Bailout Expectations, Default Risk and the Dynamics of Bank Credit Spreads*

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Abstract

This paper studies the role of bailout expectations in shaping the dynamics of bank credit spreads and the implications for bank risk-taking behavior. I propose a dynamic model of financial intermediation with bank default and time-varying bailout probabilities. Credit spreads are driven by both fundamental risk and bailout expectations. These two forces have contrasting implications for the joint comovement of credit spreads and default probabilities. Combining the model with US bank credit default swap spreads and option-implied default probabilities, I indirectly infer the relative importance of fundamentals and bailout expectations as drivers of spreads. I find that 28 basis points out of the 34-basis-point rise in credit spreads after 2010 are due to lower perceived bailout probabilities, and that the remainder reflects weaker fundamentals and is partly offset by tighter capital requirements. Finally, I use the model to measure the effect of lower bailout expectations and tighter regulation on the expected returns of bank assets and the cost of bank credit. Abstracting from lower bailout expectations overstates the importance of regulatory tightening by a factor of two.

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1 Introduction

After the Global Financial Crisis (GFC), US regulators introduced two main sets of reforms aimed at making the financial system safer. On one hand, Basel III increased banks' required equity buffers. On the other hand, Title II of Dodd–Frank[1] was designed to reduce bailout expectations by establishing that insolvency losses are imposed on unsecured creditors rather than rescuing them with public funds.[2] While a large literature has studied the first dimension, higher capital requirements and their effects on bank behavior, the second dimension remains relatively unexplored: whether regulators' attempts to reduce bailout expectations were perceived as credible by markets and what the consequences of that credibility are remain open questions. Consistent with lower perceived bailout probabilities, credit spreads on unsecured bank debt remained well above their precrisis levels after 2010, even as leverage came down. However, weaker fundamentals, such as poorer asset quality that raised default risk, may also have driven higher spreads.

This paper measures the importance of bailout expectations in shaping the dynamics of bank credit spreads and studies the resulting consequences for banks' willingness to take risks. I combine a dynamic model of financial intermediation with bank credit default swap (CDS) spreads and risk-neutral default probabilities that I recover from equity option prices. Data alone cannot disentangle fundamentals from bailout expectations because default probabilities are equilibrium outcomes of banks' choices and depend on both forces. I show that the comovement of credit spreads and default probabilities is informative about the relative importance of the two components. If higher credit spreads are associated with lower default probabilities, the model attributes the increase to lower bailout expectations. I find that about 28 basis points of the 34-basis-point rise in credit spreads after 2010 are due to lower perceived bailout probabilities. Fundamentals drive the remaining 18 basis points, and are partly offset by tighter regulations that lowered default risk and reduced spreads by roughly 12 basis points.

I then use the recovered path of bailout probabilities and fundamentals to evaluate how the Dodd–Frank act and the post-2010 regulatory landscape reshaped banks' risk-bearing capacity by changing their funding costs and capital structure. Lower bailout expectations and tighter regulatory requirements contributed roughly equally to the increase in risk premia on banks' assets and lending rates after 2010. This rationalizes banks' retreat from risky asset markets, higher expected returns in segments dominated by banks, and a rise in the overall cost of bank credit. Ignoring bailout expectations there-

[1] Dodd–Frank Wall Street Reform and Consumer Protection Act, Pub. L. 111–203 (2010).

[2] A similar shift occurred in Europe with the Single Resolution Mechanism (SRM) under the Banking Union, which resolves failing banks via creditor 'bail-ins', converting debt to equity and imposing losses on investors instead of taxpayers.

fore implies overstating the importance of stricterregulation by a factor of two.

I start my analysis with a simple decomposition of credit spreads into a risk-neutral probability of default (i.e., an expected probability of default adjusted for risk compensation) and an expected loss given default component. I aim to empirically isolate the movements in spreads that are not directly driven by default risk. I proceed in two steps. First, building on the methodology of Carr & Wu (2011), I estimate the market-implied chance of default from prices of put options on the bank's stock. Second, I combine these option-implied default probabilities with credit default swap (CDS) spreads to recover an estimate of the risk-neutral loss given default as a residual. The expected loss given default equals the probability of no bailout multiplied by the loss creditors bear without government support. I find that, although risk-neutral default probabilities return to their precrisis levels after 2010, spreads remain elevated. This implies higher expected losses given default. Expected creditor losses conditional on default were about 10% before the GFC, surged to roughly 40% in 2007-09, and have remained elevated: they hover near 30% through much of the 2010s and around 20% by 2020.[3]

However, the role of bailout expectations in driving credit spreads cannot be inferred solely from changes in the expected loss given default. Default probabilities and recovery values are equilibrium outcomes of banks' endogenous decisions and thus reflect both fundamentals and bailout expectations. I therefore develop a dynamic general equilibrium model of financial intermediation with bank default and time-varying bailout probabilities and use it as a measurement device to isolate the role of bailout expectations. My framework combines elements from the intermediary-asset pricing literature (He & Krishnamurthy 2013, 2018) with institutional features of the banking sector (Elenev et al. 2021, Mendicino et al. 2019).

I consider an endowment economy in which financial intermediaries (banks) invest in risky assets by using their own net worth and issuing a combination of deposits, equity, and debt to households. Raising equity capital is costly and banks are subject to an occasionally binding regulatory constraint. Banks operate under limited liability and have the option of defaulting on their debt obligations. Deposits pay below-market rates and are fully insured by the government. In contrast, bank debt is priced to reflect both bank fundamentals and the time-varying bailout probability. When a bailout is granted, the government pays the full shortfall to debt holders. Otherwise, creditors recover a frac-

[3] Over time, movements in expected losses given default within banks explain about 60% of the variation in credit spreads. Higher expected losses more than fully account for the rise in spreads in the post-2010 shift, while the concurrent decline in default risk offsets roughly one-third of that increase. To ensure this is not a liquidity artifact, I construct an adjusted series that removes movements linked to option bid–ask spreads, trading volume and open interest, CDS market depth, and proxies for intermediation capacity (TED–SOFR and VIX). The adjustment is sizable during 2008–11 and small otherwise, and leaves the post-2010 level and persistence of expected losses largely unchanged.

tion of the post-default asset value. A positive probability of bailout effectively subsidizes the price of bank debt relative to actuarially fair pricing.

The bank's optimal leverage ratio mainly trades off two forces. First, issuing one additional dollar of debt is attractive because it provides cheap and subsidized funding relative to equity. However, intermediaries internalize that more leverage increases the probability of default and associated deadweight losses; this discourages risk-taking. This is further reinforced by equity issuance costs, which reduce banks' risk-taking ex-ante, since banks want to hold more equity in order to avoid issuing in states of the world in which losses are high. At the same time, capital requirements directly constrain banks' leverage choices.

In the model, credit spreads vary due to fundamental risk, namely the risk that the bank's assets generate cash flows insufficient to meet its debt obligations and changes in bailout expectations. These two driving forces have very different implications for the dynamics of the model-implied risk-neutral default probabilities. In fact, an increase in credit spreads is driven by a deterioration in fundamentals and is associated with an increase in the expected probability of a bank default, even after banks reduce their leverage in response to the worsening fundamentals. If the increase in credit spreads is instead driven by a reduction in perceived bailout probabilities, we then associate the increase with a reduction in expected default probabilities. If the bank faces a lower debt subsidy, it finds that reducing its leverage is optimal and thereby reduces its probability of default.

The comovement of credit spreads and default probabilities is therefore informative about the importance of bailout expectations versus fundamentals. All else being equal, the model interprets the observation of persistently higher credit spreads associated with higher default probabilities as evidence of a quantitatively sizable role for fundamentals. In contrast, an increase in credit spreads accompanied by a declining default probability indicates that bailout expectations are the underlying source.

A potentially confounding factor is the tightening of regulation post-2010. Lower default probabilities could reflect tighter regulatory requirements rather than lower bailout expectations. If regulation were the dominant force, postcrisis spreads should have fallen; instead, they persistently remain higher. Precise inferences about bailout expectations and fundamentals therefore require explicitly accounting for postcrisis regulatory tightening. Following the GFC, policymakers tightened regulations along multiple dimensions and implemented them on a staggered timeline. Constructing a single, reliable measure of regulatory stringency is therefore difficult. I recover the tightness of regulation by exploiting the observation that, in the model, regulation moves credit spreads and downside equity volatility in the same direction, contrary to expected bailouts. Tighter regulation lowers credit spreads and downside equity risk by forcing debt holders to share losses ex-ante, which reduces effective leverage and flattens spreads. Conversely, when bailouts seem less likely, spreads widen as expected losses rise, but banks cut leverage. Left-tail equity variance therefore declines. Consequently, I discipline the parameter governing capital requirements by matching the change in the elasticity of CDS spreads to downside volatility of equity returns from before 2008 to after 2010.

After fitting the model to US data, I turn to the main quantitative experiment of the paper, which quantifies the extent to which bailout expectations contributed to the post-2010 increase in bank credit spreads. I use the particle filter to the model and extract the sequence of structural shocks that accounts for the behavior of credit spreads and risk-neutral default probabilities before, during, and after the GFC. While doing this, I increase capital requirements from 8% to 10.5%. This increase matches the change in the slope of the relationship between credit spreads and the left-tail variance of equity returns estimated in the data.[4] The recovered bailout probabilities are very high prior to 2008 (around 94%), drop around the collapse of Lehman Brothers in late 2008, and decline further to 75% with the 2009Q3 announcement and July 2010 enactment of the Dodd–Frank act. They remain at that level through 2013 and then recover only gradually to a level below their precrisis benchmark of around 85%.

Equipped with this path of structural shocks, I back out the contribution of bailout expectations to the post-2010 increase in spreads. I construct the counterfactual credit spreads that would have emerged if bailout probabilities were fixed at their precrisis level while feeding in the same sequence of fundamental shocks and changes in regulation. The bailout component of credit spreads, which is computed as the difference between actual and counterfactual spreads, explains about 40% of the post-2010 plateau in spreads, with the remainder accounted for by fundamental risk and regulation. The average unsecured spread paid by large US banks increases by 34 basis points between the pre-2008 and the post-2010 periods. In the counterfactual scenario that holds the precrisis bailout probability at its high level, the same spread rises by only 6 basis points. The remaining 28 basis points, almost three quarters of the observed increase, are therefore a pure bailout premium that investors demand once they expect to bear losses. Deteriorating fundamentals account for an 18 basis point increase in spreads, while tighter postcrisis capital requirements reduced them by about 12 basis points. The intuition is that, by reducing the leverage ratio of the intermediary and forcing it to hold more equity, the subsequent increase in capital requirements would have pushed down the credit spread by reducing

[4] I measure the downside (left-tail) risk-neutral variance from equity options using the model-free put–call approach, which aggregates out-of-the-money put prices up to the forward. I estimate the slope of CDS spreads on this downside measure. To purge fundamentals, I use the corresponding right-tail variance, constructed from out-of-the-money call options and orthogonalize the downside component with respect to the upside within a panel specification with bank and date fixed effects and bank-specific VIX loadings.

its insolvency risk.

Changes in the cost of funding translate into changes in banks' capital structure: as debt funding becomes more expensive or equity requirements tighten, banks optimally delever. In the model-implied decomposition of leverage, the post-2010 decline is about 3 percentage points relative to pre-2008 levels, with roughly 1.5 percentage points attributable to lower bailout expectations and 1.2 percentage points to tighter regulation and fundamentals playing a comparatively smaller role.

I finally use the model to analyze the effect of changes in perceived bailout probabilities and regulation on banks' willingness to pay for risky assets. After 2010, intermediaries reallocated away from riskier market segments (e.g., leveraged loans, junk bonds, and market-making).[5] Moreover, empirical studies document that stricter capital requirements prompted banks to tighten their lending standards (see Baker & Wurgler (2015) and Plosser & Santos (2024), among others) and, by constraining banks' intermediation capacity, they increased expected returns in asset markets where banks are main actors (Fleckenstein & Longstaff 2018, Boyarchenko et al. 2018, Du et al. 2023).

The model rationalizes these trends as a response to both lower bailout expectations and tighter regulation. I decompose the model-implied expected returns on bank assets into an *adjusted risk-free rate* that reflects the average compensation required for holding every asset and a *risk premium* that rewards for holding assets that pay out less in bad aggregate states. Intuitively, when the adjusted risk-free rate rises, banks' willingness to pay falls for all assets, irrespective of their risk exposure. When the risk premium rises, required compensation increases for assets that are more procyclical (i.e., assets that pay off in good times and underperform in downturns). Lower bailout expectations and tighter regulation increase the adjusted risk-free component by shifting funding toward costly equity and away from cheap debt. They also raise risk premia. A decline in bailout expectations shifts bad-state losses back onto creditors. This leads to a rise in funding costs in downturns and and a tilt of the intermediary price of risk more heavily toward bad states. At the same time, the anticipation that leverage constraints will bind during recessions further amplifies this bad-state tilt and raises the compensation intermediaries require for exposures that load more heavily on aggregate risk (Aiyagari & Gertler 1999, Bocola 2016).

Quantitatively, changes in risk premia account for about 60% of the postcrisis increase

[5] Kim et al. (2018) analyze the US Federal Reserve Board's Interagency Leveraged Lending Guidance of 2013 and show that, after supervisory clarifications, large and closely supervised banks curtailed leveraged-loan underwriting and holdings, and that activity migrated to nonbanks. Bao et al. (2018) show that Volcker-affected dealers reduced corporate-bond market-making and inventories, and that stressed/speculative-grade bonds faced the sharpest liquidity deterioration. Allahrakha et al. (2019) exploit the underwriting-exemption DiD and confidential trade data to find higher customer costs (20–45 basis points) and declining market share for Volcker-covered dealers in corporate bonds.

in expected returns of around 100 basis points. The decline in bailout expectations explains around half of the rise in risk premia, with the other half mainly driven by tighter regulation. A similar pattern is observed with lending rates, which increase by 50 basis points after 2010. Omitting bailout expectations therefore systematically overstates the impact of postcrisis regulation on banks' funding costs, leverage, and risk pricing.

Contribution to the literature. My paper contributes to three strands of the literature. In doing so, it bridges theory and measurement at the intersection of macrofinance, asset pricing and bank regulation.

My paper quantifies the moral hazard channel through which anticipated public support distorts banks' leverage and portfolio choices and builds on the seminal work of Kareken & Wallace (1978) and more recent contributions that include those of Schneider & Tornell (2004), Acharya & Yorulmazer (2007), Panageas (2010), Diamond & Rajan (2012), Farhi & Tirole (2012), Bianchi (2016), Chari & Kehoe (2016), Nosal & Ordoñez (2016), Bianchi & Mendoza (2018), Dávila & Walther (2020) and Dovis & Kirpalani (2022). The core idea that unites these papers is that the lack of commitment regarding ex-post optimal policies influences the ex-ante behavior of banks. I build on this insight and use the model as a measurement device to identify its role. My analysis is positive rather than normative: I evaluate the effects of lower bailout expectations on banks' funding costs and on their risk-taking incentives. More broadly, I offer a first attempt to quantify, through the lens of a model, the implications of regulators' limited commitment.

My paper complements empirical efforts to price the *bailout subsidy*. With regard to equity, prior work examines how expectations of public support are capitalized into equity valuations (Veronesi & Zingales 2010, Gandhi & Lustig 2015, Kelly et al. 2016, Atkeson et al. 2019, Minton et al. 2019, Gandhi et al. 2020, Flanagan & Purnanandam 2024). With regard to debt, Schweikhard & Tsesmelidakis (2011), Acharya et al. (2016), Hett & Schmidt (2017), and Berndt et al. (2025) examine the effect of guarantees on banks' funding costs. My paper belongs to the latter stream of literature. My contribution to this literature is twofold. First, my paper shows that accurately measuring the role of policies in driving the dynamics of spreads requires a general equilibrium framework that accounts for the responses of economic agents to those policies and their feedback into equilibrium prices; these are benefits that partial equilibrium expositions do not provide. Second, by using a microfounded model of financial intermediation, I can not only disentangle the role of fundamentals, bailout expectations, and regulation in moving banks' credit spreads, but I can also derive additional implications about how lower bailout expectations and tighter capital requirements affect banks' willingness to take risks.

The model adopts the intermediary asset-pricing perspective that financial institutions' net worth and their frictions drive risk premia (Garleanu & Pedersen 2011, Adrian & Boyarchenko 2012, He & Krishnamurthy 2013, Brunnermeier & Sannikov 2014, Adrian et al. 2014, Krishnamurthy & Muir 2017, Fleckenstein & Longstaff 2018, Boyarchenko et al. 2018, He & Krishnamurthy 2018, Haddad & Muir 2021, Du et al. 2023), but innovates by allowing the strength of the government guarantee to feed back into equilibrium leverage, which amplifies the cyclicality of expected returns. I argue that changes in perceived state-contingent promises and formal rules (e.g., capital requirements) should be considered jointly when interpreting premia in asset markets in which intermediaries invest since they both affect their funding costs and capital structure decisions. Moreover, my contributions pertain not only to the pricing of financial assets in which intermediaries invest, but also to the pricing of intermediary liabilities. While much of the literature resorts to behavioral arguments to replicate the boom–bust pattern in credit valuations (Maxted 2024, Krishnamurthy & Li 2025), I show in my main exercise that the same dynamics can be replicated with movements in the perceived probability of a government bailout together with changes in fundamentals.

This paper is organized as follows. Section 2 presents a simple valuation framework to estimate the risk-neutral losses given default from option prices and CDS spreads. Section 3 documents the time series properties of expected losses. Section 4 presents the model and Section 5 characterizes the properties of the equilibrium. Section 6 presents the calibration strategy. Section 7 decomposes observed spreads into bailout, fundamental, and regulation components. Section 8 assesses how bailout expectations and capital regulation changed banks' cost of capital and risk exposures after 2010. Section 9 concludes.

2 Measuring Expected Losses Given Default

This section presents an empirical framework to infer the risk-neutral losses given default using option prices and CDS contracts. Ultimately, the goal is to net out the component of observed credit spreads that is due to default risk and study the behavior of the remaining component. The framework considers a bank whose assets generate cash flows allocated between debt and equity, with default occurring when these cash flows are insufficient to meet debt obligations. Upon default, equity is completely wiped out, while debt holders may be protected by a government bailout and ensured full repayment. I then show how to back out the risk-neutral probability of default from American put options on the bank's equity, following Carr & Wu (2011), and how to combine this with CDS spreads to extract a measure of the risk-neutral losses given default.

2.1 Pricing Debt, Equity and the Credit Spread

Let A_t be the market value of the bank's assets at date t and let Y_t denote the cash flow rate (interest and principal) produced by those assets over $[t, t+1)$. Expectations $\mathbb{E}_t^*[\cdot]$ are taken under the risk-neutral measure denoted by the superscript $*$ and $R_{f,t}$ is the one-period gross risk-free rate observed at t.[6] For ease of notation, we define the risk-free discount factor from t to τ as

$$\beta_{t,\tau} = \prod_{s=t}^{\tau-1} \frac{1}{R_{f,s}}.$$

The risk-neutral present value of the asset cash flows is

$$V_t = \sum_{\tau=t+1}^{\infty} \beta_{t,\tau} \mathbb{E}_t^* [Y_\tau A_\tau].$$

Denote by D_t the face value of the bank's outstanding debt and P_t^D the contractual repayment rate (interest plus amortization) per unit of face value due at t. Default occurs when current asset cash flow cannot cover the debt repayment:

$$\Delta_t = \mathbf{1}_{\{Y_t A_t < P_t^D D_t\}},$$

where Δ_t is the default indicator. If default takes place, the government implements a bailout with probability π_t; otherwise, debtholders recover $\hat{V}_t \leqslant P_t^D D_t$. The payoff per unit of face value is therefore

$$\widetilde{P}_t^D = (1 - \Delta_t) P_t^D + \Delta_t \big[\pi_t P_t^D + (1 - \pi_t) \hat{V}_t / D_t \big].$$

The market value of the debt equals the discounted stream of these per-unit payoffs scaled by the outstanding face value:

$$S_t^D = \sum_{\tau=t+1}^{\infty} \beta_{t,\tau} \mathbb{E}_t^* [D_\tau \widetilde{P}_\tau^D].$$

Equityholders receive what is left once the scheduled debt payment is met; they get nothing in default:

$$\widetilde{P}_t^E = (1 - \Delta_t) \big[Y_t A_t - P_t^D D_t \big], \qquad S_t^E = \sum_{\tau=t+1}^{\infty} \beta_{t,\tau} \mathbb{E}_t^* \big[\widetilde{P}_\tau^E \big],$$

[6] The risk-neutral measure is a formal equivalent martingale measure under which all discounted asset prices are martingales; asset prices therefore equal the discounted expectation of future payoffs under this probability measure.

Because equity is wiped out at the first default event, it is economically equivalent to a perpetual (American) call on the bank's asset value that expires if the debt payment cannot be met (i.e., if the bank defaults). Adding debt and equity then yields the condition for the valuation of the bank

$$S_t \equiv S_t^D + S_t^E = V_t + \underbrace{\sum_{\tau=t+1}^{\infty} \beta_{t,\tau}\, \mathbb{E}_t^*\big[\pi_\tau \Delta_\tau \big(P_\tau^D D_\tau - \hat{V}_\tau\big)\big]}_{\text{value of implicit government guarantee}}.$$

The last term reflects the fact that, in default, the state covers part of the repayment shortfall to creditors; this appears as an implicit subsidy to the bank's franchise value.[7]

The approach above allows us to decompose the credit spread into:

$$CS_{t,\tau} \simeq \underbrace{\mathbb{F}_{t,\tau}^*}_{\text{risk-neutral probability of default}} \times \underbrace{LGD_{t,\tau}^*}_{\text{risk-neutral expected loss given default}}. \tag{1}$$

In Appendix A.1, I provide the detailed derivations of (1). I begin there from the full multi-period pricing identity that writes discounted expected losses as the product of risk-neutral default probabilities and losses conditional on default, derive the general maturity-specific expression for $LGD_{t,\tau}^*$, and then show how (1) obtains under three assumptions: (i) a one-year horizon (rolling multi-maturity quotes to a 1y par spread), (ii) par couponing with unit face value, and (iii) a small-spread approximation.

The final step involves two key operations. First, I extract the risk-neutral default probability from American put option prices on the bank's equity, following the methodology of Carr & Wu (2011). Second, I combine this extracted default probability with observable CDS spreads to solve for the market-implied risk-neutral expected loss given default, LGD^*.

2.2 Recovering Default Probabilities from Option Prices

Following Carr & Wu (2011), I model the bank's equity value as a stochastic process that remains strictly positive in solvent states but jumps to zero at default. Let S_t^E denote equity and let $\mathcal{E} > 0$ be the lowest equity value attainable prior to default. Default is the first time equity hits zero,

$$\mathcal{T} = \inf\{t \geqslant 0 : S_t^E = 0\},$$

[7] Formally, the government guarantee is equivalent, up to the factor π_τ introduced above, to a series of digital put options on the bank's assets, each paying $P_\tau^D D_\tau - \hat{V}_\tau$ in the event $Y_\tau A_\tau < P_\tau^D D_\tau$ and zero otherwise.

so that, conditional on solvency, the equity price satisfies $S_t^E \in [\mathcal{E}, \infty)$. This structure is consistent with large regulated banks whose market capitalizations rarely drift arbitrarily close to zero in normal times due to capital regulation, supervisory intervention, and access to outside equity, but can collapse abruptly once losses breach regulatory or economic thresholds.

To connect this structure to option prices, consider a put option written on the bank's equity with strike K and maturity T. Let $\text{Put}_t(K, T)$ be the market price at $t \leqslant T$ and define the risk-free discount factor $\beta_{t,T} = \prod_{s=t}^{T-1} R_{f,s}^{-1}$. Under the risk-neutral measure introduced above, the time-t value of a put option written on bank equity is

$$\text{Put}_t(K, T) = \beta_{t,T}\, \mathbb{E}_t^*\big[(K - S_T^E)^+\big] = \beta_{t,T} \int_0^K (K - s)\, dF_t^*(s),$$

where F_t^* denotes the risk-neutral distribution of S_T^E and $\beta_{t,T}$ is the risk-free discount factor. The put price is the discounted present value of the expected shortfall of equity below the strike at maturity.

The Carr & Wu (2011) assumption implies that there is no risk-neutral mass in the interval $(0, \mathcal{E}]$: any probability assigned to values below $\mathcal{E}$ is concentrated at zero and corresponds to default. Consequently, for any strike $K \in (0, \mathcal{E}]$, the equity price satisfies $S_t^E \geqslant \mathcal{E} \geqslant K$ at all times $t < T$ on the no-default path, so the intrinsic value $(K - S_u^E)^+$ is identically zero before default. Exercising strictly before default would therefore forgo any remaining time value and is never optimal. Under these assumptions, the option's value coincides with that of a contract that pays K if default occurs before T and zero otherwise. Let

$$\mathbb{F}_{t,T}^* := \mathbb{E}_t^*\big[\mathbf{1}_{\{\mathcal{T} \leqslant T\}}\big]$$

denote the risk-neutral probability of default before T. We can then decompose the put price into the point mass at zero and capture default and the continuous component over equity values strictly above the floor:

$$\text{Put}_t(K, T) = \beta_{t,T} \left[K\, \mathbb{F}_{t,T}^* \; + \; \int_{\mathcal{E}}^K (K - s)\, dF_t^*(s) \right].$$

The first term reflects the payoff earned when the equity jumps to zero at $\mathcal{T}$; the second term aggregates states in which equity ends above $\mathcal{E}$ and the put finishes in the money.

Within the *default region* $K \in (0, \mathcal{E}]$, the second term drops out because, under the equity-floor assumption, the equity price cannot realize values in $(0, \mathcal{E}]$ prior to default. In this region, the put payoff is therefore an indicator of default scaled by the strike. For any strike not exceeding the floor,

$$\mathrm{Put}_t(K, T) = \beta_{t,T}\, K\, \mathbb{F}^*_{t,T}, \qquad K \in (0, \mathcal{E}].$$

This expression highlights a central implication of the framework: in the default region, put prices are *strictly linear* in the strike and the ratio $\mathrm{Put}_t(K, T)/K$ is constant and equal to the discounted risk-neutral default probability $\beta_{t,T}\mathbb{F}^*_{t,T}$. For strikes above the equity floor, the continuous integral term becomes active and the put price transitions from a linear schedule to a strictly convex function of K. This shift from a flat segment at deep out-of-the-money strikes to a smoothly convex curve once non-default states contribute to the payoff provides the empirical leverage to recover risk-neutral default probabilities from observed option prices.[8]

Figure 1 plots the American put price in the left panel and the corresponding scaled price $\mathrm{Put}_t(K, T)/K$ in the right panel for Morgan Stanley on January 28, 2009 ($T - t =$ 80 days). The vertical line marks the estimated upper bound $\mathcal{E}$ of the default region. Inside that region (shaded area in right panel), the price–strike graph is *linear* and its slope equals $\beta_{t,T}\mathbb{F}^*_{t,T}$. Outside the region, the usual convex option profile reemerges and reflects dependence on predefault equity dynamics.

