk-regularity Assumption 1, optimal tailoring is strictly increasing in volatility:*

$$\frac{\partial x^*}{\partial \sigma} > 0.$$

Proof: *See Appendix B.3.*

2.5 Borrower Sorting

In this section, we characterize how different firms sort into the available financing options. The results will leverage the entrepreneur's optimal contract conditional on a financing option derived in the previous section, where we showed that firms of lower quality, along both profitability and volatility, choose more tailored contracts. Proposition 4 is effectively a comparative advantage result, whereby firms that value tailoring the most sort into the lenders who can provide it more cheaply, namely, the low c_x lenders.

We denote by $V^k(\bar{y}, \sigma)$ the entrepreneur's optimized value under the financing option k, which is summarized by the effective cost pair $\{c_o^k, c_x^k\}$. We then consider two non-dominated financing options k and ℓ satisfying

$$c_x^k < c_x^\ell, \qquad c_o^k > c_o^\ell. \tag{12}$$

Option k therefore has a comparative advantage in tailoring, whereas option ℓ has a comparative advantage in standardized lending.

Proposition 4 (Borrower sorting). *Consider two non-dominated financing options k and ℓ satisfying (12), and assume that each option is preferred to the other by some firms in their common feasible region. Then:*

1. *Holding volatility σ fixed, there is a unique cutoff $\bar{y}^*_{k\ell}(\sigma)$ such that*

$$V^k(\bar{y}, \sigma) > V^\ell(\bar{y}, \sigma) \iff \bar{y} < \bar{y}^*_{k\ell}(\sigma).$$

2. *Suppose in addition that Assumption 1 holds when both contracts are tailored at the boundary, or that the analogous condition for a vanilla contract stated in Appendix* **??** *holds when one of them is at the vanilla corner. Then the boundary is differentiable and strictly increasing, $\mathrm{d}\bar{y}^*_{k\ell}(\sigma)/\mathrm{d}\sigma > 0$. Consequently, holding expected output $\bar{y}$ fixed,*

there is a unique cutoff $\sigma^*_{k\ell}(\bar{y})$ such that

$$V^k(\bar{y},\sigma) > V^\ell(\bar{y},\sigma) \iff \sigma > \sigma^*_{k\ell}(\bar{y}).$$

Proof: *See Appendix B.*

The economics are a standard comparative-advantage mechanism. Lender k, the low-c_x option, is relatively costly for a simple loan but relatively cheap at providing state contingency. Therefore, low quality firms who value tailoring the most sort towards that lender.

The proposition applies pairwise to private credit, bank-retained lending, and bank-distributed lending. Whenever the cost to distribute tailored loans η is positive, we immediately get that $c_x^{br} < c_x^{bd}$. Instead, the positioning of c_x^f is an empirical question. Under the empirically relevant order, as predicted by our estimation in Section 6, we obtain $c_x^f < c_x^{br} < c_x^{bd}$, the proposition predicts that firms of the lowest quality sort into private credit, firms of the intermediate and high quality get a loan from banks, and within that group the best firms obtain standardized loans that banks distribute.

2.6 Capital Requirements and Contract Tailoring

In the following proposition, we characterize a result which is useful to understand the interconnection between capital requirements and lending technology in our model.

Proposition 5 (**Capital requirements as a tax on tailored lending**). *Consider any combination of parameters such that in the corresponding equilibrium and in any equilibria in the vicinity of those parameters, all bank loans that are sold are vanilla and all bank loans that are retained are tailored ($x > 0 \iff z = 0$).[5] Then, at the margin, a tightening of banks' leverage limit by $-\partial\phi$ is equivalent to the following tax on tailored bank loans:*

$$\tau(x) = \frac{\lambda_e}{\phi^2}\,\partial\phi\;\mathbb{1}_{x>0} \tag{13}$$

Proof: *See Appendix B.*

Proposition 5 shows that in any equilibrium where banks sell only vanilla loans, then there is a perfect equivalence between two government policies: a tightening of capital requirements on banks, and the imposition of a tax on tailored loans. The intuition for this result is straightforward: under the stated parameter restrictions, a tightening of bank's capital requirement has no effect on vanilla loans ($x = 0$), since these are distributed, but leads to a marginal increase

[5] The direction $z = 0 \implies x > 0$ is true whenever there are any distributed loans in equilibrium, so the material restriction here is that all distributed loans are vanilla ($x > 0 \implies z = 0$).

in the cost of loans that are retained on the balance sheet of λ_e/ϕ^2. Because there is a perfect correspondence between loans retained on balance sheet and loans that are tailored in these equilibria, this policy is equivalent to the tax in equation (13).

2.7 Summary of Model Predictions

The framework we developed, while simple, offers rich predictions about loan distribution, intermediary specialization, and borrower sorting, both in the cross-section and in response to changes in capital requirements. Before moving to the data, we summarize the model's main predictions.

First, Proposition 1 shows that banks retain sufficiently tailored loans, while they distribute sufficiently standardized ones. Therefore, we expect more tailored bank loans to be less likely to be distributed.

Second, Propositions 2 and 3 characterize how firms optimally choose their borrowing contract conditional on a financing option, as a function of both firm characteristics—expected output and volatility—and the lender's effective cost of tailoring. In particular, firms with lower expected output and higher volatility choose more tailored contracts. Proposition 4 then shows that these differences in the demand for tailoring translate into borrower sorting: firms with lower profitability and higher volatility sort toward financing options that can provide tailoring more cheaply. Within banks, the ordering follows directly from the cost structure, since distributed loans face the additional tailoring cost η and are therefore relatively more expensive to tailor than retained loans. In the empirically relevant case, private credit has the greatest comparative advantage in tailoring and consequently attracts lower-quality borrowers.

Finally, Proposition 5 shows that capital requirements act as a tax on tailored bank lending. A tightening of capital requirements therefore raises the relative cost of retained, tailored loans and pushes banks toward more standardized, readily distributable lending, while strengthening private credit's comparative advantage in tailored financing.

Sections 4 and 5 test these predictions in the data.

3 Institutional Setting and Data

We next map the model to the institutional setting and describe the data used in the empirical analysis. The key distinction in the model is between banks, for which retained lending uses scarce balance-sheet capacity, and private credit funds, which operate with substantially less leverage and rely more heavily on hold-to-maturity lending. We first document these differences and explain why Business Development Companies (BDCs) provide a useful observable segment of the private credit market. We then describe our bank and BDC loan data and construct empirical measures of loan distribution, contractual tailoring, and borrower characteristics.

3.1 Banks and Private Credit

Private credit refers to direct corporate lending by nonbank investment vehicles, typically outside public debt and broadly syndicated loan markets. Relative to banks, private credit lenders rely less on deposit funding, operate under a different regulatory regime, and often specialize in more bespoke, hold-to-maturity lending. These differences map directly into the key intermediary asymmetry in our model: balance-sheet capacity is substantially more costly for banks, creating a stronger incentive to distribute loans rather than retain them. Moreover, these features make private credit a natural setting for studying how intermediary funding structure and regulation shape both lender-borrower matching and contract design.

Because much of private credit operates through opaque private vehicles, we focus empirically on publicly traded Business Development Companies (BDCs), a prominent and observable segment of the market. Unlike most private credit funds, these publicly traded BDCs disclose relatively rich information on balance sheets, portfolio holdings, and loan characteristics in their 10-Ks; we use this data, as processed by Robinson and Wallskog (2025). The observability makes BDCs a tractable empirical laboratory for comparing private credit with bank lending. At the same time, BDCs do not represent the entire private credit universe, so our empirical results should be interpreted as speaking most directly to this visible segment of the market.

The balance-sheet differences between banks and private credit funds are substantial. Using assets-to-equity as the measure of leverage, Matvos, Piskorski, and Seru (2026) document that private credit funds typically operate with ratios of approximately 1.25–1.5, compared with around 9 for banks. The difference remains stark when focusing specifically on BDCs. BDCs are subject to a statutory debt-to-equity limit of 2:1, and faced a tighter 1:1 limit prior to a 2018 reform. By comparison, non-equity liabilities of the U.S. banking sector are approximately nine times bank equity.[6] Thus, even at their regulatory leverage limit, BDCs operate with substantially more equity financing than banks.

Public BDCs also raise equity much more frequently. For instance, on average, banks issue equity only 0.03 times per year, while the average BDC issues equity 0.25 times per year. Conditional on issuing equity in a seasoned equity offering (SEO), BDCs issue stock equivalent to 11% of their assets, while banks only issue 2% of their asset value.[7] Moreover, Avalos, Doerr, and Pinter (2025) document that BDCs also have a lower cost of equity than banks. Indeed, greater equity issuance by BDCs and their lower cost of equity are consistent with the fact that BDCs operate with significantly less leverage than banks.

Finally, the two intermediary types also differ in how they manage originated loans. Davydiuk, Marchuk, and Rosen (2024) highlight that BDCs generally hold loans until repayment or maturity, whereas syndicated bank lending relies much more heavily on an originate-to-distribute model. This distinction is central to our mechanism. Distribution allows banks

[6] To compute the banking sector's ratio of non-equity liabilities to equity, we use aggregate equity and non-equity liabilities from the FDIC's Quarterly Banking Profile.

[7] We calculate these figures based on data from SDC Platinum.

to economize on scarce balance-sheet capacity, but becomes less attractive when contractual features make loans difficult to standardize and sell to outside investors. The combination of greater bank leverage and a stronger reliance on distribution therefore creates a natural link between intermediary balance-sheet structure and the type of loan contracts each lender can competitively provide.

3.2 Data and Sample Construction

Our empirical analysis combines deal-level data on bank lending from DealScan with data on BDC investments from Robinson and Wallskog (2025). We focus on corporate lending at origination over the 2010–2023 period, for which we have the strongest overlap between the two datasets.

Bank lending. We obtain bank loans from DealScan, which provides detailed information on large syndicated corporate loans and their contractual features. We restrict the sample to deals made to U.S. corporate borrowers for which the lead lender's parent is a U.S. bank, and retain loan originations rather than amendments. Because DealScan records loans at the tranche level, we construct deals by grouping all tranches associated with the same origination and total deal value. Our baseline sample contains 19,816 bank deals.

Private credit. We obtain BDC investments from the security-level data constructed by Robinson and Wallskog (2025) from BDCs' Schedule of Investments. We define an origination as the first year in which a BDC reports an investment in a given borrower. For each such borrower-BDC pair, we aggregate all debt and equity securities reported at origination into a single deal. We require each deal to contain at least one debt security and to have positive, non-missing deal value. This yields 22,689 BDC deals.[8]

As can be seen in Table 3 at the end of this section, the two datasets cover economically different segments of corporate credit markets. Bank deals in DealScan are substantially larger and contain more tranches than BDC deals. The average bank deal is approximately \$470 million and contains 8.1 tranches, compared with roughly \$12 million and 1.4 tranches for BDC deals. Median deal sizes are \$158 million and \$5 million, respectively. These differences partly reflect the focus of DealScan on large syndicated loans and motivate our use of flexible controls for deal size and tranche structure when comparing bank and BDC lending.

For a subset of borrowers, we match the lending data to Compustat and CRSP, leveraging the crosswalk in Fang and Nini (2026). Compustat provides borrower accounting characteristics, while CRSP allows us to measure equity-market risk. In particular, our borrower-sorting analysis uses EBITDA relative to assets as a measure of profitability and the standard deviation of monthly stock returns in the year prior to loan origination as a measure of borrower risk. The matched sample contains 7,447 bank deals and 1,626 BDC deals with Compustat borrowers; the

[8] BDCs may co-invest or syndicate loans with other lenders, but our data capture only the securities retained by the reporting BDC.

samples used in particular regressions are smaller when we additionally require the borrower-risk measures.

We next describe how we map the model's two central contract dimensions, loan distribution and contractual tailoring, into observable characteristics of these deals.

3.3 Measuring Distribution and Tailoring

The empirical analysis centers on two objects that correspond directly to the model: whether a bank loan is retained or distributed, and the degree of contractual tailoring. We construct deal-level measures of each using the information available in DealScan and the BDC data.

Loan distribution. DealScan does not directly report the share of an originated loan ultimately retained by the lead bank. We therefore predict the lead lender's holding share using the model estimates from Blickle et al. (2026). For each tranche originated by the deal lead, we predict the percentage retained by the bank and aggregate these predictions to the deal level using tranche values as weights. Our baseline binary measure classifies a deal as *likely distributed* when the predicted holding share is below 50%. More details are available in Appendix A

Contractual tailoring. To map the model's tailoring variable x into the data, we focus on contractual features that make the lender's exposure or payoff contingent on the borrower's realized state. Because the specific forms of state contingency differ between bank and BDC lending, we construct a common deal-level state-contingency score based on three dimensions. First, *exposure-size contingency* captures whether the lender's eventual exposure can vary with the borrower's state. Second, *payment-timing contingency* captures whether the timing of cash payments can vary with borrower outcomes. Third, *performance participation* captures whether the lender directly shares in borrower upside or downside.

Table 2 summarizes the mapping from observed contract features into these dimensions. Each dimension contributes one third to the score for a given feature. Credit lines and pricing grids each introduce one dimension of state contingency and therefore receive a score of $1/3$. PIK interest and preferred equity affect two dimensions and receive a score of $2/3$.[9] Common equity and warrants expose the lender to all three dimensions and receive a score of one.

We construct the deal-level score by summing the contributions of all features present in a deal. Thus, a vanilla loan with none of these features receives a score of zero, while deals combining several state-contingent features receive progressively higher scores. The maximum score observed in our sample is $10/3$.[10] This measure is intended to capture the overall degree of state contingency in the contract, consistent with the interpretation of x in the model.

[9] Note that preferred equity holders receive fixed, but deferred, payments akin to debt payments, and so do not directly share in upside like other equity-holders.

