Lending Technology and Investment

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Abstract

I develop and estimate a structural model of multi-dimensional lending technology in which firms and lenders choose from a contract space spanning tangible collateral and earnings-based monitoring. Estimating the model across six credit-cycle regimes from 2002 to 2023, I find that substitution capacity between pledging and monitoring expanded tenfold, making it the dominant feature of the lending technology. The covenant premium on intangible borrowers peaked during the financial crisis and subsequently collapsed. These estimated changes track observed firm outcomes: the non-monotonic covenant premium inversely tracks intangible firm leverage, and the expansion of substitution capacity is strongly associated with declining tangible investment rates as the collateral motive for holding physical capital weakens.

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Intangible capital (innovation, organizational knowledge, customer relationships, software) is central to the modern economy and growing as a share of firm value (Crouzet and Eberly, 2019; He et al., 2024). Yet financing intangible investment through external capital is hard. These assets are difficult to verify, transfer, or liquidate, and classic models of information frictions predict that firms relying on them should face costlier external finance (Stiglitz and Weiss, 1981; Myers and Majluf, 1984; Holmstrom and Tirole, 1997). But the cost of reducing information asymmetry and committing to repay is itself an output of lending technology. Lenders do not passively accept the pledgeability that a firm's assets offer; they actively innovate to produce it. Through earnings covenants, cash flow sweeps, KPI-linked facilities, and lender intervention rights, intermediaries convert continuation value, future cash flows, and operational transparency into credible commitments to repay. Expanding what can be pledged, how repayment is enforced, and what information is extracted expands the feasible set of lending relationships.

The empirical lending literature documents this evolution. Contract types have shifted from asset-based to earnings-based (Lian and Ma, 2021), covenant design responds to borrower characteristics and lender conditions (Murfin, 2012; Roberts and Sufi, 2009), and direct lending has expanded the frontier of performance-linked credit (Jang et al., 2025). The contract terms observed in the data (how much collateral is pledged, how tight the covenants are, whether the loan is asset-based or earnings-based) are equilibrium outcomes that reflect both the underlying lending technology and the willingness of borrowers and lenders to use it. The technology itself is not directly observable: how substitutable pledging and monitoring are, how lenders differentiate across borrower types, and how these capabilities have evolved must be inferred from the patterns they leave in contracts, investment, and leverage. As a result, it is difficult to study how changing contract structures affect real decisions like investment without a structural framework that can separate the lending technology from the firm characteristics it interacts with.

I develop a general equilibrium model of multi-dimensional lending, estimate it across six credit-cycle regimes from 2002 to 2023, and use the estimates to quantify how the evolution of the lending technology has shaped firm investment, leverage, and borrowing costs. The central contribution is to show how the lending technology (how effectively collateral substitutes for monitoring, how much lenders tighten covenants on opaque borrowers) shapes the contract, leverage, and investment decisions that firms and lenders make in equilibrium. Observed outcomes like covenant strictness, collateral pledging, and borrowing levels are jointly determined by borrower characteristics, lender constraints, and the lending technology. The structural model separates these forces, estimates

how the technology has evolved across credit cycles, and connects those changes to firm behavior. The model, by allowing for substitution and rotation along contract terms, generates major trends in debt market structure, including the covenant-lite revolution and the rise of private-debt-style underwriting, as endogenous outcomes of the estimated technology rather than imposing them as assumptions.

In the model, heterogeneous firms choose from a continuous two-dimensional contract space: tangible asset pledging (s_K) and earnings-based pledging (s_{GC}), with covenant strictness (m) determined endogenously. A competitive intermediary lends subject to capital and monitoring capacity constraints, generating endogenous shadow prices (μ_N, μ_M) that shape the cost and structure of credit. The model is estimated by SMM using cross-sectional moments from the Compustat panel over six regimes spanning pre-crisis through post-COVID, and solved using deep equilibrium networks (Azinovic et al., 2022) conditioned on the lending technology parameters.

The central quantitative finding is that the ability to substitute between contract types (pledging tangible collateral versus accepting covenant-based monitoring) is the dominant feature of the lending technology, and it has expanded dramatically over the past two decades. The estimated pledging–monitoring substitution parameter rises monotonically from 0.62 (pre-crisis) to 6.0 (COVID era). The intangible covenant premium, the additional covenant burden lenders impose on intangible-intensive borrowers, follows an inverted-U, peaking during the financial crisis and collapsing as substitution capacity expanded. This paper estimates the structural technology underlying recent empirical findings on the shift from asset-based to cash-flow-based lending, the role of asset specificity in recovery, and the effect of lender capacity on covenant tightness. The ability to trade off between these dimensions, not any single one, is what matters most for firm outcomes.

The estimated technology generates the covenant-lite revolution endogenously: expanding substitution capacity means lenders no longer need intensive covenants, and equilibrium covenant strictness falls from $m = 0.95$ (pre-crisis) to $m = 0.37$ (COVID). The rise of direct lending is captured by the same expansion. Direct lenders combine asset-based and cash-flow-based underwriting within single facilities, precisely the pledging–monitoring substitution the model estimates has grown over time.

Connecting the estimated technology to firm outcomes, the non-monotonic pattern in the intangible covenant premium inversely tracks intangible firm leverage in the data (correlation -0.70), and the expansion of substitution capacity is strongly associated with declining tangible investment rates (correlation -0.94) as firms shed the collateral motive for holding physical capital. A

historical counterfactual, applying pre-crisis lending technology to the actual sequence of firms and financial conditions from 2002–2023, shows that intangible firms' tangible investment rate would be 29% lower and their spreads 300–500 basis points higher without the evolution of the lending technology.

These predictions find support in reduced-form evidence. Exogenous lender shocks produce contract rotation: spreads rise, covenants loosen, and collateral pledging increases. Firms with access to both pledging and monitoring channels experience 178 basis points less spread sensitivity to lender shocks ($t = -6.52$). Under tight credit, high-leverage intangible firms shift investment toward tangible capital ($t = 7.18$), consistent with the model's prediction that firms at the contract frontier are forced to build collateral.

The remainder of the paper is organized as follows. Section I develops the model. Section II describes the estimation strategy. Section III presents the quantitative results. Section IV reports counterfactual exercises. Section V presents supporting empirical evidence. Section VI concludes.

.A. *Related Literature*

The empirical literature on debt contracting studies how covenant design, collateral requirements, and contract terms respond to borrower characteristics and lender conditions (Demerjian, 2011; Bradley and Roberts, 2015; Gopalan et al., 2014). Murfin (2012) provides causal evidence that lender health shapes covenant strictness, establishing the supply-side identification this paper exploits in Section V. Roberts and Sufi (2009) show that covenant violations shift control rights and alter real outcomes, a mechanism the model formalizes through the monitoring channel. This paper departs from the existing literature by modeling the joint determination of tangible pledging, earnings-based pledging, and covenant strictness in general equilibrium, generating an endogenous contract rotation mechanism in which firms substitute across instruments as intermediary shadow prices shift.

A related literature documents the evolution of lending markets toward cash-flow-based and earnings-based credit. Lian and Ma (2021) establish that 80% of U.S. corporate debt is cash-flow-based rather than asset-based, providing the empirical foundation for the model's two-dimensional contract space. Jang et al. (2025) document that direct lenders in private credit write collateral claims focused on continuation value, consistent with the earnings-based pledging technology at the center of the model. The broader literature on syndicated lending and information asymmetry (Sufi, 2007; Ivashina, 2009; Ivashina and Scharfstein, 2010) documents how supply-side shocks

propagate through contract terms as well as quantities. This paper provides a structural equilibrium framework for interpreting these patterns as the outcome of intermediaries expanding the lending technology frontier in response to the growing demand for intangible-intensive credit.

The paper connects two strands of the literature on intangible capital and financial frictions. One strand documents that intangible assets generate qualitatively different financial constraints than physical capital: asset specificity limits pledgeability (Kermani and Ma, 2023), intangible-intensive firms hold more cash and issue less debt (Falato et al., 2022), and customer capital and organizational capital represent a growing share of aggregate firm value (He et al., 2024; Eisfeldt and Papanikolaou, 2014; Corrado et al., 2009a; Peters and Taylor, 2017). A second strand shows that financial frictions distort investment composition toward more pledgeable assets (Rampini and Viswanathan, 2013, 2010; Rauh and Sufi, 2010), while canonical structural models focus on investment levels and treat capital as homogeneous (Hennessy and Whited, 2007; Ottonello and Winberry, 2020). This paper bridges the two by endogenizing the contract response to intangible intensity: when monitoring capacity tightens, the model generates a composition distortion toward tangible capital that is invisible in aggregate data but detectable in the cross-section.

The intermediary constraints literature establishes that financial sector health is a key determinant of credit supply and asset prices (He and Krishnamurthy, 2013; Brunnermeier and Pedersen, 2009; Adrian and Shin, 2010). Gilchrist and Zakrajsek (2012) show that the excess bond premium — the component of credit spreads orthogonal to default risk — captures intermediary health and predicts real activity; Chodorow-Reich (2014) establishes a causal credit supply channel through bank-firm matched data. This paper connects the intermediary constraints literature to contract design: the dual capital and monitoring constraints generate richer dynamics than a single capital constraint, with monitoring shocks binding disproportionately for intangible firms and producing the asymmetric spread responses this paper tests empirically.

The model is solved using the deep equilibrium network approach of Azinovic et al. (2022), extended with FiLM conditioning (Perez et al., 2018) for efficient SMM estimation across lending technology parameter vectors. Maliar et al. (2021) and Fernandez-Villaverde et al. (2023) survey the broader literature on deep learning methods for heterogeneous agent models that informs this implementation.

I. Model

I.A. Environment

Time is discrete and the horizon is infinite. The economy consists of a continuum of heterogeneous firms and a competitive financial intermediary. Each firm i enters period t with state vector $(K_{it}, H_{it}, C_{it}, a_{it}, B_{it})$: tangible capital K, intangible capital H, internal cash C, idiosyncratic productivity a, and outstanding debt B. Firms choose investment, borrowing, equity issuance, and cash retention. The financial intermediary lends to the cross-section subject to capacity constraints, generating endogenous shadow prices (μ_N, μ_M) that determine credit conditions in equilibrium.

The key compositional variable is a firm's *intangible intensity*,

$$\eta_i \equiv \frac{H_i}{K_i + H_i}, \tag{1}$$

which determines how the firm interacts with the lending technology through three channels: collateral pledgeability, continuation value, and monitoring intensity.

I.B. Firm Technology

Firms produce output using tangible and intangible capital:

$$Y_{it} = A \cdot a_{it} \cdot \left(\alpha\, K_{it}^{\rho_K} + (1-\alpha)\, H_{it}^{\rho_H}\right), \tag{2}$$

where A is the aggregate productivity level, a_{it} is firm-specific productivity, α is the capital share (fixed at 0.5), and ρ_K, ρ_H govern diminishing returns. The additively separable structure ensures each capital type contributes independently to output, with $\rho < 1$ generating diminishing returns.