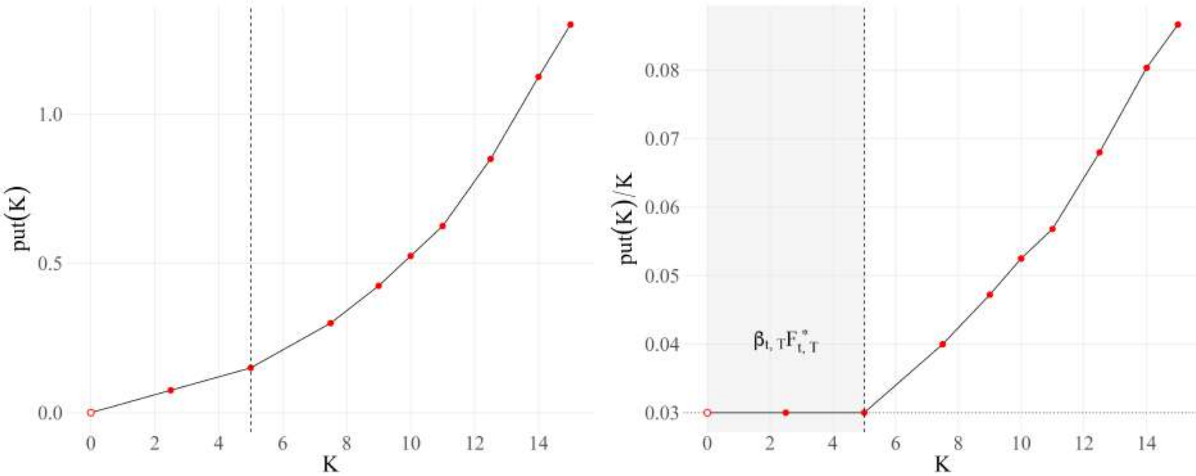
Finally, I use Equation (1) to back out $\mathrm{LGD}^*_{t,T}$ from the option-implied default probability $\mathbb{F}^*_{t,T}$ and the CDS spread $\mathrm{CS}_{t,T}$ such that:

$$\mathrm{LGD}^*_{t,T} \;\simeq\; \frac{\mathrm{CS}_{t,T}}{\mathbb{F}^*_{t,T}}. \tag{2}$$

$\mathbb{F}^*_{t,T}$ is recovered from deep-out-of-the-money American-put prices on the bank's equity while $\mathrm{CS}_{t,T}$ is the par CDS premium for the same reference entity. Given these two market observables, (2) delivers a simple measure of risk-neutral losses given default that is internally consistent with both the option and CDS markets.

[8] There is evidence that bailout expectations are priced by equity holders (see Kelly et al. (2016), among others) and, during the GFC the Paulson plan involved capital injections that supported equity values (Veronesi & Zingales 2010). If there is a positive perceived probability that authorities inject equity conditional on distress so that default is averted, then the upper bound of the default region is not identified, i.e. the put price remains strictly convex in the strike and never exhibits the linear segment that characterizes default states. The procedure I develop in Section 3 to identify the default region is therefore robust to this scenario.

Figure 1: Put Option Price and Put Option Scaled Price Curves



(a) Put Option Price versus Strike **(b) Put Option Scaled Price versus Strike**

Notes: the left panel plots the put option price as a function of strike for Morgan Stanley on 01/28/2009, maturity 80 days. The right panel plots the put option scaled price as a function of strike for Morgan Stanley on 01/28/2009, maturity 80 days. The vertical line marks the default-region upper bound $\mathcal{E}$ and the shaded area represents the default region. The slope of the put price–strike graph in the default region equals the discounted risk-neutral default probability $\beta_{t,T}\mathbb{F}^*_{t,T}$.

3 Empirical Implementation

3.1 Data

Data on CDS are obtained from IHS Markit. The initial sample consists of daily representative CDS quotes on all entities in the financial sector covered by Markit over the period from January 2000 through December 2024. While the five-year contract is generally thought to be the most liquid, the sample used here includes data on all maturities available for every company. When CDS rates are quoted for primary and nonprimary coupons, the former is retained. A similar rule is applied to the primary curve identifier. Whenever available, all CDS quotes are for a contractual definition of default known as "no restructuring". Options data are obtained from OptionMetrics. For each selected date, I examine the options data to identify companies with put options that satisfy the following criteria: (1) the bid price is greater than zero, (2) the offer price is greater than 0.05, (3) the offer price is no more than five times the bid price, (4) the open interest and the bid-ask spread are both greater than zero, and (5) the absolute value of the put's delta does not exceed 15%. Options prices are constructed as averages of the highest closing bid and lowest closing ask prices.

The data from IHS Markit, OptionMetrics and CRSP are merged based on the *permco* identifier for each bank. The final sample with both CDS and options includes 48 banks from 2000 to 2024.

Detecting the default boundary. The empirical framework described earlier assumes the existence of a default region $[0, \mathcal{E}]$, which the stock price cannot enter. The location of this region is unknown ex-ante. If American put prices were observable across a continuum of strikes at the same maturity, the default region would reveal itself because American put prices are linear in the strike price within the region.

The main innovation introduced here lies in the implementation of the following adaptive detection approach to identify the default region $[0, \mathcal{E}]$. Beginning with the two lowest strikes $\{K_1, K_2\}$, for each time t, maturity T and candidate window size m ranging from 2 to n, a no-intercept linear regression is estimated:

$$\text{Put}\,(K_i) = \beta K_i + \epsilon_i \quad \text{for} \quad i = 1, \dots, m.$$

The model's goodness-of-fit is quantified through a modified R^2 metric appropriate for regression through the origin:

$$R^2 = 1 - \frac{\sum_{i=1}^{m} \left(\text{Put}\,(K_i) - \hat{\beta} K_i\right)^2}{\sum_{i=1}^{m} \text{Put}\,(K_i)^2}.$$

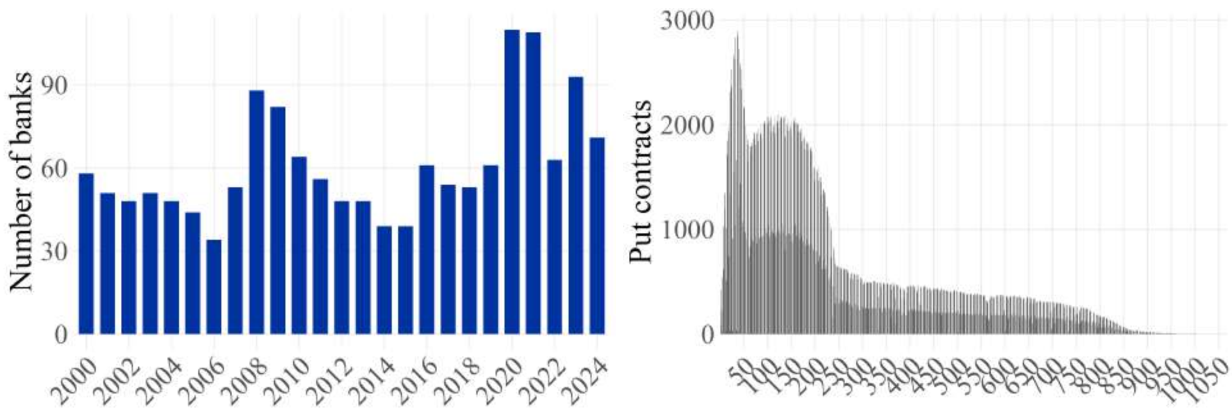
Statistical validity is maintained by continuing window expansion only while R^2 remains above 0.98. This process identifies the maximal strike K_{m^*} where the linear pricing relationship holds, thereby defining the upper region boundary $\mathcal{E} = K_{m^*}$. Within the identified region $\{K_1, \dots, K_{m^*}\}$, the parameter β is estimated via constrained least squares:

$$\hat{\beta} = \left(\sum_{i=1}^{m^*} K_i \cdot \text{Put}\,(K_i)\right) \Big/ \left(\sum_{i=1}^{m^*} K_i^2\right)$$

This estimator represents the slope of the linear pricing relationship and corresponds to the present value of the risk-neutral default probability $\beta_{t,T}\mathbb{F}^*_{t,T}$, as derived from the fundamental pricing equation for default-contingent claims. Appendix A.2 provides a robustness check for the measure using the Theil–Sen estimator, which allows for robust estimation of the slope of the regression line even when there are large outliers in the underlying data. It also corresponds to a trading strategy: for any strike pair $i < j$, buy $(K_j - K_i)^{-1}$ units of the put spread that buys strike K_j and writes strike K_i. This normalized spread pays exactly 1 if default happens and its cost is $\left[\text{Put}(K_j) - \text{Put}(K_i)\right]/(K_j - K_i)$. A single normalized spread therefore gives one slope estimate; the Theil–Sen estimator takes the median of these costs across all strike pairs within the identified region.

For equity options, the number of banks at each week ranges from around 30 to 100, with an average of 60 banks. At the reference date, maturities span 1 to 955 days, with an average of around 150 days. The left panel of Figure 2 plots the number of selected banks at each reference date of the sample period. The number of companies increased markedly since mid-2007 and coincided with the start of the financial crisis and again during the COVID-19 crisis of 2019-22. The right panel of Figure 2 shows where the found put spreads are available across times to maturity and documents the distribution of identified put-spread observations by maturity.

Figure 2: Sample Selection



(a) Number of Banks per Year **(b) Put Contracts per Maturity**

Notes: the left panel plots the number of banks in each year of the sample period. The right panel plots the number of chosen put options across different times to maturity (days).

Equity options exhibit the greatest depth and liquidity at short maturities, especially within one year, while the benchmark CDS contract trades most actively at the five-year tenor. To align the two markets whenever I combine data from both CDS contracts and options, I consider a common one-year horizon. Table 1 reports the summary statistics of CDS spreads and default probabilities estimated from options for one-year maturity. The statistics show that CDS spreads and default probabilities are similar in statistical behaviors but magnitudes are different. The estimates from the put options have a larger sample mean and median, and a slightly larger standard deviation, than the CDS spreads.[9]

Figure 3 plots the median risk-neutral default probability $\mathbb{F}^*_{t,T}$ (left panel) and CDS spread $CS_{t,T}$ (right panel) for $T = 365$ days. Default probabilities and spreads display strong comovements, especially after the GFC. Both series reach their peaks during the

[9] A reported CDS spread of 0.99 is not economically plausible: it would imply an annual premium equal to 99% of notional, a level that is not observed in traded CDS markets. In the raw data, observations with CDS spreads greater than 0.1 account for only 0.77% of all quotes. For all empirical analyses, I exclude observations with CDS spreads above 0.1.

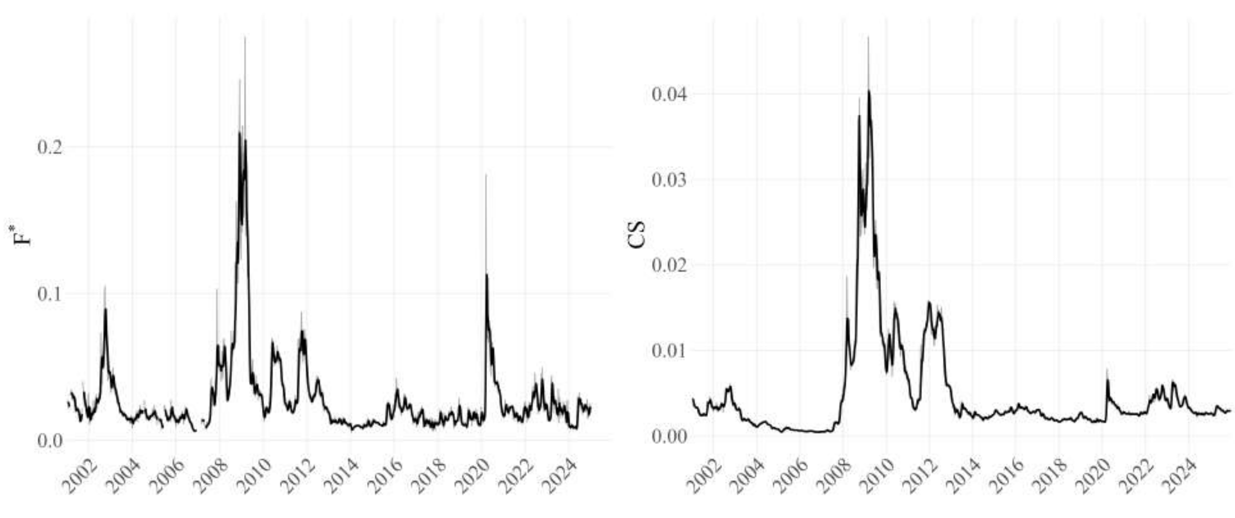
Table 1: Summary Statistics for $T = 365$

	mean	median	std	min	max
$CS_{t,365}$	0.010	0.003	0.039	0.0001	0.994
$\mathbb{F}^*_{t,365}$	0.038	0.025	0.043	0.003	0.575

Notes: the table reports the summary statistics (mean, median, standard deviation, minimum, maximum) for CDS spreads and default probabilities for one-year maturity.

GFC but while default probabilities return to their pre-GFC levels, CDS spreads remain elevated. Remarkably, the COVID-19 crisis is associated with a spike in default probabilities but a very modest increase in CDS spreads when compared to levels after the GFC. This divergence is consistent with temporarily elevated bailout expectations during COVID-19, which would compress CDS spreads despite higher perceived default risk. As documented in Appendix A.6, the same pattern is not observed for non-financials companies during the same period.

Figure 3: Risk-Neutral Default Probability and CDS Spread for $T = 365$



(a) Median $\mathbb{F}^*_t$ **(b) Median CS_t**

Notes: the left panel plots the risk-neutral default probability at 365 days (gray) and the 4-week moving average (black). The right panel plots the CDS spreads at 365 days (gray) and the 4-week moving average (black).

3.2 Expected Losses Given Default

The left panel of Figure 4 plots the time series of the median $\text{LGD}^*_{t,T}$ for $T = 365$ days. $\text{LGD}^*_{t,T}$ varies strongly with business cycle conditions. Both the risk-neutral default probability $\mathbb{F}^*_{t,T}$ and expected losses $\text{LGD}^*_{t,T}$ are particularly countercyclical. Under the constant-recovery assumption often used to back out default probabilities from CDS, the implied mapping is

$$\widehat{\mathbb{F}}^{\text{CDS}}_{t,T} \equiv \frac{\text{CS}_{t,T}}{\bar{\text{LGD}}} = \frac{\text{LGD}^*_{t,T}}{\bar{\text{LGD}}} \mathbb{F}^*_{t,T}.$$

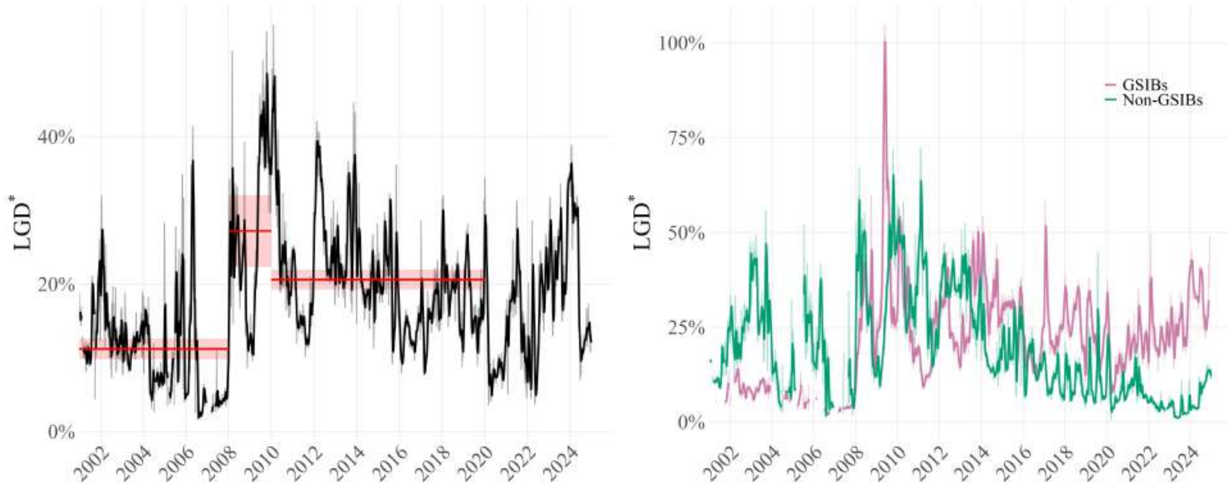
Because $\text{LGD}^*_{t,T}$ tends to be higher in downturns, when $\mathbb{F}^*_{t,T}$ is also high, the factor $\text{LGD}^*_{t,T}/\bar{\text{LGD}}$ amplifies variation in $\widehat{\mathbb{F}}^{\text{CDS}}_{t,T}$ and makes it more volatile and right-skewed than the option-implied $\mathbb{F}^*_{t,T}$.[10]

I compare the mean $\text{LGD}^*_{t,T}$ before the GFC (2000–07) with the postcrisis decade (2010–19) and construct Newey–West heteroskedasticity and autocorrelation consistent (HAC) confidence intervals to account for serial correlation. The mean rises from about 11% precrisis to about 21% postcrisis: this is an increase of roughly 10 percentage points that is highly statistically significant (HAC-robust $t = 10.6$, $p < 10^{-24}$). The horizontal red segments in the figure display these period averages with translucent confidence bands and underscore a persistent and economically meaningful elevation in expected losses after 2010. Consistent with this pattern, the average log credit spread increases by 0.409 over 2010–19. A simple decomposition attributes +0.556 to higher expected losses given default, $\text{LGD}^*_{t,T}$ and −0.147 to a decline in the risk-neutral default probability, $\mathbb{F}^*_{t,T}$, leaving a negligible residual. Equivalently, $\text{LGD}^*_{t,T}$ explains about 136% of the post-2010 increase, with $\mathbb{F}^*_{t,T}$ offsetting roughly 36%.[11] The right panel of Figure 4 shows that the average expected losses for Globally Systemically Important Banks (GSIBs) are lower than for non-GSIBs pre-GFC but higher post-2010. This indicates that most of the post-2010 shift in the median $\text{LGD}^*_{t,T}$ is concentrated among GSIBs; this is consistent with Berndt et al. (2025), who emphasize a structural change in bailout expectations for systemically important institutions. A potential concern is that the observed variation could instead reflect constraints faced by the principal sellers of CDS protection (major dealers), but if dealer-side frictions were the dominant driver, we would expect a similar pattern across all banks; the fact that the shift is concentrated among GSIBs argues against that alternative.

[10] Appendix A.3 shows that higher $\text{LGD}^*_{i,t,365}$ predicts short-horizon increases in $\mathbb{F}^*_{i,t+\Delta t,365}$ and decreases in $\text{CS}_{i,t+\Delta t,365}$ ($\Delta t \in \{7, 30\}$ days). This is consistent with cross-market adjustment. Appendix A.4 reports a variance decomposition that indicates that that expected losses explain approximately 60% of the within-bank time-series variation in CDS spreads.

[11] The decomposition regresses $\log(\text{CS}_{t,T})$ on $\log(\text{LGD}^*_{t,T})$ and $\log(\mathbb{F}^*_{t,T})$ with bank fixed effects and multiplies the estimated coefficients by the changes in the average values of $\log(\text{LGD}^*_{t,T})$ and $\log(\mathbb{F}^*_{t,T})$ between the pre-2008 and post-2010 periods. Component contributions are given by $\beta_j \times \Delta\bar{x}_j$ and shares are computed relative to the total change in $\log(\text{CS}_{t,T})$.

Figure 4: Expected Losses Given Default for $T = 365$



(a) Median $\text{LGD}^*_{t,T}$ **(b) Average $\text{LGD}^*_{t,T}$ for GSIBs and non-GSIBs**

Notes: the left panel plots the expected losses $\text{LGD}^*_{t,T}$ for a 365-day maturity at weekly frequency (grey line) and 4-weeks moving average (black line). The red horizontal segments report sample means for the pre-GFC (2000–07) and post-GFC (2010–19) periods; shaded red bands show 95% confidence intervals computed with Newey–West HAC standard errors (excluding observations after 2020). The right panel plots the expected losses for GSIBs (magenta) and non-GSIBs (green) at weekly frequency with 4-weeks moving average.

Motivated by the preceding discussion, I next test whether variation in $\text{LGD}^*_{t,T}$ reflects time-varying market liquidity that raise required premia in both options and CDS markets. In Appendix A.5, I construct a liquidity-adjusted series of expected losses. Following Conrad et al. (2020), I regress changes in the logarithm of $\text{LGD}^*_{t,T}$ on changes in security-level and aggregate liquidity proxies: option bid–ask spreads, volume, and open interest; CDS depth; TED–SOFR, and VIX. I interpret TED–SOFR and VIX as proxies for intermediation constraints and then accumulate the regression residuals to obtain an adjusted series that strips out transitory illiquidity and variation in risk-bearing capacity. The goal is to isolate movements in expected losses driven by underlying credit fundamentals rather than by liquidity frictions or intermediation-capacity variation that can mechanically depress or inflate the raw measure. The adjusted series tracks the original series closely implying that liquidity effects are not a dominant driver of expected losses. Full regression specification and estimates used to build the adjustment are reported in Appendix A.5.[12]

Collectively, these facts suggest that after 2010, spreads remained elevated even as

[12] In principle, shifts in CDS counterparty risk could confound the analysis: because CDS are traded largely among financial institutions, a lower perceived bailout probability can raise counterparty risk and reduce willingness to pay for protection, mechanically lowering quoted spreads. In practice, evidence indicates that counterparty risk is negligible given extensive collateralization; see Arora et al. (2012).

risk-neutral default probabilities normalized.[13] However, it is difficult to determine from reduced-form evidence alone whether this pattern reflects shifts in underlying credit fundamentals (e.g., asset values, balance-sheet strength, and liquidation conditions) or changes in bailout expectations that alter creditors' effective recoveries. To separately identify these forces, I now introduce a general equilibrium model of financial intermediation with an explicit bailout margin. Through the lens of the model, the joint dynamics of $\mathbb{F}^*_{t,T}$ and $CS_{t,T}$ are informative about the relative importance of fundamentals and bailout expectations because these forces affect intermediaries' capital structure differently.

4 Model

I consider a standard model of financial intermediation. Similarly to models introduced in the macrobanking literature (see Elenev et al. (2021), Mendicino et al. (2019) among others), my model features bank default risk, deposit insurance, and capital regulation but in the context of an endowment economy. Notably, I consider government bailouts of debt holders. The probability of a government bailout varies over time according to a reduced-form stochastic process.

4.1 Environment

Time is infinite and discrete. The economy is populated by a large number of households, a continuum of intermediaries, and a government.

Preferences. Households have Epstein–Zin preferences over consumption streams $\{C\}$ with intertemporal elasticity of substitution ν and risk aversion γ,

$$U = \left\{ (1-\beta)\, C^{1-\frac{1}{\nu}} + \beta \left(\mathbb{E}\left[(U')^{1-\gamma} \right] \right)^{\frac{1-\frac{1}{\nu}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\nu}}}, \tag{3}$$

where the discount factor is $\beta \in (0,1)$.

[13] Amid the 2023 stress among U.S. regional banks, several sizable institutions failed or approached failure. Treatment of bond investors differed across cases: unsecured debt at Silicon Valley Bank and Signature Bank absorbed losses and did not receive support, whereas in some other resolutions bondholders benefited from official interventions. These outcomes imply a significant increase in expected loss given default, $LGD^*_{t,T}$, but the increase was not persistent as the measure fell back quickly by 2025.

Technology. There is a set of islands indexed by ω. Within each island ω, there is a unit continuum of Lucas trees indexed by z. Tree z on island ω delivers the per-period payoff

$$y = z\,\omega\,Y \quad \text{where} \quad Y = Ze^{-\zeta d} \tag{4}$$

where $z > 0$ is an i.i.d. tree-specific productivity shock, $\omega > 0$ is an i.i.d. island shock, $Z > 0$ represents aggregate productivity, and $d \in \{0, 1\}$. $d = 1$ indicates a disaster state; in that event, output is reduced by the factor $e^{-\zeta}$. Let $g(\cdot)$ and $f(\cdot)$ denote the density functions of tree-specific and island shocks, respectively.

Market Structure. There are five types of assets: debt and equity claims backed Lucas trees, noncontingent debt, and deposit and equity claims issued by financial intermediaries. Financial intermediaries (banks) are profit-maximizing entities that invest in the debt claims backed by Lucas trees (while the residual equity claim is rebated to households). Unlike banks, households do not have access to the corporate credit market. This assumption provides a role for intermediaries in transforming long-term risky debt into short-term safe debt. Intermediaries fund these loans by issuing deposits and bonds and raising equity capital from households. Importantly, intermediaries face equity issuance costs which make their net worth the relevant state variables for asset pricing (He & Krishnamurthy 2013, 2018) as described later in more detail. Moreover, intermediaries operate under limited liability and they can default. Finally, the government collects deposit insurance fees from intermediaries and lump-sum taxes from households in order to finance bailouts to debt holders and deposit insurance payouts.[14]

I consider a Recursive Competitive Equilibrium (Prescott & Mehra 2005). Denote by $\mathbf{S}$ the vector that collects the current values of the state variables (both endogenous and exogenous) and by $\mathbf{S}'$ the next period's state vector. In principle, the state must keep track of the entire cross-sectional distributions of household and intermediary assets. In the model, households can be represented by a stand-in household with wealth W and the banking sector aggregates so that the cross-sectional distribution of intermediaries is summarized by aggregate liabilities $L = D + B$.[15] I therefore work with the state

[14] I assume that the government only covers the shortfall of all creditors but does not bail out equity holders. This assumption is *not* without loss of generality since the model-implied default probabilities are consistent with the data counterpart if bailouts only pertain to bondholders. In Appendix G.1, I provide an extension of the model in which the government injects equity capital into the intermediary conditional on default and takes ownership of the intermediary. While all the properties of the model would remain intact, identification now requires default probabilities that account for the government's equity injections.

[15] In Appendix B.2, I show that at the time banks choose their new portfolio, all banks have the same value and face the same optimization problem. Three properties of the bank problem allow us to obtain this aggregation result. First, island shocks ω are uncorrelated over time. Second, the value function is

vector $\mathbf{S} = [L, W, \pi, Z, d]$. Expectations $\mathbb{E}_{\mathbf{S}}[\cdot]$ are taken with respect to the conditional distribution of $\mathbf{S}'$ implied by the state transition law $\Gamma(\mathbf{S}) = \mathbf{S}'$.

We now describe intermediaries and households' problems as well as the government in more detail. The full set of Bellman equations and first-order conditions is provided in Appendix B.

4.2 Financial Intermediaries

Individual intermediaries begin each period with net worth

$$n = \mathcal{P}(\omega, \mathbf{S})\, a - d - b. \tag{5}$$

Here, $\mathcal{P}(\omega, \mathbf{S})a$ is the payoff from the asset portfolio given the realization of the island shock ω, while d and b are, respectively, deposit and bond repayments due. Intermediaries default when $n < 0$; they otherwise continue operating. The rest of this subsection proceeds in three steps: firstly, I characterize the asset payoff; secondly, I describe the problem of solvent intermediaries; and thirdly, I detail the bankruptcy/default resolution.

4.2.1 Intermediaries Assets

Intermediaries hold long-term debt backed by Lucas trees. Long-term debt has face value a, market price $p(\mathbf{S})$, amortization rate $\delta \in (0, 1)$ and coupon c. The promised per-period cash flow is therefore $c + (1 - \delta) + \delta p(\mathbf{S})$. Default by a borrower occurs whenever the realized payoff from the tree is insufficient (i.e., when $y < c + (1 - \delta)$). The per-period payoff of an intermediary's loan portfolio, conditional on its own shock ω, is

$$\mathcal{P}(\omega, \mathbf{S}) = \left[c + (1 - \delta) + \delta p(\mathbf{S})\right] \int_{\underline{z}(\omega, Y)}^{\infty} g(z)\, dz \;+\; (1 - \eta)\omega Y \int_{0}^{\underline{z}(\omega, Y)} z\, g(z)\, dz, \tag{6}$$

where the default threshold that solves $y = c + (1 - \delta)$ is given by

$$\underline{z}(\omega, Y) = \frac{c + (1 - \delta)}{\omega\, Y}. \tag{7}$$

homogeneous of degree one in individual net worth n. Third, at the start of each period intermediaries are randomly reassigned across islands, so an intermediary's island identity is i.i.d. over time and independent of its own balance sheet. Without this reassignment, persistent sorting across islands would generally break exact aggregation. These properties are used to write the bank value function in terms of the value per unit of wealth $v(\mathbf{S}) = V(n; \mathbf{S})/n$, which only depends on the aggregate state vector $\mathbf{S}$.