[10] While we do not observe it, we could have deals with scores of $12/3$, which would feature a line of credit (+1), a pricing grid (+1), PIK interest (+2), preferred equity (+2), common equity (+3), *and* warrants (+3). In practice, the maximum we observe is $10/3$ (BDC deals featuring all of but a line of credit and a pricing grid).

Table 2: State-contingency score rubric

Tranche type/feature	Exposure size	Payment timing	Performance participation	Score contribution
Vanilla term loan				0
Line of credit	✓			1/3
Pricing grid	✓			1/3
PIK interest	✓	✓		2/3
Preferred equity	✓	✓		2/3
Common equity	✓	✓	✓	1
Warrants	✓	✓	✓	1

Notes: This table presents rubric for our state-contingency score. We assess whether a deal has at least one of each feature (e.g., 1+ credit lines) and then sum across the features to get a deal-level score.

The available contract features differ across lender types. For bank deals, we observe credit lines and pricing grids, while the BDC data additionally allow us to observe PIK interest, preferred and common equity, and warrants. Financial covenants provide another important form of state contingency in bank loans, since they condition lender rights on borrower performance. We use covenants as an additional outcome in our bank-only analysis, but do not include them in the common bank–BDC state-contingency score because comparable covenant information is not available for BDC deals.

Table 3 summarizes the resulting deal-level samples and the main variables used in the analysis. Several differences between bank and BDC lending are immediately apparent. Bank deals are large, complex, and display more variation in retention. The lead bank is predicted to retain, on average, approximately 42% of deal value, while roughly 65% of deals are classified as likely distributed. Credit lines appear in 66% of bank deals, while pricing grids and financial covenants each appear in approximately 12%. Among bank deals matched to Compustat, these features are more prevalent, with credit lines appearing in 73% of deals and pricing grids and financial covenants in roughly 30%.

BDC contracts exhibit a different set of state-contingent features. PIK interest appears in 9% of deals, while preferred equity, common equity, and warrants appear in 3%, 7%, and 5%, respectively. The raw average state-contingency score is 0.26 for bank deals and 0.20 for BDC deals, although this comparison reflects the very large differences in deal size and structure across the two markets. As we show in Section 4, once we condition on these characteristics, more state-contingent contracts are substantially more likely to be provided by BDCs.

Table 3: Summary statistics of bank and BDC deals

	N	Mean	Median	StdDev	Min	Max
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All bank deals						
Deal size (million $)	19,816	469.66	158.40	779.79	0.33	4100.00
# tranches	19,816	8.13	5.00	11.02	1.00	246.00
Share held	19,571	41.86	38.95	21.84	0.00	100.00
Distributed	19,571	0.65	1.00	0.48	0.00	1.00
Any credit lines	19,816	0.66	1.00	0.47	0.00	1.00
Any pricing grids	19,816	0.12	0.00	0.33	0.00	1.00
Any financial covenants	19,816	0.12	0.00	0.33	0.00	1.00
State-contingency score	19,816	0.26	0.33	0.20	0.00	0.67
Panel B: Bank deals with Compustat borrowers						
Deal size (million $)	7,447	870.37	450.00	1045.76	1.18	4100.00
# tranches	7,447	12.23	8.00	15.39	1.00	246.00
Share held	7,304	33.43	27.20	23.56	0.00	100.00
Distributed	7,304	0.80	1.00	0.40	0.00	1.00
Any credit lines	7,447	0.73	1.00	0.45	0.00	1.00
Any pricing grids	7,447	0.29	0.00	0.45	0.00	1.00
Any financial covenants	7,447	0.30	0.00	0.46	0.00	1.00
State-contingency score	7,447	0.34	0.33	0.22	0.00	0.67
Panel C: All BDC deals						
Deal size (million $)	22,689	12.45	4.98	25.64	0.00	1023.18
# tranches	22,689	1.41	1.00	0.82	1.00	20.00
Any credit lines	22,689	0.00	0.00	0.05	0.00	1.00
Any PIK interest	22,689	0.09	0.00	0.29	0.00	1.00
Any preferred equity	22,689	0.03	0.00	0.17	0.00	1.00
Any common equity	22,689	0.07	0.00	0.25	0.00	1.00
Any warrants	22,689	0.05	0.00	0.21	0.00	1.00
State-contingency score	22,689	0.20	0.00	0.43	0.00	3.33
Panel D: BDC deals with Compustat borrowers						
Deal size (million $)	1,626	15.46	7.40	26.30	0.00	317.60
# tranches	1,626	1.32	1.00	0.81	1.00	15.00
Any credit lines	1,626	0.00	0.00	0.00	0.00	0.00
Any PIK interest	1,626	0.08	0.00	0.28	0.00	1.00
Any preferred equity	1,626	0.02	0.00	0.13	0.00	1.00
Any common equity	1,626	0.03	0.00	0.17	0.00	1.00
Any warrants	1,626	0.07	0.00	0.26	0.00	1.00
State-contingency score	1,626	0.17	0.00	0.40	0.00	2.67

Notes: This table presents unweighted summary statistics at the deal level.

4 Cross-Sectional Evidence

We now examine the model's cross-sectional predictions for loan distribution, contract design, and lender choice. The model predicts that more tailored loans are harder to distribute and that this link between tailoring and distribution shapes the comparative advantage of banks and private credit. In particular, private credit should specialize relatively more in tailored lending, while banks should have a greater advantage in standardized loans that can be readily distributed. The model also predicts that borrower characteristics affect both contract design and lender choice, as firms with greater demand for tailoring sort toward financing regimes that can provide it more cheaply.

We examine these predictions in two steps. We first study the relationship between state contingency, loan distribution, and private credit. We then examine how borrower profitability and risk are related to lender choice, distribution, and contract tailoring. These cross-sectional relationships are descriptive rather than causal. Their purpose is to establish that the key margins emphasized by the model are present in the data. In Section 5, we use changes in bank capital requirements to test the model's central comparative static causally.

4.1 Tailoring and Loan Distribution

The central mechanism in the model is that contractual tailoring makes loans more difficult to distribute. Banks therefore have a comparative advantage in standardized lending that can be moved off balance sheet, while lenders that rely more heavily on retention can have a comparative advantage in tailored contracts. Table 4 examines both parts of this mechanism.

Columns (1) and (2) compare contract design across banks and private credit. The dependent variable is an indicator for a BDC deal, and the main explanatory variable is the state-contingency score defined in Section 3.3. All specifications control flexibly for deal size, the number of tranches, and origination year. More state-contingent deals are substantially more likely to be provided by BDCs. In the full sample, the coefficient on the state-contingency score is 0.228 and is statistically significant at the one-percent level. A one-standard-deviation increase in the score is therefore associated with an approximately 8 percentage point increase in the probability that a deal is provided by a BDC. The relationship remains positive and highly significant when we restrict attention to borrowers matched to Compustat, although the magnitude falls.

These conditional comparisons are important because the raw characteristics of bank and BDC deals differ considerably. As documented in Section 3.2, bank deals are much larger and contain many more tranches, and their unconditional average state-contingency score is in fact slightly higher than that of BDC deals. Once we compare deals of similar size and tranche structure, however, the relationship reverses: state-contingent contracts are disproportionately associated with private credit. This is consistent with the model's prediction that private credit has a comparative advantage in the provision of tailored financing.

Columns (3) and (4) examine the other side of the same mechanism within bank lending. The dependent variable is now our indicator for whether a bank deal is likely distributed. The relationship between tailoring and distribution is strongly negative. In the full bank sample, a one-unit increase in the state-contingency score is associated with a 23.5 percentage point lower probability of distribution. Given a standard deviation of the score of 0.20, a one-standard-deviation increase in tailoring corresponds to approximately a 4.7 percentage point reduction in the probability that the loan is distributed. In the Compustat sample, the corresponding effect is approximately 1.9 percentage points. Both estimates are statistically significant at the one-percent level.

Taken together, the two sets of estimates provide the key cross-sectional pattern underlying the model. State-contingent loans are less likely to be distributed by banks, and the same type of lending is relatively more prevalent in private credit. Thus, the hold-versus-distribute margin within banks is mirrored by a bank-versus-private-credit margin across intermediaries: the contracts that are most difficult for banks to move off balance sheet are precisely those in which private credit appears to have a comparative advantage.

Table 4: State-contingent features by lender and distribution likelihood

Dep Var:	BDC deal		Likely distributed	
Sample:	All deals		Bank deals	
Borrowers:	All	Compustat	All	Compustat
	(1)	(2)	(3)	(4)
State-contingency score	0.228***	0.072***	-0.235***	-0.086***
	(0.005)	(0.012)	(0.013)	(0.015)
Year FEs	x	x	x	x
Value Ventile FEs	x	x	x	x
# Tranche FEs	x	x	x	x
N	42,474	9,038	19,539	7,266
Mean(Dep var)	0.53	0.18	0.65	0.80
Mean(Score)	0.23	0.31	0.26	0.34
StdDev(Score)	0.35	0.27	0.20	0.22

Note: This table shows that state-contingent features (lines of credit, pricing grids, PIK interest, and equity) are more common among BDC deals (columns (1)-(2)) and non-distributed bank deals (columns (3)-(4)), conditional on deal size.

4.2 Borrower Sorting

The model further predicts that borrower characteristics shape both lender choice and contract design. Riskier firms have greater demand for state-contingent financing because tailoring allows repayment to adjust with borrower performance, thus reducing bankruptcy frictions. They should therefore be more likely to select financing regimes with a comparative advantage in tailoring and, conditional on lender type, to receive more tailored contracts. We examine these predictions using EBITDA relative to assets as a measure of borrower profitability and inverse stock-return volatility as a measure of borrower quality, where stock-return volatility is the standard deviation of monthly stock returns. We use inverse volatility so that lower values of both measures indicate weaker borrower quality. Both are measured in the year before loan origination. Table 5 presents the results. All specifications include year-by-sector fixed effects and flexible controls for deal size and the number of tranches. We examine separately how borrower characteristics relate to lender choice, the distribution of bank loans, and the degree of state contingency within bank and BDC contracts.

Columns (1) and (2) first examine lender choice. Lower-profitability firms are substantially more likely to borrow from private credit. The coefficient on EBITDA/assets is −0.225 and is statistically significant at the one-percent level. A 10 percentage point increase in EBITDA/assets is therefore associated with a 2.25 percentage point lower probability of borrowing from a BDC. Relative to a mean BDC share of approximately 8 percent in this sample, this is economically substantial. Inverse stock-return volatility also enters negatively and is statistically significant, implying more volatile borrowers are more likely to use private credit.

Columns (3) and (4) turn to the distribution decision among bank loans. Lower inverse stock-return volatility predicts less loan distribution, with a statistically significant coefficient of 0.006. By contrast, EBITDA/assets is not significantly related to bank loan distribution. Thus, among bank borrowers, greater measured risk is associated with lending that is more likely to remain on bank balance sheets.

Columns (5) and (6) show that this same risk measure is also related to contract design. Lower inverse stock-return volatility is associated with a higher state-contingency score, with a coefficient of 0.011 that is statistically significant at the one-percent level. Taken together with the distribution result, this implies that more volatile bank borrowers receive loans that are both more tailored and less likely to be distributed, consistent with the model's link between borrower risk, tailoring, and retention.[11]

The BDC results in columns (7) and (8) also closely align with the model. Lower-profitability borrowers receive more state-contingent BDC contracts: the coefficient on EBITDA/assets is −0.089 and statistically significant at the ten-percent level. Inverse stock-return volatility also enters negatively, although the estimate is imprecise. Statistical power is lower in these specifications because the matched BDC samples contain only around 300 deals.

Overall, Table 5 reveals a coherent pattern of borrower sorting. Lower profitability and greater volatility are both associated with sorting toward private credit, while volatility is also associated with receiving tailored, retained financing within banks. The results support the model's prediction that borrower characteristics jointly shape lender choice and contract design.

[11] The within bank profitability result is less aligned with the model as EBITDA/assets enters positively in column (5). This may reflect some state-contingent features being used to offer favorable terms to stronger borrowers.

Table 5: Sorting of borrowers to BDC, distributed, and state-contingent deals

Dep Var:	BDC deal		Likely distributed		State-contingent score			
Sample:	All deals		Bank deals		Bank deals		BDC deals	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EBITDA/Assets	-0.225***		0.059		0.038***		-0.089*	
	(0.031)		(0.049)		(0.010)		(0.046)	
Inverse stock return vol		-0.004***		0.006**		-0.011***		-0.019
		(0.001)		(0.002)		(0.002)		(0.020)
Year-Sector FEs	x	x	x	x	x	x	x	x
Value Pctl FEs	x	x	x	x	x	x	x	x
# Tranche FEs	x	x	x	x	x	x	x	x
N	4,989	5,319	4,491	4,840	4,587	4,946	339	312
Mean(Dep var)	0.08	0.07	0.83	0.84	0.11	0.35	0.07	0.21
Mean(Char)	0.11	3.48	0.12	3.58	0.12	3.57	-0.04	2.23
StdDev(Char)	0.13	1.83	0.10	1.84	0.10	1.84	0.25	1.16

Note: This table demonstrates that Compustat borrowers with higher EBITDA/asset and lower monthly stock return volatility (standard deviation) in the year prior to the deal origination sort into contracts with different lenders, distribution, and state-contigent features. EBITDA/assets and monthly stock return volatility are both winsorized at the top and bottom percentile of the entire sample.

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All columns include deal year-sector, deal size (value) ventile (based on the distribution of deal size in our full sample of bank and BDC deals), and number of tranches fixed effects. All columns are deal-weighted.