Idiosyncratic productivity follows an AR(1) in logs:

$$\log a_{it+1} = \rho_a \log a_{it} + \sigma_a\, \varepsilon^a_{it+1}, \qquad \varepsilon^a \sim \mathcal{N}(0,1). \tag{3}$$

Capital accumulates with type-specific depreciation:

$$K_{it+1} = (1-\delta_K)K_{it} + I^K_{it}, \qquad H_{it+1} = (1-\delta_H)H_{it} + I^H_{it}, \tag{4}$$

where $\delta_H > \delta_K$ reflects faster obsolescence of intangible capital. Adjustment costs are quadratic:

$$\Phi^K(I^K, K) = \frac{\phi_K}{2}\left(\frac{I^K}{K}\right)^2 K, \qquad \Phi^H(I^H, H) = \frac{\phi_H}{2}\left(\frac{I^H}{H}\right)^2 H. \tag{5}$$

I.C. Financial Decisions

The firm's budget constraint is

$$Y_i + C_i + B_i^{\text{new}} + e_i = I_i^K + I_i^H + \Phi_i^K + \Phi_i^H + (1 + r_i^{\text{eff}})B_i + C_i' + d_i, \tag{6}$$

where r_i^{eff} is the firm-specific effective borrowing rate (determined by the contract), $e_i \geq 0$ is equity issuance, C_i' is retained cash, and d_i is the residual dividend. The budget constraint incorporates several additional features not shown explicitly: interest payments are tax-deductible at rate τ, equity issuance carries a linear cost λ_e with an opacity premium for intangible firms, cash earns a return $r_C < r_f$, and retained cash is subject to an agency cost ϕ_{agency} following Jensen (1986). These are detailed in Table II.

Equity issuance is costly, with the cost increasing in intangible intensity:

$$\Lambda(e_i) = \lambda_e \cdot e_i, \qquad \lambda_e(\eta) = \lambda_e^{\text{base}} + \lambda_e^{\text{opacity}} \cdot \eta. \tag{7}$$

The complementarity condition $d_i \geq 0$, $e_i \geq 0$, $d_i \cdot e_i = 0$ ensures firms do not simultaneously distribute and raise equity.

I.D. The Contract Space

When a firm borrows, it chooses a contract from a two-dimensional menu offered by the lender. The contract specifies:

- $s_K \in [0, 1]$: *tangible pledging intensity* — the fraction of tangible capital pledged as collateral. Higher s_K improves the lender's recovery in liquidation but imposes a direct cost $\delta_s \cdot s_K \cdot K$/assets on the borrower (restricted asset use, monitoring of collateral condition).

- $s_{GC} \in [0, 1]$: *earnings-based pledging intensity* — the fraction of the firm's continuation value pledged to the lender. This captures a broad class of performance-linked debt: cash flow sweeps, earnings-based covenants, KPI-linked facilities, assignment of receivables, or blanket liens on enterprise value. The key feature is that the claim is on the firm's ongoing

performance rather than specific physical assets. Unlike tangible pledging, earnings-based pledging *requires monitoring* to be effective, because the lender must verify and certify the cash flows or performance metrics that back the claim.

Given the contract choice (s_K, s_{GC}), a third variable is determined endogenously:

$$m_i = \sigma\left(\kappa_0 + \kappa_H\,\eta_i + \eta_{sgc}\,s_{GC,i} - \eta_{sk}\,\frac{s_{K,i}\,K_i}{B_i} + \varphi\,\mu_M\right), \tag{8}$$

where $m \in (0,1)$ is the *covenant strictness* — the probability of a covenant violation triggering lender intervention. Following Murfin (2012), m captures the tightness of the lending relationship. It increases with intangible intensity (κ_H), earnings-based pledging (η_{sgc}, since performance-linked lending requires oversight), and lender tightening ($\varphi \cdot \mu_M$), and decreases with tangible coverage (η_{sk}, since collateral substitutes for monitoring).

The firm chooses (s_K, s_{GC}) to minimize total borrowing cost. m follows from the contract choice and equilibrium conditions. This yields an endogenous mapping from firm characteristics and credit conditions to observed contract structures.

I.E. Pricing

The effective borrowing rate has two components: credit risk compensation and monitoring cost:

$$r_i^{\text{eff}} = r_f + \underbrace{(\text{PD}_i + \mu_N)\cdot \text{LGD}_i}_{\text{credit risk + intermediation}} + \underbrace{\delta_m \cdot m_i}_{\text{monitoring cost}}, \tag{9}$$

where r_f is the risk-free rate and μ_N is the intermediary's shadow price on capital.

The credit risk term $(\text{PD}_i + \mu_N)\cdot \text{LGD}_i$ captures both the actuarial expected loss ($\text{PD}\cdot\text{LGD}$) and the intermediary's capital charge ($\mu_N \cdot \text{LGD}$). The intermediary prices capital scarcity through μ_N, which is determined endogenously by a convex cost function of aggregate capital utilization (Section I.I.F). Firms can reduce this term by pledging collateral (lowering LGD through s_K and s_{GC}), but the LGD floor $\underline{\ell}$ prevents borrowing costs from collapsing to zero even with perfect collateralization.

The monitoring cost $\delta_m \cdot m_i$ is the direct cost to the borrower of covenant compliance: legal expenses, reporting requirements, and restrictions on managerial discretion. It is calibrated to $\delta_m = 0.025$, consistent with estimates of compliance costs at 1–2% of loan value (Roberts and Sufi, 2009).

Probability of default. Default probability follows a Merton-style distance-to-default model with a moral hazard channel:

$$\text{PD}_i = \Phi(-\text{DD}_i), \qquad \text{DD}_i = \frac{\log\left(\frac{Y_i + C_i}{(1+r_f)(B_i - C_i)^+}\right)}{\sigma_i^{\text{firm}}}, \tag{10}$$

where $(B_i - C_i)^+ = \max(B_i - C_i, 0)$ is net debt (cash offsets debt for default risk purposes) and $\sigma_i^{\text{firm}} = \kappa_\sigma \, \sigma_a \cdot (1 + \sigma_{mh} \cdot (1 - h_{pd}(m_i)) \cdot \eta_i)$. The function $h_{pd}(m) = m^{\alpha_{pd}}$ captures how monitoring reduces moral hazard: tighter covenants constrain managerial discretion, reducing the excess volatility that arises from agency problems. The moral hazard channel operates through intangible intensity η because intangible-intensive firms have greater scope for risk-shifting.

Loss given default. Recovery in default depends on both tangible collateral and continuation-value recovery through monitoring:

$$\text{LGD}_i = \underline{\ell} + (1 - \underline{\ell}) \cdot \sigma\left(\ell_0 - \zeta_K \, \frac{s_{K,i} \, K_i}{B_i} - \zeta_m \, h_{lgd}(m_i) \cdot \frac{s_{GC,i} \cdot \text{GCV}_i}{B_i}\right), \tag{11}$$

where $\text{GCV}_i = Y_i + \gamma_{gcv} \, H_i$ is the continuation value of the firm—the value of the enterprise as an ongoing business, including the contribution of intangible capital to future earnings. $h_{lgd}(m) = m^{\alpha_{lgd}}$ captures monitoring effectiveness for recovery, and ℓ_0 is the base loss rate. The floor $\underline{\ell}$ is estimated via SMM and ensures that even perfectly collateralized loans carry a minimum loss rate, reflecting the frictions inherent in the bankruptcy process: legal costs, time to resolution, asset deterioration, and fire-sale discounts. Moody's reports approximately 15–25% loss on senior secured bank loans. Tangible collateral ($s_K \cdot K$) provides direct recovery in liquidation. Continuation-value recovery ($s_{GC} \cdot \text{GCV}$) requires monitoring ($h_{lgd}(m)$) to be effective—the lender must be able to preserve and extract the firm's enterprise value in distress, which requires active oversight.

The two channels of monitoring. Monitoring operates through two distinct channels with separate effectiveness parameters:

- $h_{lgd}(m) = m^{\alpha_{lgd}}$: monitoring improves continuation-value recovery in default (LGD channel).
- $h_{pd}(m) = m^{\alpha_{pd}}$: monitoring reduces moral hazard volatility (PD channel).

The concavity parameters α_{lgd} and α_{pd} are estimated separately via SMM, allowing the data to determine the relative effectiveness of monitoring in each channel.

I.F. The Financial Intermediary

The intermediary faces costs of deploying both capital and monitoring capacity. Rather than a hard constraint with a shadow price that jumps from zero to positive, I model the intermediary's pricing through a convex cost function:

$$\mu_N = \kappa \cdot \left(\frac{\sum_i \text{RW}_i \cdot \text{LGD}_i \cdot B_i}{NW} \right)^{\gamma}, \qquad \mu_M = \kappa \cdot \left(\frac{\sum_i m_i \cdot B_i}{\xi_M \cdot NW} \right)^{\gamma}, \tag{12}$$

where $\text{RW}_i = \text{PD}_i^{rw}$ is the risk weight, NW is the intermediary's net worth, and ξ_M scales monitoring capacity. The parameters κ and γ govern the level and convexity of intermediation costs. This formulation ensures that μ_N and μ_M are always positive—reflecting the base cost of intermediation (funding, operations, required return on equity)—and rise smoothly as the intermediary approaches capacity. At low utilization, intermediation is cheap; near capacity, costs rise sharply, generating the credit tightening dynamics that matter for crisis episodes.

The capital shadow price μ_N enters the borrower's effective rate through $(\text{PD}_i + \mu_N) \cdot \text{LGD}_i$, raising spreads for all firms but especially for those with high PD and high LGD. The monitoring shadow price μ_M enters through $\varphi \cdot \mu_M$ in the covenant strictness function (8), tightening covenants and shifting the contract frontier.

II. Solution and Estimation

II.A. Equilibrium and Solution

A competitive equilibrium consists of firm policies, contract choices, and intermediary prices such that all agents optimize and markets clear. Specifically, two prices clear two markets: the capital shadow price μ_N clears the capital market, where aggregate risk-weighted lending demand $\sum_i \text{RW}(\text{PD}_i) \cdot \text{LGD}_i \cdot B_i$ must be consistent with the intermediary's net worth NW; and the monitoring shadow price μ_M clears the monitoring market, where aggregate monitoring demand $\sum_i m_i \cdot B_i$ must be consistent with monitoring capacity $\xi_M \cdot NW$. I solve the model using deep equilibrium networks (Azinovic et al., 2022). The neural network treats the firm's idiosyncratic state (K_i, H_i, C_i, a_i), the borrowing decision B_i^{new}, and the equilibrium prices (μ_N, μ_M) as inputs, and outputs investment (I_i^K, I_i^H), equity issuance e_i, and cash retention C_i', with dividends d_i as the budget-constraint residual. Given these policies and the candidate B_i^{new}, the firm chooses optimal contract terms $(s_{K,i}^*, s_{GC,i}^*)$ by bisection to minimize total borrowing cost, with covenant strictness

m_i^* determined by equation (8). Once trained, the equilibrium solver determines (μ_N, μ_M) via tâtonnement on the intermediary's convex cost function (12), and optimal B_i^{new} via grid search over a value-function rollout, iterating until firm borrowing decisions and intermediary prices are mutually consistent. Details of the network architecture, training procedure, and convergence diagnostics are in Appendix D.

II.B. Estimation Procedure

The model has 11 lending technology parameters θ that govern how lenders price risk, structure contracts, and allocate monitoring. These parameters are not directly observable but shape the cross-sectional distribution of investment, leverage, and contract terms. I estimate 10 free parameters by the simulated method of moments (SMM), matching cross-sectional moments from the Compustat annual panel separately for each of six credit-cycle regimes (Section III). The remaining parameter, φ (the sensitivity of covenant strictness to the monitoring shadow price), is fixed at 2.0 based on the absence of an aggregate covenant-tightening relationship in the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS).