The first term in (6) represents performing loans that deliver the full contractual payment. The second captures recoveries from defaulted loans, which transfer a fraction $1-\eta$ of the realized tree payoff to debtholders. In my framework, bank assets are portfolios of debt-like securities exposed to non-fully diversifiable credit risk: intermediaries can diversify across trees within an island but not across islands, so island-level shocks remain undiversified in their portfolios. Consequently, bank-asset returns have limited upside and substantial downside risk (Mendicino et al. 2019). A decline in fundamentals Y depresses the portfolio payoff $\mathcal{P}(\omega, \mathbf{S})$ and thereby erodes the intermediary's net worth and raises its default probability.

4.2.2 Solvent Intermediaries

If intermediaries are solvent (namely, if their individual net worth is positive), $n > 0$, they solve a portfolio choice problem. They maximize shareholders value by choosing the amount of assets to purchase for next period a', the amount of deposits to issue to households d' at price $q^d(\mathbf{S}) = \frac{1}{1+r^d(\mathbf{S})}$, the amount of bonds to issue b' at price $q(d', b', a'; \mathbf{S})$ and dividend payouts, x. Intermediaries have a payout target that is a fraction ϕ_0 of net worth, n. They can deviate from this target and raise additional equity e; that is, they can pay out $x = \phi_0 n - e$, but this comes at a convex cost $\frac{\phi_1}{2}\left(\frac{e}{n}\right)^2 n$. The intertemporal budget constraint of the bank can then be written as

$$n + \left(q^d(\mathbf{S}) - \kappa\right) d' + q\left(d', b', a'; \mathbf{S}\right) b' = p(\mathbf{S})\, a' + x + \frac{\phi_1}{2}\left(\frac{x}{n} - \phi_0\right)^2 n. \tag{8}$$

The first term represents the book value of equity that the intermediary has at her disposal at the beginning of the period. The second and third terms denote new funds from deposits and bond issuance at prices $q(d', b', a'; \mathbf{S})$ and $q^d(\mathbf{S})$. The fourth term is new assets purchased at price $p(\mathbf{S})$. The last two terms represent the dividend payout and the associated issuance cost. Intermediaries pay deposit insurance fees κ to the government per unit of deposits. They internalize that the price of their debt, $q(b', d', a'; \mathbf{S})$, is a function of their default risk and thus their capital structure.

Intermediaries are also subject to the leverage constraint

$$b' + d' \leqslant \xi p(\mathbf{S})\, a'. \tag{9}$$

Constraint (9) is a Basel-style regulatory bank capital constraint. It requires that debt is collateralized by the intermediary's portfolio. The parameter ξ determines how much debt can be issued against each dollar of assets. The assets on the right-hand side of (9) are evaluated at market prices because levered financial intermediaries face regulatory constraints that depend on market prices.

The intermediary's portfolio problem is characterized recursively using the value function $V(n;\mathbf{S})$. Intermediaries discount future payoffs by $\mathcal{M}(\mathbf{S}',\mathbf{S})$, which is the stochastic discount factor (SDF) of households, their equity holders. They operate under limited liability. The intermediary solves

$$V(n;\mathbf{S}) = \max_{x,a',b',d'} x + \mathbb{E}_{\mathbf{S}}\left[\mathcal{M}\left(\mathbf{S}',\mathbf{S}\right)\max\left\{V\left(n';\mathbf{S}'\right),0\right\}\right] \tag{10}$$

subject to the budget constraint (8), the capital requirement constraint (9) and the constraint that $d' \leqslant n\bar{D}'$, where $\bar{D}'$ is a maximum amount of deposits that can be issued by the intermediary. This constraint captures the fact that intermediaries face costs of running their deposit business, such as the cost of maintaining a branch network and thus cannot issue unlimited deposits despite being the least costly source of funding. I assume the maximum deposit capacity to be correlated with the business cycle, such that $\bar{D}' = \bar{D} - \zeta^{\bar{D}}Y$. The coefficient $\zeta^{\bar{D}}$ governs the negative correlation between deposit demand and the business cycle and captures flight to safety events during economic downturns (e.g., Martin et al. (2018)).

4.2.3 Bankruptcy

At the beginning of each period, a fraction of intermediaries defaults when $n \leqslant 0$ before paying dividends to shareholders and choosing the portfolio for next period. The government takes ownership of these bankrupt intermediaries and liquidates them to recover some of the outstanding debt to be paid to debtholders. Bankrupt intermediaries are replaced by newly started ones that households endow with initial equity n^0 per bank. These new intermediaries then solve problem (10) with $n = n^0$.

Denote aggregate net worth of surviving and newly started intermediaries by N and the ratio of new equity over net worth as $\tilde{e} = e/N$. This ratio is identical across intermediaries due to scale invariance. The aggregate dividend to households is then:

$$\Pi^I(\mathbf{S}) = N\left(\phi_0 - \tilde{e}\right) - \int_{\omega\in\mathcal{D}} n^0 dF(\omega),$$

where $\mathcal{D}$ is the set of defaulting intermediaries (and $\mathcal{D}^c$ is the set of non-defaulting intermediaries). The dividend has two parts: (i) all intermediaries, both surviving and newly started, pay a dividend share $\phi_0 - \tilde{e}$, out of their net worth, and (ii) newly started intermediaries, equal in mass to bankrupt intermediaries, receive initial equity n^0.

4.3 Household

Each period, households receive the payoffs from owning all equity and debt claims on intermediaries and trees, and yield financial wealth w. They further pay taxes $T(\mathbf{S})$. Deposit quantities D in the model are demand determined; in other words, they are decided by the intermediaries. The households view them as a transfer of resources independent of their actions. At the same time, households choose consumption c and bonds, b' to maximize utility (3) subject to their intertemporal budget constraint

$$w - T(\mathbf{S}) \geqslant c + q(\mathbf{S})\, b' + q^{d}(\mathbf{S})\, D'. \tag{11}$$

The transition law for household financial wealth w is given by

$$w = \Pi(\mathbf{S}) + \Pi^{I}(\mathbf{S}) + D + b\left[\int_{\omega\in\mathcal{D}^c} 1 dF(\omega) + \int_{\omega\in\mathcal{D}} (\pi + (1-\pi)RV(\omega,\mathbf{S}))\, dF(\omega)\right], \tag{12}$$

where $RV(\omega, \mathbf{S})$ is the recovery value of bonds of the defaulting intermediaries given by

$$RV(\omega,\mathbf{S}) \equiv \frac{\max\{(1-\chi)A\mathcal{P}(\omega,\mathbf{S}) - D, 0\}}{B}.$$

During the bankruptcy process, a fraction χ of the asset value of intermediaries is lost. I assume that depositors are senior to other debt holders in bankruptcy; consequently, bondholder recoveries are computed from the residual asset value net of deposits.

Households hold the residual equity tranche of every tree and perfectly diversify across islands

$$\Pi(\mathbf{S}) = \int\int_{\underline{z}(\omega,Y)}^{\infty} \left[z\omega Y - \big(c + (1-\delta) + \delta p(\mathbf{S})\big)A\right] g(z)\, f(\omega)\, dz\, d\omega \; + \; p(\mathbf{S}).$$

The double integral is the residual equity payoff, while $p(\mathbf{S})$ is the market value of debt carried into the next period.

Finally, the deposit rate $r^d(\mathbf{S})$ may differ from the risk-free rate $r^f(\mathbf{S})$ to capture the fact that changes to risk-free rates do not pass through one-for-one to deposits.[16] Following Elenev & Liu (2024), the relationship between the deposit rate and the risk-free rate is given by

$$r^d(\mathbf{S}) = \left(\bar{r}^f - \alpha_D\right) + \beta_D\left(r^f(\mathbf{S}) - \bar{r}^f\right),$$

with $\alpha_D \geqslant 0$ and $\beta_D \in (0, 1]$. The parameter α_D captures the average spread between risk-

[16]While this paper does not directly study the role of interest rate risk in driving the banks' franchise value (Drechsler et al. 2017, Jiang et al. 2024, DeMarzo et al. 2024), it is important to account for the contribution of deposits to banks' cost of capital.

free and deposit rates, while β_D captures the degree of deposit rate sensitivity to risk-free rate deviations from its mean. When $\alpha_D = 0$ and $\beta_D = 1$, the two rates are always equal.[17]

4.4 Government

Defaulting intermediaries are liquidated by the government. The government's aggregate fiscal cost is given by

$$\mathrm{TC}(\mathbf{S}) = \pi \int_{\omega \in \mathcal{D}} \left(1 - \frac{\max\{(1-\chi)A\mathcal{P}(\omega,\mathbf{S}) - D, 0\}}{B}\right) B \, dF(\omega) + \int_{\omega \in \mathcal{D}} \left(1 - \frac{\min\{(1-\chi)A\mathcal{P}(\omega,\mathbf{S}), D\}}{D}\right) D \, dF(\omega). \tag{13}$$

The first integral captures the expected transfer to bondholders in default states, conditional on a bailout being granted with probability π (i.e., the shortfall of bonds after depositors are made whole); the second integral captures the expected deposit-insurance payout that covers any shortfall of deposits relative to par.

The government is assumed to run a balanced budget so that

$$T(\mathbf{S}) + \kappa D' = \mathrm{TC}(\mathbf{S}). \tag{14}$$

The fiscal cost of bailouts and deposit insurance is financed by lump-sum taxes $T(\mathbf{S})$ to households and fees $\kappa D'$ to intermediaries.

4.5 Market Clearing and Equilibrium

After combining the budget constraints of all the agents in the economy and the government, we obtain the aggregate resource constraint

$$Y = C + \frac{\phi_1}{2}\left(\frac{e}{N}\right)^2 N + \chi A \int_{\omega \in \mathcal{D}} \mathcal{P}(\omega,\mathbf{S}) f(\omega) d\omega + \eta Y \int \int_0^{\underline{z}(\omega,Y)} \omega z \, g(z) f(\omega) \, dz \, d\omega. \tag{15}$$

We define the Recursive Competitive Equilibrium as follows:

Definition 1. *A Recursive Competitive Equilibrium for this economy is given by value functions for households and intermediaries* $\{V^H(w,\mathbf{S}), v(\mathbf{S})\}$, *policy functions for households*

[17] In Appendix G.3, I provide a microfoundation for the deposit rate by allowing households to have preferences for liquidity, D. Similar to my specification, deposits will trade below the risk-free rate since households derive nonpecuniary benefits to hold them. The *liquidity premium* is decreasing in the amount of deposits: when deposits are scarce, the liquidity premium is higher. Intermediaries have market power in deposit markets; they therefore internalize the effect of their choice of deposit funding on the price they receive. This generates an interior liability funding structure without the need of the constraint $D' \leqslant \bar{D}'$.

$\{C(\mathbf{S}), B'(\mathbf{S})\}$, *policy functions for the representative intermediary* $\{A'(\mathbf{S}), D'(\mathbf{S}), B'(\mathbf{S}), e(\mathbf{S})\}$, *prices* $\{p(\mathbf{S}), q(A', B', D'; \mathbf{S}), q^d(\mathbf{S})\}$ *and taxes* $\{T(\mathbf{S})\}$ *such that (i) intermediaries' and households' policies and value functions solve their decision problems; (ii) the government budget constraint is satisfied; (iii) the market for assets clears,* $\int a(\omega; \mathbf{S})\, dF(\omega) = A = 1$*; (iv) the market for debt clears,* $\int b(\omega; \mathbf{S})\, dF(\omega) = B$*; (v) the goods market clearing condition* (15) *holds; and (vi)* $\Gamma(\cdot)$ *is consistent with agents' optimization and the exogenous aggregate state process.*

5 Equilibrium Characterization

In the environment presented in the previous section, credit spreads are driven by both fundamental risk Y, and bailout expectations π. Ultimately, my goal is to use the model as a measurement device to decompose credit spreads into their fundamental and bailout components. To that end, in this section I first characterize the properties of the equilibrium debt price and intermediary leverage. Having clarified its driving forces, I then study how credit spreads respond to changes in fundamentals and bailout probabilities and, leveraging on these results, conclude by outlining my proposed indirect inference approach.

5.1 Optimality Conditions

Before discussing the behavior of debt prices and the intermediaries' optimal debt choice, it is useful to first clarify how equity issuance frictions and the default decision shape both the marginal value of net worth and how intermediaries value payoffs across states of the world.

Letting $\tilde{e} \equiv e/N$ denote new equity issued relative to existing net worth, the intermediary's envelope condition can be written as

$$v(\mathbf{S}) = \phi_0 + \mu(\mathbf{S})(1 - \phi_0),$$

where $v(\mathbf{S})$ is the (scaled) value function and ϕ_0 is the target payout fraction. The first-order condition with respect to equity issuance pins down $\mu(\mathbf{S})$, the shadow price attached to a dollar of equity injections:

$$\mu(\mathbf{S}) = \frac{1}{1 - \phi_1 \tilde{e}}$$

Dividing the envelope condition through by $\mu(\mathbf{S})$ gives a compact expression for the "marginal value" of net worth:

$$\tilde{\nu}\left(\mathbf{S}'\right) \equiv \frac{\nu\left(\mathbf{S}'\right)}{\mu(\mathbf{S})} = (1-\phi_1\tilde{e})\left(\phi_0 + \frac{1-\phi_0}{1-\phi_1\tilde{e}'}\right), \tag{16}$$

If $\phi_1 = 0$ (no issuance frictions), it follows that the marginal value reduces to 1. As $\phi_1 > 0$, issuing equity becomes costly: increasing $\tilde{e}$ raises the shadow value $\mu(\mathbf{S})$ above one, so that each additional dollar of net worth is valued more highly and endogenous payout/injection policies hinge on the trade-off between internal financing (at marginal value $\mu(\mathbf{S})$) and external issuance, which faces a marginal cost wedge $\phi_1\tilde{e}'$. First, it reduces bank risk-taking ex-ante, since banks hold more equity to save on issuance costs in states of the world where losses are large but not large enough to make bankruptcy optimal. Second, conditional on being in a recession, the positive issuance costs make bank recapitalization more costly and thus amplify intermediary frictions. The issuance costs further increase the excess return banks require to hold risky assets.

Crucially, because default is endogenous, intermediaries value payoffs differently across states as the likelihood of insolvency varies. Intermediaries optimally default when $\omega < \omega^*(\mathbf{S})$, which sets their net worth to zero:

$$\mathcal{P}(\omega^*(\mathbf{S}),\mathbf{S}) - D - B = 0. \tag{17}$$

Let $\mathbb{F}(\mathbf{S}) \equiv F(\omega^*(\mathbf{S}))$ denote the mass of defaulting intermediaries (the realized default probability). This makes valuation explicitly state-contingent. If the intermediary survives ($\omega \geqslant \omega^*(\mathbf{S})$), it honors its liabilities and receives the full asset payoff; an extra dollar of net worth next period is valued at the shadow marginal value $\tilde{\nu}(\mathbf{S}')$, which embeds issuance frictions. If it defaults ($\omega < \omega^*(\mathbf{S})$), equity is wiped out and the intermediary incurs deadweight resolution costs $\chi\,\mathcal{P}(\omega^*(\mathbf{S}),\mathbf{S})$; creditors recover $RV(\omega^{-\prime},\mathbf{S}')$ per unit of face value unless a bailout occurs. With probability π' a bailout prevents losses to creditors, so default losses are borne only with probability $1-\pi'$.

Debt Price. From the first-order condition of the households problem with respect to b', we obtain

$$q(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\Big[\mathcal{M}(\mathbf{S}',\mathbf{S})\left\{1-\mathbb{F}(\mathbf{S}') + \mathbb{F}(\mathbf{S}')\big(\pi' + (1-\pi')RV(\omega^{-\prime},\mathbf{S})\big)\right\}\Big] \tag{18}$$

The price $q(\mathbf{S})$ equals the discounted expectation of the payoff that creditors receive across survival and default states. The term $1-\mathbb{F}(\mathbf{S}')$ captures full repayment when the intermediary remains solvent. When default occurs with mass $\mathbb{F}(\mathbf{S}')$, creditors are made whole with probability π' due to a bailout; with complementary probability $1-\pi'$, there is no bailout and creditors recover only $\mathrm{RV}(\omega^{-\prime}, \mathbf{S})$ per unit of face value. The stochastic discount factor $\mathcal{M}(\mathbf{S}', \mathbf{S})$ prices these state-contingent payoffs.

The debt price $q(\mathbf{S})$ declines when the likelihood of default $\mathbb{F}(\mathbf{S}')$ rises (e.g., as leverage B increases and the default region expands) and when recoveries $\mathrm{RV}(\omega^{-\prime}, \mathbf{S})$ are lower. A higher bailout probability π' increases $q(\mathbf{S})$ and, by shifting probability mass within default states from low-recovery outcomes to full repayment, reduces the sensitivity of the price to default risk. The left panel of Figure 5 illustrates these effects: the debt price schedule shifts up and flattens as π increases, especially when default risk is elevated.

Optimal Leverage. The choice of noncontingent debt is central to the analysis in that it endogenously pins down the solvency risk of the financial intermediary as a function of the underlying aggregate sources of risk and the intermediaries' frictions, as shown in Equation (17). When choosing the quantity of noncontingent debt B', the intermediary balances the cheapness of debt financing against the expected cost of default while taking into account the tightness of the regulatory requirement. Formally, by combining the first-order condition of the intermediary's problem with respect to b' with the one of the household, we obtain[18]

$$\mathbb{E}_{\mathbf{S}}\left\{\mathcal{M}\left(\mathbf{S}', \mathbf{S}\right)\left[\underbrace{\left(1-\mathbb{F}(\mathbf{S}')\right)\left(1-\tilde{\nu}\left(\mathbf{S}'\right)\right)+\mathbb{F}(\mathbf{S}')\,\pi'}_{\substack{\text{marginal benefits} \\ \text{(valuation difference + bailout subsidy)}}}\right]\right\} = \tilde{\lambda}(\mathbf{S})$$

$$+\,\mathbb{E}_{\mathbf{S}}\left\{\mathcal{M}\left(\mathbf{S}', \mathbf{S}\right)\underbrace{\left(1-\pi'\right)\chi\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}')f(\omega^*(\mathbf{S}'))\frac{d\omega^*(\mathbf{S}')}{dB'}}_{\substack{\text{marginal costs} \\ \text{(default)}}}\right\}. \quad (19)$$

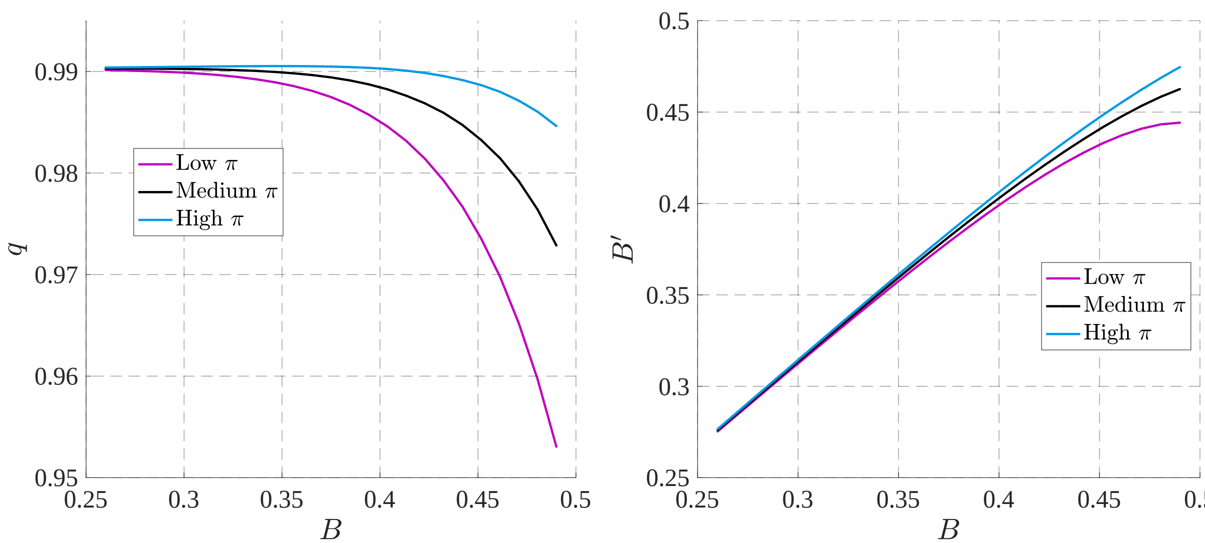
where $\tilde{\lambda}(\mathbf{S})$ reflects the tightness of the intermediary's leverage constraint (i.e., the shadow cost of a dollar of debt). Intermediaries choose their capital structure by trading off the benefits of borrowing against its costs. The benefit reflects a valuation difference: because intermediaries are effectively less patient than households, they prefer to front-load payouts by issuing debt. This shows up in the survival states as a gain proportional to $(1 - \mathbb{F}(\mathbf{S}'))(1 - \tilde{\nu}(\mathbf{S}'))$. In default states, the expected bailout subsidy is captured by $\mathbb{F}(\mathbf{S}')\,\pi'$. The cost is that more debt raises the likelihood of default, which destroys value through deadweight resolution losses only (creditor shortfalls are internalized in the bond price $q(\mathbf{S})$ and drop out once the household first-order condition is imposed) captured by $\chi\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}')$ and by the sensitivity of default risk to leverage, $\partial\mathbb{F}(\mathbf{S}')/\partial B'$.

A higher expected bailout probability π tilts this tradeoff toward borrowing in two

[18] See Appendix B for the full set of agents' first-order conditions.

ways. First, it lowers the marginal cost of debt by scaling down expected default losses one-for-one via the factor $(1-\pi')$. Second, it increases the state-contingent subsidy in default states, $\mathbb{F}(\mathbf{S}')\pi'$, effectively making debt cheaper ex-ante. Together, these forces reduce the weight on default costs and raise the net marginal benefit of issuing debt. The right panel of Figure 5 depicts the decision rule for debt issuance B' as a function of the debt level B for three values of the bailout probability π (medium in black, low in magenta, and high in cyan).[19] In particular, the debt policy is more sensitive to the bailout probability π when the intermediary is more levered (B is higher).

Figure 5: Debt Price Schedule and Debt Policy Function



(a) Debt Price Schedule q for different π **(b) Debt Policy B' for different π**

Notes: policy functions evaluated at the ergodic means of D and $d = 0$. The left panel plots the debt price schedule $q(\mathbf{S})$ as a function of debt B for three values of bailout probability π (baseline in black, low in magenta and high in cyan). The right panel plots the debt policy B' as a function of B for three value of fundamentals π (baseline in black, low π in magenta, and high π in cyan).

After having described the debt price and the intermediary's choice of debt, the next section analyzes the impact of bailout expectations and fundamentals on credit spreads by taking into account the differential effects on intermediaries' default probabilities through B'.

[19]These results (and the following ones) are based on the fully calibrated model, described in detail in Section 6.

5.2 Credit Spreads, Fundamentals, and Bailout Expectations

The credit spread on one-period defaultable debt is given by:

$$\underbrace{CS(\mathbf{S})}_{\text{Credit Spread}} = \underbrace{\frac{\mathbb{E}_{\mathbf{S}}\Big[\mathcal{M}(\mathbf{S}',\mathbf{S})\,(1-\pi')\,\mathbb{F}(\mathbf{S}')\,\big(1-RV(\omega^{-,\prime},\mathbf{S}')\big)\Big]}{\mathbb{E}_{\mathbf{S}}[\mathcal{M}(\mathbf{S}',\mathbf{S})]}}_{\text{Expected Default Loss}} \tag{20}$$

Default losses embed three critical elements: the bailout probability π' (government intervention likelihood), default probability $\mathbb{F}(\mathbf{S}')$, and asset recovery rate $RV(\omega^{-,\prime},\mathbf{S}')$ per unit, conditional on default.

The bailout probability π' affects the credit spread through two distinct channels, as in the following proposition:[20]

Proposition 1. *The derivative of the credit spread with respect to the bailout probability is given by:*

$$\frac{\partial CS(\mathbf{S})}{\partial \pi'} = \frac{1}{\mathbb{E}_{\mathbf{S}}\big[\mathcal{M}(\mathbf{S}',\mathbf{S})\big]}\mathbb{E}_{\mathbf{S}}\left\{\mathcal{M}\left(\mathbf{S}',\mathbf{S}\right)\left(\underbrace{(1-\pi')\frac{\partial B'}{\partial \pi'}\frac{1}{B'}\Omega(\mathbf{S}')}_{\textit{Indirect Effect}} - \underbrace{\mathbb{F}(\mathbf{S}')\left[1-RV(\omega^{-,\prime},\mathbf{S}')\right]}_{\textit{Direct Effect}}\right)\right\},$$

where the term $\Omega(\mathbf{S}')$ is defined as:

$$\Omega(\mathbf{S}') \equiv \chi\mathcal{P}(\omega^*(\mathbf{S}'),\mathbf{S}')f(\omega^*(\mathbf{S}'))\cdot\frac{d\omega^*(\mathbf{S}')}{dB'} + \mathbb{F}(\mathbf{S}')RV(\omega^{-,\prime},\mathbf{S}') \geqslant 0.$$

The sign of the derivative is ambiguous since the direct and indirect effects have opposite signs.

Proof. The proof can be found in Appendix C. □

The term $-\mathbb{F}(\mathbf{S}')[1-RV(\omega^{-,\prime},\mathbf{S}')]$ reflects the *direct* reduction in expected default losses when the bailout probability π' increases. Higher π' *directly narrows* credit spreads because external intervention is anticipated. On the other hand, an increase in π' *widens* spreads, partially offsetting the direct effect through the indirect effect. The intuition is that an increase in π' incentivizes intermediaries to take on more debt, which in turn increases the probability of default and the credit spread. The term $(1-\pi')\frac{\partial B'}{\partial \pi'}\frac{1}{B'}\Omega'(\mathbf{S}')$ captures how increased bailout probabilities π' incentivize banks to adjust their debt levels B'. If the semielasticity of leverage increases with respect to the bailout probability $\frac{\partial B'}{\partial \pi'}\frac{1}{B'} > 0$ (i.e., banks take on more debt if π' increases), the sign of this effect depends

[20] The analysis abstracts from the effect of changes in the bailout probability operating via the stochastic discount factor $\mathcal{M}(\mathbf{S}',\mathbf{S})$ and the loan price $p(\mathbf{S})$. Moreover, intermediaries always choose to issue as many deposits as they can up to the capacity constraint since the cost of issuing deposits is always lower then or equal (in the case of no default or full bailout) to the cost of issuing debt.

on Ω'. The first subterm represents increased expected losses from extending the default threshold $\omega^*(\mathbf{S}')$ as debt rises and it is positive since $\frac{d\omega^*(\mathbf{S}')}{dB'} > 0$. The second subterm reflects dilution of recovery values across existing debt and it is always positive.

Next we discuss the effect of changes in fundamentals on credit spreads in the following proposition:

Proposition 2. *The derivative of the credit spread with respect to the fundamental risk is given by:*

$$\frac{\partial CS(\mathbf{S})}{\partial Y'} = \frac{1}{\mathbb{E}_{\mathbf{S}}\big[\mathcal{M}(\mathbf{S}',\mathbf{S})\big]}\mathbb{E}_{\mathbf{S}}\Bigg\{\mathcal{M}\left(\mathbf{S}',\mathbf{S}\right)(1-\pi')\Bigg(\underbrace{\frac{\partial B'}{\partial Y'}\frac{1}{B'}\Omega(\mathbf{S}')}_{\textit{Indirect Effect}}$$
$$+\underbrace{\left[(1-RV(\omega^{-,\prime},\mathbf{S}'))f(\omega^*(\mathbf{S}'))\frac{d\omega^*(\mathbf{S}')}{dY'} - \mathbb{F}(\mathbf{S}')\frac{\partial RV(\omega^{-,\prime},\mathbf{S}')}{\partial Y'}\right]}_{\textit{Direct Effect}}\Bigg)\Bigg\}.$$

The sign of the derivative is ambiguous since the direct and indirect effects have opposite signs.