5 Natural Experiment: Capital Requirements and Tailoring

The cross-sectional evidence is consistent with the model's predicted relationships between tailoring, loan distribution, and lender type, but does not establish that bank balance-sheet constraints *cause* changes in contract design. We therefore turn to variation in bank capital requirements to test the model's central comparative static: tighter capital requirements raise the relative cost of tailored lending and should induce banks to offer less state-contingent contracts.

5.1 Regulatory Setting and Empirical Design

We exploit the introduction of the enhanced supplementary leverage ratio (eSLR), announced in 2014 and effective in 2018. The supplementary leverage ratio (SLR) requires large banking organizations to maintain Tier 1 capital relative to their total leverage exposure, including both on- and off-balance-sheet exposures. Banks subject to the SLR face a minimum requirement of 3%, while Global Systemically Important Banks (G-SIBs) became subject to a higher 5% requirement under the eSLR. The reform therefore tightened the leverage constraint more strongly for G-SIBs than for other large banks.

Our model predicts that this differential tightening should increase the relative cost of loans that rely on bank balance sheets and, because such loans are endogenously more tailored, reduce the state contingency of contracts originated by affected banks. Conditional on contract design, the model also predicts a greater incentive to distribute loans. We do this in an event study framework. Because large banks can be very different from small banks for many reasons, we restrict our sample to the large banks that face the SLR rule, and estimate differences over time between G-SIBs — who face a larger constraint — and non-G-SIB banks. Specifically, we estimate regressions of the structure

$$y_{l,i,j,t} = \sum_{t=2010}^{2019} \delta_t \times \mathbf{1}\{\text{G-SIB}_b\} + \mathbf{X}_l \eta + \gamma_i + \gamma_t + \gamma_b + \epsilon_{l,i,j,t} \tag{14}$$

where $y_{l,i,j,t}$ is a characteristic of deal l made to company i by (deal lead parent) bank j in year t.[12] We estimate year-by-G-SIB coefficients as our main coefficients of interest; we omitted the 2013 interaction, as the year before the rule was announced. We include loan controls (deal size percentile, number of tranches, and (non-parent) bank fixed effects) as well as fixed effects for the parent bank (γ_j) and year (γ_t) fixed effects; in some specifications, we control for borrower fixed effects (γ_i) in order to control for time invariant borrower characteristics. $\epsilon_{l,i,j,t}$ captures idiosyncratic noise. Standard errors are clustered at the bank-level. We restrict our analysis to years up until 2019, as there were changes to the SLR rule in 2020.

[12] While there can be multiple banks involved in a deal, we focus on the deal lead, and categorize deals by the G-SIB status of the lead's parent.

5.2 Results

Figure 1 presents the dynamic response of contract design and loan distribution to the tightening of capital requirements. The clearest response is in the use of state-contingent contract features. Following the announcement of the eSLR, G-SIB-led deals become progressively less likely to feature pricing grids and financial covenants, with the declines becoming particularly pronounced around implementation of the rule in 2018. The pre-treatment coefficients are relatively stable and do not display a clear differential trend leading into the announcement.

The pooled difference-in-difference estimates in Table A.1 confirm these patterns. In 2018–2019, the probability that a G-SIB-led deal contains a pricing grid falls by 13.4 percentage points relative to other SLR banks in the baseline specification and by 19.7 percentage points when borrower fixed effects are included. Financial covenants decline by 11.1 and 15.2 percentage points, respectively. All four estimates are statistically significant. Importantly, the borrower fixed-effect specifications compare contracts extended to the same borrower over time, suggesting that the results reflect changes in banks' contract design rather than simply changes in the composition of borrowers.[13]

Consistent with interpreting pricing grids and financial covenants as forms of hard-to-distribute tailoring, both features are also significantly less prevalent in deals containing TLB lending and are associated with a lower share of deal value in TLB tranches (Table A.2). These cross-sectional patterns reinforce the interpretation that the contract features most affected by tighter capital requirements are precisely those associated with lending that is less oriented toward distribution.

We also find that the distribution response moves in the direction predicted by the model, although it is estimated less precisely than the changes in contract design. In the baseline specification, the probability that a G-SIB-led deal is likely distributed rises by 15.2 percentage points in 2018–2019; with borrower fixed effects, the estimate remains positive at 7.3 percentage points but is imprecisely estimated. We therefore view the distribution results as qualitatively supportive of the mechanism, with the strongest evidence coming from the response of contract design.[14]

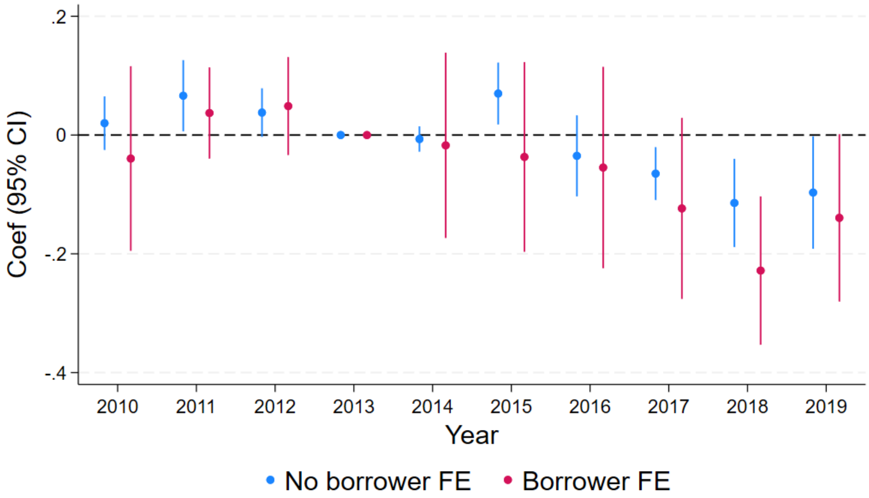
Taken together, the results provide direct support for the model's central comparative static. When regulation makes bank balance-sheet capacity more costly, banks reduce the use of precisely those state-contingent contract features that are associated with less distributable lending. Capital requirements therefore affect not only the quantity or ultimate holder of bank credit, but also the contractual form in which banks supply it.

[13] We also estimate the response of credit lines, reported in Appendix Figure A.1 and Table A.1. The estimates are considerably noisier and do not display a systematic response to the capital-requirement change. Credit lines may differ from the other contract features considered here because, in addition to introducing state contingency, they provide an important form of committed liquidity insurance against future funding needs (see for example Holmström and Tirole, 1998 and Acharya, Almeida, and Campello, 2013).

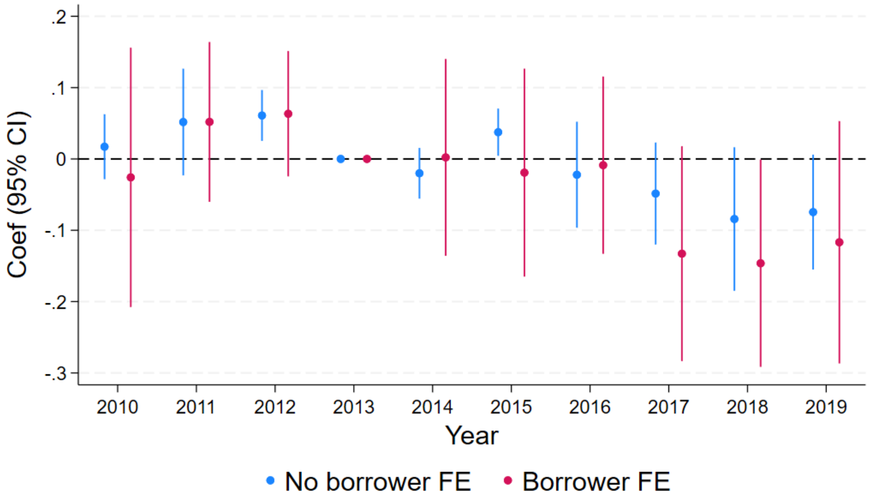
[14] Term loan B usage itself does not respond systematically to the reform (Table A.1), consistent with the broader distribution response being less precisely estimated than the change in contract design.

Figure 1: GSIB deals become less state-contingent as capital requirements strengthen

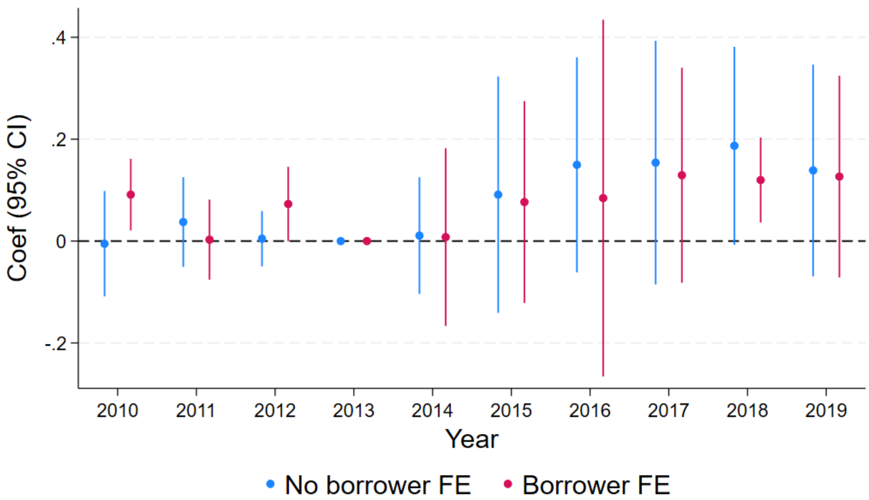
(a) 1+ pricing grids



(b) 1+ financial covenants



(c) Likely distributed



This figure presents estimates from event study model (14), where the treatment variable is an indicator for the deal lead's (i.e., the "lender's") parent bank being a GSIB and the two post periods being after the increased capital requirements are announced by not enforced (2014-2017) and after the requirements are enforced (2018-2019).

6 Quantitative Results

The previous sections provide empirical support for the key mechanism of the model. Cross-sectionally, tailored loans are less likely to be distributed and are relatively more prevalent in private credit, while borrower characteristics predict both lender choice and contract design. Using the eSLR reform, we further show that tighter bank capital requirements causally reduce the use of tailored contract features. We now return to the model to assess the quantitative importance of this interaction between bank regulation and lending technology.

We discipline the model using moments on lender choice, loan retention, and contract tailoring from the data.

To make the model amenable to estimation, we make one major change to the setup outlined in Section 2, which is to introduce preference shocks across lenders. The primary reason why this helps with the estimation is that in the baseline model, the mapping between the parameters and the model moments is highly non-linear. For instance, when two lenders have identical technology parameters, an infinitesimal change in one of those parameters would shift the entire mass of firms from one lender to the other. The shock stands in for match-specific factors outside the contracting problem, such as existing relationships, sector expertise, geographic presence, or the timing of the deal, which make a particular lender more or less attractive to a particular borrower.

In particular, in the quantitative model firms do not choose a lender deterministically. Alongside the value V_k delivered by lender k's optimal contract, a firm draws an idiosyncratic preference shock ε_k for each of the four alternatives (exit, a private credit fund, a bank-retained loan, and a bank-distributed loan) and selects the option that maximises $V_k + \varepsilon_k$. The shocks are independent across alternatives and across firms and follow a Type-1 Extreme Value (Gumbel) distribution with scale λ, which yields multinomial logit choice probabilities $P_k = \exp(V_k/\lambda)/\sum_j \exp(V_j/\lambda)$. We enforce exit for firms who cannot obtain funding from any of the lenders, irrespective of their preference shocks. The scale λ is estimated jointly with the cost parameters; as $\lambda \to 0$ choice becomes deterministic in V_j, so the framework nests frictionless sorting as a limiting case.

We first examine whether the calibrated model reproduces the observed sorting of borrowers and contracts across private credit, retained bank lending, and distributed bank lending. We then use the model to address two quantitative questions. First, how much do bank capital requirements contribute to private credit's comparative advantage in tailored lending? Second, what does private credit provide that banks do not—access to financing for otherwise excluded firms, or more suitable contracts for firms that could also borrow from banks?

The first counterfactual relaxes bank capital requirements, allowing us to separate differences in underlying lending technology from those induced by banks' balance-sheet constraints. The second removes private credit from the economy and traces where its borrowers would obtain financing instead. Together, these exercises quantify how the interaction between regulation and contract design shapes the bank–private credit boundary.

6.1 Calibration

There are two groups of parameters to calibrate. The first comprises the risk-free discount rate β and the bankruptcy loss rate δ, which are standard and calibrated externally to 0.96 and 0.3, respectively. The second set is comprised of the parameters needed to populate the cost functions of Table 1, which govern competition among banks and credit funds. We estimate these parameters to match some of the empirical moments documented in Section 2.

First of all, we let $\psi = \lambda_e/\phi$ denote bank liability-related parameters, which capture the extent of financial constraints on banks, since the model does not allow us to identify λ_e and ϕ separately and only depend on their ratio. Of the remaining 7 parameters of Table 1, we can only identify 6: c_s cannot be identified. Therefore, we just assume it is zero for the estimation exercise (if we externally calibrate it to be positive, this will simply shift up the estimated values for ψ and down that for τ_o^b).

Then we have six parameters of the cost functions to calibrate, which determine the extent of competition in the lending market. Three relate to levels of costs: τ_o^b, τ_o^f, and ψ. Three relate to slope costs of tailoring: τ_x^b, τ_x^f, and η. Additionally, we also estimate the magnitude of the preference shock λ, which helps to smooth firm choices at the boundary and substantially improves the estimation efficacy.

We identify these parameters using eight independent moments of the data, (since notice that the three market shares sum to one), as per the following table.