II.C. Estimated Parameters

The central object of estimation is the lending technology θ—the set of parameters that determine how lenders transform borrower characteristics into contract terms, prices, and credit access. In standard models with a single collateral constraint, the lending technology reduces to a single parameter (the fraction of assets that can be pledged). Here, the lending technology is multi-dimensional: it governs how lenders value different types of collateral in default, how they set and enforce covenants, and how they trade off monitoring for pledging. These parameters are not directly observable, but they leave distinct fingerprints in the cross-section of firm investment, leverage, and borrowing composition. I estimate them by matching these cross-sectional patterns.

The 10 estimated parameters fall into three groups. The first and most important group governs the contract space: how lenders value continuation assets (γ_{gcv}), how covenant tightness varies with firm type (κ_0, κ_H), and how pledging and monitoring substitute for each other (η_{sk}, α_{lgd}, α_{pd}). These are the parameters that distinguish this model from one-dimensional collateral models, and they are identified from cross-sectional differences in investment and leverage between tangible and intangible firms. The second group consists of adjustment costs (ϕ_K, ϕ_H), which are not directly part of the lending technology but interact with it: whether firms respond to financial shocks by

Table I: **Estimated Lending Technology Parameters.** Each parameter governs a distinct channel through which the lending technology shapes contract terms, pricing, and firm decisions.

Parameter	Description	Identifies
γ_{gcv}	Continuation value of intangibles	How much H is worth in default
κ_σ	DD volatility multiplier	Mapping from leverage to default risk
κ_0	Baseline covenant tightness	Average covenant strictness across all firms
κ_H	Intangible covenant tightening	How much tighter covenants are for intangible firms
η_{sk}	Pledging–monitoring substitution	How much collateral reduces need for covenants
α_{lgd}	Monitoring → LGD effectiveness	Concavity of monitoring in reducing loss given default
α_{pd}	Monitoring → PD effectiveness	Concavity of monitoring in reducing default probability
ϕ_K	Tangible adjustment cost	Friction on tangible investment
ϕ_H	Intangible adjustment cost	Friction on intangible investment
$\underline{\ell}$	LGD floor	Minimum loss in default (bankruptcy frictions)

adjusting investment or restructuring contracts depends on the relative magnitude of adjustment frictions and financing frictions. These are identified from investment rates and are standard in the structural corporate finance literature (Hennessy and Whited, 2007). The third group (κ_σ, $\underline{\ell}$) anchors the level of credit risk and recovery, disciplining the absolute spread level against DealScan data. Table I summarizes each parameter and its economic role.

II.D. Externally Calibrated Parameters

Table II reports the externally calibrated parameters. I discuss the less standard choices below.

Intangible depreciation $\delta_H = 0.25$ reflects BEA estimates of 15–25% for R&D capital and 20–33% for software (Corrado et al., 2009b). Equity issuance cost $\lambda_e = 0.09$ follows the upper bound of Hennessy and Whited (2007), with an additional opacity premium $\lambda_e^{\text{opacity}} = 0.05$ for intangible firms facing greater adverse selection (Myers and Majluf, 1984). The agency cost of cash $\phi_{\text{agency}} = 0.03$ follows Jensen (1986).

The collateral pledging cost $\delta_s = 0.02$ reflects the direct and opportunity costs of maintaining perfected security interests—negative pledge clauses, lien perfection, and restrictions on asset disposal. The covenant compliance cost $\delta_m = 0.025$ is calibrated from Roberts and Sufi (2009) and Nini et al. (2012), who document that covenant violations reduce investment by approximately 1% of capital and debt issuance by 2.5% of assets. At the average covenant violation probability $m \approx 0.05$, this implies expected operational drag of approximately 12.5 basis points.

The moral hazard parameter $\sigma_{mh} = 0.5$ captures the Kermani and Ma (2023) finding that monitoring reduces the gap between continuation value and liquidation value: an unmonitored pure-intangible firm faces 50% higher effective volatility. The earnings-based pledging parameter

Table II: **Externally Calibrated Parameters.**

Parameter	Description	Value	Source
Standard			
β	Discount factor	0.96	Annual
r_f	Risk-free rate	0.02	Fed funds
τ	Corporate tax rate	0.21	Statutory
ρ_a	Productivity persistence	0.90	Compustat
σ_a	Productivity volatility	0.10	Compustat
Production and depreciation			
α	Tangible capital share	0.50	Symmetric baseline
ρ_K, ρ_H	Returns to scale	0.50, 0.50	Diminishing returns
δ_K	Tangible depreciation	0.10	BEA fixed assets
δ_H	Intangible depreciation	0.25	BEA; Corrado et al. (2009b)
Financing			
λ_e	Equity issuance cost	0.09	Hennessy and Whited (2007)
$\lambda_e^{\text{opacity}}$	Opacity premium	0.05	Myers and Majluf (1984)
r_C	Return on cash	0.01	Below r_f
ϕ_{agency}	Agency cost of cash	0.03	Jensen (1986)
Contract costs			
δ_s	Collateral pledging cost	0.02	DealScan secured spread discount
δ_m	Covenant compliance cost	0.025	Roberts and Sufi (2009); Nini et al. (2012)
σ_{mh}	Moral hazard volatility	0.50	Kermani and Ma (2023)
η_{sgc}	Earnings-based pledging requires monitoring	3.0	Jang et al. (2025)
LGD			
ℓ_{base}	LGD intercept	-0.5	Moody's: 38% unsecured LGD
ζ_K	Tangible recovery effectiveness	1.5	Moody's secured/unsecured gap
ζ_m	Monitoring recovery effectiveness	1.5	Kermani and Ma (2023)
Intermediary			
φ	Monitoring–μ_M sensitivity	2.0	SLOOS (no aggregate relationship)
κ	Lender cost scale	0.08	Calibrated to baseline spread
γ	Lender cost convexity	2.0	He-Krishnamurthy curvature
ξ_M	Monitoring capacity	2.0	Calibrated to utilization

$\eta_{sgc} = 3.0$ reflects Jang et al. (2025)'s finding that blanket liens are used almost exclusively by lenders with active monitoring capability (direct lenders: 79% blanket liens vs. banks: 15%), implying that earnings-based pledging without monitoring is prohibitively costly.

The LGD intercept $\ell_{\text{base}} = -0.5$ implies baseline unsecured LGD of 38% ($\sigma(-0.5) = 0.38$), matching Moody's average unsecured recovery. The recovery parameters $\zeta_K = \zeta_m = 1.5$ are calibrated so that full tangible pledging reduces LGD from 38% to approximately 20%, consistent with the Moody's senior secured–unsecured recovery gap. Monitoring recovery is set symmetrically, reflecting Kermani and Ma's finding that continuation-value recovery is comparable in magnitude.

For the intermediary, I set $\kappa = 0.08$ and $\gamma = 2.0$ in the convex cost function, producing baseline spreads of approximately 247 basis points matching DealScan (2015–2019). The convexity $\gamma = 2.0$

generates nonlinear amplification consistent with He and Krishnamurthy (2013). The monitoring sensitivity $\varphi = 2.0$ is fixed based on the absence of a systematic covenant-tightening relationship in the Federal Reserve's SLOOS at business-cycle frequency. Monitoring capacity $\xi_M = 2.0$ is set so that monitoring utilization is approximately 1.3 at baseline.

II.E. Targeted Moments

I target 11 moments chosen to discipline three categories of model decisions. The first category is *leverage and financing*: mean leverage by firm type ($\overline{B'/A}$ for tangible and intangible firms) and cross-sectional leverage dispersion (std B'/A). These moments pin down how much firms borrow and how borrowing varies across the asset composition distribution, identifying the default risk parameters (κ_σ, $\underline{\ell}$) and the LGD structure that makes debt cheaper or more expensive for different firm types.

The second category is *investment levels and composition*: mean tangible investment for tangible firms ($\overline{I^K/A}$), mean intangible investment for intangible firms ($\overline{I^H/A}$), the tangible investment rate ($\overline{I^K/K}$) for both firm types, the capex share of total investment for intangible firms, and the cross-sectional correlation between tangible investment and intangibility. These moments discipline the adjustment costs (ϕ_K, ϕ_H) and, crucially, the interaction between financing frictions and real decisions. The ratio of intangible to tangible firms' capex rates is particularly informative about the contract space parameters: if the lending technology makes it easy for intangible firms to borrow (high γ_{gcv}, low κ_H), they invest more, and the gap narrows.

The third category is *pricing*: the mean loan spread from DealScan (247 basis points, 2015–2019). This moment comes from a separate data source and is included with zero cross-covariance to the Compustat moments. It anchors the absolute level of intermediation costs and prevents the model from matching investment and leverage patterns with unrealistic spread levels.

Ten moments come from the Compustat annual panel (2015–2019, excluding financials and utilities); the eleventh is from DealScan. All investment and leverage moments are computed as means of firm-level ratios, weighting each firm equally.

The objective function is the quadratic form $(m^{\text{model}} - m^{\text{data}})' W (m^{\text{model}} - m^{\text{data}})$, where W is diagonal with weights proportional to $1/m_j^{\text{data}2}$, ensuring percentage deviations are penalized equally. Optimization uses Nelder-Mead with 5 random restarts.

Table III: **Targeted Moments.** All investment moments are firm-level ratios averaged across firms. Leverage uses $B_i^{\text{new}} = B_{i,t+1}$ (next-period debt) divided by current total assets. Tangible: $\eta < 0.33$; Intangible: $\eta \geq 0.66$.

Moment	Definition	Data	Model
$\overline{I^K/A}$ (tang)	mean($\text{capx}_i/\text{AT}_i$)	0.062	0.071
$\overline{I^H/A}$ (intang)	mean(xrd_i/AT_i)	0.110	0.057
$\overline{B'/A}$ (tang)	mean($B_i^{\text{new}}/\text{AT}_i$)	0.247	0.394
$\overline{B'/A}$ (intang)	mean($B_i^{\text{new}}/\text{AT}_i$)	0.304	0.322
corr(I^K/A, η)	cross-sectional correlation	-0.203	-0.318
capx share (intang)	mean($\text{capx}_i/(\text{capx+xrd})_i$)	0.515	0.541
I^K/A ratio	intang / tang	0.220	0.282
std(B'/A)	cross-sectional dispersion	0.284	0.278
$\overline{I^K/K}$ (tang)	mean($\text{capx}_i/\text{ppegt}_i$)	0.178	0.129
$\overline{I^K/K}$ (intang)	mean($\text{capx}_i/\text{ppegt}_i$)	0.225	0.187
mean spread	DealScan AISD (2015–2019)	0.025	0.027

III. Quantitative Results

I divide the sample into six regimes: pre-crisis (2002–2006), crisis (2008–2010), post-crisis (2011–2014), normal (2015–2019), COVID (2020–2021), and post-COVID (2022–2023), and estimate the lending technology separately for each. I first show that the model fits observed investment, leverage, and spread patterns across regimes, establishing that the estimated parameters are grounded in data. I then examine what the estimated lending technology reveals about how the contract space evolved, and connect those changes to observed firm outcomes.

III.A. Model Fit Across Regimes

Figure 1 compares key targeted moments across regimes (the full set of eleven moments is reported in Table VII in the Appendix). The model fits the normal, COVID, and post-COVID periods well (scores 1.1), with most moments within 15–30% of data values. Appendix B discusses the sources of misfit in the crisis and pre-crisis periods. In the normal period, the model closely matches the tangible investment rate (I^K/K: 0.129 versus 0.178), intangible firms' capex share (0.541 versus 0.515), leverage dispersion (0.278 versus 0.284), and the mean loan spread (2.7% versus 2.5%). The correlation between tangible investment and intangibility is correctly negative in both data and model.