Proof. The proof can be found in Appendix C. □

The *direct* effect captures how Y' shifts the default probability $\mathbb{F}(\mathbf{S}')$ and recovery $RV(\omega^{-,\prime},\mathbf{S}')$. When fundamentals deteriorate, $\mathbb{F}(\mathbf{S}')$ increases and recoveries $RV(\omega^{-,\prime},\mathbf{S}')$ lower, raising expected default losses; the opposite holds when fundamentals improve. The *indirect* effect reflects leverage adjustments through $\frac{\partial B'}{\partial Y'}$. When intermediaries increase leverage as fundamentals improve (i.e., $\frac{\partial B'}{\partial Y'} > 0$) the indirect effect raises the spread and therefore moves in the opposite direction of the direct effect (which lowers the spread as Y' improves). If instead intermediaries delever as fundamentals improve (i.e., $\frac{\partial B'}{\partial Y'} < 0$) the indirect effect is negative and reinforces the direct channel. Consequently, the overall sign is ambiguous in general. In particular, given $\Omega(\mathbf{S}') \geqslant 0$, the credit spread is decreasing in fundamentals whenever the direct effect dominates the indirect effect.

Inferring the role of bailout expectations. To be consistent with the data definition in (1), define the risk-neutral expectation as

$$\mathbb{E}^*_{\mathbf{S}}[X'] = \frac{\mathbb{E}_{\mathbf{S}}\big[\mathcal{M}(\mathbf{S}',\mathbf{S})\,X'\big]}{\mathbb{E}_{\mathbf{S}}\big[\mathcal{M}(\mathbf{S}',\mathbf{S})\big]}.$$

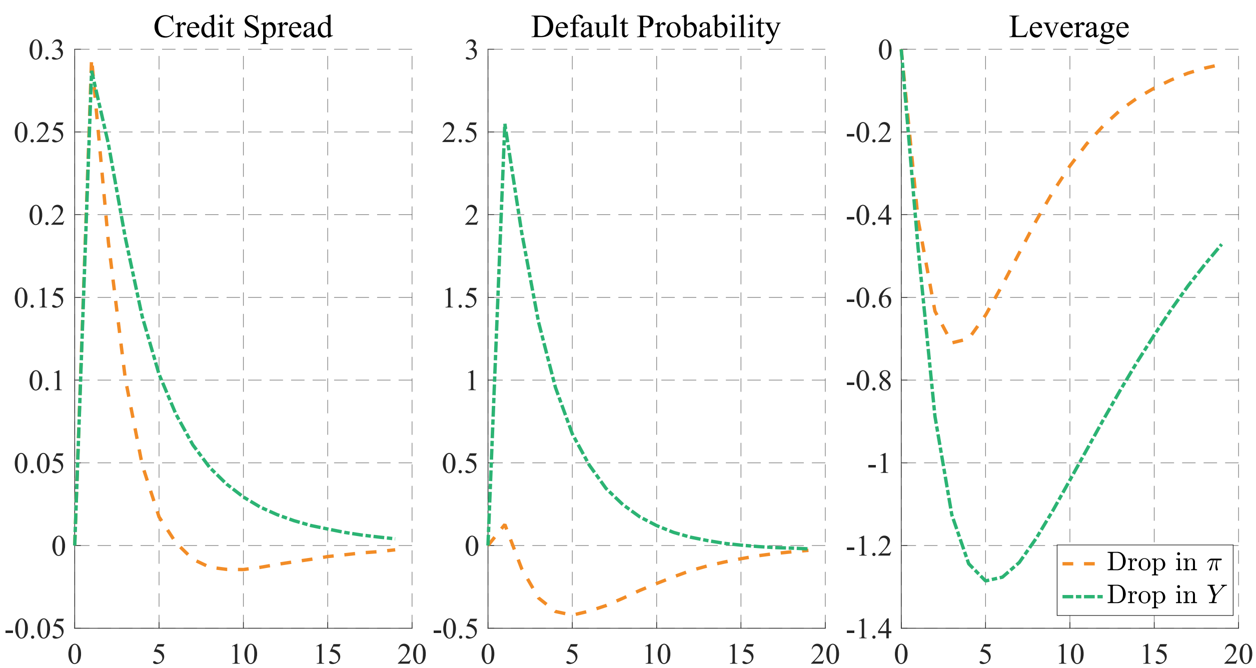
The expression for the credit spread in (20) then becomes

$$\begin{aligned} \mathrm{CS}(\mathbf{S}) &= \mathbb{E}^*_{\mathbf{S}}\Big[(1-\pi')\,\mathbb{F}(\mathbf{S}')\,[1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}')]\Big] \\ &= \underbrace{\mathbb{E}^*_{\mathbf{S}}[\mathbb{F}(\mathbf{S}')]}_{\mathbb{F}^*} \times \underbrace{\mathbb{E}^*_{\mathbf{S}}[(1-\pi')(1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}'))]}_{\mathrm{LGD}^*}, \end{aligned}$$

where $\mathbb{F}^*(\mathbf{S})$ is the model counterpart of the risk-neutral default probability.

The logic in Propositions 1 and 2 anticipates distinct joint movements of spreads and default risk under bailout versus fundamental shocks. When π moves, the spread reacts through a *direct* change in expected losses and an *indirect* response via the balance-sheet choice B'. A lower π raises required spreads mechanically but, because intermediaries optimally scale back debt, it also shifts down the default threshold $\omega^*(\mathbf{S}')$ and reduces risk-neutral default probabilities. In contrast, when Y worsens, both the default probability and recoveries move adversely *directly* and makes spreads and default risk rise together. Deleveraging partially mitigates the higher default risk.

Figure 6: Impulse Responses to Drop in Bailout Probability and Drop in Fundamentals



Notes: the graphs show the average path of the economy through a decrease in the bailout probability π (orange-dashed) and a drop in fundamentals Y (green-dashed-dotted) such that the credit spread increases by the same amount. Both shocks start at $t = 1$. Each line is the mean of 50,000 Monte-Carlo paths of length 20 years, all starting from the ergodic state at $t = 0$.

Figure 6 reports generalized impulse responses to two shocks: (i) a decline in π and (ii) a fall in fundamentals Y obtained by a drop in Z such that the credit spread increases by the same amount. We plot the one-period credit spread, the risk neutral default probability, and leverage. Bailout expectations and fundamentals leave distinct joint footprints in spreads and default risk. A decline in π reduces expected public support, mechanically raising required spreads; at the same time, intermediaries optimally delever, which lowers the risk-neutral default probability, so spreads rise while default risk falls. In contrast, a fall in Y worsens cash flow prospects and recoveries and increases both the risk-neutral default probability and required spreads; deleveraging partially mitigates but does not overturn the higher default risk, so both spreads and default rise. This contrast in comovements, spread up with default down for π shocks versus spread up with default up for Y shocks, allows us to infer whether higher (lower) credit spreads are driven by lower (higher) bailout expectations or by deteriorating (improving) fundamentals. In contrast, an increase in credit spreads accompanied by a declining default probability indicates that bailout expectations are the underlying source.

A natural concern is that the post-2010 tightening of capital and liquidity regulation could mechanically force intermediaries to delever, which could lead to a lowering of risk-neutral default probabilities, and thereby confound movements attributed to bailout expectations. In theory, changes in regulation do not pose a threat to the identification strategy proposed because, even though tightening regulations could reduce risk-neutral default probabilities, it would then, via that channel, compress spreads and not raise them, which is what is observed in the data. However, for this reason, it is crucial to discipline the trajectory of regulatory tightness after 2010 to avoid overstating (or understating) the bailout component. To do so, I provide a cross-equation restriction that separates regulatory stringency from bailout expectations by exploiting their opposite loadings on CDS spreads relative to the downside component of the risk-neutral equity variance (conditional on fundamentals) as described in Appendix A.7. I ensure accordingly that any remaining variation is not mechanically attributed to regulation and does not artificially inflate (or deflate) the estimated bailout contribution.

6 Quantitative Analysis

The model is calibrated to US bank-level data at the annual frequency from 2000 to 2019. For consistency, the calibration considers the same sample of banks from which risk-neutral default probabilities and expected losses are constructed in Section 3.[21] Table 2 lists all parameters and organizes them into four sets: fundamental risk, preferences, the

[21] High-frequency series (CDS rates and option-implied default probabilities) are aggregated to the annual frequency as follows: for each calendar quarter, we take the observation on the last trading day of the quarter (end of quarter) to form a quarterly series and the annual value is the simple average of the four quarter-end observations within the year. The persistence and volatility targets in Table 3 are computed from these annual series.

financial intermediaries' balance sheets, and bailout expectations. For each parameter, we report its value and the empirical target or source used to discipline it. Parameters governed by well-measured objects or established in the literature are fixed to those values, and parameters that can be identified without solving the full model are chosen to match reduced-form moments. The remaining parameters are estimated to match moments that require the full model solution using the method of simulated moments. Appendix E provides detailed information on the data sources and variables' definitions.

The presence of large shocks, substantial risk, and occasionally binding constraints make prices and quantities highly nonlinear functions of the state space. The model is therefore solved globally using a transition function iteration algorithm adapted from Elenev et al. (2021) and described in Appendix D. To generate the model moments, I run 80 independent simulations, each with 10,000 periods following a 500-period "burn-in" and report bootstrapped statistics. The model-generated values, unless otherwise specified, are computed from a sample conditional on no disaster realization.

Fundamental risk. It is important that the model captures the dynamics of asset risk realistically since these dynamics shape both default probabilities and the pricing of bank liabilities. Risk is not constant but rises disproportionately in downturns; this reflects the concavity of banks' underlying claims and the endogenous amplification of volatility when fundamentals weaken (Nagel & Purnanandam 2020). Models that miss this feature understate default risk in normal times and do not capture the sensitivity of equity returns to negative shocks. To discipline this dimension, I calibrate the parameters governing fundamental risk to match moments of the option-implied Bank of America (BofA) investment-grade corporate-bond spreads, which serve as a proxy for the credit-risk factor in bank portfolios (Begenau et al. 2015). I average the spreads across their rating classes from AAA to BBB. I define a disaster as a period in which the spread is 2.5 standard deviations above its mean. The time series of the average spread is shown in Figure E.1 in Appendix E.

Aggregate productivity follows a log-AR(1) process,

$$\ln Z' = \rho \ln Z + (1-\rho)\mu + \sigma\varepsilon^{Z}, \tag{21}$$

where $\varepsilon^{Z} \sim \mathcal{N}(0,1)$, μ is the long-run mean of $\ln Z_t$ (normalized to unity), $\rho \in (0,1)$ governs persistence and $\sigma > 0$ controls aggregate volatility. The persistence parameter, ρ, is set to match the spread's first-order autocorrelation of 0.47. The innovation volatility, σ, targets the unconditional standard deviation of the spread of 0.69%.

Table 2: Model parameters

Parameter	Value	Targets
Panel A: Fundamental risk		
π_d	0.036	Disaster onsets frequency
π_s	0.212	Disaster-state frequency
η	0.658	Bond and loan recovery losses (Elenev et al. 2021)
δ	0.937	Corporate debt duration (Elenev et al. 2021)
ζ	0.15	Simulated Method of Moments
ρ	0.90	Simulated Method of Moments
σ	0.05	Simulated Method of Moments
σ^z	0.70	Simulated Method of Moments
σ^ω	0.11	Simulated Method of Moments
Panel B: Preferences		
β	0.987	Simulated Method of Moments
ν	2	Simulated Method of Moments
γ	7	Simulated Method of Moments
Panel C: Financial intermediaries		
ξ	0.92	Basel 8% Capital Requirement
κ	0.001 72	Deposit insurance fee (Begenau & Landvoigt 2022)
α_D	0.005	Deposit spread target (Drechsler et al. 2017)
β_D	0.34	Deposit rate sensitivity (Elenev & Liu 2024)
χ	0.332	Bankruptcy cost (Bennett et al. 2015)
ζ^D	−0.4	Correlation of insured deposits and output
ϕ_0	0.02	Dividend payouts by book equity
ϕ_1	5	Simulated Method of Moments
$\bar{D}$	0.4	Simulated Method of Moments
n_0	0.22	Simulated Method of Moments
Panel D: Bailout expectations		
$\bar{\pi}$	0.87	Simulated Method of Moments
ρ^π	0.7	Simulated Method of Moments
σ^π	0.6	Simulated Method of Moments

To guarantee positivity of (4), the two idiosyncratic shocks are modeled as log-normal

$$\ln z = \sigma^z \varepsilon, \quad \ln \omega = \sigma^\omega \eta, \tag{22}$$

with $\varepsilon, \eta \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,1)$. The parameters σ^z and σ^ω pin down the cross-sectional dispersion of tree and island shocks, respectively. The standard deviation of tree specific shocks σ^z is set to match the average spread over the sample period which corresponds to 1.37%. We set the standard deviation of the island risk, σ^ω, to target the median risk-neutral default probability of the banking sector as estimated from equity options in Section 3 and equal to 2.42%.

The binary disaster indicator evolves according to the Markov transition matrix

$$\mathbb{P}_d = \begin{pmatrix} 1-\pi_d & \pi_d \\ 1-\pi_s & \pi_s \end{pmatrix}, \tag{23}$$

where π_d is the probability of a disaster next period conditional on a normal state this period, and π_s is the probability of the disaster state next period if there is a disaster in the current period. The disaster-arrival probability, π_d, and the conditional survival probability, π_s, are selected to replicate, respectively, the empirical frequency of disaster onsets of 3.6% and the fraction of periods classified as disasters of 21.2% (the stationary probability of the disaster state in the data). With annual data, $\pi_s = 0.212$ implies an expected disaster spell length of $1/(1-\pi_s) \approx 1.27$ years. The disaster-severity coefficient, ζ, is chosen so that the model reproduces the mean spread observed during disaster episodes of 4.8%.

The loss-severity parameter, $\eta = 0.658$, is calibrated to the bond and loan recovery losses documented by Elenev et al. (2021) of 52%. I similarly set $\delta = 0.937$ as in Elenev et al. (2021) to match the observed duration of corporate debt which corresponds to 6.84 years.

Preferences. The time discount factor affects the mean of the short-term interest rate. The subjective discount factor is set to $\beta = 0.987$ to match the observed average short-term interest rate measured by the 3-month US Treasury bill rate of 1.56% and the intertemporal elasticity of substitution is set to $\nu = 2$ to match its volatility of 1.78%. The risk aversion parameter is set to $\gamma = 7$ to match the financial-sector ratio of the credit risk premium to the CDS rate reported by Berndt et al. (2018), which is equal to 0.39 over their sample period (2002–15).[22]

[22] Berndt et al. (2018) construct the credit risk premium as Prem = CDS − ExpL, where ExpL is the expected default loss computed from Moody's Analytics EDF default probabilities (using a term-structure fit across 1y/5y EDFs and longer refined PDs) together with Markit recovery assumptions; their Table III presents statistics for five-year CDS contracts, whereas my model focuses on one-year credit spreads, so

Financial intermediaries. The intermediary borrowing constraint parameter ξ can be interpreted as a minimum regulatory equity capital requirement. This parameter is set to $\xi = 0.92$ in the baseline calibration, or a 8% equity capital requirement, and conforms to the Basel limits. The deposit insurance fee is set to $\kappa = 0.172\%$ following Begenau & Landvoigt (2022) and the convenience yield on deposits α_D is set to match deposit spreads of 0.32% in the data (Drechsler et al. 2017). The deposit rate sensitivity is set to $\beta_D = 0.34$ following Elenev & Liu (2024). The parameter $\chi = 0.332$ is set following Bennett et al. (2015). The equity injection parameter n_0 is set to 0.22 to match the observed average market-to-book value ratio of 1.4. To determine the dividend target ϕ_0 of banks, time series of dividends, share repurchases, equity issuances, and book equity are constructed. Over the sample period, banks paid out around 2% of their book equity per year as dividends and share repurchases, which is the value I set for ϕ_0. The marginal equity issuance cost for intermediaries, $\phi_1 = 5$, is calibrated using the same data. With this parameter, I target the median equity issuance ratio of the financial sector, defined as equity issuances divided by book equity. A higher equity issuance cost makes issuing external equity more expensive and lowers the equity issuance ratio. Since banks issue equity on average, the equity issuance rate is 0.38% in the data. The mean of the insured deposit limit $\bar{D}$ determines the insured-deposit share of liabilities. The model generates a value of 50% versus the data counterpart of 46%. Finally, the correlation of insured deposits and output is set to $\zeta^D = -0.4$ to match the observed correlation in the data.

Bailout expectations. The bailout probability follows an AR(1) process[23]

$$\tilde{\pi}' = (1-\rho^\pi)\bar{\pi} + \rho^\pi\tilde{\pi} + \sigma^\pi\varepsilon^\pi, \qquad \varepsilon^\pi \sim \mathcal{N}(0,1).$$

The parameters $\bar{\pi}$, ρ^π and σ^π are chosen to match, respectively, the median CDS spread of 0.37%, its first-order autocorrelation of 0.58 and its standard deviation of 0.40% in the data.

their statistics represent an upper bound for my model's implied one-year ratio.

[23]Bailout expectations can be read as a political and institutional process, rather than a mechanical response to contemporaneous fundamentals. For purposes of identification, bailout expectations are kept exogenous and orthogonal to real variables to separate policy from fundamentals. If bailout probability were instead to rise endogenously in stress (i.e., when intermediaries' net worth falls or realized default probabilities increase), intermediaries would optimally delever less and would thereby raise default risk relative to the case in which bailout beliefs are orthogonal to fundamentals. Hence, my proposed approach to distinguish two forces would remain intact.

6.1 Model Fit

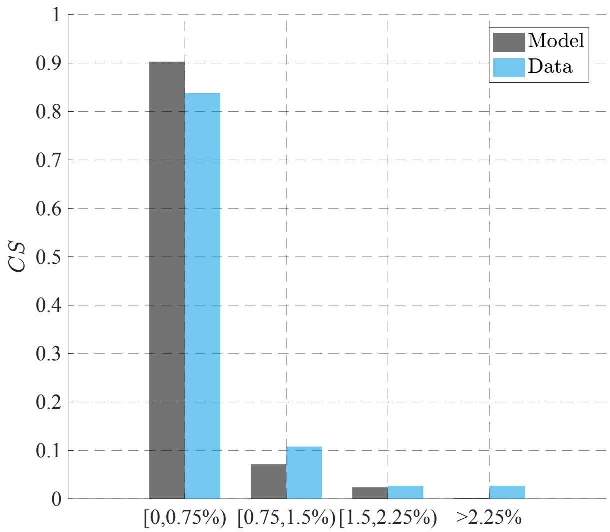
Table 3 collects the empirical targets and the corresponding model-implied moments used in the calibration. The model captures time-varying risk premia across equity and debt while tracking default risk. On the asset side, BofA IG option-adjusted bond spreads average 1.15% in the model against 1.37% in the data, with persistence and volatility in the right range. In disaster states $d = 1$, spreads reach 4.10% in the model versus 4.77% in the data. On the liabilities side, CDS premia average 0.38% in the model and 0.37% in the data, with slightly less persistence but comparable volatility. In equity markets, the model reproduces a large and clearly time-varying risk-neutral variance of intermediaries' equity returns, 0.054 in the model versus 0.08 in the data, rising in stress. Risk-neutral default probabilities average 3.24% in the model against 2.42% in the data and move with spreads; they help sustain observed credit premia while they preserve the shape of the empirical distribution.

Table 3: Empirical targets: data vs. model

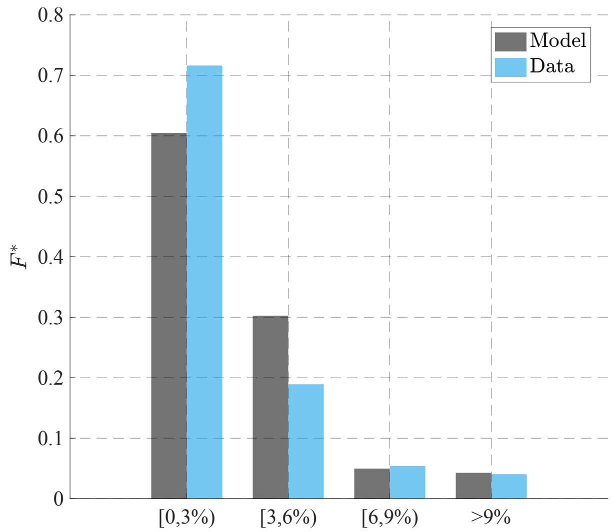
Targets	Data	Model
BofA IG Bond Spread	0.0137	0.0115
BofA IG Bond Spread in $d = 1$	0.0477	0.0410
AR(1) of BofA IG Bond Spread	0.47	0.53
BofA IG Bond Spread volatility	0.0067	0.0091
Intermediaries risk-neutral default probability	0.0242	0.0324
Intermediaries market-to-book value	1.4	1.2
Intermediaries equity issuance rate	0.0038	0.0050
Insured-deposits share of liabilities	0.46	0.50
Risk-free rate	0.0156	0.0126
Risk-free rate volatility	0.0178	0.0179
Credit risk premium to CDS rate	0.39	0.34
CDS rate	0.0037	0.0038
AR(1) of CDS rate	0.58	0.49
CDS rate volatility	0.0040	0.0034

Figure 7 complements these comparisons. The left panel shows that one–year credit spreads are right–skewed in both the data and the model, with similar mass over low-to-moderate spreads and thinner model-implied tails at the highest realizations. The right panel documents that risk–neutral default probabilities concentrate near low values in both series; the model shifts the mean upward modestly, consistent with Table 3, while preserving the overall shape of the empirical distribution. By jointly matching spreads on both the asset and liability sides, the model effectively pins down equity risk and, through that mapping, closely replicates the distribution of risk–neutral default probabilities.

Figure 7: Distributions of Credit Spreads and Default Probabilities



(a) Credit Spreads



(b) Default Probabilities

Notes: histograms for model-simulated and empirical distributions, 2000–20. The left panel plots one-year credit spreads (data described in Section 3 and the simulated sample used for Table 3). The right panel plots risk-neutral default probabilities based on the same data and simulation.

7 Decomposing Credit Spreads

This section presents the main experiment of the paper, namely, to measure the importance of bailout expectations before, during, and after the GFC. I apply the model to annual data over 2004–15 to recover the latent bailout probability process and to decompose observed credit spreads.

The model is used to generate the following nonlinear state-space system

$$\begin{aligned} \mathbf{Y}_t &= \mathbf{g}(\mathbf{S}_t) + \boldsymbol{\eta}_t, \\ \mathbf{S}_t &= \mathbf{f}(\mathbf{S}_{t-1}, \boldsymbol{\varepsilon}_t), \end{aligned} \tag{24}$$

where

$$\mathbf{S}_t = \left[\, L_t, W_t, \pi_t,\ Z_t,\ d_t \right]^\top, \qquad \boldsymbol{\varepsilon}_t = \left[\varepsilon_t^{\pi},\ \varepsilon_t^{Z},\ \varepsilon_t^{d}\right]^\top,$$

and the vector $\mathbf{Y}_t$ collects the two observable variables:

$$\mathbf{Y}_t = \left[CS_{t,365},\ \mathbb{F}^*_{t,365}\right]^\top,$$

namely, the credit spread differential $CS_{t,365}$ and the risk neutral default probability $\mathbb{F}^*_{t,365}$ (both constructed in Section 3). $\boldsymbol{\eta}_t$ represents the measurement errors vector. The mapping $\mathbf{g}(\cdot)$ delivers the model-implied one-year credit spread $g_1(\mathbf{S}_t)$ and risk-neutral default probability $g_2(\mathbf{S}_t)$, respectively.

Given the model's nonlinear mapping $\mathbf{g}(\cdot)$, the latent state path $\{\mathbf{S}_t\}_{t=1}^T$ is estimated using a particle filter algorithm (see Appendix F for details). The filter pins down the entire sequence of shocks $\{\varepsilon_t\}$, including the bailout probability shock ε_t^π, that is consistent with observed spreads and default probabilities.

Empirically, credit spreads are strictly positive and right-skewed, whereas default probabilities lie on the open-unit interval. To respect these distributional features, the measurement errors are modeled as log-normal and beta random variables rather than Gaussian noise:

$$CS_{t,365} = g_1(\mathbf{S}_t)\exp(\eta_t^{CS}), \quad \eta_t^{CS} \sim \mathcal{N}\big(-\tfrac{1}{2}\sigma_{CS}^2,\ \sigma_{CS}^2\big),$$

$$\mathbb{F}^*_{t,365} = g_2(\mathbf{S}_t) + \eta_t^{Q}, \quad \eta_t^{Q} \sim \text{Beta}\big(\alpha_t, \beta_t\big) - \mathbb{E}\big[\text{Beta}(\alpha_t, \beta_t)\big],$$

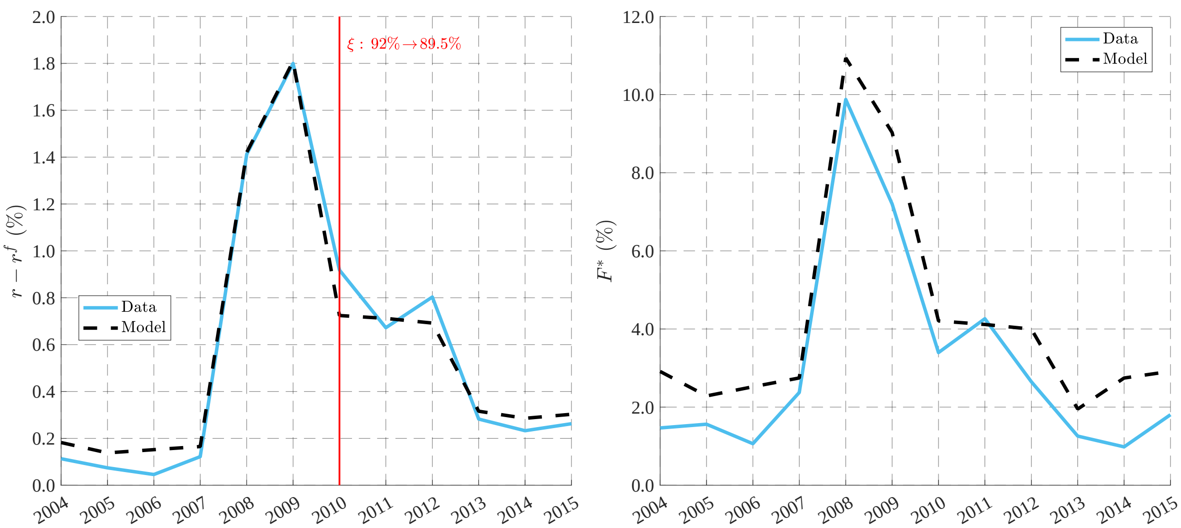
where the beta parameters (α_t, β_t) are calibrated each period to match $g_2(\mathbf{S}_t)$ and a variance set equal to $0.01\,\widehat{\sigma}^2\big(\mathbb{F}^*_{t,365}\big)$. The log-variance σ_{CS}^2 is fixed analogously at $0.01\,\widehat{\sigma}^2\big(CS_{t,365}\big)$. Independent log-normal and beta likelihoods are thus used within the particle filter to update the state vector in each year.