Table 6: Targeted moments: data vs. model

	Data	Model
Fraction of firms		
Private credit	0.436	0.434
Bank retained	0.189	0.190
Bank distributed	0.375	0.376
Average x		
Private credit	0.431	0.438
Bank retained	0.090	0.120
Bank distributed	0.000	0.000
Average σ		
Private credit	1.210	1.177
Bank retained	1.003	0.925
Bank distributed	0.827	0.871

Table 7: Cost structure across financing regimes

Financing regime	c_o		c_x	
Private credit	τ_o^f	0.007	τ_x^f	0.185
Bank retained	$\tau_o^b + \lambda_e/\phi$	0.004	τ_x^b	0.205
Bank distributed	τ_o^b	0.000	$\tau_x^b + \eta$	0.330

The estimated parameter values clarify how the empirical moments are interpreted through the model. In the data, we observe that firms obtain loans of all three types possible, and that loans exhibit a tailoring order as follows: syndicated bank loans are the least tailored, bank retained loans have an intermediate level of tailoring, and private credit loans are the most tailored. To match the pecking order of tailoring, the parameters are estimated so that $\tau_x^f < \tau_x^b < \tau_x^b + \eta$, reflecting a higher cost of tailoring in banks due to both the origination technology (τ_x^b) and—for distributed loans—the distribution cost $+\eta$. Secondly, for all lenders to be active in the model, the order of the cost parameters c_o must be the flip side of that of c_x. Otherwise, one type of loan would dominate another, and no firm would ever seek credit from the dominated lender. Therefore, origination costs for plain vanilla loans are highest in private credit, and they are lower in banks, particularly so for distributed loans that are not affected from the equity shadow cost: $\tau_o^f > \tau_o^b + \psi > \tau_o^b$.

6.1.1 Technology-only alternative calibration

To illustrate the role of the balance sheet constraint in shaping lending technology, we re-estimate the model in an alternative, technology-only setup. This is the case when $\eta = 0$, and therefore capital requirements shift bank's ability to hold on balance sheet but not the type of loans they can originate.

Table 9 shows that in this misspecified version of the model, bank tailoring costs τ_x^b are about 18 percent larger than those of private credit funds, τ_x^f. This difference is almost twice the 10 percent difference implied in the baseline estimates of Table 7, which uses the full model to unpack how much of the observed differences between private credit and bank tailoring stems from origination technology τ_x^b and from the distribution costs η instead.

The exercise illustrates that observed differences in contract design should not be interpreted one-for-one as primitive differences in lending technology. Indeed, once we account for the interaction between tailoring and distribution, part of banks' apparent disadvantage in providing tailored contracts is instead attributed to the additional cost of distributing such loans. As a result, the primitive technological difference between banks and private credit required to match the data is substantially smaller in the full model.

Table 8: Targeted moments: data vs. model

	Data	Model
Fraction of firms		
Private credit	0.436	0.438
Banks	0.564	0.562
Average x		
Private credit	0.431	0.444
Banks	0.030	0.037
Average σ		
Private credit	1.210	1.180
Banks	0.886	0.882

Table 9: Estimated cost parameters

Lender		c_o		c_x
Private Credit	τ_o^f	0.008	τ_x^f	0.184
Banks	τ_o^b	0.000	τ_x^b	0.217

6.2 Equilibrium sorting

The model reveals clear sorting patterns of firms, with a pecking order that depends on their profitability and volatility. Figure 2 shows the optimal choice of lender for each firm $(\bar{y}, \sigma)$. We report the inverted volatility, σ^{-1}, on the y-axis, to make the figure more interpretable. Firms close to the origin, with high volatility and especially low profitability, are unable to obtain any loans and exit the market. As firms become marginally more profitable or less risky, they borrow from private credit funds. Funds have a comparative advantage in lending with highly tailored loans, a type of contract that is particularly valuable for high-risk, low-profitability firms. Indeed, as shown in Panel A of Figure A.3, firms right across the exit boundary obtain highly tailored loans. As firms improve further, they obtain tailored loans from banks and as they improve yet more, they obtain vanilla loans from banks which are subsequently distributed.

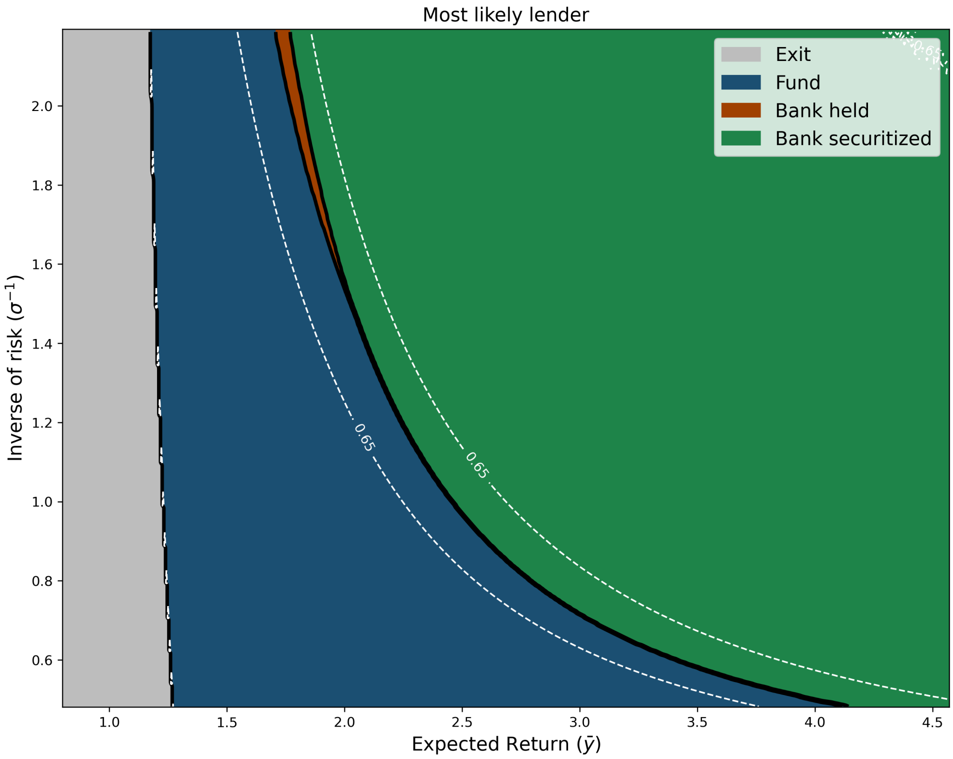


Figure 2: Optimal choice of the entrepreneur for each $(\bar{y}, \sigma)$. The x-axis reports firm expected output, $\bar{y}$, while the y-axis reports the inverse of its volatility, σ^{-1}.

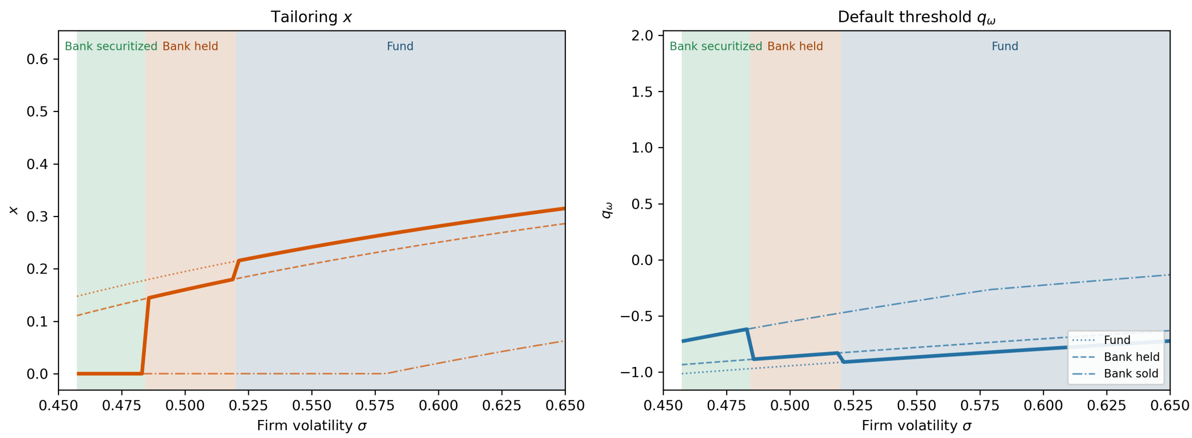


Figure 3: Dashed lines capture the optimal contract choice (q, x) for each lender for a firm with a certain output volatility σ, which varies on the x-axis. The solid line captures the actual contract choice, given the optimal lender choice for each firm.

Figure 3 illustrates the optimal contract choice for different firms, which are sorted by their underlying output volatility. Firms with low volatility choose vanilla loans, and still have a very low default threshold q. These firms find it optimal to borrow from banks, with a loan that ends up getting distributed. This is the cheapest form of borrowing, and these firms have little appetite for costly loan tailoring: very low-volatility firms would obtain vanilla loans even if they were forced to borrow from private credit. As firm volatility increases, their default probability goes up, and their latent demand for tailoring increases. At some point, firms find it optimal to choose a loan with more tailoring, that banks optimally retain on their balance sheet, even if this comes at a higher baseline cost. When firm volatility goes up further, firms choose to switch to private credit, with a high degree of tailoring which helps contain their default risk. In the counterfactual case where, absent private credit, high-volatility firms are forced to borrow from a bank, they would choose a lower degree of tailoring, as they incorporate that banks find tailoring costly to supply, and would thus end up with a higher default risk compared to their baseline scenario of borrowing from private credit.

Policy functions conditional on borrowing from one specific lender (in this case, the private credit fund) are reported in Figure A.2. We notice that as firms become more profitable and less risky they quickly reduce the optimal degree of tailoring x, and then gradually reduce the default threshold q. Figure A.3 reports the policies conditional on the optimal lender choice. We notice similar patterns as in Figure A.2, but also that some discontinuities emerge at the boundary where firms switch lenders. Moving from the top-right towards the origin, we see that firms initially borrow with vanilla loans with low q and thus low probability of default. As they move towards the origin, they gradually start to demand tailored loans ($x > 0$) as their default threshold increases. At some point, they find it optimal to get a loan that is retained on the bank's balance sheet, and at such boundary we observe a sharp increase in tailoring and a decline in the probability of default. A similar pattern occurs at the boundary where firms switch from bank-retained loans to private credit funds.

6.3 Model counterfactuals

In this section, we use our calibrated model to study two model counterfactuals. First, we study what happens in our model when bank capital requirements are removed, which highlights the interaction between capital requirements and lending technology already discussed in Section 6.1.1. Then, we study the social value created by private credit and its sources by analyzing a counterfactual economy with banks only.

6.3.1 Bank capital requirements and private credit

The first counterfactual we carry out is that of removing capital requirements on banks. As we explain next, this allows us to cleanly decompose the drivers of private credit within the model between capital constraints and lending technology.

Removing capital requirements on banks boils down to letting $\phi \to \infty$, which means that banks become financially unconstrained. This counterfactual is particularly informative in our model because it removes any differences between banks and private credit funds stemming from the liability side of these lenders' balance sheets. In this counterfactual, competition only operates through the primitive origination technologies $\{\tau_o^f, \tau_x^f\}$ and $\{\tau_o^b, \tau_x^b\}$, as well as the preference shock, which could be interpreted as an unexplained source of lender differentiation.

	Baseline	Counterfactual	Change
Fraction of firms			
Private credit	0.434	0.332	-0.102
Bank overall	0.566	0.668	+0.102
Bank retained	0.190	0.415	+0.225
Bank distributed	0.376	0.253	-0.123
Average x			
Private credit	0.438	0.472	+7.743%
Bank overall	0.040	0.082	+103.935%
Bank retained	0.120	0.132	+10.136%
Bank distributed	0.000	0.000	-21.569%
Average σ			
Private credit	1.177	1.211	+2.887%
Bank overall	0.889	0.917	+3.064%
Bank retained	0.925	0.947	+2.342%
Bank distributed	0.871	0.867	-0.446%
Average $\bar{y}$			
Private credit	2.093	2.039	-2.605%
Bank overall	3.118	2.988	-4.170%
Bank retained	2.852	2.817	-1.220%
Bank distributed	3.252	3.267	+0.468%

Table 10: This table shows the outcome of the model in the baseline calibration (left column), and in an alternative counterfactual calibration where bank capital requirements are removed (central column). The right column reports changes between the baseline and the counterfactual economy, reported in percentage points for the fraction of firms and in percentage change for the other statistics.

Table 10 delivers two main insights. First, in the counterfactual where we remove capital requirements on banks, lending by private credit shrinks by about a quarter. This suggests that a quarter of the size of private credit is explained by capital requirements alone. The remaining three quarters are explained by two forces. The first is the underlying lending technology and superior ability at originating tailored loans, as detected by the estimated parameters τ. The second is the unexplained preferences for different lenders, captured by the Gumbel preference shocks, which alone can push some firms to borrow from private credit. Importantly, capital requirements substantially affect the internal organization of bank loans, with bank loan retention jumping from about one third to two thirds in the absence of capital requirements.

The second crucial insight that emerges from Table 10 is that capital requirements do not just lead to a quantity shift between banks and private credit: they alter the selection of firms that borrow from private credit and the type of loans that banks can offer. Alongside the internal reorganization towards loan retention, banks are also able to extend substantially more tailored loans, with the average x more than doubling, and to expand their lending to riskier firms who have a higher appetite for such tailoring. This is consistent with the estimated parameters, whereby a meaningful portion of banks' disadvantage at loan tailoring stems from the distribution cost η, which loses relevance once capital constraints are removed, rather than from a fundamental technological disadvantage in τ_x^b. That is, banks' lending technology is not far from that of private credit lenders once we remove the capital constraint, which allows them to retain loans on their balance sheet at lower cost and avoid the η cost.