Across regimes, tangible investment rates (I^K/K) show a striking pattern: both data and model spike during the crisis period—tangible firms from 0.171 to 0.219 (data) and 0.127 to 0.259 (model), intangible firms from 0.320 to 0.241 (data) and 0.226 to 0.470 (model)—then decline

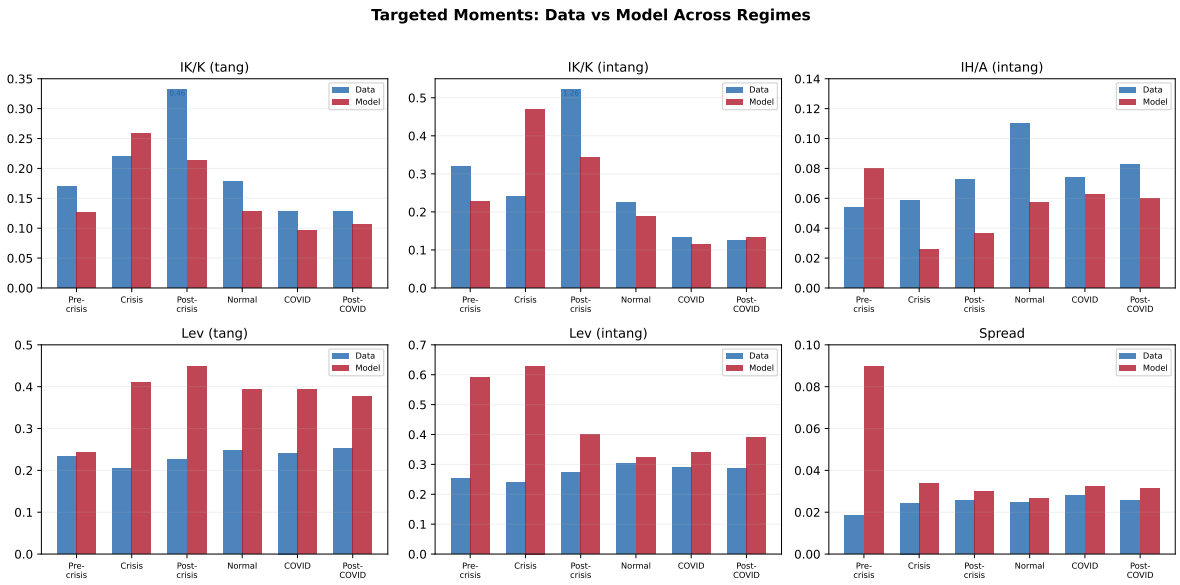


Figure 1: **Targeted moments: Data vs. Model across regimes.** Blue bars are data, red bars are model. Post-crisis I^K/K data values are truncated (annotated); these reflect small-denominator measurement issues in PPEGT.

through COVID. The direction of tangible investment per unit of assets (I^K/A) matches in all five regime transitions (data and model both follow $[+ - - - +]$), with the COVID collapse matched precisely (both 0.046). The mean spread matches well for recent periods (model 2.7–3.2% versus data 2.5–2.8%) but is substantially overstated for the pre-crisis period (model 9.0% versus data 1.8%), reflecting the risk-free rate mismatch: the policy network was trained at $r_f = 2\%$, while the pre-crisis period had $r_f \approx 3.5\%$.

The crisis and pre-crisis fits are weaker. The crisis tangible investment rate (I^K/K) spikes more in the model (0.259) than data (0.219), and the adjustment cost parameters ($\phi_K = 0.50$, $\phi_H = 13.70$) absorb variation that the financial model alone cannot generate, indicating that real-side frictions played a role during 2008–2010.

III.B. Estimated Lending Technology

Given that the model fits the data reasonably across regimes, what do the estimated parameters reveal about how lending technology evolved? Table IV reports the estimates.

Two parameters stand out. The pledging–monitoring substitution capacity (η_{sk}) expands monotonically from 0.62 to 6.0 across regimes. This parameter governs how effectively tangible collateral substitutes for covenant protection: at $\eta_{sk} = 0.62$, pledging buys little covenant relief; at $\eta_{sk} = 6.0$,

Table IV: **Estimated Lending Technology by Regime.** SMM estimates for each period. $\varphi = 2.0$ fixed. * denotes parameter at bound.

	Pre-crisis (02–06)	Crisis (08–10)	Post-crisis (11–14)	Normal (15–19)	COVID (20–21)	Post-COVID (22–23)
γ_{gcv}	5.00*	5.00*	5.00*	3.94	1.75	1.44
η_{sk}	0.62	1.08	1.08	3.00*	5.99*	6.00*
κ_H	2.76	2.99*	0.00*	0.72	0.14	1.94
κ_0	−1.00*	−1.00*	−1.75	−1.00*	−2.54	−3.16
κ_σ	1.55	1.59	4.74	4.98	5.93	3.76
α_{lgd}	0.05*	0.88	0.05*	0.05*	0.20	0.27
α_{pd}	0.94	0.62	0.95*	0.95*	0.81	0.95
ϕ_K	8.39	0.50*	0.97	7.47	19.90	15.79
ϕ_H	3.01	13.70	7.59	2.70	0.76	2.37
$\underline{\ell}$	0.05*	0.05*	0.05*	0.05*	0.05*	0.05*
Score	164.4	35.1	5.4	1.1	1.1	1.1

pledging and monitoring are nearly perfect substitutes. The expansion is consistent with institutional developments—the growth of unitranche facilities, covenant-lite lending, and direct lending platforms that combine asset-based and cash-flow-based underwriting.

The intangible covenant premium (κ_H) follows an inverted-U: 2.76 (pre-crisis), 2.99 (crisis peak), 0.00 (post-crisis collapse), 0.72 (normal), 0.14 (COVID), 1.94 (post-COVID rebound). In the early periods, lenders managed intangible-firm risk primarily by imposing tighter covenants. As substitution capacity expanded, this approach became unnecessary—firms could pledge tangible assets in exchange for covenant relief. The post-COVID rebound in κ_H suggests that tightening monetary conditions partially reactivate the covenant channel.

Baseline covenants (κ_0) loosen from -1.0 through normal to -3.16 (post-COVID), consistent with the covenant-lite trend. During the crisis, monitoring effectiveness (α_{lgd}) spikes to 0.88—near-linear returns to lender intervention—suggesting that active restructuring was unusually productive during 2008–2010.

In the equilibrium, these parameter changes produce large shifts in contract terms. Intangible firms' monitoring intensity drops from near-saturation ($m = 0.95$ pre-crisis, 0.99 crisis) to moderate levels ($m = 0.77$ normal, 0.37 COVID) as alternative channels develop. Their pledging expands from $s_K = 0.19$ (pre-crisis) to 0.98 (normal). The contract space transitions from effectively one-dimensional—covenants as the only tool—to genuinely two-dimensional, with firms and lenders freely trading off between pledging and monitoring.

Two major trends in debt market structure emerge endogenously from the estimated lending technology. First, the covenant-lite revolution: the combination of loosening baseline covenants

(κ_0: $-1.0 \to -3.16$), collapsing intangible covenant premium (κ_H: $2.99 \to 0.14$), and expanding substitution capacity (η_{sk}: $0.62 \to 6.0$) produces the decline in monitoring intensity from $m = 0.95$ to $m = 0.37$ over two decades. The model does not impose covenant-lite lending—it arises as the equilibrium response to a lending technology that no longer requires intensive covenants to manage intangible-firm risk. Second, the rise of private debt and direct lending is reflected in the η_{sk} expansion. Direct lenders combine asset-based and cash-flow-based underwriting within single credit facilities, precisely the kind of pledging–monitoring substitution that η_{sk} captures. While the model does not distinguish lender types, the estimated technology parameter captures the capability that these institutional innovations brought to the market.

III.C. Lending Technology and Intangible Firm Outcomes

The regime estimates identify lending technology parameters that are not directly observable. The question is whether the estimated changes in these parameters can help explain the observed patterns in investment and leverage—patterns that are visible in the data but whose underlying causes are not.

Covenant tightening and intangible firm leverage. The estimated intangible covenant premium κ_H and observed intangible firm leverage move inversely across regimes:

	Pre-crisis	Crisis	Post-crisis	Normal	COVID	Post-COVID
κ_H	2.76	2.99	0.00	0.72	0.14	1.94
B'/A intang (data)	0.253	0.240	0.272	0.304	0.288	0.287

The pattern is non-monotonic and the inverse relationship holds across the key transitions. As κ_H peaks during the crisis (2.99), intangible firm leverage dips to its lowest level (0.240). When κ_H collapses post-crisis and remains low through normal times ($0.00 \to 0.72$), intangible leverage rises to its highest level (0.304). The post-COVID partial rebound in κ_H (1.94) coincides with a leveling off in intangible leverage (0.287). The model's mechanism is direct: higher κ_H tightens financial maintenance requirements specifically for intangible-intensive borrowers, raising their effective cost of debt. When the lending technology evolves to reduce the intangible covenant premium, borrowing costs fall and leverage rises.

This relationship is not something the data alone can reveal. Intangible firm leverage rising from 0.240 to 0.304 between the crisis and normal periods could reflect lower interest rates, stronger earnings, or greater demand for debt. The model identifies a specific channel—the reduction in the

covenant premium on intangible borrowers—and shows that it is quantitatively consistent with the observed leverage increase. The non-monotonic pattern in κ_H provides stronger identification than a simple trend: the leverage dip during the crisis coincides with peak covenant tightening, not with the worst macroeconomic conditions.

Substitution capacity and investment composition. The monotonic expansion of pledging–monitoring substitution (η_{sk}: 0.62 → 6.0) is strongly correlated with two investment patterns in the data:

	Pre-crisis	Crisis	Post-crisis	Normal	COVID	Post-COVID
η_{sk}	0.62	1.08	1.08	3.00	5.99	6.00
I^K/A tang (data)	0.091	0.096	0.090	0.062	0.046	0.058
capx share intang (data)	0.618	0.592	0.560	0.515	0.482	0.476

As substitution capacity expands, tangible firms' tangible investment declines (correlation −0.94) and intangible firms shift their investment mix away from capex (correlation −0.94). Both relationships are also present in the model (correlations −0.73 and −0.60). The mechanism: when pledging and monitoring are weak substitutes (η_{sk} low), the contract space constrains how firms can access credit, and tangible investment serves partly as collateral-building. As substitution capacity grows, this collateral motive weakens—firms no longer need to maintain tangible capital buffers to secure favorable contract terms, and investment can follow productivity rather than financing needs.

The COVID period is instructive as a boundary case. The estimated lending technology is the most favorable in the sample ($\eta_{sk} = 6.0$, $\kappa_H = 0.14$), yet intangible investment falls sharply (0.110 → 0.074). The model cannot explain this decline through the lending technology channel—it predicts intangible investment should *rise* with more flexible contracts. The gap reveals the pandemic as a real shock that overwhelmed the financial channel: even the most accommodative lending technology cannot offset a collapse in the demand for intangible investment. The partial recovery post-COVID (0.074 → 0.083) occurs as these real-side forces abate.