To account for the tightening of regulation after 2010, I impose a deterministic policy break at the start of 2010 and evaluate the model's policy functions under a stricter capital requirement from that date onward. For $t < 2010$, the likelihood and the model-implied observables $\mathbf{g}(\mathbf{S}_t)$ are computed under the baseline leverage cap $\xi = 0.92$, which corresponds to an 8% minimum equity capital requirement. Starting in 2010, the same objects are instead evaluated under a tighter requirement that raises the minimum equity share to 10.5%. This break only changes the policy mapping used by the particle filter (and thus the measurement density) and leaves the measurement-error specification unchanged. The magnitude of the post-2010 tightening is pinned down using the increase in the downside slope (elasticity) of the spread–downside-variance relation of 0.20 estimated in Appendix A.7 from pre-2008 to post-2010.[24] This identification exploits that, holding fun-

[24] Appendix A.7 develops an identification strategy to disentangle regulation from bailout expectations by exploiting that, holding fundamentals fixed, regulation moves CDS spreads and downside risk-neutral variance in the same direction, whereas lower bailout protection moves them in opposite directions. I construct model-free upside and downside tail variances from option prices, residualize both on bank and date fixed effects and bank-specific VIX slopes (to control for asymmetric changes in tails due to fundamental shocks [i.e., downward jumps]) and use the projection of the downside tail on the upside tail to build subsample-specific orthogonalized shifters (pre-2008 and post-2010). I then estimate an interacted 2SLS of log CDS spreads on the log tail variances, and instrument each interacted tail regressor with its corresponding orthogonalized shifter and cluster by bank and date. The post-2010 downside slope is larger than

damentals fixed, a decline in expected bailout support raises CDS spreads while lowering the downside risk-neutral equity variance, whereas a tightening of capital requirements compresses leverage and reduces both spreads and downside variance. Consequently, an upward break in the spread–variance correlation is informative about stronger regulation rather than weaker bailout protection. I therefore calibrate post-2010 ξ so that the model reproduces this increase in the downside slope, which implies a 2.5 percentage-point increase in the equity capital requirement (from 8% to 10.5%), and equivalently, a decrease in ξ by 0.025.[25]

Figure 8: The Dynamics of Credit Spreads and Default Probabilities



(a) Credit Spreads **(b) Default Probabilities**

Notes: the left panel plots one-year credit spread, model-implied (black-dashed) versus data (cyan-solid). The right panel plots one-year bank default probability, model-implied (black-dashed) versus data (cyan-solid). The red vertical line in 2010 represents the increase in capital requirements implied by the model from 8% to 10.5%.

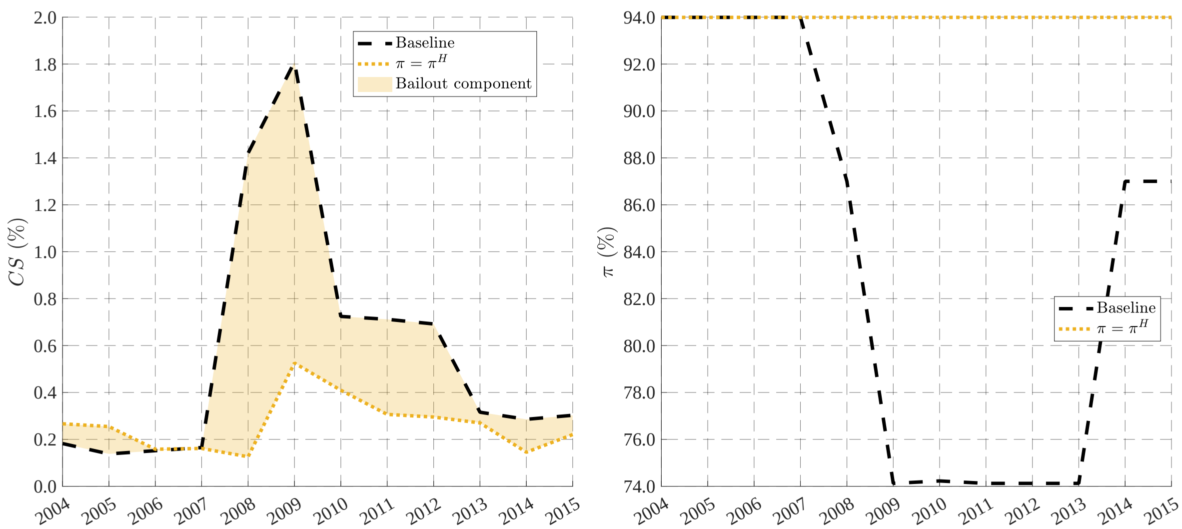
Figure 8 compares the model-implied average path for one-year credit spreads and risk-neutral default probabilities with their data counterparts. The model captures the dynamics in both series, including the run-up to the crisis and the subsequent decline after the 2010 increase in capital requirements. It also matches the relative timing of peaks and troughs and the comovement between spreads and default risk. In contrast, the model overstates default probabilities before and during the crisis. Finally, while default probabilities returned to their 2007 levels by 2012, credit spreads remained permanently higher

pre-2008 and the spread–downside slope increases by about 0.20; this identifies tighter capital regulation rather than lower bailout expectations via the monotonic mapping in Proposition 3.

[25]When matching the post-2010 increase in the spread–downside-variance slope, I first net out the component driven by fundamentals from both series so that the resulting change isolates the impact of bailout expectations and tighter capital regulation. More details can be found in Appendix F.

than precrisis levels.

Figure 9: Counterfactual Credit Spreads



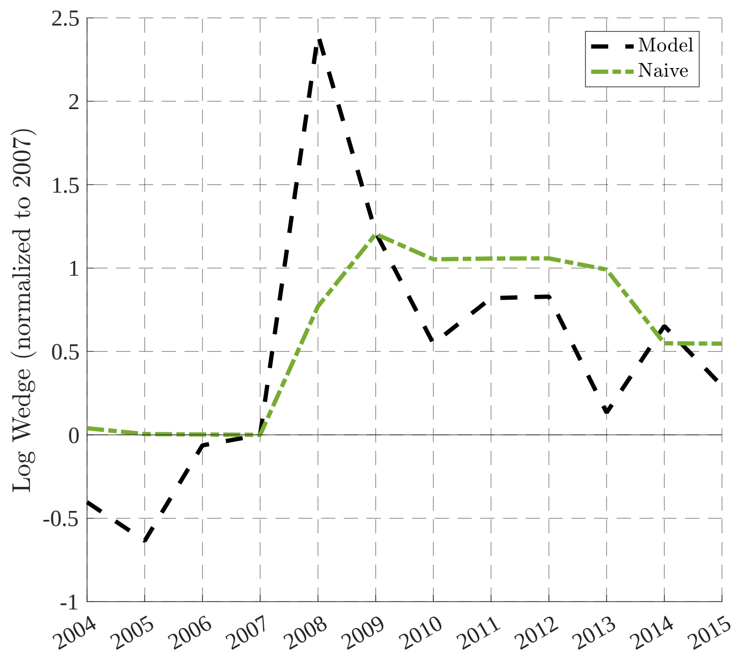
(a) Credit Spreads **(b) Bailout Probability**

Notes: the left panel plots model spread (black-dashed) and the counterfactual with high bailout probability (orange-dotted). The orange-shaded area represents the *bailout component*; it is the difference between model-implied and counterfactual spread with $\pi = \pi^H$. The right panel plots recovered bailout probability π from the state-space filter (black-dashed) and the counterfactual bailout probability (orange-dotted).

The right panel of Figure 9 reports the recovered bailout probability path π as a black dashed line. The inferred bailout probability is elevated before the crisis and exhibits two distinct drops. The first drop occurs in late 2008 around the time of the collapse of Lehman Brothers and is partly tempered by the enactment of the Paulson Plan (TARP); a second, more persistent decline begins in 2009 following the 2009Q3 announcement of the Dodd–Frank act and its July 2010 enactment; the probability falls from about 94% to 75% by 2009 and remains subdued through 2013. It then recovers only gradually, to a level below its precrisis level. This is consistent with the short-lasting nature of regulatory credibility: although the single-point-of-entry (SPOE) resolution strategy was articulated in 2013, uncertainty about implementation persisted, and only in 2024 did the FDIC and the Federal Reserve issue final joint guidance for the resolution plans of large banks. Overall, this pattern is consistent with the findings in Berndt et al. (2025).

With the recovered latent state path in hand, I now measure the contribution of the bailout probability to the credit spreads. To do so, the filtered states are fed to the model's policy functions, with the exception that π is set to its precrisis level, which corresponds to the highest state π^H for all t in the sample. The left panel of Figure 9 reports the counterfactual spread as an orange dotted line together with the model-implied spread as a black dashed line. The orange shaded area represents the difference between the filtered credit spread and the counterfactual one and nets out the impact of bailout expectations. I define this difference as the *bailout component of credit spreads*. The right panel of Figure 9 reports the counterfactual bailout probability as an orange dotted line. The counterfactual spread rose during the GFC by less than half of the model-implied spread and returned to its precrisis level by 2012.

Figure 10: Model-Implied Bailout Component vs. Naive Measure



Notes: black-dashed: $\log \mathrm{CS}_t - \log \mathrm{CS}_t(\pi = \pi^H)$, the model-implied bailout component computed as the log difference between the model-implied spread and the counterfactual spread that fixes bailout probability at its precrisis level π^H. Green-dashed-dotted: $\log \mathrm{CS}_t - \log \mathbb{F}^*_{t,T}$, a *naive* measure obtained by subtracting the log risk–neutral default probability from the log spread. Both series are normalized to zero in 2007.

How different would the recovered bailout component be relative to a naive measure which follows the empirical approach described in Section 2? Figure 10 reports the log difference between the model-implied spread and the counterfactual spread with $\pi = \pi^H$ (black dashed line) and the *naive* measure which subtracts the log of the risk-neutral default probability from the log of the model-implied spread (green dashed-dotted). The latter mechanically attributes to bailout expectations everything that is not captured by default risk. Both measures are normalized at zero in 2007.

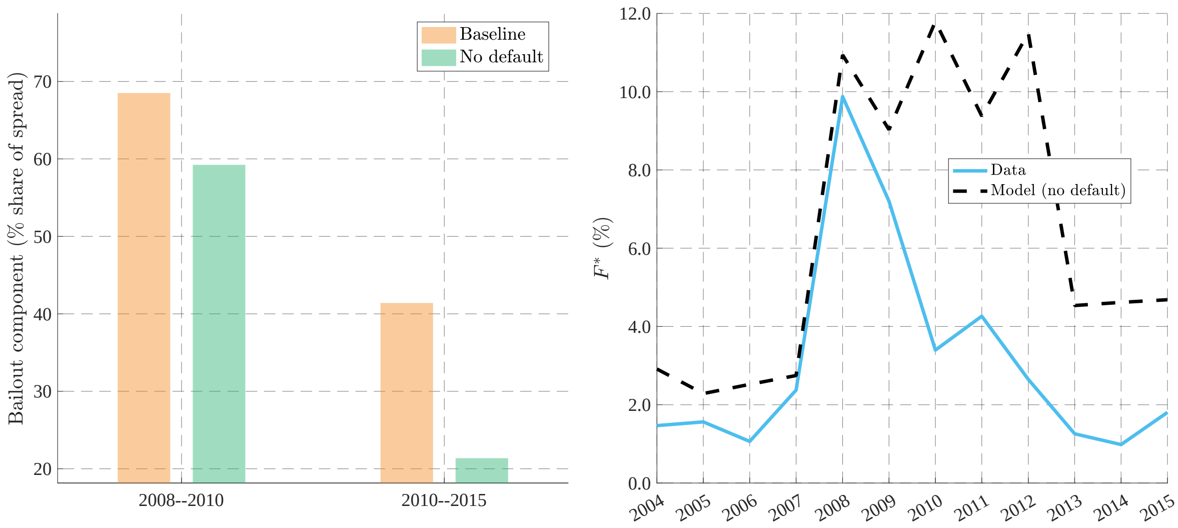
During the 2008–09 crisis, fundamentals deteriorated abruptly while perceived bailout probabilities fell. In the model, this combination raises spreads through two reinforcing channels: weaker fundamentals directly increase expected default losses and lower bailout expectations make those losses more likely to be borne by creditors. Because both forces move spreads and default probabilities in the same direction, the naive measure interprets the entire surge in spreads as fundamental and thereby understates the role of bailout expectations. The model instead recognizes that such a sharp spread increase cannot be explained by fundamentals alone once banks' endogenous deleveraging response is taken into account.

After the crisis, in contrast, the naive measure *overstates* the bailout component. When π declines, banks reduce leverage, which lowers observed default probabilities even though fundamentals remain weak. The naive measure mistakes this stability of $\mathbb{F}^*$ for an improvement in fundamentals and thus attributes too much of the post-2010 spread elevation to bailout expectations. Differently, in the model, lower leverage and weaker fundamentals offset each other and yield a more accurate decomposition of spreads across the two forces.

To discipline how much of spreads is attributed to bailout beliefs versus failure risk, I include observed default probabilities in the state-space filter. Default probabilities revert toward their precrisis levels by 2010–11, while banks' CDS spreads remain elevated for several years. If the default-rate series is omitted, the filter can rationalize high spreads by keeping model failure probabilities persistently high and can thereby shrink the portion of spreads assigned to bailout expectations. Consistent with this mechanism, the right panel of Figure 11 shows that, when default probabilities are excluded from the filter, the model-implied default probability stays too high relative to the data. As a result, the estimated bailout component is markedly smaller in that specification: it explains 59% of the spread increase in 2009–10 and only 20% in 2010–15, compared with 67% and 43%, respectively, in the baseline with default probabilities included.

A behavioral story can also explain the wider credit spreads after the GFC. Before the crisis, many creditors did not truly believe that banks could fail (Gennaioli & Shleifer 2018). When Lehman Brothers collapsed and several other large financial services firms nearly followed, creditors suddenly recognized a failure risk that had been present all along but badly underestimated. The jump in spreads would then reflect a higher perceived chance of insolvency, not a change in expected bailout support. However, the persistence of those wider spreads implies that the post-Lehman shift in perceived failure risk lasted for years and that insolvency was not the case; this is consistent with the behavior of default probabilities presented in the right panel of Figure 11. The evidence is therefore inconsistent with a potential behavioral explanation of changes in intermediaries' debt funding costs. More broadly, standard intermediary asset-pricing models (He & Krishnamurthy 2013, Brunnermeier & Sannikov 2014) struggle to reproduce boom–bust episodes in credit valuations without invoking behavioral mechanisms; behavioral frictions generate such dynamics via shifts in beliefs (Maxted 2024, Krishnamurthy & Li 2025). In my framework, in contrast, the evolution of bailout expectations helps reproduce the boom–bust pattern while keeping the dynamics of default risk consistent with

Figure 11: The Information Content of Default Probabilities



(a) Bailout Component **(b) Default Probabilities**

Notes: the left panel plots the bailout component in the baseline economy (orange) and in the case in which default probabilities are excluded from the filter (green) as a share of the respective model spreads over 2008–2010 and 2010–2015 (percent). The bailout component is the difference between the model-implied spread and the counterfactual spread with bailout fixed at its precrisis level. The right panel plots model default probability when the default probabilities are excluded from the filter (black-dashed) versus the data counterpart (cyan solid).

the data.[26]

Table 4 report the percentage change in credit spreads and leverage post-2010 relative to their precrisis average in the first column with the relative contributions of bailout probabilities and regulation in the second and third column. Relative to the pre-2008 benchmark, the average unsecured spread paid after 2010 rises by 34 basis points in the baseline model, yet by only 6 basis points when the high precrisis bailout probability (π^H) is kept in place. The difference of roughly 28 basis points, almost three-quarters of the observed increase, can therefore be attributed directly to the reassessment of government support. In other words, unsecured debt spreads would have been roughly four times lower had investors continued to believe in large-scale bailouts. Tighter capital requirements after 2010 contributed to the reduction in leverage and insolvency risk in the banking system and helped keep spreads about 12 basis points lower. Thus, even if tighter regulation lowered observed default probabilities, that force would push spreads down, not up. The persistence of elevated spreads alongside lower default probabilities therefore cannot be explained by regulation alone. If anything, it reinforces the inference of weaker bailout protection and raises the estimated bailout component of spreads.

[26] Krishnamurthy & Li (2025), among others, argue that unusually low credit spreads can precede crises when they reflect optimistic beliefs rather than low risk. In my setting, low spreads forecast distress only when they arise from elevated bailout expectations that spur risk taking and raise default ex-post.

8 Reassessing Post-2010 Reforms

Table 4: The Impact of Lower Bailout Expectations and Tighter Regulation

	Baseline	**Bailout Expectations**	**Regulation**
Credit spread (bp)	34.3	27.9	−11.7
Leverage (%)	−2.99	−1.49	−1.20
(Adjusted) Risk-free rate (bp)	43.6	13.4	26.6
Risk premium (bp)	64.4	32.4	26.3
Loan yield to maturity (bp)	50.9	32.8	15.6

Notes: The first column shows changes in post-2010 averages versus pre-2008 averages for the baseline economy. The second and third columns show the contributions of lower bailout expectations (π) and tighter capital requirements (ξ), respectively, to these changes. Spreads and rates are in basis points; leverage is in percentage points. Positive values indicate increases relative to pre-2008. The loan yield to maturity is calculated as $\frac{\delta\, p(\mathbf{S})}{p(\mathbf{S})+\delta-1-c}$.

As shown in the previous section, a decline in bailout expectations and tighter capital requirements raised intermediaries' funding costs and compressed leverage. I now examine how the changes in the cost and composition of funding transmit to the pricing of risk on the asset side of intermediaries' balance sheets.

A growing empirical literature documents that, after the GFC and the subsequent wave of regulatory tightening, banks retrenched from risky asset markets and curtailed balance-sheet intermediation of complex credit products (Bao et al. 2018, Allahrakha et al. 2019, Kim et al. 2018). This pullback was accompanied by a migration of risk toward nonbank financial intermediaries and a secular shift away from on-balance-sheet lending by banks, as documented by Irani et al. (2021), Buchak et al. (2018, 2024), and banks increased allocations to safer segments such as AAA-rated securitization tranches and longer-maturity government securities. Moreover, expected returns have increased in asset markets where banks are the primary intermediaries (Fleckenstein & Longstaff 2018, Boyarchenko et al. 2018, Du et al. 2023). At the same time, stricter capital regulation has tightened lending standards and raised the cost of bank credit (Baker & Wurgler 2015, Plosser & Santos 2024). While the literature typically explained these trends solely through stricter regulation, here I evaluate the role of higher funding costs induced by lower bailout expectations. I first characterize the intermediary stochastic discount factor and the asset demand condition, and I then use them to quantify the implications for expected returns, risk premia and the cost of credit.

The intermediary's choice of risky asset holdings α' determines the expected returns and so the intermediary's willingness to be exposed to fundamental aggregate risk. Formally, from the first-order condition of the intermediary's problem with respect to a', we obtain

$$p(\mathbf{S}) - \frac{\partial q(\mathbf{S})}{\partial A'}B' - \lambda(\mathbf{S})\xi p(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\{\mathcal{M}^{I}(\mathbf{S}', \mathbf{S})\mathcal{P}(\omega^{+\prime}, \mathbf{S}')\}, \tag{25}$$

where $\mathcal{M}^{I}(\mathbf{S}', \mathbf{S})$ is the intermediary stochastic discount factor defined as

$$\mathcal{M}^{I}(\mathbf{S}', \mathbf{S}) \equiv \mathcal{M}(\mathbf{S}', \mathbf{S})\tilde{v}(\mathbf{S}')(1 - \mathbb{F}(\mathbf{S}')). \tag{26}$$

On the left, $p(\mathbf{S})$ is the price paid today for the risky asset. The term $\frac{\partial q(\mathbf{S})}{\partial A'}B'$ captures that the intermediary internalizes how additional asset exposure affects both default likelihood and expected recovery in default states. Because $\frac{\partial q(\mathbf{S})}{\partial A'} > 0$, this component raises the asset's price. The term $\lambda(\mathbf{S})\,\xi\,p(\mathbf{S})$ represents the marginal value of relaxing the leverage constraint (9). On the right, the expression is the expected discounted payoff using the intermediary stochastic discount factor (SDF).

In general, variation in the cost and composition of funding that occurs by altering the intermediary's net worth will influence the behavior of expected returns. In order to understand that, we can rearrange Equation (25) as follows:

$$\mathbb{E}_{\mathbf{S}}\big[R^{A}(\mathbf{S}', \mathbf{S})\big] = \underbrace{R^{I}(\mathbf{S})(1 - \lambda(\mathbf{S})\,\xi - \phi(\mathbf{S}))}_{\text{Regulation/Default Adjusted Risk-Free Rate}} + \underbrace{\mathrm{cov}_{\mathbf{S}}\left(-\frac{\mathcal{M}^{I}(\mathbf{S}', \mathbf{S})}{\mathbb{E}_{\mathbf{S}}[\mathcal{M}^{I}(\mathbf{S}', \mathbf{S})]}\,,\ R^{A}(\mathbf{S}', \mathbf{S})\right)}_{\text{Risk Premium}} \tag{27}$$

where I define the (shadow) risk-free gross rate implied by the intermediary SDF as $R^{I}(\mathbf{S}) \equiv 1/\mathbb{E}_{\mathbf{S}}[\mathcal{M}^{I}(\mathbf{S}', \mathbf{S})]$, $\phi(\mathbf{S}) = \frac{1}{p(\mathbf{S})}\frac{\partial q(\mathbf{S})}{\partial A'}B'$ and $R^{A}(\mathbf{S}', \mathbf{S}) = \frac{x\mathcal{P}(\omega^{+\prime}, \mathbf{S}')}{p(\mathbf{S})}$. Equation (27) shows that the expected return on the risky asset is the sum of two components: the risk-free rate adjusted for intermediary constraints and the risk premium. Changes in each component are informative about intermediaries' willingness to invest in the cross section of asset risk exposures. A higher adjusted risk-free rate raises the common hurdle rate for all assets, namely, their average cost of financing. This effect is stronger for assets with small excess returns and it would therefore push intermediaries to scale down the exposure to safer, low-spread markets first. In contrast, a higher risk premium, which reflects a stronger tilt of the intermediary SDF toward bad states, raises the compensation required for bearing risk in downturns. In this case, intermediaries would shift away first from asset exposures that are highly cyclical or lose value in recessions.

Changes in regulation and in perceived bailout probabilities change expected returns by altering funding costs and the composition of intermediaries' liabilities (debt vs. equity). While both tighter capital requirements and lower expected bailouts reduce effective leverage, they do so through different channels. Tighter capital requirements (i.e., lower effective ξ) force intermediaries to hold more equity and so they increase their average cost of capital since equity is more expensive than debt. This raises the adjusted risk-free rate. Moreover, anticipation that the constraint may bind in the future raises required returns today by increasing risk premia (Aiyagari & Gertler 1999, Bocola 2016). When the constraint binds (higher $\lambda(\mathbf{S})$), intermediaries need to delever to meet capital ratios; they thus depress prices and lower ex-post returns precisely when the marginal value of intermediary equity $\tilde{v}(\mathbf{S}')$ is high. This, in turn, increases their required compensation for holding risky assets. Lower perceived bailout probabilities remove state-contingent transfers to creditors in bad states. This raises the cost of debt funding directly and pushes intermediaries to hold more equity and raises the adjusted risk-free rate. Lower π increases the sensitivity of funding costs to default risk: with less expected support, required debt spreads load more on default probabilities rather than on recovery values. Because default probabilities spike in downturns, funding costs rise most in bad states, precisely when issuing equity is most costly, and shrink intermediaries' net worth and raise $\tilde{v}(\mathbf{S}')$. As a result, the intermediary SDF is more *tilted* toward bad states of the world; thus, the risk premium is higher.

The last three rows of Table 4 report the contribution of the postcrisis fall in the perceived bailout probability and tighter capital requirements to the intermediary adjusted risk-free rate, the risk premium, and lending rates.

Changes in funding costs appear as a higher intermediary-adjusted risk-free rate and a higher risk premium in expected returns. In the baseline, expected excess returns rise by about 107 basis points relative to the pre-2008 benchmark, with roughly 43 basis points contributed by the adjusted risk-free rate and 64 basis points by the risk premium. In terms of contributions, lower bailout expectations (column π^H) contribute about 13 basis points to the increase in the adjusted risk-free rate, while the tightening of capital requirements (column ξ) contributes about 27 basis points. On the risk-premium side, lower bailout probabilities contribute about 32 basis points to the increase in the risk premium (roughly half of the total), while tighter capital requirements contribute about 26 basis points.[27]

The behavior of expected returns is consistent with a sluggish recovery in lending standards post-2010. In the baseline, the loan yield to maturity is around 50 basis point above its pre-2008 average with more then half of the drop accounted for by lower bailout expectations. Both lower bailout probabilities and tighter capital requirements increase intermediaries' reliance on expensive equity; banks' recapitalization are therefore more costly, slow down the recovery in their net worth, and induce a persistent increase in

[27] Because postcrisis capital regulation raises requirements more for riskier assets through higher risk weights, the aggregate decomposition likely understates the effect of tighter regulation on the cost of capital and risk premia, especially for high-risk exposures.

lending rates.[28] Comparing the baseline to the ξ counterfactual suggests that, once lower bailout expectations already induced intermediaries to endogenously delever, the post-2010 tightening of regulation pushed funding further toward costly equity and increased the cost of credit even more.

Taken together, these findings show that the post-2010 repricing of government guarantees played a major role in driving higher risk premia, prompted a reallocation away from very risky assets toward safer ones, and increased the cost of credit to firms and households. More broadly, my results highlight a crucial identification issue when studying the impact of regulation on risk premia, bank credit supply, and lending rates in markets where intermediaries invest. If bailout expectations are not explicitly accounted for, one would risk overattributing these effects to regulatory changes alone. In reality, perceived state-contingent promises and formal rules (e.g., capital requirements) operate as a joint system that codetermines funding costs, capital structure and ultimately the pricing of risks on intermediaries' assets.

9 Conclusion

This paper provides a model-based decomposition of bank credit spreads into fundamental, regulatory, and bailout components. Quantitatively, diminished bailout expectations account for roughly 28 basis points of the post-2010 34-basis-point increase in unsecured funding costs, with the remaining 18 basis points due to fundamentals and partly offset by tighter regulation, which lowered spreads by about 12 basis points.

Post-2010, lower bailout expectations and tighter regulations jointly raised the compensation banks require to hold risk and increased the cost of credit to the real economy. Quantitatively, movements in risk premia account for about 60% of the postcrisis increase in expected returns, with roughly half of that rise driven by lower bailout expectations. Lending rates increased by around 50 basis points over the same period. This repricing of government guarantees emerges as an important driver of banks' post-2010 retreat from tail-exposed asset markets, higher risk premia, and the tightening of lending conditions; this emphasizes that failing to account for bailout expectations would bias upward the estimated impact of regulation.

These findings have important policy implications. First, my paper highlights the importance of credible commitment mechanisms in financial regulation and suggests that the effectiveness of capital requirements may depend crucially on the broader policy environment, including expectations about government intervention in times of stress. If

[28] By jointly lowering perceived bailout probabilities and tightening capital requirements, the model also rationalizes the persistently higher option-adjusted bond spread post-2010; see Appendix E.

regulators could commit to not providing bailouts, then the optimal capital requirement may be lower than currently warranted. The mere expectation of government support could reduce banks' risk-taking incentives, even without actual bailouts occurring, but at potentially lower economic costs than tighter regulation.[29] Second, my analysis suggests that it may be useful to extend capital regulation approaches that rely on credit spreads as a gauge of financial health and a trigger of regulatory actions (e.g., countercyclical capital buffers). The decomposition reveals that credit spreads reflect not only fundamental risk but also expectations about government intervention. Policymakers using credit spreads as early warning indicators of financial crisis and to initiate regulatory measures should account for bailout expectations to avoid misinterpreting changes in spreads as purely fundamental risk signals.

[29] In Appendix H, I solve for the social planner problem in a two-period version of my model economy and show that the optimal level of capital requirements is an increasing function of the bailout probability.

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Appendix

A Empirical evidence: details and additional results

A.1 Detailed derivations of LGD^*

First define the promised contractual debt cash flow at $\tau \geqslant t+1$ as $C_\tau = P^D_\tau D_\tau$. Using this definition, the default indicator and post-default payoffs can be rewritten as

$$\Delta_\tau = \mathbf{1}_{\{Y_\tau A_\tau < C_\tau\}}, \qquad \widetilde{P}^D_\tau = C_\tau - (1-\pi_\tau)\big(C_\tau - \hat{V}_\tau\big)\Delta_\tau.$$

The market price of debt is therefore

$$S^D_t = \sum_{\tau=t+1}^{\infty} \beta_{t,\tau}\, \mathbb{E}^*_t[\widetilde{P}^D_\tau] = \underbrace{\sum_{\tau=t+1}^{\infty} \beta_{t,\tau}\, \mathbb{E}^*_t[C_\tau]}_{\equiv A_t} - \underbrace{\sum_{\tau=t+1}^{\infty} \beta_{t,\tau}\, \mathbb{E}^*_t\big[(1-\pi_\tau)(C_\tau - \hat{V}_\tau)\Delta_\tau\big]}_{\equiv L_t},$$

where A_t is the risk-free present value of promised coupons and L_t is the present value of expected losses.