6.3.2 The social value of private credit

The counterfactual of removing private credit is straightforward to implement in the model. It is sufficient to solve an alternative problem of the firm with:

$$V = \max\{V_b^{distributed}, V_b^{retained}, 0\}$$

This allows us to derive what would happen to firms in the model absent private credit financing, thus answering the question of whether private credit simply substitutes bank lending or instead allows more firms to obtain financing.

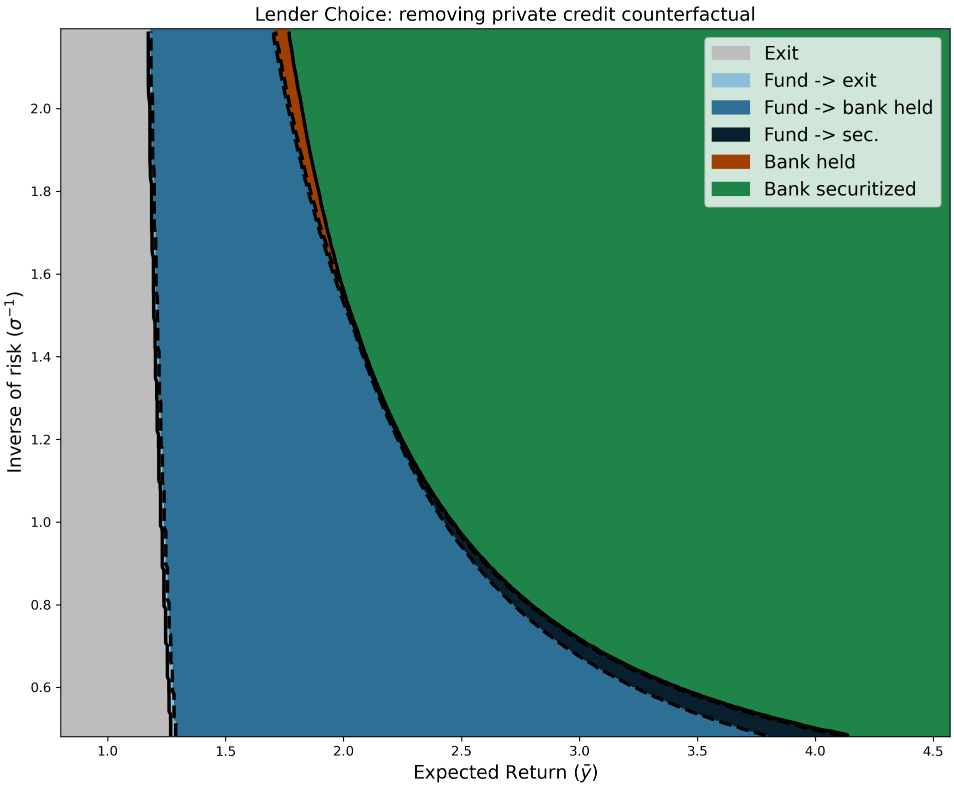


Figure 4: Optimal choice of the entrepreneur for each $(\bar{y}, \sigma)$. The x-axis reports firm expected output, $\bar{y}$, while the y-axis reports the inverse of its volatility, σ^{-1}.

We find that private credit funds primarily lend to firms that could obtain credit from banks, rather than providing credit to firms that would otherwise be excluded from credit markets. More precisely, about 99 percent of firms that borrow from a private credit fund would switch to banks if funds were not available. Of these, the vast majority would opt for a loan that banks choose to retain, consistently with private credit being in closest competition with bank retained and partially tailored loans. Instead, only around 1 percent of private credit borrowers would be forced to exit. This means that most firms borrow from private credit thanks to the value they obtain from receiving a tailored contract.

Table 11: Counterfactual financing regime for private credit borrowers

Exit	Bank retained	Bank distributed
0.97%	95.73%	3.30%

Table 12 shows that, within the model, the vast majority of welfare gains generated by private credit lenders occur through switchers—firms that funds attract from banks thanks to their ability to offer tailored solutions more affordably. Only a fraction of the welfare gains occur through firms that are only able to get funding thanks to private credit and would otherwise exit.

Table 12: Counterfactual aggregate change in consumption and decomposition of the two drivers

	Total	= Entrants	+ Switchers
Consumption	0.208%	0.003%	0.205%
of which, operating through:			
Gross output	0.360%	0.360%	–
Investment costs	-0.302%	-0.302%	–
Bankruptcy losses	0.436%	-0.010%	0.446%
Tailoring costs	-0.172%	-0.043%	-0.129%
Origination costs	-0.114%	-0.002%	-0.112%

7 Conclusion

Private credit and bank regulation are often viewed through separate lenses: regulation determines where credit is intermediated, while differences in lending technology determine the contracts borrowers receive. This paper shows that these two margins are jointly determined. When tailored loans are more difficult to distribute, bank capital requirements disproportionately raise the cost of providing tailored lending. Banks consequently shift toward standardized, distributable contracts, widening private credit's comparative advantage in serving borrowers that place greater value on state-contingent financing.

The empirical evidence supports the key margins of this mechanism. Within bank lending, more state-contingent loans are less likely to be distributed, while conditional on deal size and structure, state-contingent contracts are relatively more prevalent in private credit. Lower-profitability and more volatile firms are more likely to borrow from private credit, and among bank borrowers greater volatility is associated with more tailored and less distributable lending. Exploiting the introduction of the enhanced supplementary leverage ratio, we further find that affected G-SIBs reduce the use of pricing grids and financial covenants, with loan distribution moving in the direction predicted by the model.

Quantitatively, the interaction between regulation and lending technology is important. Removing bank capital requirements reduces private credit lending by roughly one quarter and more than doubles average tailoring among bank loans. Conversely, when private credit is removed, most private credit borrowers obtain bank financing rather than exit. The welfare gains from private credit therefore arise primarily from providing more suitable contracts to firms that could otherwise borrow from banks, rather than from expanding credit access. More broadly, the results show that bank regulation affects not only how much credit banks provide or where lending migrates, but also the types of contracts that competing intermediaries can offer.

References

Acharya, Viral V, Heitor Almeida, and Murillo Campello. 2013. "Aggregate risk and the choice between cash and lines of credit." *The Journal of Finance* 68 (5):2059–2116.

Avalos, Fernando, Sebastian Doerr, and Gabor Pinter. 2025. "The global drivers of private credit." *BIS Quarterly Review* :13.

Becker, Bo and Victoria Ivashina. 2016. "Covenant-light contracts and creditor coordination." Tech. rep., Sveriges Riksbank working paper series.

Begenau, Juliane and Tim Landvoigt. 2022. "Financial regulation in a quantitative model of the modern banking system." *The Review of Economic Studies* 89 (4):1748–1784.

Blickle, Kristian, Quirin Fleckenstein, Sebastian Hillenbrand, and Anthony Saunders. 2026. "Do Lead Arrangers Retain Their Lead Share?" *Journal of Finance* Forthcoming.

Block, Joern, Young Soo Jang, Steven N Kaplan, and Anna Schulze. 2024. "A survey of private debt funds." *The Review of Corporate Finance Studies* 13 (2):335–383.

Boot, Arnoud WA and Anjan V Thakor. 2000. "Can relationship banking survive competition?" *The Journal of Finance* 55 (2):679–713.

Bozanic, Zahn, Maria Loumioti, and Florin P Vasvari. 2018. "Corporate loan securitization and the standardization of financial covenants." *Journal of Accounting Research* 56 (1):45–83.

Chernenko, Sergey, Isil Erel, and Robert Prilmeier. 2022. "Why do firms borrow directly from nonbanks?" *The Review of Financial Studies* 35 (11):4902–4947.

Chernenko, Sergey, Robert Ialenti, and David Scharfstein. 2025. "Bank capital and the growth of private credit." *Available at SSRN* 5097437.

Davydiuk, Tetiana, Isil Erel, Wei Jiang, and Tatyana Marchuk. 2024. "Common investors across the capital structure: Private debt funds as dual holders." *Johns Hopkins Carey Business School Research Paper* (25-17).

Davydiuk, Tetiana, Tatyana Marchuk, and Samuel Rosen. 2024. "Market discipline in the direct lending space." *The Review of Financial Studies* 37 (4):1190–1264.

DeMarzo, Peter and Darrell Duffie. 1999. "A liquidity-based model of security design." *Econometrica* 67 (1):65–99.

DeMarzo, Peter M. 2005. "The pooling and tranching of securities: A model of informed intermediation." *The Review of Financial Studies* 18 (1):1–35.

Diamond, Douglas W and Raghuram G Rajan. 2000. “A theory of bank capital.” *the Journal of Finance* 55 (6):2431–2465.

Drucker, Steven and Manju Puri. 2009. “On loan sales, loan contracting, and lending relationships.” *The Review of Financial Studies* 22 (7):2835–2872.

Erel, Isil and Eduard Inozemtsev. 2025. “Evolution of debt financing toward less-regulated financial intermediaries in the United States.” *Journal of Financial and Quantitative Analysis* 60 (3):1234–1271.

Fang, Chuck and Greg Nini. 2026. “Go with the flow: Debt structure changes and monetary policy transmission.” *Available at SSRN 4937970* .

Gorton, Gary B and George G Pennacchi. 1995. “Banks and loan sales marketing nonmarketable assets.” *Journal of monetary Economics* 35 (3):389–411.

Holmström, Bengt and Jean Tirole. 1998. “Private and public supply of liquidity.” *Journal of political Economy* 106 (1):1–40.

Irani, Rustom M, Rajkamal Iyer, Ralf R Meisenzahl, and Jose-Luis Peydro. 2021. “The rise of shadow banking: Evidence from capital regulation.” *The Review of Financial Studies* 34 (5):2181–2235.

Ivashina, Victoria. 2025. “Private Credit: What Do We Know?” *Unpublished Working Paper* .

Jang, Young Soo. 2025. “Are Direct Lenders More Like Banks or Arm’s-Length Investors?” *Unpublished Working Paper* .

Jang, Young Soo, Dasol Kim, and Amir Sufi. 2025. “The Lending Technology of Direct Lenders in Private Credit.” Tech. rep., National Bureau of Economic Research.

Kashyap, Anil K, Raghuram Rajan, and Jeremy C Stein. 2002. “Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking.” *The Journal of Finance* 57 (1):33–73.

Matvos, Gregor, Tomasz Piskorski, and Amit Seru. 2026. “Private Credit, Balance Sheets and Financial Stability.” Tech. rep., National Bureau of Economic Research.

Parlour, Christine A and Guillaume Plantin. 2008. “Loan sales and relationship banking.” *The Journal of Finance* 63 (3):1291–1314.

Rintamäki, Paul and Sascha Steffen. 2025. “Pik now and pay later-how deferred interest reshapes private credit.” *Available at SSRN* 5341145.

Robinson, David T and Melanie Wallskog. 2025. “Why is Private Lending So Popular?” *Working Paper* .

A Data Appendix

We have two main data sources: DealScan for bank loans and 10-K data for BDCs, taken from Robinson and Wallskog (2025). For both of these data sources, we focus on deals at origination made to corporate borrowers.

A.1 Additional Empirical Results

Table A.1: GSIBs decrease tailoring when capital requirements become stricter

Dep Var:	Likely distributed		1+ credit lines		1+ pricing grids		1+ financial covenants		1+ term loan Bs	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
GSIB × 2014-2017	0.087	0.022	0.064*	-0.050	-0.038**	-0.069*	-0.045***	-0.062	-0.011	0.014
	(0.072)	(0.088)	(0.029)	(0.028)	(0.013)	(0.033)	(0.013)	(0.036)	(0.016)	(0.016)
GSIB × 2018-2019	0.152*	0.073	0.054	-0.078	-0.134***	-0.197***	-0.111**	-0.152**	-0.014	0.009
	(0.076)	(0.047)	(0.052)	(0.074)	(0.040)	(0.049)	(0.040)	(0.054)	(0.028)	(0.045)
Year FEs	x	x	x	x	x	x	x	x	x	x
Lender Parent FEs	x	x	x	x	x	x	x	x	x	x
Lender FEs	x	x	x	x	x	x	x	x	x	x
Value Pctl FEs	x	x	x	x	x	x	x	x	x	x
# Tranche FEs	x	x	x	x	x	x	x	x	x	x
Borrower FEs		x		x		x		x		x
N	10,260	5,371	10,260	5,371	10,260	5,371	10,260	5,371	10,260	5,371
Mean(Dep var)	0.71	0.80	0.70	0.71	0.17	0.23	0.17	0.23	0.13	0.15

Notes: This table presents estimates from difference-in-difference regressions, where the treatment variable is an indicator for the deal lead's (i.e., the "lender"'s) parent bank being a GSIB and the two post periods being after the increased caplital requirements are announced by not enforced (2014-2017) and after the requirements are enforced (2018-2019).

Sample: bank deals between 2010 and 2019 in which the deal lead's parent is ever subject to SLR (as a GSIB or not).

Dependent variables: (1) Indicator variable for whether the predicted holding shares of the lead arranger is below half, where the value is the value-weighted mean across tranches; indicators for the deal featuring any (2) credit lines, (3) pricing grids, (4) financial covenants, and (5) term loan Bs.

* for p<.10, ** for p<.05, and *** for p<.01. SEs clustered at firm level. Constants omitted.