Contract rotation within and across regimes. The lending technology parameters determine not just the level of borrowing costs but the economy's *resilience* to financial shocks. Figure 2 varies intermediary net worth from 2.0× to 0.4× baseline at the normal-period θ, showing the buffering mechanism in action. As intermediary capital tightens, firms respond by restructuring contracts rather than cutting investment: tangible pledging (s_K) rises while monitoring (m) adjusts, and

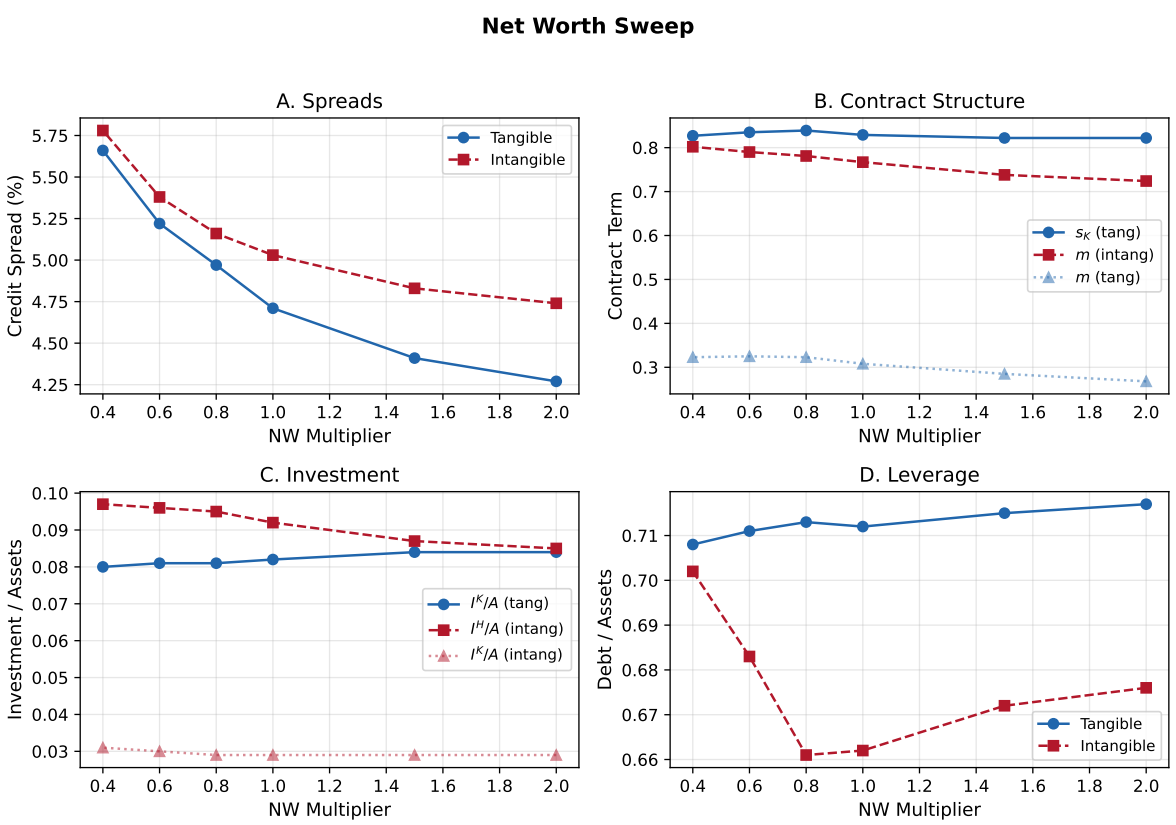


Figure 2: **Net worth sweep at normal θ.** Equilibrium outcomes as intermediary capital varies from 2.0× to 0.4×. (A) Spreads rise for both firm types. (B) Contract rotation: s_K rises while m adjusts. (C) Investment is buffered. (D) Leverage absorbs the shock.

investment moves by less than 1.5 percentage points across a fivefold NW range.

The same exercise at crisis θ produces a qualitatively different response. Figure 3 overlays the NW sweep under normal and crisis lending technologies. Under crisis θ ($\eta_{sk} = 1.08$, $\kappa_H = 2.99$), monitoring is saturated at $m \approx 0.97$ and all rotation occurs through pledging alone. Intangible investment is frozen at half the normal level ($I^H/A \approx 0.04$ versus 0.09) and is completely insensitive to intermediary conditions.

The contrast is the central implication of the regime estimates. The lending technology does not merely scale borrowing costs—it determines the structure of the equilibrium response to financial shocks. At crisis θ, the contract space is effectively one-dimensional, and the economy behaves like a standard single-constraint model. At normal θ, the multi-dimensional contract space provides sufficient degrees of freedom to buffer real investment from financial shocks. Appendix C reports additional sensitivity analysis varying individual lending technology parameters (γ_{gcv}, κ_0) at the baseline θ.

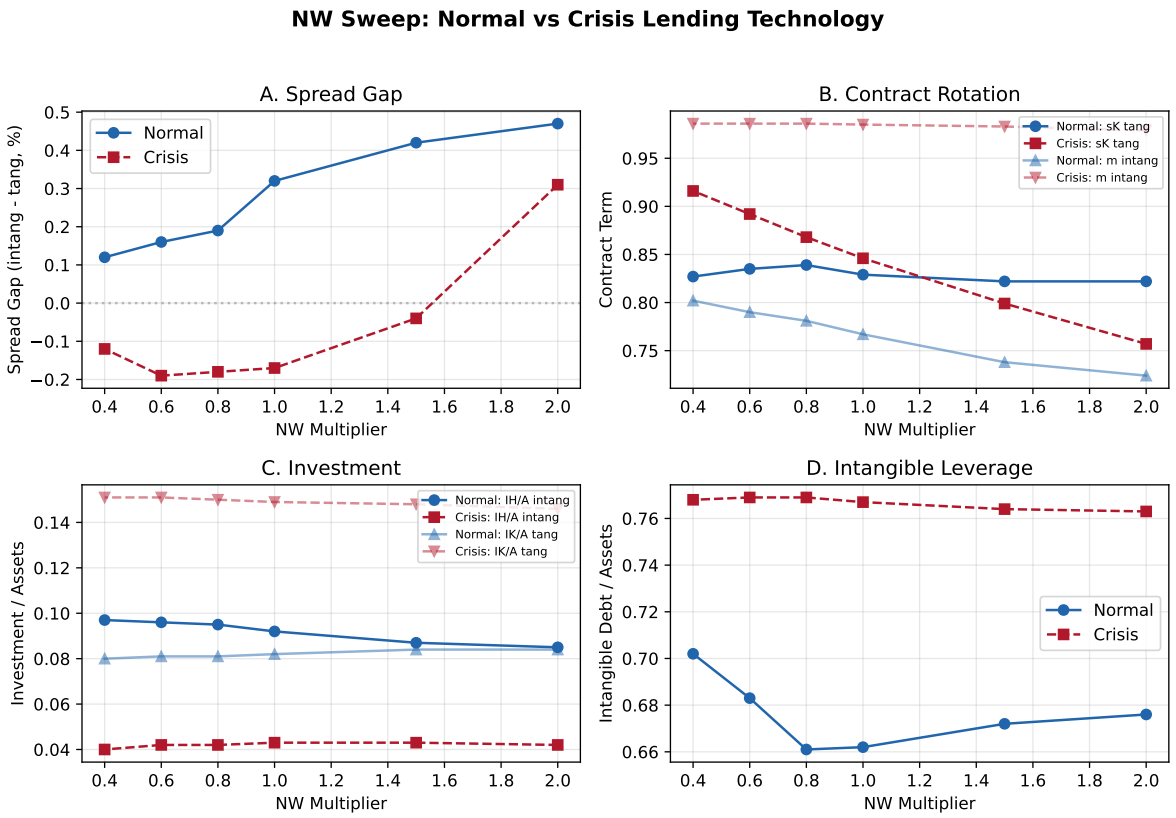


Figure 3: **NW sweep: Normal vs. Crisis lending technology.** Same NW range, different estimated θ. (A) Spread gap reverses sign across regimes. (B) Crisis: monitoring saturated, only pledging rotates. Normal: both margins adjust. (C) Crisis intangible investment is half the normal level and insensitive to NW. (D) Crisis leverage is higher but flat.

IV. Counterfactuals

The regime estimates and model fit establish that the lending technology evolved substantially over the past two decades and that the model captures the associated changes in investment and leverage patterns. This section uses the estimated parameters to conduct two counterfactual exercises. The first holds the lending technology fixed at its pre-crisis level and asks how much worse intangible firm outcomes would have been as the economy shifted toward intangible production. The second decomposes the lending technology into its constituent channels to identify which dimensions matter most.

IV.A. Historical Counterfactual: The Value of Financial Innovation

To quantify the value of lending technology evolution, I solve the model at each year's actual Compustat cross-section and FDIC intermediary net worth from 2002 through 2023, under two

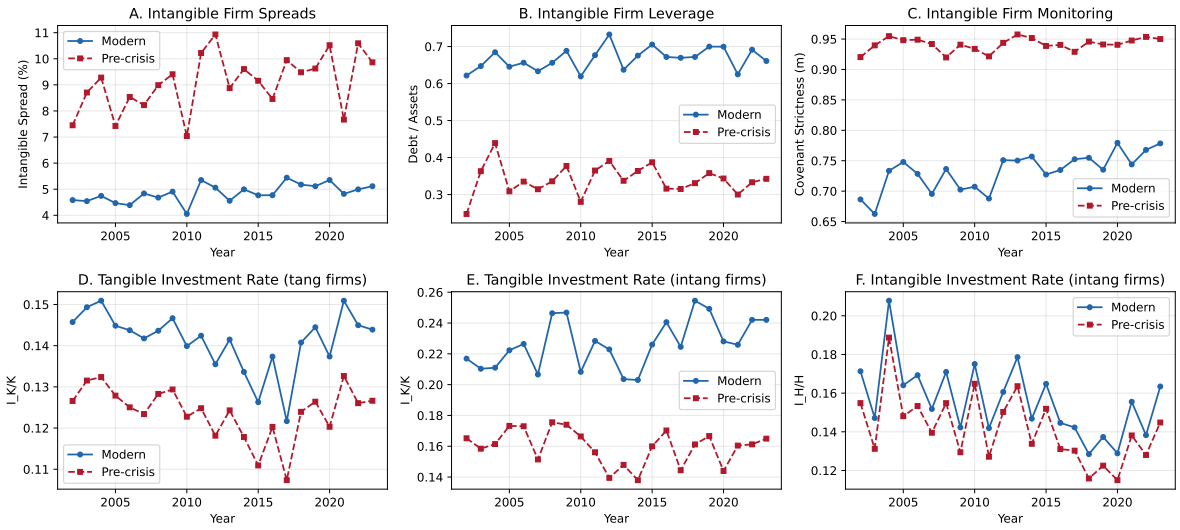


Figure 4: **Historical counterfactual: Modern vs. pre-crisis lending technology.** Each year uses that year's Compustat cross-section and FDIC intermediary net worth. "Modern" is the normal-period (2015–2019) estimated θ; "Pre-crisis" is the 2002–2006 estimated θ. (A) Intangible firm spreads are 300–500bp higher under pre-crisis technology. (B) Intangible firm leverage is nearly double under modern technology. (C) Pre-crisis technology locks firms into near-maximum monitoring ($m \approx 0.95$). (D) Tangible investment rate (I^K/K) for tangible firms is 12% higher under modern technology. (E) Intangible firms' tangible investment rate (I^K/K) is 29% higher under modern technology—the largest investment gap. (F) Intangible investment rate (I^H/H) is 9% higher under modern technology.

scenarios: the estimated normal-period θ ("modern") and the estimated pre-crisis θ (2002–2006). Both are SMM estimates, so the comparison uses two data-driven lending technologies applied to the same sequence of firms and financial conditions.