We can now define the credit spread CS_t as the non-negative scalar s that solves

$$S^D_t = \sum_{\tau=t+1}^{\infty} \beta_{t,\tau} \frac{C_\tau}{(1+s)^{\tau-t}}.$$

Substituting $S^D_t = A_t - L_t$ gives

$$L_t = \sum_{\tau=t+1}^{\infty} \beta_{t,\tau}\, \mathbb{E}^*_t[C_\tau]\left[1 - (1+CS_t)^{-(\tau-t)}\right]. \tag{A.1}$$

Equation (A.1) expresses L_t entirely in terms of observed credit spreads CS_t, the cash flow schedule $\{C_\tau\}$ and discount factors $\{\beta_{t,\tau}\}$.

We further define the risk-neutral default probability

$$\mathbb{F}^*_{t,\tau} = \mathbb{E}^*_t[\Delta_\tau],$$

and the losses conditional on default

$$\mathrm{LGD}^*_{t,\tau} = \mathbb{E}^*_t\big[(1-\pi_\tau)(C_\tau - \hat{V}_\tau) \mid \Delta_\tau = 1\big].$$

The single-period discounted expected loss is

$$\ell_{t,\tau} = \beta_{t,\tau}\, \mathbb{F}^*_{t,\tau}\, \mathrm{LGD}^*_{t,\tau}. \tag{A.2}$$

If $L_t = \sum_{\tau=t+1}^{\infty} \ell_{t,\tau}$, we can rearrange (A.2) using (A.1) to get

$$\text{LGD}^*_{t,\tau} = \frac{\ell_{t,\tau}}{\beta_{t,\tau}\,\mathbb{F}^*_{t,\tau}} = \frac{\mathbb{E}^*_t[C_\tau]\left[1-(1+\text{CS}_t)^{-(\tau-t)}\right]}{\mathbb{F}^*_{t,\tau}}, \tag{A.3}$$

delivering the risk-neutral loss-given-default for every maturity $\tau > t$.

Given (A.3), the last step is to back out the simplified version in Equation (1) in the main text. Provided the following simplifying assumptions hold:

1. **Single-period horizon.** Set $\tau = t+1$. Multi-period CDS contracts are rolled into a one-year par spread, so the term $(\tau - t) = 1$.

2. **Par coupon schedule.** The reference bond underlying the CDS is assumed to trade at par with unit face value: $\mathbb{E}^*_t[C_{t+1}] = 1$.

3. **Small-spread approximation.** For annualized spreads of a few hundred basis points,
$$1-(1+\text{CS}_t)^{-1} = \frac{\text{CS}_t}{1+\text{CS}_t} \simeq \text{CS}_t.$$

Under (1)–(3), the numerator of (A.3) reduces to $\text{CS}_{t,T}$, yielding the compact relationship

$$\text{CS}_{t,T} \;\simeq\; \mathbb{F}^*_{t,T}\text{LGD}^*_{t,T}. \tag{A.4}$$

A.2 Alternative estimator for risk-neutral default probabilities

An alternative method to estimate the default region relies on the Theil–Sen estimator rather than ordinary least squares (OLS). I specifically preserve the progressive window expansion framework, beginning with the two lowest strikes $\{K_1, K_2\}$ and incrementally increasing the candidate window size m from 2 to n. For each time t, maturity T and proposed window $\{K_1, \dots, K_m\}$, the Theil–Sen slope estimate is given by

$$\hat{\beta}_{TS} \;=\; \text{median}_{1\leqslant i<j\leqslant m}\left\{\frac{\text{Put}(K_j)-\text{Put}(K_i)}{K_j-K_i}\right\}.$$

Once $\hat{\beta}_{TS}$ is obtained, the modified coefficient of determination through the origin,

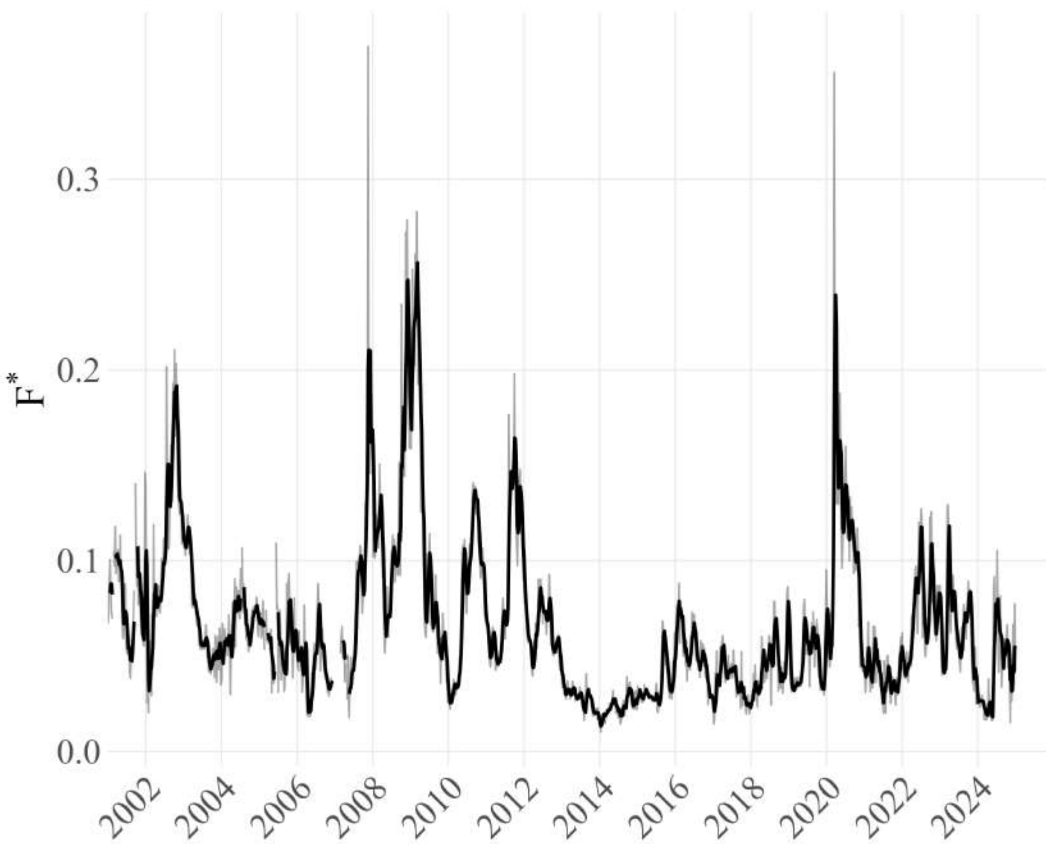
$$R^2 \;=\; 1 \;-\; \frac{\sum_{i=1}^{m}\left(\text{Put}(K_i)-\hat{\beta}_{TS}\,K_i\right)^2}{\sum_{i=1}^{m}\text{Put}(K_i)^2},$$

is computed to evaluate the goodness-of-fit. As long as R^2 exceeds a predefined threshold $\tau = 0.98$, the procedure allows the window size m to expand. The iteration terminates when adding an additional strike K_{m+1} causes R^2 to drop below τ. Denoting by m^* the largest m for which the threshold requirement holds, I identify the upper boundary of the default region as $\mathcal{E} = K_{m^*}$. Finally, within this region of strikes $\{K_1, \dots, K_{m^*}\}$, the Theil–Sen slope

$$\hat{\beta}_{TS} = \text{median}_{1 \leqslant i < j \leqslant m^*} \left\{ \frac{\text{Put}(K_j) - \text{Put}(K_i)}{K_j - K_i} \right\}$$

serves as the estimate of the risk-neutral default probability. The average estimate for maturity of 365 days is reported in Figure A.1. The time series looks very similar to the one obtained using OLS in the left panel of Figure 4.

Figure A.1: Median $\mathbb{F}^*_{t,T}$ for $T = 365$ using the Theil–Sen estimator



Notes: risk–neutral default probability at a 365-day horizon, $\mathbb{F}^*_{t,T}$, estimated using the Theil–Sen procedure at weekly frequency; 4-week moving average in black.

A.3 Information spillovers between options and CDS markets

To study cross-market information flow, I ask whether expected loss, $\text{LGD}^*_{i,t,365}$, contains predictive content for subsequent adjustments in the option-implied risk–neutral default probability and in CDS spreads. If contemporaneous variation in $\mathrm{LGD}^*_{i,t,365}$ primarily captures transitory noise or temporary implementation/model deviations in the options market, we should observe mean reversion in the option-implied measure (a positive slope in the regression for $\Delta\mathbb{F}^*$) and little power for CDS. Conversely, if $\mathrm{LGD}^*_{i,t,365}$ embeds credit information that is slow to be incorporated into CDS quotes, it should forecast corrective movements in CDS, with the sign of the coefficient indicating which contract is catching up. In practice, these mechanisms can coexist: LGD^* may include a high-frequency transitory component that mean-reverts in $\mathbb{F}^*$ (implying $\beta^p > 0$) alongside a slower-moving informational component that CDS quotes incorporate over time (implying $\beta^c < 0$). This perspective reconciles the hypothesis test with the empirical finding that both coefficients are significant with opposite signs. Guided by this logic, I estimate the following panel predictability regressions with issuer and date fixed effects:

$$\Delta\mathbb{F}^*_{i,t\to t+\Delta t} = \alpha_i + \tau_t + \beta^p\,\mathrm{LGD}^*_{i,t,365} + \varepsilon^p_{i,t+\Delta t}, \tag{A.5}$$

$$\Delta\mathrm{CS}_{i,t\to t+\Delta t} = \alpha_i + \tau_t + \beta^c\,\mathrm{LGD}^*_{i,t,365} + \varepsilon^c_{i,t+\Delta t}, \tag{A.6}$$

where $\Delta\mathbb{F}^*_{i,t\to t+\Delta t}$ and $\Delta\mathrm{CS}_{i,t\to t+\Delta t}$ denote future changes over horizon Δt in the risk–neutral default probability and the one-year CDS spread, respectively. The fixed effects (α_i, τ_t) absorb bank and date effects and standard errors are two-way clustered by bank and date.

Across both forecasting horizons (7 and 30 days), higher $\mathrm{LGD}^*_{i,t,365}$ today is followed by an increase in the option-implied risk–neutral default probability and a decline in one-year CDS spreads. The signs imply that the expected loss tends to continue in the direction of higher default risk while CDS quotes partially compress, consistent with cross-market adjustment. Estimates are statistically precise under issuer and date fixed effects with two-way clustered standard errors and, as expected in a high-frequency setting, the within-variation explained is intentionally modest. Comparing horizons, the CDS adjustment is stronger at 30 days than at 7 days, whereas the option-implied adjustment is more front-loaded at the 7-day horizon.

A.4 The variation in credit spreads explained by expected losses

To assess the degree to which variation in credit spreads mirrors changes in expected losses, I estimate

$$\log\big(\mathrm{CS}_{i,t,365}\big) = \beta_0 + \beta_1 \log\big(\mathrm{LGD}^*_{i,t,365}\big) + \alpha_i + \tau_t + \varepsilon_{i,t}, \tag{A.7}$$

Table A.1: Predictability from LGD^*: $\Delta\mathbb{F}^*$ and ΔCS at 7 and 30 days

(a) $\Delta t = 7$ days

Dependent Variables:	$\Delta\mathbb{F}^*_{7\,d}$	$\Delta CS_{7\,d}$
Model:	(1)	(2)
Variables		
$\mathrm{LGD}^*_{i,t,365}$	0.0120***	-0.0026***
	(0.0022)	(0.0006)
Fixed-effects		
Bank	Yes	Yes
Date	Yes	Yes
Fit statistics		
Observations	31,084	31,084
R^2	0.40982	0.22131
Within R^2	0.01225	0.00746

Clustered (permco & date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

(b) $\Delta t = 30$ days

Dependent Variables:	$\Delta\mathbb{F}^*_{30\,d}$	$\Delta CS_{30\,d}$
Model:	(1)	(2)
Variables		
$\mathrm{LGD}^*_{i,t,365}$	0.0210***	-0.0074***
	(0.0043)	(0.0016)
Fixed-effects		
Bank	Yes	Yes
Date	Yes	Yes
Fit statistics		
Observations	30,394	30,394
R^2	0.47759	0.30870
Within R^2	0.01849	0.02536

Clustered (permco & date) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: regressor is $\mathrm{LGD}^*_{i,t,365}$. All specifications include bank and date fixed effects. Two-way clustered SEs by bank and date.

where $CS_{i,t,365}$ denotes the one-year CDS spread and $LGD^*_{i,t,365}$ the corresponding risk-neutral expected loss at time t for bank i. Equation (A.7) is estimated under four sets of fixed effects. Table A.2 summarizes the results.

Across all four specifications, the elasticity of one-year CDS spreads to expected losses is strictly below one and highly significant. In the two-way fixed-effects model, the coefficient on $\log(LGD^*_{t,365})$ equals 0.736 with a clustered standard error of 0.066, so the null hypothesis of unit elasticity is rejected at the one-percent level. Because the regression is based on risk-neutral objects, the elasticity need not equal one even under risk-neutral valuation. Writing $\log CS \approx \log \mathbb{F}^* + \log LGD^*$, omitting $\log \mathbb{F}^*$ induces an omitted-variable term proportional to $\mathrm{Cov}\big(\log \mathbb{F}^*, \log LGD^* \mid FE\big)$. When this conditional covariance is negative, the elasticity on $\log LGD^*$ falls below unity. The subunit coefficient therefore reflects the covariance channel and should not be interpreted as evidence on the market price of default risk, which would require comparing risk-neutral to physical probabilities.

The overall coefficient of determination R^2 rises monotonically with the inclusion of fixed effects and reaches 0.935 in the full model; this indicates that cross-sectional and temporal dummies absorb nearly all variation in levels. The within-bank R^2 climbs from 0.312 when only bank effects are added to 0.682 with date effects alone, then settles at 0.604 in the two-way specification. These fit statistics show that expected losses remain the primary driver of time-series variation in spreads after accounting for extensive heterogeneity, while the subunit elasticity is consistent with the conditional covariance between $\log \mathbb{F}^*$ and $\log LGD^*$.

A.5 Liquidity-adjusted expected losses

Differences in risk-neutral default probabilities from options and CDS spreads may reflect variation in losses given default, but they could also result from market frictions. Out-of-the-money options used to estimate risk-neutral moments and option-implied default probabilities may be thinly traded. Similarly, the liquidity of some CDS contracts is low. Therefore, the observed decrease in losses given default during crises may instead reflect changes in market liquidity. The approximate relation between CDS spreads, option-implied default probabilities, and losses given default, discussed in Section 3, implies that, in the absence of market frictions, the ratio between the CDS spread and the default probability approximates the losses given default. To examine the extent to which market liquidity influences this relationship, I estimate the variation in this ratio as a function of liquidity measures.

Illiquidity in the CDS and options markets may reflect both security-specific and market-wide factors. For options, I use bid-ask spreads, open interest, and volume as

Table A.2: Estimates of the panel data regression (A.7)

Dependent Variable:	$\log(CS_{t,365})$			
Model:	(1)	(2)	(3)	(4)
Variables				
Constant	-3.814***			
	(0.1725)			
$\log(LGD^*_{t,365})$	0.9003***	0.7278***	0.8772***	0.7361***
	(0.0698)	(0.0606)	(0.0850)	(0.0659)
Fixed-effects				
Bank		Yes		Yes
Date			Yes	Yes
Fit statistics				
Observations	31,302	31,302	31,302	31,302
R^2	0.48528	0.58845	0.86263	0.93474
Within R^2		0.31213	0.68151	0.60409

Clustered (Bank) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: specifications include bank and date fixed effects. Two-way clustered SEs by bank and date. Credit spreads and expected losses are measured in decimals.

liquidity measures. Since default probabilities derived from options primarily depend on out-of-the-money options, I compute $\mathtt{SPREAD}^{O}_{t}$, the average percentage bid-ask spread for such options. Additionally, $\mathtt{VOL}^{O}_{t}$ and $\mathtt{OPEN}^{O}_{t}$ represent the sum of volume and open interest for these contracts. For CDS, I measure bank-specific liquidity using five-year depth, $\mathtt{DEPTH}^{C}_{t}$ and assume other maturities co-move with it.[30]

Aggregate liquidity is captured by combining the Treasury-Eurodollar (TED) spread, defined as the difference between the 90-day LIBOR and the 90-day Treasury Bill yield until 2022, with the difference between the 90-day SOFR and the 90-day Treasury Bill yield thereafter. The corresponding measure is denoted as $\mathtt{FinStress}_{t}$. An increase in this spread signals increased interbank counterparty credit risk and reduced funding liquidity. These data are obtained from the FRED Database. Additionally, equity market liquidity is proxied using the VIX index, $\mathtt{VIX}_{t}$, as higher VIX levels are associated with larger risk premia and reduced liquidity provision in equity markets (Nagel 2012). Data on the VIX are also sourced from the FRED Database.

The effects of liquidity on the expected losses are estimated by regressing changes in

[30]Depth is the quantity tradable at prevailing quotes, a liquidity proxy increasing with dealer activity and traded notional. Five-year CDS are the on-the-run benchmark and anchors liquidity across maturities as dealers hedge off-the-run with the five-year. Reliable high-frequency depth exists at five years, so I use $\mathtt{DEPTH}^{C}_{t}$ as a curve-wide proxy.

the logarithm of expected losses on changes in the logarithm of liquidity variables at the aggregate level for every maturity T, following Conrad et al. (2020):

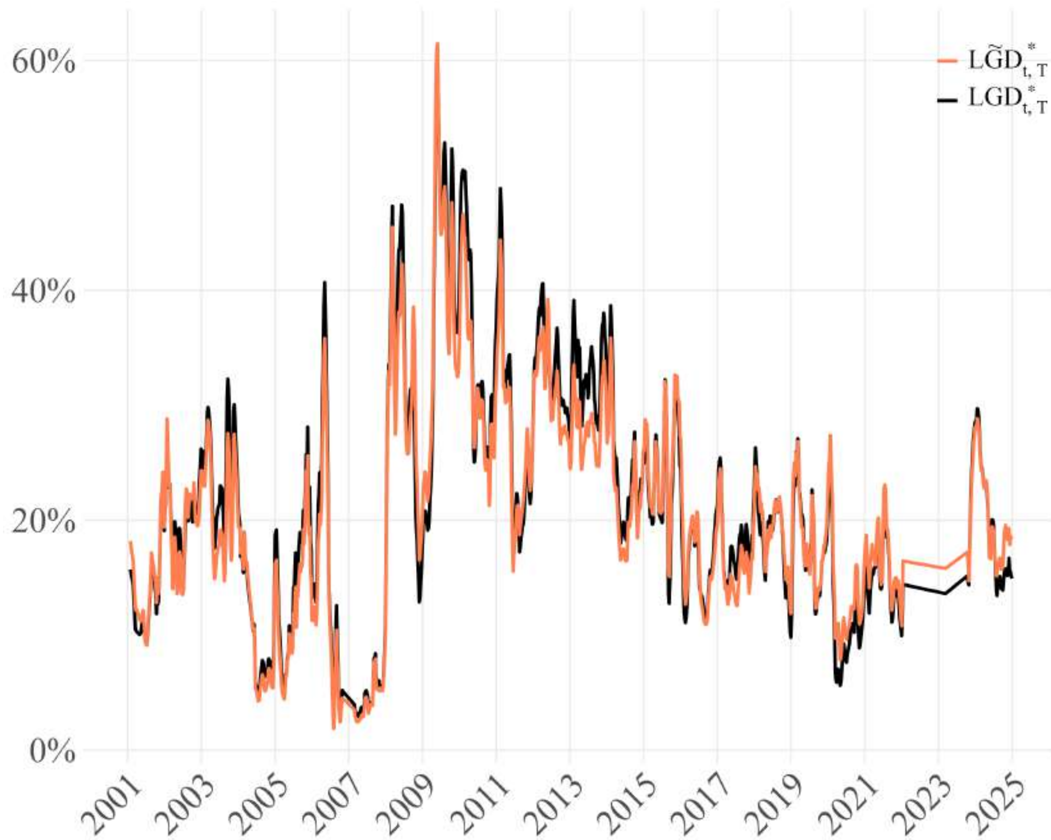
$$\begin{aligned}\Delta \log(\mathrm{LGD}^{*}_{t,T}) = a_T + b_1 \Delta \log \mathsf{FinStress}_t + b_2 \Delta \log \mathsf{VIX}_t + b_3 \Delta \log \mathsf{SPREAD}^{O}_{t,T} \\ + b_4 \Delta \log \mathsf{VOL}^{O}_{t,T} + b_5 \Delta \log \mathsf{OPEN}^{O}_{t,T} + b_6 \Delta \log \mathsf{DEPTH}^{C}_{t,T} + e_{t,T}. \end{aligned} \quad (A.8)$$

The residuals from this regression are then used to construct a liquidity-adjusted measure of expected losses. Specifically, $\mathrm{L\tilde{G}D}^{*}_{t,T}$ is calculated by cumulating the residuals as follows:

$$\mathrm{L\tilde{G}D}^{*}_{t,T} = \exp\left(\hat{a}_T + \sum_{j=0}^{t} \hat{e}_{t-j,T}\right),$$

where $\mathrm{L\tilde{G}D}^{*}_{t,T} = \mathrm{LGD}^{*}_{t,T}$ at $t = 1$ (January 2000) and each period's value incorporates the residual from the regression above.

Figure A.2: $\mathsf{LGD}^{*}_{t,T}$ **versus** $\mathrm{L\tilde{G}D}^{*}_{t,T}$ **for** $\mathsf{T} = 365$ **days**



Notes: original expected losses $\mathsf{LGD}^{*}_{t,T}$ (solid black) versus liquidity-adjusted $\mathrm{L\tilde{G}D}^{*}_{t,T}$ (solid orange) at weekly frequency for a maturity of 365 days.

Figure A.2 plots the time series of $\tilde{\text{LGD}}^*_{t,T}$ and $\text{LGD}^*_{t,T}$ for $T = 365$ days. $\tilde{\text{LGD}}^*_{t,T}$ closely tracks the original $\text{LGD}^*_{t,T}$ throughout the sample. Deviations between the two series are small and not systematic, including during and after the financial crisis. Accordingly, the liquidity adjustments we consider leave the level and dynamics of expected losses essentially unchanged.

Table A.3: Estimates of the time–series regression (A.8) for $T = 365$ days

Dependent Variable:	$\Delta \log(\text{LGD}^*_{t,T})$
Model:	(1)
Variables	
Constant (α_T)	-0.0001
	(0.0037)
$\Delta \log\left(\text{VOL}^O_{t,T}\right)$	-0.0033
	(0.0021)
$\Delta \log\left(\text{OPEN}^O_{t,T}\right)$	0.0363***
	(0.0085)
$\Delta \log\left(\text{SPREAD}^O_{t,T}\right)$	-0.0655***
	(0.0157)
$\Delta \log(\text{FinStress}_t)$	-0.0143
	(0.0411)
$\Delta \log(\text{VIX}_t)$	-0.2848***
	(0.0467)
$\Delta \log\left(\text{DEPTH}^C_{t,T}\right)$	0.0196
	(0.0186)
Fit statistics	
Observations	4,082
R^2	0.01976
Adjusted R^2	0.01832

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

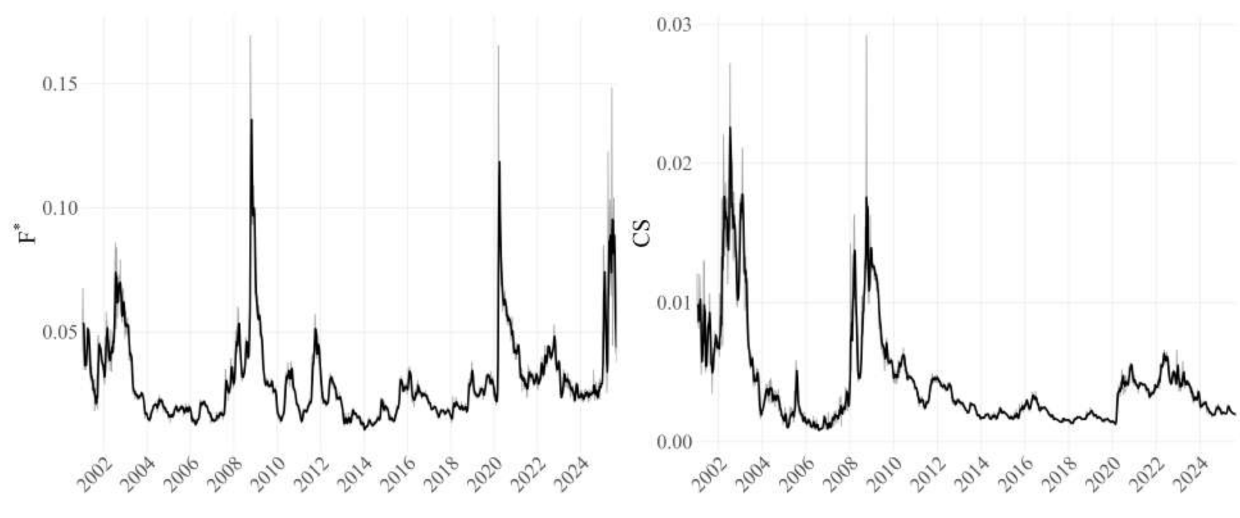
Notes: the dependent variable is the daily log change in expected losses, $\Delta \log(\text{LGD}^*_{t,T})$. The regression relates changes in expected losses to changes in liquidity measures for options and CDS markets, as well as aggregate liquidity proxies following Conrad et al. (2020). Standard errors are reported in parentheses.

Table A.3 reports the estimates of equation (A.8) for $T = 365$ days. The coefficients on the option-implied liquidity measures are consistent with the notion that illiquidity distorts the raw measure of expected losses. Increases in open interest are particularly associated with higher expected losses, while wider bid–ask spreads are associated with lower expected losses; this reflects the impact of thin trading conditions. The negative and statistically significant coefficient on the VIX indicates that periods of heightened market volatility coincide with reductions in the unadjusted expected loss measure, consistent with increased expected government support (higher bailout probability) during volatility spikes, since LGD^* is increasing in $(1-\pi)$. Overall, the regression explains only a small fraction of the daily variation ($R^2 \approx 0.02$), in line with the objective of isolating residual liquidity effects rather than fully accounting for movements in expected losses.

A.6 Credit spreads and expected losses for non-financial companies

This appendix reports the same diagnostics for broad non-financial companies (NFCs) to provide a clean benchmark for the financial sector results. Unlike financials, NFCs do not benefit from an explicit public backstop and are not subject to resolution regimes designed to preserve systemic stability. Comparing their option-implied risk-neutral default probability, $\mathbb{F}_t^*$, and CDS spreads, CS_t, with those of financials helps separate generic credit-cycle forces from movements attributable to bailout expectations. It also reassures that the patterns documented for financials are not mechanical artifacts of measurement or sample construction.