Table A.2: Credit lines, pricing grids, and financial covenants are used in low-TLB deals

Dep Var:	1+ Term Loan Bs				Share of tranche value in TLBs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
+1 credit lines	-0.020			-0.018	-0.045**			-0.043**
	(0.021)			(0.021)	(0.019)			(0.019)
+1 pricing grids		-0.084***		-0.053**		-0.060***		-0.039***
		(0.017)		(0.017)		(0.011)		(0.011)
1+ financial covenants			-0.080***	-0.043**			-0.056***	-0.028***
			(0.016)	(0.014)			(0.009)	(0.008)
Year FEs	x	x	x	x	x	x	x	x
Lender Parent FEs	x	x	x	x	x	x	x	x
Lender FEs	x	x	x	x	x	x	x	x
Value Pctl FEs	x	x	x	x	x	x	x	x
# Tranche FEs	x	x	x	x	x	x	x	x
N	10,260	10,260	10,260	10,260	10,260	10,260	10,260	10,260
Mean(Dep var)	0.13	0.13	0.13	0.13	0.09	0.09	0.09	0.09

Notes: This table presents correlates of the presence and value share of TLBs in deals with other deal features.
* for p<.10, ** for p<.05, and *** for p<.01. SEs clustered at firm level. Constants omitted. Table A.3 presents a robust version of these results without controlling for the number of tranches, as doing so builds in a mechanical negative correlation between types of tranches (i.e., conditional on only have 1 tranche, if that tranche is a credit line, there cannot also be a term loan B).

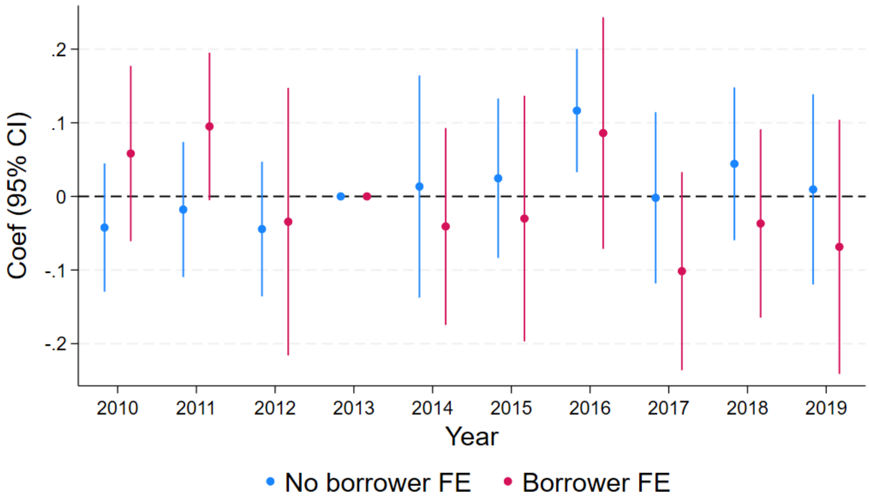
Table A.3: Credit lines, pricing grids, and financial covenants are used in low-TLB deals: Robustness (no tranche count fixed effects)

Dep Var:	1+ Term Loan Bs				Share of tranche value in TLBs			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
+1 credit lines	-0.022			-0.017	-0.056**			-0.051*
	(0.026)			(0.026)	(0.025)			(0.024)
+1 pricing grids		-0.087***		-0.056***		-0.079***		-0.052***
		(0.018)		(0.017)		(0.015)		(0.012)
1+ financial covenants			-0.080***	-0.040**			-0.072***	-0.031***
			(0.016)	(0.014)			(0.014)	(0.009)
Year FEs	x	x	x	x	x	x	x	x
Lender Parent FEs	x	x	x	x	x	x	x	x
Lender FEs	x	x	x	x	x	x	x	x
Value Pctl FEs	x	x	x	x	x	x	x	x
# Tranche FEs								
N	10,260	10,260	10,260	10,260	10,260	10,260	10,260	10,260
Mean(Dep var)	0.13	0.13	0.13	0.13	0.09	0.09	0.09	0.09

Notes: This table presents correlates of the presence and value share of TLBs in deals with other deal features, without controling for the number of tranches.
* for p<.10, ** for p<.05, and *** for p<.01. SEs clustered at firm level. Constants omitted.

Figure A.1: GSIB deals become less state-contingent as capital requirements strengthen

(a) 1+ credit lines



This figure presents estimates from event study model (14), where the treatment variable is an indicator for the deal lead's (i.e., the "lender's") parent bank being a GSIB and the two post periods being after the increased capital requirements are announced but not enforced (2014-2017) and after the requirements are enforced (2018-2019).

B Theory

B.1 Detailed Bank Problem

Consider a bank lending to firm i with contract C. The bank chooses equity e, debt b, the amount of loans originated L_0, and the fraction $z \in [0,1]$ of originated loans that it distributes. The remaining fraction $1 - z$ is retained on balance sheet. The bank solves

$$\max_{e,b,L_o,z} \quad -(1+\lambda_e)e + \beta E[(1-z)f(y,C)L_o - b]$$

$$\text{s.t.} \quad \underbrace{(1 + C_o^b(x))L_o}_{\text{origination}} - \underbrace{z\big(q^i(C) - C_s(x)\big)L_o}_{\text{loan distribution}} = e + q_b b \qquad \textit{(budget)}$$

$$(1-z)L_o \leq \phi e \qquad \textit{(leverage constraint)}$$

In this Section, we show that the bank problem is scale-invariant, which combined with free-entry implies a zero-profit condition (or otherwise banks would choose infinite size and make infinite profits).

Proposition 0: *The problem of the bank is scale-invariant and proportional to L_0. For any choice of bank size L_0, the bank makes zero profit when offering a contract (R,x) to a firm*

$(\bar{y}, \sigma)$ *under the following condition:*

$$\underbrace{1 + \lambda_e \frac{(1-z)}{\phi}}_{\textit{cost of funds}} + \underbrace{C_o^b(x)}_{\textit{origination cost}} + \underbrace{C_s(x)z}_{\textit{resale cost}} = \beta E\left[M_1 f(y, R, x)\right]$$

Proof:

First, we need to show that the leverage constraint always binds. Suppose by contradiction that it does not bind. Then, we can show that the value of the bank can be improved by reducing e by one unit and increasing b by q_b^{-1} units. This leaves time-0 budget unchanged. Reduces cash-flows tomorrow by q_b^{-1}, which reduces bank value by $\beta E[M_1]q_b^{-1} = 1$. But reducing equity by 1 increases bank value by $1 + \lambda_e$. C.V.D.

Now, we can write $e = \frac{(1-z)}{\phi} L_0$.

From time-0 budget, we can write b as:

$$\begin{aligned}
q_b b &= \underbrace{L_o(1 - zq_l)}_{\text{retained loans}} + \underbrace{C_o^b(x)L_o}_{\text{origination costs}} + \underbrace{C_s(x)zL_o}_{\text{resale costs}} - \underbrace{e}_{\text{equity}} \\
&= \underbrace{L_o(1 - zq_l)}_{\text{retained loans}} + \underbrace{C_o^b(x)L_o}_{\text{origination costs}} + \underbrace{C_s(x)zL_o}_{\text{resale costs}} - \frac{(1-z)L_0}{\phi} \\
&= L_0\Big[\underbrace{(1 - zq_l)}_{\text{retained loans}} + \underbrace{C_o^b(x)}_{\text{origination costs}} + \underbrace{C_s(x)z}_{\text{resale costs}} - \frac{(1-z)}{\phi}\Big] \qquad \text{(A.1)}
\end{aligned}$$

That is:

$$b = L_0 \frac{\left[(1 - zq_l) + C_o^b(x) + C_s(x)z - \frac{(1-z)}{\phi}\right]}{q_b} \qquad \text{(A.2)}$$

But then we can rewrite bank problem as follows.

$$\max L_0\left[\underbrace{-(1+\lambda_e)\frac{(1-z)}{\phi}}_{\text{equity issuance}} + \beta E\Big[M_1\big[\underbrace{(1-z)f(y,R,x)}_{\text{retained loans}} - \underbrace{\frac{(1 - zq_l) + C_o^b(x) + C_s(x)z - \frac{(1-z)}{\phi}}{q_b}}_{\text{borrowing}}\big]\Big]\right]$$

Which is scale invariant!

Bank zero-profit condition

We can simplify bank profits by noticing that the borrowing term is non-stochastic and that $q_b = \beta E[M_1]$.

Therefore:

$$\max L_0\left[\underbrace{-(1+\lambda_e)\frac{(1-z)}{\phi}}_{\text{equity issuance}}+\beta E\Big[M_1\big[\underbrace{(1-z)f(y,R,x)}_{\text{retained loans}}\big]\Big]\underbrace{-\big[(1-zq_l)+C_o^b(x)+C_s(x)z-\frac{(1-z)}{\phi}\big]}_{\text{borrowing}}\right]$$

Either profits are infinite and L_0 is infinite, or we get a well-defined zero-profit condition:

$$\underbrace{-(1+\lambda_e)\frac{(1-z)}{\phi}}_{\text{equity issuance}}+\beta E\Big[M_1\big[\underbrace{(1-z)f(y,R,x)}_{\text{retained loans}}\big]\Big]\underbrace{-\big[(1-zq_l)+C_o^b(x)+C_s(x)z-\frac{(1-z)}{\phi}\big]}_{\text{borrowing}}=0$$

Which we can rearrange as:

$$\underbrace{\lambda_e\frac{(1-z)}{\phi}}_{\text{equity issuance}}+\underbrace{\big[(1-zq_l)+C_o^b(x)+C_s(x)z\big]}_{\text{borrowing}}=\beta E\Big[M_1\big[\underbrace{(1-z)f(y,R,x)}_{\text{retained loans}}\big]\Big]$$

That is:

$$\underbrace{1+\lambda_e\frac{(1-z)}{\phi}}_{\text{cost of funds}}+\underbrace{C_o^b(x)}_{\text{origination cost}}+\underbrace{C_s(x)z}_{\text{resale cost}}=\underbrace{zq_l}_{\text{sold loans}}+\beta E\Big[M_1\big[\underbrace{(1-z)f(y,R,x)}_{\text{retained loans}}\big]\Big]$$

Now recall from bond loan pricing that:

$$q_l=\beta E\Big[M_1\big[f(y,R,x)\big]\Big]$$

Therefore, the **bank zero profit loan pricing condition is**:

$$\underbrace{1+\lambda_e\frac{(1-z)}{\phi}}_{\text{cost of funds}}+\underbrace{C_o^b(x)}_{\text{origination cost}}+\underbrace{C_s(x)z}_{\text{resale cost}}=\beta E\big[M_1 f(y,R,x)\big]$$

B.1.1 Proof of Corollary to Proposition 1

Corollary: *The bank's optimal securitization choice z for contract C takes the following corner solution:*

$$z(C)=\begin{cases}1 & \text{if} \quad x\le C_s^{-1}(\lambda_e/\phi)\\ 0 & \text{if} \quad x> C_s^{-1}(\lambda_e/\phi)\end{cases} \tag{A.3}$$

That is, banks retain sufficiently complex loans, with a threshold increasing in their balance sheet constraint λ_e/ϕ. We can therefore rewrite the upper-envelope of zero-profit condition offered by banks as:

$$1 + C_o^b(x) + \min\{\frac{\lambda_e}{\phi}, C_s(x)\} = \beta E^i\left[f(y, C)\right] \tag{A.4}$$

Proof:

Notice that the bank zero profit condition is a function $g(z, R, x) = 0$. It implicitly defines a function $R(z, x)$. Now, for each x, the relevant portion of the g function is the upper envelope w.r.t. z. That is, if a firm wants a loan with complexity x, they do not care whether the loan is distributed or not, i.e., z does not affect the firm's payoff. Therefore, the firm will simply pick the z that minimizes R given x. $g(z, R, x) = 0$ implies that there are other zero-profit combinations that banks could offer with suboptimal securitization choice, but they are irrelevant in equilibrium.

Lender's payoff f must be increasing in R at the optimum.[15] Therefore, the lower R is achieved by choosing z to minimize the LHS (given x).

$$\min -z\frac{\lambda_e}{\phi} + C_s^b(x)z$$

We get the following bang-bang solution:

- keep on balance sheet ($z = 0$) if the loan is sufficiently complex $C_s^b(x) > \frac{\lambda_e}{\phi}$
- securitize the loan ($z = 1$) if the loan is sufficiently vanilla $C_s^b(x) \leq \frac{\lambda_e}{\phi}$

Where notice that the securitization threshold captures how leverage-constrained the bank is, highlighting the trade-off between securitization costs and equity capital cost. A higher equity issuance cost λ_e or a tighter leverage constraint ϕ pushes the bank towards more securitization.

B.2 Proof of Proposition 2

Proposition 2: *The interior optimum default threshold ω when borrowing from a lender with tailoring cost c_x solves:*

$$\underbrace{c_x\left(-Y'(\omega)\right)}_{\text{tailoring costs}} = \underbrace{B'(\omega)}_{\text{bankruptcy costs}} \tag{9}$$

Proof:

Recall the problem of a firm borrowing from a lender $\{c_o, c_x\}$.

$$\max_{\omega, x} \quad (1 - x)\,\bar{y}\,Y(\omega)$$

[15] Notice that f may not be globally increasing in R, as higher R increases repayment in survival regions but also enlarges the default region. However, for any optimal contract, f must be increasing in R. If not, we could achieve a Pareto improvement by lowering R and raising the values for both the lender and the entrepreneur.

$$\text{s.t.} \quad \beta^{-1}(1+c_o) = [\underbrace{1 - Y(\omega) - B(\omega)}_{\text{vanilla loan net payoff}} + \underbrace{(1-c_x)xY(\omega)}_{\text{equity stake net payoff}}]\,\bar{y}$$

$$\omega \geq 0, \quad 0 \leq x \leq 1$$

The first order conditions for an interior solution read as follows:

$$x \; : \; -Y(\omega) + \lambda\,(1-c_x)Y(\omega) = 0$$

$$\omega \; : (1-x)Y'(\omega) + \lambda[-Y'(\omega) - B'(\omega) + (1-c_x)xY'(\omega)] = 0$$

$$\lambda \; : \; 1 - Y(\omega) - B(\omega) + (1-c_x)xY(\omega) = (1+c_o)/(\beta\bar{y})$$

The FOC for x simplifies to: $\lambda = 1/(1-c_x)$. This simply captures the fact that, when $x > 0$, the firm is effectively issuing equity through the lender at cost c_x, which pins down the shadow value of equity λ.