Figure 4 reports the results. The financial differences are large and persistent. Intangible firm spreads are 300–500 basis points higher under pre-crisis technology (Panel A), and intangible firm leverage is nearly double under modern technology ($B/A \approx 0.65$ versus 0.30, Panel B). The contract structure (Panel C) reveals the mechanism: under pre-crisis technology ($\eta_{sk} = 0.62$, $\kappa_H = 2.76$), monitoring is near saturation ($m \approx 0.93$–0.95), while under modern technology ($\eta_{sk} = 3.0$, $\kappa_H = 0.72$), monitoring settles at moderate levels ($m \approx 0.70$–0.78) with the remaining risk managed through pledging.

The investment effects are substantial when measured as rates per unit of capital. Intangible firms' tangible investment rate (I^K/K, Panel E) is 29% higher under modern technology on average—the largest investment gap in the counterfactual. This reflects the complementarity between lending technology and tangible capital: with higher substitution capacity, tangible as-

Table V: **Channel decomposition.** Each row shuts down one mechanism by setting its parameter to zero at a benchmark θ, holding all other parameters fixed. $N = 1.0\times$.

Experiment	B/A_I	spr_I	m_I	I_T^K/A	I_I^H/A
Baseline	0.178	8.5%	0.35	0.076	0.089
No ζ_K (tangible recovery)	0.179	5.5%	0.46	0.076	0.083
No ζ_m (monitoring recovery)	0.154	8.9%	0.15	0.076	0.088
No γ_{gcv} (continuation value)	0.155	8.5%	0.33	0.078	0.090
No η_{sk} (pledging–monitoring sub.)	0.216	10.3%	0.47	0.072	0.086
No σ_{mh} (moral hazard)	0.188	8.4%	0.29	0.076	0.090
No δ_m (monitoring cost)	0.192	7.8%	0.52	0.076	0.089

sets become more valuable as pledgeable collateral, increasing the return to tangible investment. Tangible firms' investment rate (I^K/K, Panel D) is 12% higher, and intangible firms' intangible investment rate (I^H/H, Panel F) is 9% higher. Under modern lending technology, firms invest more in *all* capital types, not just intangibles—the expanded contract space relaxes financing constraints broadly rather than narrowly favoring one type of investment.

IV.B. Channel Decomposition

The lending technology operates through multiple channels simultaneously—tangible recovery (ζ_K), monitoring recovery (ζ_m), continuation value (γ_{gcv}), pledging–monitoring substitution (η_{sk}), moral hazard reduction (σ_{mh}), and covenant compliance costs (δ_m). To isolate the contribution of each, I shut down one channel at a time from a benchmark θ and re-solve the full equilibrium at baseline NW ($N = 1.0\times$). The benchmark θ is chosen to produce interior contract terms for both firm types, ensuring each channel is active before being shut down. Table V reports the results.

Three findings emerge. First, the *pledging–monitoring substitution channel* (η_{sk}) has the largest effect on spreads and the only meaningful effect on investment. Shutting it down raises intangible firm spreads by 180 basis points (8.5% $\rightarrow$ 10.3%), increases monitoring (m: 0.35 $\rightarrow$ 0.47), and reduces tangible investment by 5%. Without substitution, firms cannot rotate between pledging and monitoring in response to financial conditions—they are locked into a single contract type, and the resulting loss of flexibility raises borrowing costs. This is consistent with the regime estimates, where η_{sk} is the parameter whose expansion most clearly tracks improvements in intangible firm outcomes.

Second, removing tangible recovery ($\zeta_K = 0$) produces a counterintuitive result: intangible firm spreads *fall* from 8.5% to 5.5%. The mechanism is contract rotation. Without the LGD

benefit of tangible collateral, pledging becomes worthless—but the equilibrium compensates by dramatically increasing monitoring (m: $0.35 \to 0.46$). The monitoring channel absorbs the function that pledging previously served. This is direct evidence that the multi-dimensional contract space provides redundancy: removing one dimension does not proportionally reduce credit access, because the other dimension expands to compensate. However, the compensation is imperfect—intangible investment falls from 0.089 to 0.083, indicating that the monitoring-only equilibrium is less efficient than the combined pledging-monitoring equilibrium.

Third, *investment is buffered across all shutdowns.* Intangible investment (I^H/A) ranges from 0.083 to 0.090 across the six experiments—a variation of less than 8% despite shutting down entire pricing channels. Tangible investment (I^K/A) is even more stable (0.072 to 0.078). The multi-dimensional contract space insulates real investment from financial channel disruptions, because firms can always restructure the remaining contract terms to partially offset the lost channel. This buffering property is a structural feature of the model: it holds regardless of which channel is removed, and it does not require any single channel to be dominant.

V. Supporting Evidence

This section presents reduced-form empirical evidence for the model's key mechanisms using syndicated loan data from DealScan and the matched DealScan-Compustat panel. I focus on three results that correspond to model predictions without direct data counterparts in the estimation: contract rotation in response to lender shocks, spread buffering through contract flexibility, and the relationship between leverage and investment composition under financial stress. Appendix A reports additional results including EBP-based investment composition regressions and secular trend analysis, all consistent with the model's predictions.

V.A. Data

DealScan. The primary loan-level data come from the Refinitiv LPC DealScan database, which covers syndicated loan facilities originated by US lenders. I use all non-financial, non-utility facilities with non-missing All-In Spread Drawn (AISD) over 2000–2023, yielding 1,142,679 facility-level observations across 33,358 borrowers. Key variables include AISD (mean 241 bps, median 200 bps), security status (52.2% secured), and financial covenant indicators (32.1% with financial covenants).

DealScan-Compustat matched panel. I match DealScan borrowers to Compustat annual fundamentals using the Chava and Roberts (2008) linking table, joining on both facility identifier and borrower company identifier. The matched panel contains 14,948 firm-years across 4,868 firms. Mean leverage is 0.331, mean intangibility ratio is 0.315, and mean loan spread is 280 bps.

V.B. Contract Rotation in Syndicated Lending

The model predicts that when intermediary capacity tightens, firms rotate across the contract space—spreads rise, covenants loosen, and collateral pledging increases (Section III.III.C, Figure 2). I test this using a lender portfolio shock following Murfin (2012): for each lender-industry-year, I compute the fraction of the lender's borrowers in *other* industries that are in financial distress. This leave-one-out construction ensures the shock is plausibly exogenous to the current borrower's credit conditions.

I aggregate to the borrower-year level and estimate:

$$y_{it} = \beta \cdot \text{LenderShock}_{it} + \gamma' X_{it} + \alpha_t + \alpha_j + \varepsilon_{it} \tag{13}$$

where y_{it} is the loan-level outcome (spread, fraction secured, fraction with financial covenants), X_{it} includes log total assets, leverage, and intangibility ratio, α_t and α_j are year and SIC-2 industry fixed effects, and standard errors are clustered by borrower.

Using the full DealScan sample (38,438 borrower-years), I find that following exogenous shocks to lender health, loan spreads increase ($t = 71$), financial covenants decrease ($t = -11$), and the fraction of secured loans increases ($t = 25$). These three facts—higher prices, fewer covenants, more collateral—are precisely the contract rotation the model predicts. When intermediary capacity tightens, lenders economize on monitoring and substitute toward collateral-based lending.

V.C. Contract Flexibility and Spread Buffering

The model's central mechanism is that access to multiple contract types buffers borrowing costs against financial shocks (Section III.III.C, Figure 3). I test this directly by classifying borrowers as "flexible" if they maintain both secured and covenant-bearing facilities in the same year—indicating simultaneous access to both pledging and monitoring channels. In the matched DealScan-Compustat panel (8,678 borrower-years), 21.5% of firm-years are classified as flexible.

Table VI: **Contract flexibility and spread buffering.** DV: loan spread. Lender portfolio shock is leave-one-out lender distress (Murfin, 2012). Flex = firm has both secured and covenant facilities. Standard errors clustered by borrower.

	(1) No FE	(2) Year + Industry FE
Lender shock	0.0518***	0.0443***
	(0.0011)	(0.0012)
Flex	0.0013***	0.0016***
	(0.0005)	(0.0005)
Shock × Flex	−0.0214***	−0.0178***
	(0.0028)	(0.0027)
Firm controls	Yes	Yes
Year FE	No	Yes
Industry FE	No	Yes
N	8,678	8,678
R^2	0.235	0.295

I estimate:

$$\text{Spread}_{it} = \beta_1 \cdot \text{LenderShock}_{it} + \beta_2 \cdot \text{Flex}_{it} + \beta_3 \cdot \text{LenderShock}_{it} \times \text{Flex}_{it} + \gamma' X_{it} + \alpha_t + \alpha_j + \varepsilon_{it} \quad (14)$$

where $\text{Flex}_{it} = \mathbf{1}[\text{any secured} \cap \text{any financial covenant}]$. The model predicts $\beta_3 < 0$.

Table VI reports the results. The interaction term is negative and highly significant ($\hat{\beta}_3 = -0.0178$, $t = -6.52$): flexible firms experience 178 basis points less spread increase per unit of lender shock. For a one-standard-deviation shock, flexible firms see roughly half the spread increase of inflexible firms. Investment (capex/assets) shows no significant differential response, consistent with the model's prediction that contract rotation absorbs the shock before it reaches real investment decisions.

V.D. Leverage and Investment Composition Under Stress

The model's crisis-regime estimates show that when covenant tightening is high ($\kappa_H = 2.99$) and substitution is limited ($\eta_{sk} = 1.08$), intangible firms face pressure to build tangible collateral (Section III.III.C). This predicts that *high-leverage* intangible firms—those most exposed to the contract frontier—should shift investment toward tangible capital under financial stress, while low-leverage firms with contract slack should not.

Using the full Compustat panel (164,593 firm-years) and the Gilchrist and Zakrajsek (2012) excess bond premium as the credit conditions measure, I estimate investment composition regressions

interacting EBP with both intangibility and leverage. The results confirm the prediction: low-leverage intangible firms shift toward R&D when credit tightens (coefficient -0.030, $t = -2.24$), while high-leverage intangible firms shift toward capex (coefficient $+0.098$, $t = 7.18$). This heterogeneity is consistent with the model's prediction that the investment response depends on the firm's position in the contract space—firms at the contract frontier are forced toward tangible investment for collateral purposes, while firms with slack maintain their preferred composition.

VI. Conclusion

This paper develops and estimates a structural model of multi-dimensional lending technology in which firms and lenders jointly choose from a contract space spanning tangible pledging and monitoring-based covenants. Estimating the lending technology separately across six credit-cycle regimes from 2002 to 2023, I find that the dominant change in the lending technology is the expansion of substitution capacity between pledging and monitoring. This tenfold increase over two decades transformed the contract space from effectively one-dimensional to fully flexible. This expansion coincides with, and helps explain, the covenant-lite revolution, the rise of direct lending, and the secular shift in investment composition away from tangible collateral-building. The estimated intangible covenant premium follows an inverted-U, peaking during the financial crisis and declining as substitution capacity rendered brute-force covenant tightening unnecessary. This non-monotonic pattern inversely tracks intangible firm leverage in the data, identifying a specific lending technology channel through which financial innovation affects real borrowing decisions.

The model generates several results that standard one-dimensional collateral models cannot. Contract rotation, the reallocation of borrowing across contract types in response to financial shocks, buffers investment levels while shifting investment composition. The same intermediary capital shock produces qualitatively different equilibrium responses depending on the lending technology in place: under crisis-era technology, monitoring is saturated and only pledging adjusts; under modern technology, both margins respond and investment is insulated. A historical counterfactual applying pre-crisis lending technology to the actual sequence of firms and financial conditions from 2002–2023 shows that intangible firms' tangible investment rate would be 29% lower, their spreads 300–500 basis points higher, and their monitoring near saturation. Reduced-form evidence from syndicated lending data confirms the model's predictions: exogenous lender shocks produce contract rotation, firms with access to multiple contract types see substantially less spread sensitiv-

ity ($t = -6.52$), and high-leverage intangible firms shift investment toward tangible capital under financial stress.