Figure A.3: Risk-Neutral Default Probability and CDS Spread for $T = 365$ for Non-Financial Companies

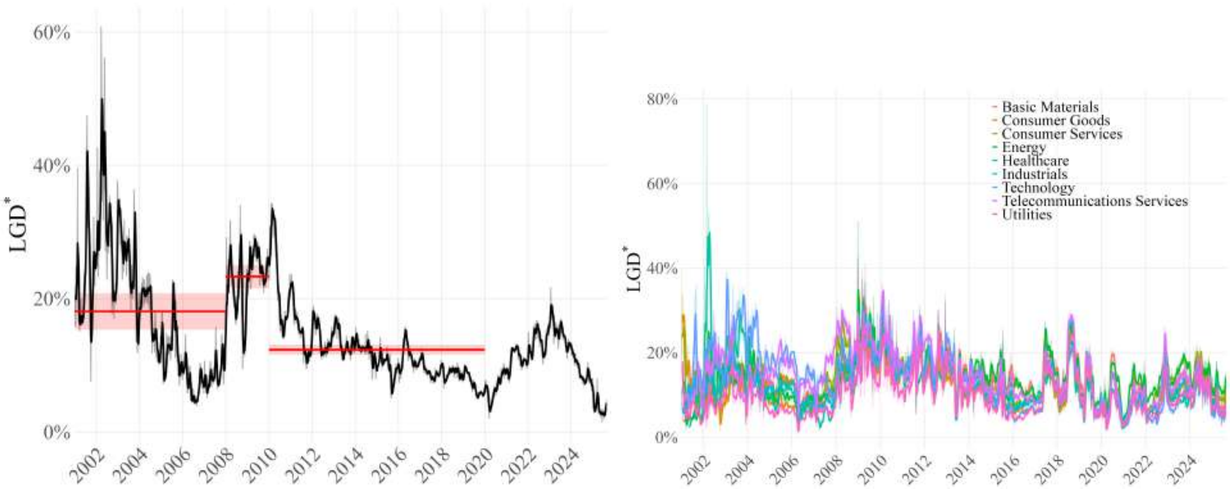


(a) Median $\mathbb{F}_t^*$ **(b) Median CS_t**

Notes: the left panel plots the risk-neutral default probability at 365 days (gray) and the 4-week moving average (black). The right panel plots the CDS spreads at 365 days (gray) and the 4-week moving average (black).

Figure A.3 summarizes one-year dynamics for NFCs' risk-neutral default probabilities and CDS spreads. For NFCs, $\mathbb{F}_t^*$ exhibits the same cyclical pattern as for financial intermediaries. By contrast, NFC CS_t are systematically higher than those of financial intermediaries before and during the GFC, with the gap narrowing markedly after 2010. A feature specific to NFCs is the early-2000s dot-com episode, a temporary rise in both $\mathbb{F}^*_t$ and CS_t, which is largely absent for financial intermediaries.

Figure A.4: Expected Losses Given Default for $T = 365$ **for Non-Financial Companies**



(a) Median $LGD^*_{t,T}$ **(b) Average** $LGD^*_{t,T}$ **by Sector**

Notes: the left panel plots the expected losses $LGD^*_{t,T}$ for a 365-day maturity at weekly frequency (grey line) and 4-weeks moving average (black line). The red horizontal segments report sample mean by sector at weekly frequency with 4-weeks moving average.

The left panel of Figure A.4 reports the resulting expected loss given default, $LGD^*_{t,T}$, corroborating the evidence from the behavior of NFCs default probabilities and CDS spreads. Expected losses were high in the early 2000s and then declined before the GFC. After a brief increase during the GFC, expected losses went back down to precrisis levels by 2010 and declined further until 2020. The right panel shows cross-sectional averages by sector. The dispersion across sectors is limited and no sector exhibits persistently low LGD^* before the GFC and persistently high LGD^* after the GFC while differences line up with standard recovery determinants (asset tangibility, seniority) rather than implicit guarantees. Taken together, the NFC evidence provides a natural counterfactual: when there is no credible public backstop, spreads and risk-neutral default probabilities comove tightly and expected losses remain high and comparatively stable.

A.7 Identifying regulatory tightness from market prices

Properly estimating changes in perceived bailout protection requires explicitly accounting for changes in bank regulatory requirements after 2010. These reforms altered banks' capital structure and resolution regimes and, by design, lowered insolvency risk. This section develops and implements an identification strategy that disentangles the effects of the post-GFC tightening of capital regulation from the effects of changes in bailout expectations. The key insight is that, once we account for fundamentals, tighter regulation moves credit spreads and the *downside* variance of equity returns in the same direction (both lower), whereas a lower bailout probability moves them in opposite directions.

We work with risk-neutral tail variances of equity returns. Let $\mathrm{Var}^{+}_{t,T}$ denote the upside variance and $\mathrm{Var}^{-}_{t,T}$ the downside variance over horizon $[t, t+T]$. Let ξ denote the *slackness* of capital regulation (higher ξ means a slacker constraint [i.e., higher permitted leverage]) and let π denote bailout probability. Around a reference point, the observables admit the local linearization

$$\Delta \log \mathrm{CS}_t = a^\top \Delta\Pi_t + e^\top \Delta Y_t + \varepsilon^S_t, \tag{A.9}$$

$$\Delta \log \mathrm{Var}^{-}_{t,T} = b^\top \Delta\Pi_t + d^\top \Delta Y_t + \varepsilon^-_t, \tag{A.10}$$

$$\Delta \log \mathrm{Var}^{+}_{t,T} = g^\top \Delta\Pi_t + c^\top \Delta Y_t + \varepsilon^+_t, \tag{A.11}$$

where $\Delta\Pi_t = (\Delta\xi_t, \Delta\pi_t)^\top$, $a = (s_\xi, s_\pi)^\top$, $b = (v_\xi, v_\pi)^\top$, $g = (w_\xi, w_\pi)^\top$ and e, d, c are conformable coefficient vectors on fundamentals ΔY_t (cash flow risk, risk appetite, rates, etc.). The residuals $(\varepsilon^S_t, \varepsilon^-_t, \varepsilon^+_t)$ collect higher-order terms and idiosyncratic noise.

The identification result rests on the following assumptions.

Assumption 1. (i) Regulation. *Tighter regulation (lower ξ) compresses leverage and reduces both CS_t and $\mathrm{Var}^{-}_{t,T}$. Written with respect to $\Delta\xi_t$, a rise in slackness raises spreads and left-tail variance: $s_\xi > 0$ and $v_\xi > 0$.* (ii) Bailouts. *Lower expected bailout support (a fall in π) increases CS_t and decreases $\mathrm{Var}^{-}_{t,T}$. In the local linearization this corresponds to $s_\pi < 0$ and $v_\pi > 0$.*

A more permissive constraint lets balance sheets lever up, widening credit spreads via higher default risk and pushing more risk-neutral mass toward the default boundary, hence raising the left-tail dispersion Var^-. By contrast, stronger bailout protection insures downside states by reducing default probability and/or loss-given-default borne by junior claimants and compresses spreads.

Assumption 2. *Changes in fundamentals ΔY_t affect $\mathrm{Var}^{-}_{t,T}$ and $\mathrm{Var}^{+}_{t,T}$ with similar signs: the loading vectors d and c are colinear.*

Aggregate volatility and cash flow news typically move both tails in the same direction. Assumption 2 states that the component of downside variance driven by fundamentals is proportional to the upside variance component. This allows us to use Var^+ as a proxy for fundamentals when purging Var^- of nonpolicy movements.

Assumption 3. *Policy shocks are orthogonal to fundamentals: $\mathbb{E}[\Delta\Pi_t \mid \Delta Y_t] = 0$. The residuals $(\varepsilon^S_t, \varepsilon^-_t, \varepsilon^+_t)$ are mean-zero with finite variance and are uncorrelated with $(\Delta\Pi_t, \Delta Y_t)$.*

This assumption treats the high-frequency innovations to regulatory slackness and bailout expectations as conditionally exogenous with respect to contemporaneous fundamentals. It rules out, for example, mechanically reacting policy shocks within the period to the same fundamental surprise that drives ΔY_t.

Assumption 2 implies there exists a scalar κ_F such that $d = \kappa_F c$. Define

$$Z_t \equiv \Delta \log \mathrm{Var}^-_{t,T} - \kappa_F \Delta \log \mathrm{Var}^+_{t,T}.$$

Using (A.10)–(A.11) and $d = \kappa_F c$,

$$Z_t = (b - \kappa_F g)^\top \Delta \Pi_t + \underbrace{\left(\varepsilon^-_t - \kappa_F \varepsilon^+_t\right)}_{\tilde{\varepsilon}_t},$$

so Z_t is a (noisy) signal of an *adjusted policy mixture* $(b - \kappa_F g)^\top \Delta \Pi_t$ that is orthogonal, in population, to the fundamentals ΔY_t.[31]

To compare subsamples, we impose a second-moment restriction on the adjusted mixture entering $(b - \kappa_F g)^\top \Delta \Pi_t$.

Assumption 4. *Let* $\Sigma \equiv \mathrm{Var}(\Delta \Pi_t)$. *Between the pre-2008 and the post-2010 subsamples: (a)* $\mathrm{Cov}(\Delta \xi_t, \Delta \pi_t)$ *is small; and (b) the* relative *contribution of regulation shocks to the variability of the adjusted downside mixture increases, in the precise sense that*

$$\frac{\nu_\xi (\nu_\xi - \kappa_F w_\xi) \mathrm{Var}(\Delta \xi_t)}{\nu_\pi (\nu_\pi - \kappa_F w_\pi) \mathrm{Var}(\Delta \pi_t)} \quad \textit{is larger post-2010 than pre-2008.}$$

Assumption 4 states that the composition of shocks shifts toward regulation-driven movements in downside risk relative to bailout-driven movements.

A mild dominance condition guarantees that the adjusted mixture preserves the sign mapping in Assumption 1.

Assumption 5. $\nu_\xi - \kappa_F w_\xi > 0$ *and* $\nu_\pi - \kappa_F w_\pi > 0$.

Assumption 5 is weak and testable indirectly (the first-stage loading of Z_t on $\Delta \log \mathrm{Var}^-_{t,T}$ is then positive).

Proposition 3 (Orthogonalized projection with upside policy loading)**.** *Consider the population regression*

$$\Delta \log CS_t = \beta \Delta \log \mathrm{Var}^-_{t,T} + u_t,$$

[31] Assumption 2 ensures that the linear combination with slope κ_F removes the ΔY_t-component from $\Delta \log \mathrm{Var}^-_{t,T}$. Policy loading in $\Delta \log \mathrm{Var}^+_{t,T}$ does not interfere with this orthogonalization; it merely changes the *policy* weights from b to $b - \kappa_F g$. In practice we estimate κ_F by projecting residualized $\log \mathrm{Var}^-_{i,t}$ on residualized $\log \mathrm{Var}^+_{i,t}$. Consistency requires that tail-specific noises are not systematically comoving after residualization, e.g., $\mathrm{Cov}(\varepsilon^-_t, \varepsilon^+_t) = 0$ (or small).

estimated by a two-stage projection that replaces $\Delta \log \mathrm{Var}^{-}_{t,T}$ *with its component orthogonal to fundamentals using* Z_t*. Under Assumptions 1–5, the coefficient equals*

$$\beta^{\mathrm{OP}} \;=\; \frac{\mathrm{Cov}(Z_t, \Delta \log \mathrm{CS}_t)}{\mathrm{Cov}(Z_t, \Delta \log \mathrm{Var}^{-}_{t,T})} \;=\; \frac{(b - \kappa_F g)^{\top} \Sigma\, a}{(b - \kappa_F g)^{\top} \Sigma\, b \;+\; \mathrm{Var}(\varepsilon^{-}_t)}.$$

If $\mathrm{Cov}(\Delta\xi_t, \Delta\pi_t)$ *is negligible, then*

$$\beta^{\mathrm{OP}} \;\approx\; \frac{s_\xi\, \tilde{\nu}_\xi\, \mathrm{Var}(\Delta\xi_t) \;+\; s_\pi\, \tilde{\nu}_\pi\, \mathrm{Var}(\Delta\pi_t)}{\nu_\xi\, \tilde{\nu}_\xi\, \mathrm{Var}(\Delta\xi_t) \;+\; \nu_\pi\, \tilde{\nu}_\pi\, \mathrm{Var}(\Delta\pi_t) \;+\; \mathrm{Var}(\varepsilon^{-}_t)}, \qquad \tilde{\nu}_j \equiv \nu_j - \kappa_F w_j,\; j \in \{\xi, \pi\}.$$

Moreover, letting Σ^{pre} *and* Σ^{post} *denote the covariance matrices across the pre-2008 and post-2010 subsamples, if Assumptions 4 and 5 hold in both subsamples, then*

$$\beta^{\mathrm{OP}}_{\mathrm{post}} - \beta^{\mathrm{OP}}_{\mathrm{pre}} \;>\; 0.$$

Proof. We begin from the linearizations

$$\Delta \log \mathrm{CS}_t = a^{\top} \Delta\Pi_t + e^{\top} \Delta Y_t + \varepsilon^{S}_t, \tag{S0.1}$$

$$\Delta \log \mathrm{Var}^{-}_{t,T} = b^{\top} \Delta\Pi_t + d^{\top} \Delta Y_t + \varepsilon^{-}_t, \tag{S0.2}$$

$$\Delta \log \mathrm{Var}^{+}_{t,T} = g^{\top} \Delta\Pi_t + c^{\top} \Delta Y_t + \varepsilon^{+}_t, \tag{S0.3}$$

with $\Delta\Pi_t = (\Delta\xi_t, \Delta\pi_t)^{\top}$ and coefficient vectors $a = (s_\xi, s_\pi)^{\top}$, $b = (\nu_\xi, \nu_\pi)^{\top}$, $g = (w_\xi, w_\pi)^{\top}$. Let $\Sigma \equiv \mathrm{Var}(\Delta\Pi_t)$, positive semidefinite. Throughout we use Assumption 3, interpreted to imply that the noise terms are mean-zero, uncorrelated with $(\Delta\Pi_t, \Delta Y_t)$ and mutually uncorrelated (so $\mathrm{Cov}(\varepsilon^{-}_t, \varepsilon^{+}_t) = \mathrm{Cov}(\varepsilon^{-}_t, \varepsilon^{S}_t) = \mathrm{Cov}(\varepsilon^{+}_t, \varepsilon^{S}_t) = 0$).

Population 2SLS identity. In the just-identified IV problem with one endogenous regressor $X_t := \Delta \log \mathrm{Var}^{-}_{t,T}$, outcome $Y_t := \Delta \log \mathrm{CS}_t$ and instrument Z_t (all understood as already partialed out of the controls used in the empirical implementation), the population 2SLS estimand equals

$$\beta^{\mathrm{OP}} \;=\; \frac{\mathrm{Cov}(Z_t,\, Y_t)}{\mathrm{Cov}(Z_t,\, X_t)}. \tag{S2.1}$$

This follows from the IV normal equation $\mathbb{E}[Z_t(Y_t - \beta X_t)] = 0$ and instrument relevance $\mathrm{Cov}(Z_t, X_t) \neq 0$.

Orthogonalization that purges fundamentals. Define

$$Z_t \;=\; \Delta \log \mathrm{Var}^{-}_{t,T} \;-\; \kappa_F\, \Delta \log \mathrm{Var}^{+}_{t,T}.$$

Substitute (S0.2)–(S0.3):

$$\begin{aligned} Z_t &= (b^\top \Delta\Pi_t + d^\top \Delta Y_t + \varepsilon_t^-) - \kappa_F\,(g^\top \Delta\Pi_t + c^\top \Delta Y_t + \varepsilon_t^+) \\ &= (b-\kappa_F g)^\top \Delta\Pi_t \;+\; (d-\kappa_F c)^\top \Delta Y_t \;+\; \big(\varepsilon_t^- - \kappa_F \varepsilon_t^+\big). \end{aligned}$$

By $d = \kappa_F c$ (Assumption 2), $(d - \kappa_F c) = 0$, hence

$$Z_t \;=\; (b-\kappa_F g)^\top \Delta\Pi_t \;+\; \tilde{\varepsilon}_t, \qquad \tilde{\varepsilon}_t \equiv \varepsilon_t^- - \kappa_F \varepsilon_t^+. \tag{S1.1}$$

By Assumption 3 and the mutual uncorrelatedness of residuals, $\tilde{\varepsilon}_t$ is mean-zero and uncorrelated with $(\Delta\Pi_t, \Delta Y_t, \varepsilon_t^S)$. Since Z_t has no ΔY_t term, Z_t is orthogonal, in population, to ΔY_t by construction. Moreover, with $\tilde{\varepsilon}_t = \varepsilon_t^- - \kappa_F \varepsilon_t^+$ and $\mathrm{Cov}(\varepsilon_t^-, \varepsilon_t^+) = 0$,

$$\mathrm{Cov}(\tilde{\varepsilon}_t, \varepsilon_t^-) = \mathrm{Var}(\varepsilon_t^-), \qquad \mathrm{Cov}(\tilde{\varepsilon}_t, \varepsilon_t^+) = -\,\kappa_F\,\mathrm{Var}(\varepsilon_t^+).$$

Numerator of (S2.1). Using (S1.1) and (S0.1):

$$\begin{aligned} \mathrm{Cov}\big(Z_t, \Delta\log CS_t\big) &= \mathrm{Cov}\Big((b-\kappa_F g)^\top \Delta\Pi_t + \tilde{\varepsilon}_t,\; a^\top \Delta\Pi_t + e^\top \Delta Y_t + \varepsilon_t^S\Big) \\ &= \mathrm{Cov}\big((b-\kappa_F g)^\top \Delta\Pi_t,\; a^\top \Delta\Pi_t\big) + \mathrm{Cov}\big((b-\kappa_F g)^\top \Delta\Pi_t,\; e^\top \Delta Y_t\big) \\ &\quad + \mathrm{Cov}\big((b-\kappa_F g)^\top \Delta\Pi_t,\; \varepsilon_t^S\big) + \mathrm{Cov}\big(\tilde{\varepsilon}_t,\; a^\top \Delta\Pi_t\big) \\ &\quad + \mathrm{Cov}\big(\tilde{\varepsilon}_t,\; e^\top \Delta Y_t\big) + \mathrm{Cov}\big(\tilde{\varepsilon}_t,\; \varepsilon_t^S\big). \end{aligned}$$

Assumption 3 implies that all terms except the first vanish. Therefore

$$\mathrm{Cov}\big(Z_t, \Delta\log CS_t\big) = \mathrm{Cov}\big((b-\kappa_F g)^\top \Delta\Pi_t,\; a^\top \Delta\Pi_t\big) = (b-\kappa_F g)^\top\, \Sigma\, a. \tag{S3.1}$$

Denominator of (S2.1). Using (S1.1) and (S0.2):

$$\begin{aligned} \mathrm{Cov}\big(Z_t, \Delta\log \mathrm{Var}^-_{t,T}\big) &= \mathrm{Cov}\Big((b-\kappa_F g)^\top \Delta\Pi_t + \tilde{\varepsilon}_t,\; b^\top \Delta\Pi_t + d^\top \Delta Y_t + \varepsilon_t^-\Big) \\ &= \mathrm{Cov}\big((b-\kappa_F g)^\top \Delta\Pi_t,\; b^\top \Delta\Pi_t\big) + \underbrace{\mathrm{Cov}\big((b-\kappa_F g)^\top \Delta\Pi_t,\; d^\top \Delta Y_t\big)}_{=0} \\ &\quad + \underbrace{\mathrm{Cov}\big((b-\kappa_F g)^\top \Delta\Pi_t,\; \varepsilon_t^-\big)}_{=0} + \underbrace{\mathrm{Cov}\big(\tilde{\varepsilon}_t,\; b^\top \Delta\Pi_t\big)}_{=0} \\ &\quad + \underbrace{\mathrm{Cov}\big(\tilde{\varepsilon}_t,\; d^\top \Delta Y_t\big)}_{=0} + \underbrace{\mathrm{Cov}\big(\tilde{\varepsilon}_t,\; \varepsilon_t^-\big)}_{=\mathrm{Var}(\varepsilon_t^-)} \\ &= (b-\kappa_F g)^\top\, \Sigma\, b \;+\; \mathrm{Var}(\varepsilon_t^-). \end{aligned}$$

Therefore,

$$\operatorname{Cov}\big(Z_t, \Delta \log \operatorname{Var}^{-}_{t,T}\big) = (b-\kappa_F g)^\top \Sigma\, b \;+\; \operatorname{Var}(\varepsilon_t^-). \tag{S4.1}$$

Population 2SLS coefficient. Plugging (S3.1) and (S4.1) into (S2.1):

$$\beta^{OP} = \frac{(b-\kappa_F g)^\top \Sigma\, a}{(b-\kappa_F g)^\top \Sigma\, b \;+\; \operatorname{Var}(\varepsilon_t^-)}.$$

Component expansion. Write Σ elementwise as variances and covariances of $(\Delta\xi_t, \Delta\pi_t)$:

$$\Sigma = \begin{bmatrix} \operatorname{Var}(\Delta\xi_t) & \operatorname{Cov}(\Delta\xi_t, \Delta\pi_t) \\ \operatorname{Cov}(\Delta\xi_t, \Delta\pi_t) & \operatorname{Var}(\Delta\pi_t) \end{bmatrix}.$$

Define $\tilde{\nu}_\xi \equiv \nu_\xi - \kappa_F w_\xi$, $\tilde{\nu}_\pi \equiv \nu_\pi - \kappa_F w_\pi$. Then

$$(b-\kappa_F g)^\top \Sigma\, a = s_\xi \tilde{\nu}_\xi \operatorname{Var}(\Delta\xi_t) + s_\pi \tilde{\nu}_\pi \operatorname{Var}(\Delta\pi_t) + (s_\xi \tilde{\nu}_\pi + s_\pi \tilde{\nu}_\xi) \operatorname{Cov}(\Delta\xi_t, \Delta\pi_t),$$

$$(b-\kappa_F g)^\top \Sigma\, b = \nu_\xi \tilde{\nu}_\xi \operatorname{Var}(\Delta\xi_t) + \nu_\pi \tilde{\nu}_\pi \operatorname{Var}(\Delta\pi_t) + (\nu_\xi \tilde{\nu}_\pi + \nu_\pi \tilde{\nu}_\xi) \operatorname{Cov}(\Delta\xi_t, \Delta\pi_t).$$

Therefore,

$$(b-\kappa_F g)^\top \Sigma\, b \;+\; \operatorname{Var}(\varepsilon_t^-) = \nu_\xi \tilde{\nu}_\xi \operatorname{Var}(\Delta\xi_t) + \nu_\pi \tilde{\nu}_\pi \operatorname{Var}(\Delta\pi_t) + (\nu_\xi \tilde{\nu}_\pi + \nu_\pi \tilde{\nu}_\xi) \operatorname{Cov}(\Delta\xi_t, \Delta\pi_t) \;+\; \operatorname{Var}(\varepsilon_t^-).$$

If $\operatorname{Cov}(\Delta\xi_t, \Delta\pi_t)$ is negligible (Assumption 4(a)), we obtain

$$\beta^{OP} \;\approx\; \frac{s_\xi \tilde{\nu}_\xi \operatorname{Var}(\Delta\xi_t) + s_\pi \tilde{\nu}_\pi \operatorname{Var}(\Delta\pi_t)}{\nu_\xi \tilde{\nu}_\xi \operatorname{Var}(\Delta\xi_t) + \nu_\pi \tilde{\nu}_\pi \operatorname{Var}(\Delta\pi_t) \;+\; \operatorname{Var}(\varepsilon_t^-)}, \quad \tilde{\nu}_j = \nu_j - \kappa_F w_j,\; j \in \{\xi, \pi\}.$$

Instrument relevance. Assumption 5 imposes $\tilde{\nu}_\xi > 0$ and $\tilde{\nu}_\pi > 0$. With $\operatorname{Var}(\Delta\xi_t), \operatorname{Var}(\Delta\pi_t) \geqslant 0$ and $\nu_\xi, \nu_\pi > 0$ (Assumption 1), it follows that

$$(b-\kappa_F g)^\top \Sigma\, b \;+\; \operatorname{Var}(\varepsilon_t^-) \;=\; \nu_\xi \tilde{\nu}_\xi \operatorname{Var}(\Delta\xi_t) + \nu_\pi \tilde{\nu}_\pi \operatorname{Var}(\Delta\pi_t) \;\; + \; \operatorname{Var}(\varepsilon_t^-) \;>\; 0$$

provided at least one of $\operatorname{Var}(\Delta\xi_t), \operatorname{Var}(\Delta\pi_t)$ is strictly positive.

Cross-subsample monotonicity. Under small cross-covariances, define the adjusted regulation share

$$R \;\equiv\; \frac{\nu_\xi \tilde{\nu}_\xi \operatorname{Var}(\Delta\xi_t)}{\nu_\pi \tilde{\nu}_\pi \operatorname{Var}(\Delta\pi_t)} \;\in\; [0, \infty).$$

Then

$$\beta^{OP} = \phi_\theta(R) \quad \text{with} \quad \phi_\theta(R) \equiv \frac{\frac{s_\xi}{\nu_\xi} R + \frac{s_\pi}{\nu_\pi}}{R + 1 + \theta}, \quad \theta \equiv \frac{\operatorname{Var}(\varepsilon_t^-)}{\nu_\pi \tilde{\nu}_\pi \operatorname{Var}(\Delta\pi_t)} \;\geqslant\; 0.$$

Differentiate:

$$\phi_\theta'(R) = \frac{\left(\frac{s_\xi}{\nu_\xi}\right)(R+1+\theta) - \left(\frac{s_\xi}{\nu_\xi}R + \frac{s_\pi}{\nu_\pi}\right)}{(R+1+\theta)^2} = \frac{\left(\frac{s_\xi}{\nu_\xi}\right)(1+\theta) - \frac{s_\pi}{\nu_\pi}}{(R+1+\theta)^2}.$$

By Assumption 1, $s_\xi > 0$, $\nu_\xi > 0$, $s_\pi < 0$ and $\nu_\pi > 0$ and since $\theta \geqslant 0$, it follows that $\left(\frac{s_\xi}{\nu_\xi}\right)(1+\theta) - \frac{s_\pi}{\nu_\pi} > 0$, so $\phi_\theta'(R) > 0$ for all $R \geqslant 0$ and any $\theta \geqslant 0$. Assumption 4(b) states that the adjusted regulation share rises post-2010: $R_{\text{post}} > R_{\text{pre}}$. If, in addition, $\text{Var}(\varepsilon_t^-)$ is stable across subsamples (so $\theta_{\text{post}} = \theta_{\text{pre}}$), then

$$\beta^{\text{OP}}_{\text{post}} - \beta^{\text{OP}}_{\text{pre}} = \phi_\theta(R_{\text{post}}) - \phi_\theta(R_{\text{pre}}) \; > \; 0,$$

which shows that the post-minus-pre increase in the downside slope identifies a relative strengthening of regulation in the adjusted mixture (and not a decline in bailout expectations). □

We implement the identification strategy in a daily bank–date panel using option-implied, model-free tail variances of equity returns. Following the static replication of the log contract, the time-t risk-neutral variance over $[t, T]$ admits the put–call integral decomposition

$$\text{Var}_{t,T} = \frac{2}{(T-t)\,R_{f,t}} \left(\frac{1}{(S_t^E)^2}\right) \left[\int_0^{F_{t,T}} \text{put}_t(K,T)\,dK + \int_{F_{t,T}}^{\infty} \text{call}_t(K,T)\,dK \right],$$

with S_t^E the equity spot, $F_{t,T}$ the forward and $R_{f,t}$ the gross risk-free rate; the first integral collects left-tail option payoffs and the second right-tail payoffs. We define the tail components as

$$\text{Var}^-_{t,T} \equiv \frac{2}{(T-t)\,R_{f,t}} \left(\frac{1}{(S_t^E)^2}\right) \int_0^{F_{t,T}} \text{put}_t(K,T)\,dK, \tag{A.12}$$

$$\text{Var}^+_{t,T} \equiv \frac{2}{(T-t)\,R_{f,t}} \left(\frac{1}{(S_t^E)^2}\right) \int_{F_{t,T}}^{\infty} \text{call}_t(K,T)\,dK. \tag{A.13}$$

We assemble a panel of banks observed daily, exclude the 2008–09 crisis window, and split the estimation into a pre-2008 subsample and a post-2010 subsample. Bank and date fixed effects absorb time-invariant heterogeneity and common day shocks. Because the VIX is an aggregate proxy for market volatility that affects both tails, we include it as a control and allow bank-specific VIX loadings to flexibly capture heterogeneous exposure to market-wide volatility innovations. Two-way clustering by bank and by date is used throughout.