We can plug the FOC-x into the FOC-ω, and get:

$$(1-c_x)(1-x)Y'(\omega) + [-Y'(\omega) - B'(\omega) + (1-c_x)xY'(\omega)] = 0$$

Which, once rearranged, delivers Equation (9).

B.2.1 Proof of Corollary to Proposition 2

Corollary to Proposition 2: *The optimality condition in Equation (9) characterizing the interior optimum default threshold can be rewritten as:*

$$\underbrace{\frac{\varphi(q)}{1-\Phi(q)}}_{\text{survival hazard}} = \frac{c_x}{\delta}\sigma \tag{10}$$

where φ and Φ are the standard normal PDF and CDF, and q is the standardized default threshold: $q \equiv \frac{\ln\omega-\mu}{\sigma} = \frac{\ln\omega+\frac{1}{2}\sigma^2}{\sigma}$.

Proof:

Let us start from Equation (9):

$$c_x\,(-Y'(\omega)) = B'(\omega)$$

Where recall the definitions of $Y(\omega)$ and $B(\omega)$.

$$Y(\omega) \equiv \mathbb{E}[(\tilde{\omega}-\omega)\mathbf{1}\{\tilde{\omega} \geq \omega\}] = \int_{\omega} (\tilde{\omega}-\omega)\,f(\tilde{\omega})d\tilde{\omega}$$

$$B(\omega) \equiv \delta\,\mathbb{E}[\tilde{\omega}\,\mathbf{1}\{\tilde{\omega} < \omega\}] = \int^{\omega} \tilde{\omega}f(\tilde{\omega})d\tilde{\omega}$$

Where f and F denote the PDF and CDF of ω. Using Leibniz' rule,

$$Y'(\omega) = -\underbrace{\mathbb{P}(\tilde{\omega} \geq \omega)}_{\text{survival probability}} = -(1 - F(\omega)),$$

$$B'(\omega) = \delta \underbrace{\omega f(\omega)}_{\text{threshold} \times \text{density}}.$$

Plugging these into (9) we obtain:

$$c_x \underbrace{(1 - F(\omega))}_{\text{survival prob.}} = \delta \underbrace{\omega f(\omega)}_{\text{threshold} \times \text{density}}. \tag{A.5}$$

Notice that what matters for tailoring costs is the CDF, while what matters for the bankruptcy costs is the PDF. Intuitively, the benefit from reducing tailoring costs scales with c_x and with the survival probability, as a higher survival probability increases the value of the equity stake. Instead, the cost of increasing bankruptcy costs scales with δ and is increasing in $\omega f(\omega)$, as at the margin we increase the probability of default by $f(\omega)$ and it induces a cost $\delta\omega$.

We can also rearrange Equation (A.5) as follows:

$$\underbrace{\frac{\omega f(\omega)}{1 - F(\omega)}}_{\substack{\text{survival hazard at } \omega \\ \text{scaled by } \omega}} = \frac{c_x}{\delta} \tag{A.6}$$

Note that all the above derivations to obtain Equations (9) and (A.5) do not depend on the distribution of $\tilde{\omega}$. We now make use of the log-normality of $\tilde{\omega}$ to further specialize Equation (A.6). To do so, define q as the standardized version of ω:

$$q \equiv \frac{\ln \omega - \mu}{\sigma} = \frac{\ln \omega + \frac{1}{2}\sigma^2}{\sigma}.$$

Then

$$1 - F(\omega) = \underbrace{1 - \Phi(q)}_{\bar{\Phi}(q)}, \qquad f(\omega) = \frac{1}{\omega\sigma}\varphi(q),$$

so (A.5) becomes

$$c_x \, \bar{\Phi}(q) = \delta \, \omega \cdot \frac{1}{\omega\sigma}\varphi(q)$$

Therefore, the cutoff for q (and thus ω) is pinned down by:

$$\underbrace{\frac{\varphi(q)}{1 - \Phi(q)}}_{\text{survival hazard}} = \frac{c_x}{\delta}\,\sigma \tag{10}$$

B.3 Proof of Proposition 3

Proposition 3 (Optimal tailoring and firm quality). *Conditional on a financing option* $\{c_o, c_x\}$*, suppose the optimal contract is interior,* $0 < x^* < 1$*. Then:*

1. *Optimal tailoring is strictly decreasing in expected output:*

$$\frac{\partial x^*}{\partial \bar{y}} < 0.$$

2. *Under the risk-regularity Assumption 1, optimal tailoring is strictly increasing in volatility:*

$$\frac{\partial x^*}{\partial \sigma} > 0.$$

Proof.

Step 1. Writing x. Recall the optimal interior choice for tailoring from Equation (11), now written with an explicit dependence on firm characteristics $(\bar{y}, \sigma)$:

$$x(\bar{y}, \sigma; \omega) = \frac{\frac{A}{\bar{y}} - L(\sigma; \omega)}{(1 - c_x)Y(\sigma; \omega)}$$

where $A = \frac{1+c_o}{\beta}$, which corresponds to $S\bar{y}$ in the notation of Equation (11).

Denote by $\omega^*(\sigma)$ the solution for ω implied by Proposition 2, which recall does not depend on $\bar{y}$. Denote the values of Y at the optimal choice of ω as $Y^*(\sigma) = Y(\sigma, \omega^*(\sigma))$, and similarly for $L^*(\sigma)$.

We can then rewrite Equation (11) as:

$$x^*(\bar{y}, \sigma) = \frac{\frac{A}{\bar{y}} - L^*(\sigma)}{(1 - c_x)Y^*(\sigma)} \tag{A.7}$$

Step 2. Expected output. Differentiating (A.7) by $\bar{y}$ gives the first result directly:

$$\frac{\partial x^*}{\partial \bar{y}} = -\frac{A}{\bar{y}^2(1 - c_x)Y^*} < 0 \tag{A.8}$$

Thus the interior degree of tailoring falls strictly with expected output.

Notice that, given σ, we can write the threshold for a vanilla loan as $y(\sigma) = A/L^*(\sigma)$. Therefore, higher $\bar{y}$ firms become vanilla sooner, and so we could extend the proposition also in the vanilla region by simply making the inequality weak rather than strong.

Step 3a. Volatility, get x^*_σ. Now hold $\bar{y}$ fixed and differentiate (A.7) with respect to σ:

$$\frac{\partial x^*}{\partial \sigma} = \frac{-L^*_\sigma(1 - c_x)Y^* - (A/\bar{y} - L^*)(1 - c_x)Y^*_\sigma}{(1 - c_x)^2(Y^*)^2}$$

Using (A.7), we can write $(A/\bar{y} - L^*) = x^*(1-c_x)Y^*$, and thus:

$$\begin{aligned}\frac{\partial x^*}{\partial \sigma} &= \frac{-L^*_\sigma(1-c_x)Y^* - x^*(1-c_x)Y^*(1-c_x)Y^*_\sigma}{(1-c_x)^2(Y^*)^2} \\ &= \frac{-L^*_\sigma - x^*(1-c_x)Y^*_\sigma}{(1-c_x)(Y^*)}\end{aligned} \tag{A.9}$$

The last, more involved, step is to show that $L^*_\sigma < 0$ is a sufficient condition for $\frac{\partial x^*}{\partial \sigma} > 0$.

To study the sign of L^* and Y^*, recall that these are total derivatives along the optimal choice of ω^*. It is thus useful to rewrite them fully as $Y(\sigma, \omega)$. In particular, we get:

$$Y^*_\sigma = \frac{\partial Y}{\partial \sigma} + \frac{\partial Y}{\partial \omega^*}\frac{\partial \omega^*}{\partial \sigma}$$

And similarly for L^*.

Step 3b. Volatility, get ω^*_σ. To get $\frac{\partial \omega^*}{\partial \sigma}$, recall that the optimal-default-threshold q from Proposition 2, omitting q^* notation for convenience, is

$$\underbrace{\frac{\varphi(q)}{1-\Phi(q)}}_{h(q)} = \frac{c_x}{\delta}\sigma. \tag{A.10}$$

where, as per our usual notation, $q = \frac{log\omega + \sigma^2/2}{\sigma}$.

We can obtain q_σ, and thus $\frac{\partial \omega^*}{\partial \sigma}$, by using the implicit function theorem on (A.10), which yields:

$$h'(q)q_\sigma = \frac{c_x}{\delta}$$

and thus:

$$q_\sigma = \frac{c_x}{\delta h'(q)}$$

Using the derivative of the Mill's ratio $h'(q) = h(q)[h(q) - q]$, and denoting for simplicity $m(q) = h(q) - q$, we can write q_σ as:

$$q_\sigma = \frac{c_x}{\delta h(q) m(q)} = \frac{1}{\sigma m(q)}$$

Since $\omega = exp\Big(\sigma q - \frac{\sigma^2}{2}\Big)$, we get:

$$\begin{aligned}\omega^*_\sigma &= exp\Big(\sigma q - \frac{\sigma^2}{2}\Big)\Big(\sigma q_\sigma + q - \sigma\Big) \\ &= \omega^*\Big(\frac{1}{m(q)} + q - \sigma\Big)\end{aligned} \tag{A.11}$$

So we now obtained ω^*_σ.

Step 3c. Volatility, get Y^*_σ. Under the log-normal assumptions of the paper, we can write Y as follows:

$$Y(\sigma,\omega) = \bar{\Phi}(q-\sigma) - \omega\bar{\Phi}(q)$$

where $\bar{\Phi}(q) = 1 - \Phi(q)$ is the complement of the normal CDF, and so $\bar{\Phi}'(q) = -\varphi(q)$. Taking the total derivative of Y by σ yields:

$$Y^*_\sigma = -\varphi(q-\sigma)[q_\sigma - 1] - \omega^*_\sigma\bar{\Phi}(q) + \omega\varphi(q)q_\sigma$$

A useful property of lognomal variables is that: $\varphi(q-\sigma) = \omega^*\varphi(q)$. Therefore, the q_σ terms simplify and we get:

$$Y^*_\sigma = \omega^*\varphi(q) - \omega^*_\sigma\bar{\Phi}(q)$$

Now plug in ω^*_σ from Step 3b:

$$Y^*_\sigma = \omega^*\varphi(q) - \omega^*\Big(\frac{1}{m(q)} + q - \sigma\Big)\bar{\Phi}(q)$$

By the definition of $h(q)$, we can write $\varphi(q) = h(q)\bar{\Phi}(q)$, and collect $\bar{\Phi}(q)$ as follows:

$$Y^*_\sigma = \omega^*\bar{\Phi}(q)\Big[h(q) - \frac{1}{m(q)} - q + \sigma\Big]$$

Using our definition of $m(q) = h(q) - q$, we finally get:

$$Y^*_\sigma = \omega^*\bar{\Phi}(q)\Big[m(q) - \frac{1}{m(q)} + \sigma\Big] \tag{A.12}$$

Step 3d. Volatility, get L^*_σ. As for Y, we can leverage our log-normal assumption to write L as follows:

$$L(\sigma,\omega) = \omega\bar{\Phi}(q) + (1-\delta)\Phi(q-\sigma)$$

As in Step 3c, take the total derivative L^*_σ (drop * for convenience).

$$L^*_\sigma = \omega_\sigma\bar{\Phi}(q) - \omega\varphi(q)q_\sigma + (1-\delta)\varphi(q-\sigma)[q_\sigma - 1]$$

Using again as in 3c $\varphi(q-\sigma) = \omega^*\varphi(q)$, we get:

$$\begin{aligned} L^*_\sigma &= \omega_\sigma\bar{\Phi}(q) - \omega\varphi(q)q_\sigma + (1-\delta)\omega^*\varphi(q)[q_\sigma - 1] \\ &= \omega_\sigma\bar{\Phi}(q) - \delta\omega\varphi(q)q_\sigma - (1-\delta)\omega\varphi(q) \end{aligned}$$

Next, collect $\omega\bar{\Phi}(q)$, to obtain:

$$L_\sigma^* = \omega\bar{\Phi}(q)\left[\frac{\omega_\sigma}{\omega} - \delta\frac{\varphi(q)}{\bar{\Phi}(q)}q_\sigma - (1-\delta)\frac{\varphi(q)}{\bar{\Phi}(q)}\right]$$
$$= \omega\bar{\Phi}(q)\left[\frac{\omega_\sigma}{\omega} - \delta h(q)q_\sigma - (1-\delta)h(q)\right]$$

Now recall from Step 3b that $\frac{\omega_\sigma}{\omega} = \left(\frac{1}{m(q)} + q - \sigma\right)$ and $q_\sigma = \frac{1}{\sigma m(q)}$.
Therefore,

$$L_\sigma^* = \omega\bar{\Phi}(q)\left[\frac{1}{m(q)} + q - \sigma - \delta\frac{h(q)}{\sigma m(q)} - (1-\delta)h(q)\right]$$

Now recall that we are along the optimal q and ω (even though we omitted the *), therefore we can use the FOC for q: $h(q) = \frac{c_x}{\delta}\sigma$, yielding:

$$L_\sigma^* = \omega\bar{\Phi}(q)\left[\frac{1}{m(q)} + q - \sigma - \frac{c_x}{m(q)} - (1-\delta)h(q)\right]$$

Merge the $\frac{1}{m(q)}$, and use the definition of $m(q)$ to substitute $q = h(q) - m(q)$, to get:

$$L_\sigma^* = \omega\bar{\Phi}(q)\left[\frac{1-c_x}{m(q)} + h(q) - m(q) - \sigma - (1-\delta)h(q)\right]$$
$$= \omega\bar{\Phi}(q)\left[\frac{1-c_x}{m(q)} - m(q) - \sigma + \delta h(q)\right]$$

Finally, the FOC for q also implies: $\delta h(q) = c_x\sigma$. Therefore we get:

$$L_\sigma^* = \omega\bar{\Phi}(q)\left[(1-c_x)\left(\frac{1}{m(q)} - \sigma\right) - m(q)\right] \tag{A.13}$$

which is our final expression for L_σ^*.