Several directions for future research are natural. First, the lending technology in this paper is exogenous to the model, estimated from data but not endogenized within the equilibrium. A richer framework would allow lending technology to evolve in response to the composition of borrowers, intermediary learning, and regulatory changes, generating the observed η_{sk} expansion as an equilibrium outcome rather than an estimated input. Second, the paper does not distinguish between demand-side and supply-side drivers of the observed lending technology changes. The regime estimates capture the joint outcome of borrower needs and lender capabilities. Disentangling these, for example by exploiting variation in lender entry and exit, would sharpen the identification of financial innovation's causal effects on investment.

Third, the model's definition of intangible capital relies on Compustat's recorded intangible assets, which primarily reflects acquisition goodwill rather than internally generated intangibles. A growing share of economically important capital (customer relationships, proprietary technology embedded in processes, organizational knowledge, and technology applications that appear as operating expenditure rather than capitalized investment) is invisible in standard balance sheet data. This "hidden growth" in intangible capital means the model likely understates the scope of the lending technology problem: the firms that most need innovative contract structures to access credit are precisely those whose assets are least visible in the data used to estimate the model. Incorporating broader measures of intangible capital, including capitalized R&D, customer acquisition costs, and technology-augmented physical capital, would provide a more complete picture of how lending technology shapes real investment in the modern economy.

REFERENCES

Adrian, Tobias, and Hyun Song Shin, 2010, Liquidity and leverage, *Journal of Financial Intermediation* 19, 418–437.

Azinovic, Marlon, Luca Gaegauf, and Simon Scheidegger, 2022, Deep equilibrium nets, *International Economic Review* 63, 1471–1525.

Bradley, Michael, and Michael R. Roberts, 2015, The structure and pricing of corporate debt covenants, *Quarterly Journal of Finance* 5, 1550001.

Brunnermeier, Markus K., and Lasse Heje Pedersen, 2009, Market liquidity and funding liquidity, *Review of Financial Studies* 22, 2201–2238.

Chava, Sudheer, and Michael R. Roberts, 2008, How does financing impact investment? The role of debt covenants, *Journal of Finance* 63, 2085–2121.

Chodorow-Reich, Gabriel, 2014, The employment effects of credit supply shocks: Evidence from the U.S. banking system, *American Economic Review* 104, 2033–2056.

Corrado, Carol, Charles Hulten, and Daniel Sichel, 2009a, Intangible capital and U.S. economic growth, *Review of Income and Wealth* 55, 661–685.

Corrado, Carol, Charles Hulten, and Daniel Sichel, 2009b, Intangible capital and us economic growth, *Review of Income and Wealth* 55, 661–685.

Crouzet, Nicolas, and Janice Eberly, 2019, Understanding weak capital investment: The role of market concentration and intangibles, in *Proceedings of the Jackson Hole Economic Policy Symposium*, 87–149, Federal Reserve Bank of Kansas City.

Demerjian, Peter, 2011, Accounting standards and debt covenants: Has the 'balance sheet approach' led to a decline in the use of balance sheet covenants?, *Journal of Accounting and Economics* 52, 178–202.

Eisfeldt, Andrea L., and Dimitris Papanikolaou, 2014, The value and ownership of intangible capital, *American Economic Review: Papers and Proceedings* 104, 189–194.

Falato, Antonio, Dalida Kadyrzhanova, and Jae W. Sim, 2022, Rising intangible capital, shrinking debt capacity, and the U.S. corporate savings glut, *Journal of Financial Economics* 142, 1–22.

Fernandez-Villaverde, Jesus, Samuel Hurtado, and Galo Nuno, 2023, Financial frictions and the wealth distribution, *Econometrica* 91, 1379–1418.

Gilchrist, Simon, and Egon Zakrajsek, 2012, Credit spreads and business cycle fluctuations, *American Economic Review* 102, 1692–1720.

Gopalan, Radhakrishnan, Fenghua Song, and Vijay Yerramilli, 2014, Debt maturity structure and credit quality, *Journal of Financial and Quantitative Analysis* 49, 817–842.

Haan, Wouter J. Den, 2010, Comparison of solutions to the incomplete markets model with aggregate uncertainty, *Journal of Economic Dynamics and Control* 34, 4–27.

He, Bianca, Lauren Mostrom, and Amir Sufi, 2024, Investing in customer capital, NBER Working Paper 33171.

He, Zhiguo, and Arvind Krishnamurthy, 2013, Intermediary asset pricing, *American Economic Review* 103, 732–770.

Hennessy, Christopher A., and Toni M. Whited, 2007, How costly is external financing? Evidence from a structural estimation, *Journal of Finance* 62, 1705–1745.

Holmstrom, Bengt, and Jean Tirole, 1997, Financial intermediation, loanable funds, and the real sector, *Quarterly Journal of Economics* 112, 663–691.

Ivashina, Victoria, 2009, Asymmetric information effects on loan spreads, *Journal of Financial Economics* 92, 300–319.

Ivashina, Victoria, and David Scharfstein, 2010, Bank lending during the financial crisis of 2008, *Journal of Financial Economics* 97, 319–338.

Jang, Young Soo, Dasol Kim, and Amir Sufi, 2025, The lending technology of direct lenders in private credit, Working Paper 34500, National Bureau of Economic Research.

Jensen, Michael C., 1986, Agency costs of free cash flow, corporate finance, and takeovers, *American Economic Review* 76, 323–329.

Kermani, Amir, and Yueran Ma, 2023, Asset specificity of nonfinancial firms, *Quarterly Journal of Economics* 138, 205–264.

Lian, Chen, and Yueran Ma, 2021, Anatomy of corporate borrowing constraints, *Quarterly Journal of Economics* 136, 229–291.

Maliar, Lilia, Serguei Maliar, and Pablo Winant, 2021, Deep learning for solving dynamic economic models, *Journal of Monetary Economics* 122, 76–101.

Murfin, Justin, 2012, Supply-side shocks to covenant strictness, *Journal of Finance* 67, 1389–1431.

Myers, Stewart C., and Nicholas S. Majluf, 1984, Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* 13, 187–221.

Nini, Greg, David C. Smith, and Amir Sufi, 2012, Creditor control rights, corporate governance, and firm value, *Review of Financial Studies* 25, 1713–1761.

Ottonello, Pablo, and Thomas Winberry, 2020, Financial heterogeneity and the investment channel of monetary policy, *Econometrica* 88, 2473–2502.

Perez, Ethan, Florian Strub, Harm de Vries, Vincent Dumoulin, and Aaron Courville, 2018, FiLM: Visual reasoning with a general conditioning layer, in *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32.

Peters, Ryan H., and Lucian A. Taylor, 2017, Intangible capital and the investment-q relation, *Journal of Financial Economics* 123, 251–272.

Rampini, Adriano A., and S. Viswanathan, 2010, Collateral, risk management, and the distribution of debt capacity, *Journal of Finance* 65, 2293–2322.

Rampini, Adriano A., and S. Viswanathan, 2013, Collateral and capital structure, *Journal of Financial Economics* 109, 466–492.

Rauh, Joshua D., and Amir Sufi, 2010, Capital structure and debt structure, *Review of Financial Studies* 23, 4242–4280.

Roberts, Michael R., and Amir Sufi, 2009, Renegotiation of financial contracts: Evidence from private credit agreements, *Journal of Finance* 64, 1657–1695.

Stiglitz, Joseph E., and Andrew Weiss, 1981, Credit rationing in markets with imperfect information, *American Economic Review* 71, 393–410.

Sufi, Amir, 2007, Information asymmetry and financing arrangements: Evidence from syndicated loans, *Journal of Finance* 62, 629–668.

Appendix A. Additional Empirical Evidence

The following results complement the main supporting evidence in Section V.

EBP and investment composition. Using the full Compustat panel (164,593 firm-years) with the Gilchrist and Zakrajsek (2012) excess bond premium, I find that credit tightening shifts intangible firms' investment composition: EBP × intangibility on capex/(capex + R&D) is −0.013 ($t = -1.87$), on capex/assets is −0.036 ($t = -13.5$), and on cash/assets is −0.018 ($t = -2.98$). Intangible firms cut tangible investment and cash holdings more than tangible firms when credit conditions tighten.

Secular trends. Among intangible-intensive firms in Compustat, the ratio of capital expenditure to total investment declined from 1.0 in 2000 to 0.32 in 2023, while intangible firm leverage rose from 17.8% in the 2000s to 25.3% in the 2020s. Both patterns are consistent with the model's estimated expansion of substitution capacity (η_{sk}): better lending technology makes debt cheaper for intangible firms while reducing the collateral motive for tangible capital.

Table VII: **Targeted moments by regime (full).** Data (D) and model (M) values for all eleven SMM moments. Investment moments are mean firm-level ratios. Leverage uses $B^{\text{new}}_{i,t+1}/A_{it}$. Tang: $\eta < 0.33$; Intang: $\eta \geq 0.66$. Spread from DealScan (data) and $r_{\text{eff}} - r_f$ (model).

	Pre-crisis		Crisis		Post-crisis		Normal		COVID		Post-COVID	
	D	M	D	M	D	M	D	M	D	M	D	M
$\overline{I^K/A}$ (tang)	.091	.074	.096	.155	.090	.129	.062	.071	.046	.046	.058	.054
$\overline{I^H/A}$ (intang)	.054	.080	.059	.026	.072	.037	.110	.057	.074	.063	.083	.060
$\overline{B'/A}$ (tang)	.233	.243	.205	.410	.226	.447	.247	.394	.242	.394	.252	.377
$\overline{B'/A}$ (intang)	.253	.591	.240	.629	.272	.400	.304	.322	.288	.341	.287	.389
corr(I^K/A, η)	−.019	−.247	−.045	−.274	−.120	−.295	−.203	−.318	−.212	−.359	−.239	−.384
capx share (int)	.618	.458	.592	.766	.560	.699	.515	.541	.482	.437	.476	.480
I^K/A ratio	.179	.417	.158	.432	.176	.331	.220	.282	.228	.270	.184	.260
std(B'/A)	.277	.304	.256	.295	.276	.252	.284	.278	.269	.287	.270	.295
$\overline{I^K/K}$ (tang)	.171	.127	.219	.259	.456	.213	.178	.129	.129	.095	.128	.107
$\overline{I^K/K}$ (intang)	.320	.226	.241	.470	1.265	.343	.225	.187	.134	.113	.125	.133
spread	.018	.090	.024	.034	.025	.030	.025	.027	.028	.032	.026	.031
Score	164.4		35.1		5.4		1.1		1.1		1.1	

Appendix B. Regime Fit Discussion

The crisis and pre-crisis SMM fits are substantially weaker than the normal period (scores 35.1 and 164.4 versus 1.1). Three factors contribute. First, the policy network was trained at a fixed

risk-free rate of $r_f = 2\%$, which is approximately correct for the normal period but too low for pre-crisis ($r_f \approx 3.5\%$) and too high for the crisis ($r_f \approx 1.5\%$). The pre-crisis spread mismatch (model 9.0% versus data 1.8%) is largely attributable to this. Second, the crisis investment pattern—tangible investment rising while intangible investment collapses—is absorbed by adjustment cost parameters ($\phi_K = 0.50$, $\phi_H = 13.70$) rather than the lending technology, suggesting that real-side frictions played a role that the financial model cannot fully capture. Third, several parameters hit their bounds in the crisis and pre-crisis periods (κ_H, κ_0, ϕ_K), limiting the optimizer's ability to find better-fitting combinations. Widening these bounds and retraining the policy network with a sampled risk-free rate are natural directions for improving the crisis-period fit.