Step 3e. Volatility, merge Y_σ^* and L_σ^*. Recall from Step 3b that we are trying to find the sign of Equation (A.9):

$$\frac{\partial x^*}{\partial\sigma} = \frac{-L_\sigma^* - x^*(1-c_x)Y_\sigma^*}{(1-c_x)(Y^*)}$$

Using Equations (A.12) and (A.13) from Steps 3c and 3d, we can obtain a useful intermediate result:

$$
\begin{aligned}
&L_\sigma^* + (1-c_x)Y_\sigma^* \\
=&\omega^*\bar{\Phi}(q)\left[(1-c_x)\left(\frac{1}{m(q)}-\sigma\right) - m(q) + (1-c_x)\left(m(q)+\sigma-\frac{1}{m(q)}\right)\right] \\
=&\omega^*\bar{\Phi}(q)\left[(1-c_x)m(q) - m(q)\right] \\
=&-\omega^*\bar{\Phi}(q)c_x m(q) < 0
\end{aligned}
$$

Now go back to our main object of interest, and rewrite it as:

$$
\begin{aligned}
\frac{\partial x^*}{\partial \sigma} &= -\frac{L_\sigma^* + x^*(1-c_x)Y_\sigma^*}{(1-c_x)Y^*} \\
&= -\frac{(1-x^*)L_\sigma^* + x^*L_\sigma^* + x^*(1-c_x)Y_\sigma^*}{(1-c_x)Y^*} \\
&= -\frac{(1-x^*)L_\sigma^* + x^*[L_\sigma^* + (1-c_x)Y_\sigma^*]}{(1-c_x)Y^*}
\end{aligned}
\tag{A.14}
$$

Given our intermediate result that $L_\sigma^* + (1-c_x)Y_\sigma^* < 0$, we immediately get the desired result:

$$
L_\sigma^* < 0 \implies \frac{\partial x^*}{\partial \sigma} > 0
$$

Q.E.D.

B.3.1 Discussion of Assumption 1

Recall that $L^*(\sigma) = L(\omega^*(c_x,\sigma),\sigma)$ is the financing capacity of the vanilla component evaluated at the optimally chosen default threshold. Its response to σ can be decomposed as

$$
L_\sigma^* = \underbrace{\left.\frac{\partial L(\omega,\sigma)}{\partial \sigma}\right|_{\omega=\omega^*}}_{\text{mechanical effect of risk at fixed }\omega} + \underbrace{L_\omega(\omega^*,\sigma)\frac{\partial \omega^*}{\partial \sigma}}_{\text{endogenous re-optimization of }\omega}. \tag{A.15}
$$

This decomposition clarifies the economic content of the condition $L_\sigma^* < 0$. The first term captures what greater risk does to the payoff of a given vanilla debt contract. The second captures how borrowers change their borrowing contract as their risk increases. The condition $L_\sigma^* < 0$ requires that this endogenous response not be strong enough to overturn the direct deterioration in vanilla financing capacity.

Under lognormality, the direct effect is

$$
\left.\frac{\partial L}{\partial \sigma}\right|_{\omega} = \varphi(q-\sigma)\left(\frac{\delta q}{\sigma} - 1\right). \tag{A.16}
$$

Hence greater risk mechanically reduces vanilla financing capacity whenever $q < \frac{\sigma}{\delta}$, which is a fairly general condition considering that $q > 0$ already implies a default probability above 50 percent. Therefore, Assumption 1 is effectively a requirement that the endogenous re-optimization of ω is not strong and positive to offset the mechanical decline in the first term.

B.3.2 A sufficient condition for Assumption 1

Lemma 1 (**A sufficient condition for risk regularity**). *Fix a financing option $\{c_o, c_x\}$ and suppose the optimal contract is interior. Then, $c_x < \delta$ is sufficient for Assumption 1 to hold.*

Proof:

Recall Equation (A.13).

$$L^*_\sigma = \omega^*[1 - \Phi(q)] \left\{(1 - c_x)\left[\frac{1}{m(q)} - \sigma\right] - m(q)\right\}. \tag{A.17}$$

Since the first two terms are positive, the sign of L^*_σ depends on the sign of the bracketed term. To assess that sign, we make use of two inequalities.

First, combining the lemma's assumption of $c_x < \delta$ with the FOC for q, which reads $h(q) = \frac{c_x}{\delta}\sigma$, we get

$$h(q) = \frac{c_x}{\delta}\sigma < \sigma. \tag{A.18}$$

Second, we use a property of the inverse Mills ratio:

$$\frac{1}{m(q)} - h(q) < m(q), \tag{A.19}$$

Using the two inequalities above we can sign the bracketed term in L^*_σ:

$$\begin{aligned}(1 - c_x)\left[\frac{1}{m(q)} - \sigma\right] - m(q) &< (1 - c_x)\left[\frac{1}{m(q)} - h(q)\right] - m(q) \\ &< (1 - c_x)m(q) - m(q) \\ &= -c_x m(q) < 0\end{aligned}$$

Which concludes the proof that

$$c_x < \delta \implies L^*_\sigma < 0$$

C Solution Algorithm

1. **Step 1.** For each σ, use Equation (10) to get the interior solution for q^*, which does not depend on $\bar{y}$. Then, use such q^* to get ω^*

2. **Step 2.** For each $(\bar{y}, \sigma)$, use the value of ω^* found in Step 1 and the zero-profit condition to back out the implied x^*

   - **Complex loan.** If $x^* \in (0, 1)$, we are done. We get an interior solution for a complex loan
   - **Exit.** If $x^* > 1$, the firm has to exit, as the lender cannot propose any financing solution and break-even
   - **Vanilla loan.** If $x^* < 0$, then we are at the corner solution where the firm borrows though a vanilla loan $x = 0$, and the value for ω is determined by the zero-profit condition.

Recall the zero-profit condition:

$$[1 - Y(\omega) - B(\omega) + (1 - c_x)xY(\omega)]\,\bar{y} = \beta^{-1}(1 + c_o)$$

Therefore, we get:

$$x(\omega) = \frac{S - L(\omega)}{(1 - c_x)Y(\omega)}$$

where recall $S = \frac{1+c_o}{\beta\bar{y}}$ is the normalized vanilla origination cost, and $L(\omega) = 1 - Y(\omega) - B(\omega)$ is the normalized vanilla loan payoff.

D Policy functions

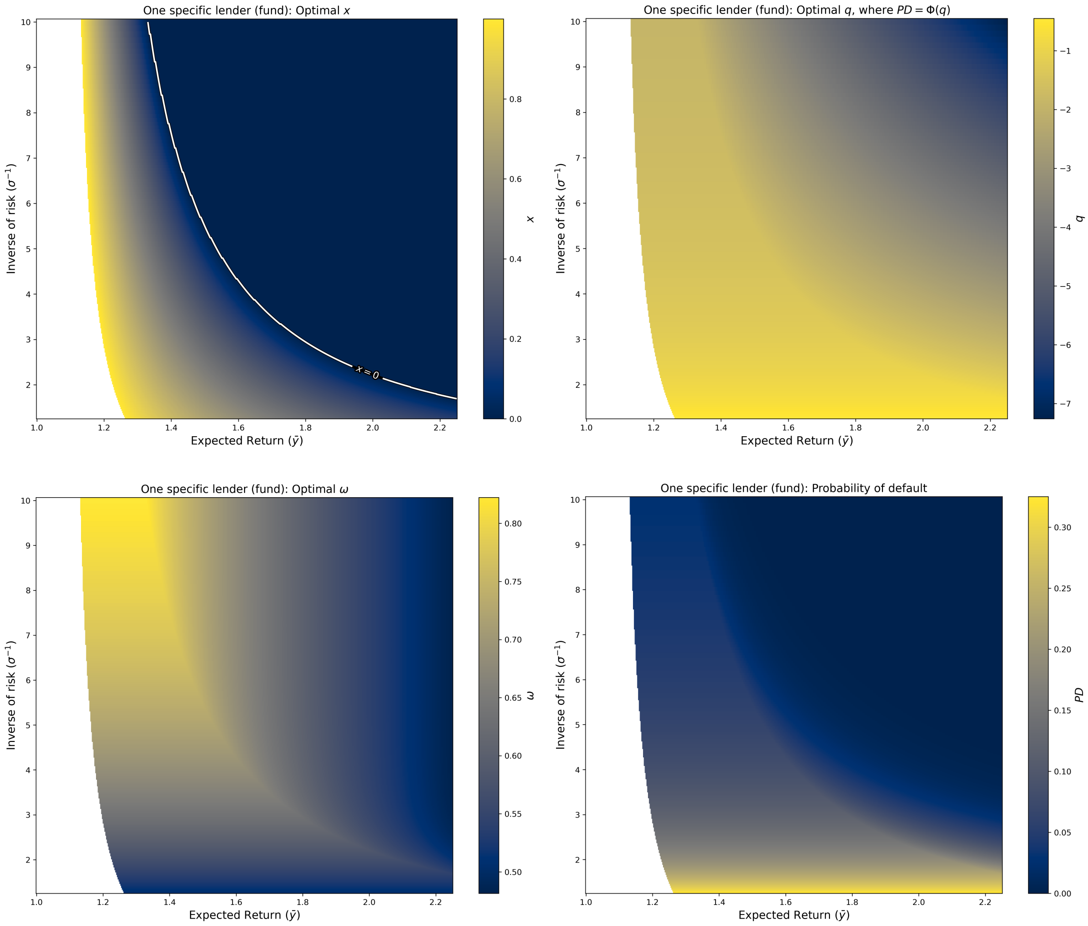


Figure A.2: Optimal policies for all firms conditional on borrowing from the private credit fund. Tailoring choice x (top-left panel), standardized default threshold q (top-right panel), default threshold ω (bottom-left panel), and probability of default $PD = \Phi(q)$ (bottom-right panel).

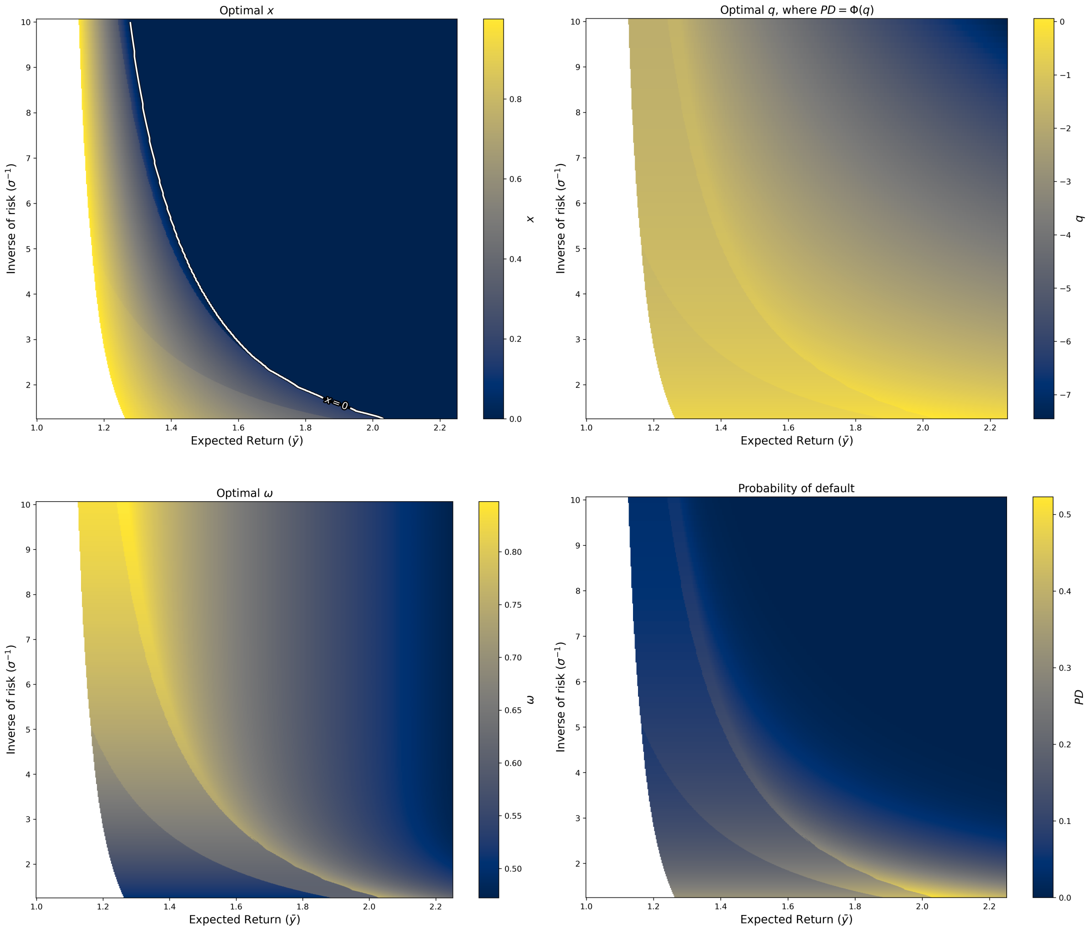


Figure A.3: Optimal policies for all firms conditional on their optimal lender choice. Tailoring choice x (top-left panel), standardized default threshold q (top-right panel), default threshold ω (bottom-left panel), and probability of default $PD = \Phi(q)$ (bottom-right panel).