Appendix C. Detailed Sweep Results

Tables VIII–X report the full numerical results from the NW, κ_0, and γ_{gcv} sweeps at the estimated normal-period θ.

Table VIII: **NW sweep (detailed).** Full equilibrium outcomes at estimated θ.

N	μ_N	μ_M	B/A_T	B/A_I	spr_T	spr_I	$s_{K,T}$	m_I	I_T^K/A	I_I^H/A
2.0	0.06	0.14	0.72	0.68	4.3%	4.7%	0.82	0.72	0.084	0.085
1.5	0.08	0.18	0.72	0.67	4.4%	4.8%	0.82	0.74	0.084	0.087
1.0	0.10	0.25	0.71	0.66	4.7%	5.0%	0.83	0.77	0.082	0.092
0.8	0.13	0.29	0.71	0.66	5.0%	5.2%	0.84	0.78	0.081	0.095
0.6	0.16	0.29	0.71	0.68	5.2%	5.4%	0.84	0.79	0.081	0.096
0.4	0.22	0.29	0.71	0.70	5.7%	5.8%	0.83	0.80	0.080	0.097

Table IX: κ_0 **sweep (detailed).**

κ_0	μ_N	μ_M	B/A_T	B/A_I	spr_T	spr_I	$s_{K,T}$	m_I	I_T^K/A	I_I^H/A
−5.0	0.11	0.03	0.73	0.75	4.4%	3.7%	0.78	0.11	0.084	0.085
−4.0	0.11	0.06	0.72	0.75	4.4%	4.0%	0.77	0.21	0.085	0.085
−3.0	0.11	0.11	0.72	0.74	4.5%	4.4%	0.76	0.38	0.085	0.086
−2.0	0.11	0.18	0.72	0.71	4.6%	4.8%	0.79	0.58	0.085	0.087
−1.0	0.10	0.25	0.71	0.66	4.7%	5.0%	0.83	0.77	0.082	0.092

Appendix D. Solution Methodology

This appendix describes the computational solution method in detail. The model is solved using the deep equilibrium network (DEQN) approach of Azinovic et al. (2022), extended with parameter

Table X: γ_{gcv} **sweep (detailed).**

γ_{gcv}	μ_N	μ_M	B/A_T	B/A_I	$s_{K,I}$	m_I	I_T^K/A	I_I^H/A
0.10	0.12	0.17	0.64	0.39	1.00	0.81	0.086	0.085
0.50	0.12	0.19	0.66	0.45	1.00	0.82	0.086	0.086
1.00	0.12	0.22	0.69	0.52	1.00	0.83	0.085	0.089
2.00	0.12	0.25	0.71	0.62	1.00	0.82	0.084	0.091
5.00	0.10	0.24	0.71	0.66	0.94	0.73	0.082	0.092

conditioning and analytical contract solvers.

A.1 Network Architecture

A neural network maps the firm state vector $x_i = (K_i, H_i, C_i, a_i, B_i, \mu_N, \mu_M, B_i^{\text{new}})$ to optimal controls $(I_i^K, I_i^H, e_i, C_i')$. The network consists of three hidden layers of 256 units with SiLU activation functions. The lending technology parameter vector $\theta \in \mathbb{R}^{11}$ enters through Feature-wise Linear Modulation (FiLM, Perez et al., 2018): a separate encoder network maps θ to per-layer affine parameters (γ_l, β_l), which scale and shift the hidden activations:

$$h_l = \text{SiLU}(\gamma_l(\theta) \odot W_l h_{l-1} + \beta_l(\theta)) \,. \tag{D1}$$

This allows the same network to represent optimal policies across the full range of θ, which is essential for SMM estimation where the objective function must be evaluated at many candidate parameter vectors.

Output transformations ensure economic feasibility: investment rates use softplus (non-negative), equity issuance uses softplus (non-negative), and cash retention uses sigmoid scaled to $[0, C_{\max}]$.

A.2 Contract Solver

Contract terms (s_K^*, s_{GC}^*) are not network outputs. Instead, they are solved analytically at each state by bisection over $[0, 1]$, minimizing the firm's total borrowing cost:

$$(s_K^*, s_{GC}^*) = \arg \min_{s_K, s_{GC} \in [0,1]^2} \left[r^{\text{eff}}(s_K, s_{GC}) + \delta_s \cdot s_K \cdot K/\text{assets} \right] . \tag{D2}$$

The optimization is performed sequentially: for each candidate s_{GC}, the optimal s_K is found by bisection (10 iterations); then s_{GC} is optimized by bisection over the outer loop (10 iterations). Covenant strictness m is computed from equation (8) at each evaluation.

A.3 Training

The network is trained by minimizing mean squared Euler equation residuals. For each iteration:

1. Sample a batch of 1,024 firm states from a stratified distribution over (K, H, C, a, B).
2. Sample $\mu_N \sim U[0.05, 0.3]$ and $\mu_M \sim U[0, 0.3]$ independently per firm.
3. Sample B^{new} as a fraction of assets from $U[0.05, 0.8]$.
4. Sample θ from $U[\theta_{\min}, \theta_{\max}]$ (2 independent draws per iteration for diversity).
5. Compute current-period controls from the network: (I^K, I^H, e, C').
6. Solve contracts (s_K^*, s_{GC}^*, m^*) analytically.
7. Compute next-period states using laws of motion.
8. Evaluate the Euler equations using Gauss-Hermite quadrature ($3^2 = 9$ nodes) over the bivariate productivity shock distribution.
9. Compute Euler residuals for I^K, I^H, and C', plus the Fischer-Burmeister complementarity condition for equity issuance.
10. Backpropagate and update network parameters via Adam (learning rate 10^{-4}, gradient clipping at 5.0).

Training runs for up to 5,000 iterations with early stopping: if all Euler equation residual EMAs fall below 10^{-2} for 500 consecutive iterations (after a minimum of 4,000 iterations), training terminates. An exponential moving average (EMA) copy of the network ($\alpha = 0.999$) is maintained for evaluation.

A.4 Equilibrium Computation

Post-training, equilibrium shadow prices (μ_N, μ_M) are determined by tâtonnement on the intermediary's convex cost function. Given a cross-section of firms, the solver iterates:

1. Set initial guesses $\mu_N = 0.10$, $\mu_M = 0.10$.
2. Solve contracts (s_K^*, s_{GC}^*, m^*) at current prices for all firms.

3. Compute aggregate capital utilization $u = (\sum_i \text{RW}_i \cdot \text{LGD}_i \cdot B_i)/NW$ and monitoring utilization $u_M = (\sum_i m_i \cdot B_i)/(\xi_M \cdot NW)$.

4. Update prices: $\mu_N = \kappa \cdot u^\gamma$, $\mu_M = \kappa \cdot u_M^\gamma$ (capped at 0.29).

5. Solve optimal B_i^{new} for each firm via rollout (see A.5).

6. Update debt: $B \leftarrow B + \delta(B^{\text{new}} - B)$ with damping $\delta = 0.3$.

7. Repeat for 10 iterations.

The convex cost function $\mu_N = \kappa \cdot u^\gamma$ ($\kappa = 0.08$, $\gamma = 2.0$) generates intermediation costs that are always positive and increase convexly with utilization, consistent with intermediary asset pricing models.

A.5 New Borrowing

During training, B^{new} is sampled as an input (not a network output) to avoid the difficulty of learning borrowing FOCs through detached contract solvers. In equilibrium, optimal B^{new} is determined by a two-step procedure. First, a rollout solver evaluates firm value at 20 candidate B^{new} levels by simulating the firm forward for 15 periods using the trained policy network, computing discounted dividends at each candidate. Second, a lightweight neural network (the "B-new head") is trained on the rollout solver's targets across 50 θ draws $\times$ 500 firms, achieving 0.96 correlation with the rollout optimum. The head provides fast B^{new} predictions inside the SMM objective function, where the full rollout would be prohibitively slow.

A.6 Accuracy

Euler equation residuals at the equilibrium allocation are reported in $\log_{10}$ units. Residuals below -3.0 (error $< 0.1\%$) are considered accurate by the standards of Haan (2010). Typical training achieves residuals of -3.0 to -3.5 across the three Euler equations.

Appendix E. Data Construction

Compustat. I use the Compustat Annual Fundamentals file (Standard format) for fiscal years 2000–2023. I exclude financial firms (SIC 6000–6999) and utilities (SIC 4900–4999). Firm-level variables are constructed as follows: tangible capital K = PPEGT (gross property, plant, and

equipment), intangible capital H = INTAN (total intangible assets, primarily acquisition goodwill under GAAP), cash C = CHE (cash and short-term investments), debt B = DLTT + DLC (long-term debt plus debt in current liabilities), total assets A = AT. Intangibility is $\eta = H/(K+H)$. Tangible firms have $\eta < 0.33$; intangible firms have $\eta \geq 0.66$. I require AT > 0 and filter leverage $B/A \leq 1.5$ to remove firms in financial distress or with data errors.

Moment construction. All investment and leverage moments are computed as means of firm-level ratios, not ratios of means. Tangible investment rate: I^K/K = CAPX / PPEGT. Intangible investment intensity: I^H/A = XRD / AT (R&D expense divided by total assets; I^H/H = XRD / INTAN is not used because INTAN primarily captures acquisition goodwill rather than internally generated intangibles, making the denominator economically mismatched with the numerator). Leverage uses next-period debt: $B_t^{\text{new}} = B_{t+1}$ (the lead of total debt), with the final year in each regime carrying forward the current value. Observations with $B^{\text{new}}/A > 1.5$ are filtered. The capex share for intangible firms is mean(CAPX$_i$ / (CAPX$_i$ + XRD$_i$)) for firms with CAPX + XRD > 0.

DealScan. Syndicated loan data come from the Refinitiv LPC DealScan database. I use facility-level observations with non-missing All-In Spread Drawn (AISD), excluding financials and utilities by SIC code. The mean spread moment targets the average AISD for each regime from raw DealScan without any Compustat merge: 185 bps (pre-crisis), 244 bps (crisis), 254 bps (post-crisis), 247 bps (normal), 281 bps (COVID), 258 bps (post-COVID). For the supporting evidence regressions, I construct a borrower-year panel by aggregating facility-level data to the borrower-year level, taking the mean spread, fraction secured, and fraction with financial covenants.

DealScan-Compustat match. For the contract flexibility and lender portfolio shock regressions, I match DealScan borrowers to Compustat using the Chava and Roberts (2008) linking table. I join on both facility identifier (LPC_Tranche_ID) and borrower company identifier (Borrower_Id), retaining observations that match on either key. The matched panel contains 14,948 firm-years across 4,868 unique firms.

FDIC net worth. Intermediary net worth for the historical counterfactual is constructed from the FDIC's quarterly bank capital ratio series. I use the October observation each year (Q3 filing) and multiply the aggregate capital ratio by mean firm debt in the model cross-section to obtain a NW level in model units.

Regime definitions. Pre-crisis: 2002–2006. Crisis: 2008–2010. Post-crisis: 2011–2014. Normal: 2015–2019. COVID: 2020–2021. Post-COVID: 2022–2023. The year 2007 is excluded as a transition year. Each regime's SMM estimation uses only firms from that regime's fiscal years.