To purge fundamentals, we first residualize the log tail variances on the same controls that will appear in the structural equation:

$$
\begin{aligned}
r^-_{i,t} &:= \widehat{\varepsilon}^-_{i,t} \;\text{ from }\; \log \mathrm{Var}^-_{i,t} = \alpha_i + \delta_t + \Gamma_i \log \mathrm{VIX}_t + \varepsilon^-_{i,t}, \\
r^+_{i,t} &:= \widehat{\varepsilon}^+_{i,t} \;\text{ from }\; \log \mathrm{Var}^+_{i,t} = \alpha_i + \delta_t + \Gamma_i \log \mathrm{VIX}_t + \varepsilon^+_{i,t}.
\end{aligned} \tag{A.14}
$$

Estimating the projection of $r^-_{i,t}$ on $r^+_{i,t}$ separately by subsample yields the sample analogues of κ_F in each subsample:

$$
\kappa^\star_{\mathrm{pre}} \equiv \arg\min_\kappa \mathbb{E}[(r^- - \kappa r^+)^2 \mid \mathrm{pre}], \qquad \kappa^\star_{\mathrm{post}} \equiv \arg\min_\kappa \mathbb{E}[(r^- - \kappa r^+)^2 \mid \mathrm{post}].
$$

We then form the subsample-specific orthogonalized downside shifters

$$
Z^{\mathrm{pre}}_{i,t} \equiv \left(r^-_{i,t} - \kappa^\star_{\mathrm{pre}} r^+_{i,t}\right) \cdot \mathbf{1}\{\mathrm{pre}\}, \qquad Z^{\mathrm{post}}_{i,t} \equiv \left(r^-_{i,t} - \kappa^\star_{\mathrm{post}} r^+_{i,t}\right) \cdot \mathbf{1}\{\mathrm{post}\}. \tag{A.15}
$$

Since upside may load on policy, I additionally construct the symmetric orthogonalized upside shifters using the projection of $r^+_{i,t}$ on $r^-_{i,t}$:

$$
\Lambda^\star_{\mathrm{pre}} \equiv \arg\min_\lambda \mathbb{E}[(r^+ - \lambda r^-)^2 \mid \mathrm{pre}], \qquad \Lambda^\star_{\mathrm{post}} \equiv \arg\min_\lambda \mathbb{E}[(r^+ - \lambda r^-)^2 \mid \mathrm{post}], \tag{A.16}
$$

$$
W^{\mathrm{pre}}_{i,t} \equiv \left(r^+_{i,t} - \Lambda^\star_{\mathrm{pre}} r^-_{i,t}\right) \cdot \mathbf{1}\{\mathrm{pre}\}, \qquad W^{\mathrm{post}}_{i,t} \equiv \left(r^+_{i,t} - \Lambda^\star_{\mathrm{post}} r^-_{i,t}\right) \cdot \mathbf{1}\{\mathrm{post}\}. \tag{A.17}
$$

By construction, $(Z^{\mathrm{sub}}_{i,t}, W^{\mathrm{sub}}_{i,t})$ are orthogonal (in population) to fundamentals proxied by the controls and co-move with the policy-shock mixtures entering the tails.

We estimate subsample-specific slopes of credit spreads on both tail variances via the interacted two-stage least squares

$$
\begin{aligned}
\log \mathrm{CS}_{i,t} = {} & \beta^{\mathrm{pre}}_- \left(\log \mathrm{Var}^-_{i,t} \cdot \mathbf{1}\{\mathrm{pre}\}\right) + \beta^{\mathrm{post}}_- \left(\log \mathrm{Var}^-_{i,t} \cdot \mathbf{1}\{\mathrm{post}\}\right) \\
& + \beta^{\mathrm{pre}}_+ \left(\log \mathrm{Var}^+_{i,t} \cdot \mathbf{1}\{\mathrm{pre}\}\right) + \beta^{\mathrm{post}}_+ \left(\log \mathrm{Var}^+_{i,t} \cdot \mathbf{1}\{\mathrm{post}\}\right) \\
& + \alpha_i + \delta_t + \Gamma_i \log \mathrm{VIX}_t + \varepsilon_{i,t},
\end{aligned} \tag{A.18}
$$

and treat the four interacted tail regressors as endogenous and replace them with the fitted values from the corresponding projections that use $(Z^{\mathrm{pre}}_{i,t}, Z^{\mathrm{post}}_{i,t}, W^{\mathrm{pre}}_{i,t}, W^{\mathrm{post}}_{i,t})$.

First-stage regressions confirm that the subsample-specific orthogonalized shifters are highly informative for their intended tail-by-subsample regressors. For the downside tail variance, the instruments

$$
Z^{\mathrm{pre}}_{i,t} \equiv \left(r^-_{i,t} - \kappa^\star_{\mathrm{pre}} r^+_{i,t}\right) \cdot \mathbf{1}\{\mathrm{pre}\}, \qquad Z^{\mathrm{post}}_{i,t} \equiv \left(r^-_{i,t} - \kappa^\star_{\mathrm{post}} r^+_{i,t}\right) \cdot \mathbf{1}\{\mathrm{post}\}
$$

load strongly on the endogenous regressors

$$\left(\log \mathrm{Var}^{-}_{i,t}\right) \cdot \mathbf{1}\{\text{pre}\} \quad \text{and} \quad \left(\log \mathrm{Var}^{-}_{i,t}\right) \cdot \mathbf{1}\{\text{post}\},$$

respectively (own-subsample coefficients of 1.334 and 1.083 with $t = 37.50$ and 12.23), while cross-subsample spillovers are much smaller in magnitude (0.222 and −0.140). For the upside tail variance, the symmetric instruments

$$W^{\text{pre}}_{i,t} \equiv \left(r^{+}_{i,t} - \Lambda^{\star}_{\text{pre}} r^{-}_{i,t}\right) \cdot \mathbf{1}\{\text{pre}\}, \qquad W^{\text{post}}_{i,t} \equiv \left(r^{+}_{i,t} - \Lambda^{\star}_{\text{post}} r^{-}_{i,t}\right) \cdot \mathbf{1}\{\text{post}\}$$

dominate the first stages for

$$\left(\log \mathrm{Var}^{+}_{i,t}\right) \cdot \mathbf{1}\{\text{pre}\} \quad \text{and} \quad \left(\log \mathrm{Var}^{+}_{i,t}\right) \cdot \mathbf{1}\{\text{post}\},$$

with own-subsample coefficients 1.258 and 1.168 ($t = 58.20$ and 18.37) and modest cross-subsample terms (0.137 and 0.260). Across all four endogenous regressors, instrument relevance is overwhelming: the first-stage F-statistics are 97,217 and 27,816 for the downside-pre and downside-post regressors and 85,356 and 32,542 for the upside-pre and upside-post regressors (all $p < 10^{-15}$), comfortably exceeding weak-IV thresholds. These patterns match the construction in (A.14)–(A.17) and support Assumption 5: own-subsample loadings are large and positive, while cross-subsample spillovers are comparatively small.

Turning to the structural stage, bank CDS spreads load positively on both tail variances in each subsample. The post-2010 downside coefficient is larger and statistically significant,

$$\widehat{\beta}^{\text{post}}_{-} = 0.419 \quad (\text{SE} = 0.181,\ p = 0.026),$$

whereas the pre-2008 downside coefficient is smaller and statistically weaker,

$$\widehat{\beta}^{\text{pre}}_{-} = 0.217 \quad (\text{SE} = 0.148,\ p = 0.152).$$

Upside coefficients are positive and precisely estimated in both subsamples,

$$\widehat{\beta}^{\text{pre}}_{+} = 0.126 \quad (\text{SE} = 0.042,\ p = 0.005), \qquad \widehat{\beta}^{\text{post}}_{+} = 0.223 \quad (\text{SE} = 0.065,\ p = 0.0015).$$

Bank and date fixed effects, together with bank-specific VIX slopes, absorb time-invariant heterogeneity and common day shocks; the model attains an adjusted R^2 of 0.863.

The subsample contrast in the downside slope is positive and economically meaningful:

$$\Delta\widehat{\beta}_{-} \;\equiv\; \widehat{\beta}_{-}^{\text{post}} - \widehat{\beta}_{-}^{\text{pre}} \;=\; 0.202 \quad [SE = 0.114], \quad t = 1.77, \quad p_{\text{one-sided}} = 0.038.$$

This increase maps monotonically to a rise in the *adjusted regulation share* of the downside policy mixture; the post-2010 steepening of the spread-downside relation therefore identifies tighter regulation (a larger regulation-driven share in the adjusted mixture), not a decline in bailout expectations. Tables A.4 and A.5 report the full projection and structural stages of the exercise.

B Equilibrium conditions

This section presents the problem faced by households and intermediaries and the implied equilibrium conditions. Recall that the states vector is $\mathbf{S} = [L, W, \pi, Z, d]$.

B.1 Stand-in household

The stand-in household solves

$$V^{H}(\mathbf{S}) = \max_{C,B'}\Big\{(1-\beta)\, C^{\,1-\frac{1}{\nu}} + \beta\, \mathbb{E}_{\mathbf{S}}[\, V^{H}(\mathbf{S}')^{1-\gamma}]^{\frac{1-\frac{1}{\nu}}{1-\gamma}}\Big\}^{\frac{1}{1-\frac{1}{\nu}}},$$

subject to

$$W - T(\mathbf{S}) \geqslant C + q(\mathbf{S})\, B' + q^{d}(\mathbf{S})\, D', \tag{B.1}$$

$$W = \Pi(\mathbf{S}) + \Pi^{I}(\mathbf{S}) + D' + B'\big[1 - \mathbb{F}(\mathbf{S}) + \mathbb{F}(\mathbf{S})\big(\pi + (1-\pi)RV(\omega^{-}, \mathbf{S})\big)\big], \tag{B.2}$$

$$\mathbf{S}' = \Gamma\big(\mathbf{S}\big). \tag{B.3}$$

Here $F \equiv \int_{\omega\in\mathcal{D}} dF(\omega)$ is the default probability and $RV(\omega^{-}, \mathbf{S})$ is the expected recovery value of the bank's bond conditional on default. The certainty equivalent of future utility is

$$CE(\mathbf{S}) \;=\; \mathbb{E}_{\mathbf{S}}[\,(V^{H}(\mathbf{S}'))^{1-\gamma}]^{\frac{1}{1-\gamma}}, \qquad \mathcal{M}(\mathbf{S}', \mathbf{S}) = \beta\left(\frac{V^{H}(\mathbf{S}')}{CE(\mathbf{S})}\right)^{\frac{1}{\nu}-\gamma}\left(\frac{C'}{C}\right)^{-\frac{1}{\nu}}.$$

Taking first–order conditions with respect to bonds yields

$$q(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\Big[\mathcal{M}(\mathbf{S}', \mathbf{S})\,\Big\{1 - \mathbb{F}(\mathbf{S}') + \mathbb{F}(\mathbf{S}')\big(\pi' + (1-\pi')RV(\omega^{-\prime}, \mathbf{S})\big)\Big\}\Big], \tag{B.4}$$

where

$$\omega^{-} = \mathbb{E}_{\omega}\left[\omega \mid \omega < \omega^{*}(\mathbf{S})\right].$$

Table A.4: Projection stage for the subsample-specific tail regressors

Dependent variables	$\log \mathrm{Var}^{-}_{i,t} \cdot \mathbf{1}\{\mathrm{pre}\}$	$\log \mathrm{Var}^{-}_{i,t} \cdot \mathbf{1}\{\mathrm{post}\}$	$\log \mathrm{Var}^{+}_{i,t} \cdot \mathbf{1}\{\mathrm{pre}\}$	$\log \mathrm{Var}^{+}_{i,t} \cdot \mathbf{1}\{\mathrm{post}\}$
Model	(1)	(2)	(3)	(4)
Instruments				
$Z^{\mathrm{pre}}_{i,t} \equiv (r^{-}_{i,t} - \hat{\kappa}_{\mathrm{pre}}\, r^{+}_{i,t}) \cdot \mathbf{1}\{\mathrm{pre}\}$	1.334***	−0.1405***	0.8198***	−0.1607***
	(0.0356)	(0.0356)	(0.0324)	(0.0324)
$Z^{\mathrm{post}}_{i,t} \equiv (r^{-}_{i,t} - \hat{\kappa}_{\mathrm{post}}\, r^{+}_{i,t}) \cdot \mathbf{1}\{\mathrm{post}\}$	0.2222**	1.083***	0.2603**	0.5738***
	(0.0886)	(0.0886)	(0.1075)	(0.1075)
$W^{\mathrm{pre}}_{i,t} \equiv (r^{+}_{i,t} - \hat{\Lambda}_{\mathrm{pre}}\, r^{-}_{i,t}) \cdot \mathbf{1}\{\mathrm{pre}\}$	0.4037***	−0.0539***	1.258***	−0.0650***
	(0.0176)	(0.0176)	(0.0216)	(0.0216)
$W^{\mathrm{post}}_{i,t} \equiv (r^{+}_{i,t} - \hat{\Lambda}_{\mathrm{post}}\, r^{-}_{i,t}) \cdot \mathbf{1}\{\mathrm{post}\}$	0.1163**	0.3619***	0.1372**	1.168***
	(0.0498)	(0.0498)	(0.0636)	(0.0636)
Bank-specific VIX slope $\Gamma_i \log \mathrm{VIX}_t$	Included (coefficients not shown)			
Fixed effects				
Bank (α_i)	Yes	Yes	Yes	Yes
Date (δ_t)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	46,042	46,042	46,042	46,042
R^2	0.99766	0.99748	0.99683	0.99634
Within R^2	0.90097	0.72070	0.88855	0.75353

Two-way clustered (bank & date) standard errors in parentheses.
Signif. codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes: instruments are $Z^{\mathrm{pre}}_{i,t}$ and $Z^{\mathrm{post}}_{i,t}$ for the downside and $W^{\mathrm{pre}}_{i,t}$ and $W^{\mathrm{post}}_{i,t}$ for the upside, constructed from residualized tails as in (A.14)–(A.17). Bank and date fixed effects and bank-specific VIX slopes included. Two-way clustered standard errors (bank, date).

Table A.5: Structural stage estimates for the spread–tail relation by subsample, estimated from (A.18)

Dependent variable	$\log \text{CS}_{i,t}$
$\log \text{Var}^{-}_{i,t} \cdot \mathbf{1}\{\text{pre}\}$	0.2168
	(0.1482)
$\log \text{Var}^{-}_{i,t} \cdot \mathbf{1}\{\text{post}\}$	0.4190**
	(0.1809)
$\log \text{Var}^{+}_{i,t} \cdot \mathbf{1}\{\text{pre}\}$	0.1262***
	(0.0423)
$\log \text{Var}^{+}_{i,t} \cdot \mathbf{1}\{\text{post}\}$	0.2228***
	(0.0650)
Bank-specific VIX slope $\Gamma_i \log \text{VIX}_t$	Included (coefficients omitted)
Fixed effects	
Bank (α_i)	Yes
Date (δ_t)	Yes
Fit statistics	
Observations	46,042
R^2	0.87654
Within R^2	0.20277

Standard errors (in parentheses) clustered by bank & date.
Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Notes: endogenous regressors: all four interacted tail variables. Regressors are replaced by their fitted values from projections using $(Z^{\text{pre}}_{i,t}, Z^{\text{post}}_{i,t}, W^{\text{pre}}_{i,t}, W^{\text{post}}_{i,t})$. Bank and date fixed effects and bank-specific VIX slopes included. Two-way clustered standard errors (bank, date).

B.2 Financial intermediaries

B.2.1 Aggregation

Given our assumed functional form for the equity issuance, the intermediary problem is homogeneous of degree 1 in net worth n. We can thus define the scaled variables $\tilde{e} = e/n$, $\tilde{a}' = a'/n$, $\tilde{d}' = d'/n$, $\tilde{b}' = b'/n$ and the value function $v(\mathbf{S})$ such that

$$V(n, \mathbf{S}) = nv(\mathbf{S}).$$

We can write the growth rate of net worth, $\tilde{n} = n/n_{-1}$, for some realization of the idiosyncratic shock ω and given assets and liabilities $\left(\tilde{a}', \tilde{d}', \tilde{b}'\right)$ as

$$\tilde{n}\left(\omega', \tilde{a}', \tilde{b}', \tilde{d}', \mathbf{S}'\right) = \mathcal{P}(\omega', \mathbf{S}')\tilde{a}' - \tilde{b}' - \tilde{d}'. \tag{B.5}$$

Thus, the growth rate next period, conditional on not defaulting, is

$$\mathbb{E}_{\omega}\left[\tilde{n}\left(\omega', \tilde{a}', \tilde{b}', \tilde{d}', \mathbf{S}'\right) \mid \omega > \omega^{*}(\mathbf{S})\right] = \tilde{n}\left(\omega^{+\prime}, \tilde{a}', \tilde{b}', \tilde{d}', \mathbf{S}'\right),$$

where

$$\omega^{+} = \mathbb{E}_{\omega}\left[\omega \mid \omega > \omega^{*}(\mathbf{S})\right].$$

Using the definition of $n\left(\omega, \tilde{a}, \tilde{b}, \tilde{d}, \mathbf{S}\right)$ in (B.5), we can write the representative intermediary problem as

$$\begin{aligned} v\left(\mathbf{S}\right) = & \max_{\tilde{e}, \tilde{a}', \tilde{d}' \leqslant \bar{D}, \tilde{b}'} \phi_0 - \tilde{e} \\ & + \mathbb{E}_{\mathbf{S}}\left[\mathcal{M}(\mathbf{S}', \mathbf{S}) v\left(\mathbf{S}'\right)\left(1 - \mathbb{F}(\mathbf{S}')\right)\tilde{n}\left(\omega^{+}, \tilde{a}', \tilde{b}', \tilde{d}', \mathbf{S}'\right)\right] \end{aligned} \tag{B.6}$$

subject to

$$1 - \phi_0 + \tilde{e} - \frac{\phi_1}{2}\left(\tilde{e}\right)^2 = p(\mathbf{S})\tilde{a}' - q\left(\tilde{a}', \tilde{b}', \tilde{d}'; \mathbf{S}\right)\tilde{b}' - (q^{d}(\mathbf{S}) - \kappa)\tilde{d}',$$

and

$$\tilde{b}' + \tilde{d}' \leqslant \xi p(\mathbf{S})\tilde{a}'.$$

Aggregation in the intermediary sector uses the following additional assumption. At the beginning of each period, intermediaries are randomly reassigned across islands, so that an intermediary's island identity is i.i.d. over time and independent of its balance sheet and portfolio choices. This prevents persistent sorting across islands and guarantees that the cross-sectional distribution of intermediaries can be summarized by aggregate intermediary net worth N. Together with (i) island shocks ω being uncorrelated over time and (ii) the value function being homogeneous of degree one in net worth, this reassignment delivers a representative-intermediary problem that depends only on the aggregate state $\mathbf{S}$.

B.2.2 First-order conditions

I denote the Lagrange multiplier on the budget constraint by $\mu(\mathbf{S})$, the Lagrange multiplier on the leverage constraint by $\lambda(\mathbf{S})$, and the Lagrange multiplier on the deposit constraint by $\lambda^d(\mathbf{S})$. The FOC with respect to $\tilde{e}$ is

$$\mu(\mathbf{S}) = \frac{1}{1-\phi_1\tilde{e}}. \tag{B.7}$$

The FOC with respect to a' is given by

$$\mu(\mathbf{S})\left(p(\mathbf{S}) - \frac{\partial q(\mathbf{S})}{\partial \tilde{a}'}\tilde{b}'\right) = \lambda(\mathbf{S})\xi p(\mathbf{S}) + \mathbb{E}_{\mathbf{S}}\{\mathcal{M}(\mathbf{S}',\mathbf{S})\nu\left(\mathbf{S}'\right)(1-\mathbb{F}(\mathbf{S}'))\mathcal{P}(\omega^{+\prime},\mathbf{S}')\}. \tag{B.8}$$

The FOC for d' is

$$\mu(\mathbf{S})\left(q^d(\mathbf{S}) - \kappa + \frac{\partial q(\mathbf{S})}{\partial \tilde{d}'}\tilde{b}'\right) = \lambda(\mathbf{S}) + \lambda^d(\mathbf{S}) + \mathbb{E}_{\mathbf{S}}\{\mathcal{M}(\mathbf{S}',\mathbf{S})\nu\left(\mathbf{S}'\right)(1-\mathbb{F}(\mathbf{S}'))\}. \tag{B.9}$$

Finally, the FOC for b' yields

$$\mu(\mathbf{S})\left(q + \frac{\partial q}{\partial \tilde{b}'}\tilde{b}'\right) = \lambda(\mathbf{S}) + \mathbb{E}_{\mathbf{S}}\{\mathcal{M}(\mathbf{S}',\mathbf{S})\nu\left(\mathbf{S}'\right)(1-\mathbb{F}(\mathbf{S}'))\}. \tag{B.10}$$

The envelope condition is

$$\nu(\mathbf{S}) = \phi_0 + \mu(\mathbf{S})(1-\phi_0).$$

We can divide by $\mu(\mathbf{S})$ and re-write more compactly

$$p(\mathbf{S}) - \frac{\partial q(\mathbf{S})}{\partial \tilde{a}'}\tilde{b}' - \tilde{\lambda}(\mathbf{S})\xi p(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\{\mathcal{M}(\mathbf{S}', \mathbf{S})\left(1 - \phi_1 \tilde{e}\right)\left(\phi_0 + \frac{1 - \phi_0}{1 - \phi_1 \tilde{e}'}\right)(1 - \mathbb{F}(\mathbf{S}'))\mathcal{P}(\omega^{+,\prime}, \mathbf{S}')\}, \tag{B.11}$$

$$q^d(\mathbf{S}) - \kappa + \frac{\partial q(\mathbf{S})}{\partial \tilde{d}'}\tilde{b}' - \tilde{\lambda}(\mathbf{S}) - \tilde{\lambda}^d(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\{\mathcal{M}(\mathbf{S}', \mathbf{S})\left(1 - \phi_1 \tilde{e}\right)\left(\phi_0 + \frac{1 - \phi_0}{1 - \phi_1 \tilde{e}'}\right)(1 - \mathbb{F}(\mathbf{S}'))\}, \tag{B.12}$$

$$q(\mathbf{S}) + \frac{\partial q(\mathbf{S})}{\partial \tilde{b}'}\tilde{b}' - \tilde{\lambda}(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\{\mathcal{M}(\mathbf{S}', \mathbf{S})\left(1 - \phi_1 \tilde{e}\right)\left(\phi_0 + \frac{1 - \phi_0}{1 - \phi_1 \tilde{e}'}\right)(1 - \mathbb{F}(\mathbf{S}'))\}. \tag{B.13}$$

where $\tilde{\lambda}(\mathbf{S}) = \frac{\lambda(\mathbf{S})}{\mu(\mathbf{S})}$ is the scaled Lagrange multiplier on the leverage constraint and $\tilde{\lambda}^d(\mathbf{S}) = \frac{\lambda^d(\mathbf{S})}{\mu(\mathbf{S})}$ is the scaled Lagrange multiplier on the deposit constraint.

B.2.3 Aggregate intermediary net worth

At the beginning of each period, a fraction of intermediaries default before paying dividends to shareholders and choosing the portfolio for next period. The government takes ownership of these bankrupt intermediaries and liquidates them to recover some of the outstanding debt. Bankrupt intermediaries are immediately replaced by newly started intermediaries that households endow with initial equity n^0 per intermediary. All intermediaries, including newly started ones, then solve the identical optimization problem in (B.6).

Denote the aggregate net worth of intermediaries when they solve their decision problem for the next period, by N. The average net worth of surviving intermediaries in $t+1$ is then recursively defined as

$$N^+ = \underbrace{\tilde{n}\left(\omega^+, \tilde{a}', \tilde{d}', \tilde{b}', \mathbf{S}'\right)}_{\text{growth rate to t+1}} \qquad \underbrace{\left(1 - \phi_0 + \tilde{e}\right) N}_{\text{net worth after payout/issuance in t}} \qquad ,$$

where $\tilde{n}\left(\omega^+, \tilde{a}', \tilde{d}', \tilde{b}', \mathbf{S}'\right)$ is the growth rate of net worth of non-defaulting intermediaries as defined in (B.5). The aggregate net worth of intermediaries thus follows the recursion

$$N = (1 - \mathbb{F}(\mathbf{S}))\, N^+ + \mathbb{F}(\mathbf{S}) n^0.$$

Given this expression of intermediary net worth, I can recover all aggregate intermediary choices, that is, $B' = \tilde{b}'N, D' = \tilde{d}'N, A' = \tilde{a}'N$ and so forth.[32]

[32] A simple sufficient lower bound on payouts that rules out unbounded equity accumulation follows

B.3 Derivatives of debt price

To obtain the partial derivatives, we need to differentiate equation (B.4). I first rewrite it as

$$q(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\Big\{\mathcal{M}(\mathbf{S}', \mathbf{S})\left[1 - \mathbb{F}(\mathbf{S}') + \mathbb{F}(\mathbf{S}')\left(\pi' + (1-\pi')\frac{(1-\chi)\mathcal{P}(\omega^{-\prime}, \mathbf{S}')A' - D'}{B'}\right)\right]\Big\}.$$

We can rewrite the recovery value times the probability of default as

$$\mathcal{R}(\omega, \mathbf{S}) \equiv \mathbb{F}(\mathbf{S}')\frac{(1-\chi)\mathcal{P}(\omega^{-\prime}, \mathbf{S}')A' - D'}{B'} = \mathbb{F}(\mathbf{S}')RV^{B}, \tag{B.14}$$

where $\omega^{-} \equiv \mathbb{E}_{\omega}(\omega \mid \omega < \omega^{*}(\mathbf{S}))$. Recall that $\omega^{*}(\mathbf{S}')$ is the default threshold, which satisfies the following equation:

$$\mathcal{P}(\omega^{*}(\mathbf{S}'))A' - D' - B' = 0.$$

First, I compute the derivative of the default threshold with respect to A', D' and B' as

$$\frac{\partial \omega^{*}(\mathbf{S}')}{\partial A'} = -\frac{\mathcal{P}(\omega^{*}(\mathbf{S}'))}{\mathcal{P}'(\omega^{*}(\mathbf{S}'))A'}$$
$$\frac{\partial \omega^{*}(\mathbf{S}')}{\partial D'} = \frac{1}{\mathcal{P}'(\omega^{*}(\mathbf{S}'))A'}$$
$$\frac{\partial \omega^{*}(\mathbf{S}')}{\partial B'} = \frac{1}{\mathcal{P}'(\omega^{*}(\mathbf{S}'))A'}.$$

Then I take derivatives of $\mathbb{F}(\mathbf{S}')$:

$$\frac{\partial \mathbb{F}(\mathbf{S}')}{\partial A'} = f'_{\omega}\frac{\partial \omega^{*}(\mathbf{S}')}{\partial A'}$$
$$\frac{\partial \mathbb{F}(\mathbf{S}')}{\partial D'} = f'_{\omega}\frac{\partial \omega^{*}(\mathbf{S}')}{\partial D'}$$
$$\frac{\partial \mathbb{F}(\mathbf{S}')}{\partial B'} = f'_{\omega}\frac{\partial \omega^{*}(\mathbf{S}')}{\partial B'}.$$

from the aggregate net worth recursion $N^{+} = \tilde{n}(\omega^{+}, \tilde{a}', \tilde{b}', \tilde{d}', \mathbf{S}')\,(1 - \phi_0 + \tilde{e})\,N$ for survivors and $N = (1 - \mathbb{F}(\mathbf{S}))N^{+} + \mathbb{F}(\mathbf{S})n^{0}$ in the cross-section. The first-order condition $\mu(\mathbf{S}) = 1/(1 - \phi_1\tilde{e})$ implies $\tilde{e} < 1/\phi_1$ (issuance is bounded by costs). Let $\bar{g} \geqslant \sup_{\mathbf{S}}(1 - F(\mathbf{S}))\,\tilde{n}(\omega^{+}, \tilde{a}', \tilde{b}', \tilde{d}', \mathbf{S}')$ be an upper bound on survival-weighted net-worth growth. Since $1 - \phi_0 + \tilde{e} \leqslant 1 - \phi_0 + 1/\phi_1$, a sufficient condition for N not to explode is $(1 - \phi_0 + 1/\phi_1)\,\bar{g} < 1$, i.e., $\phi_0 > 1 + 1/\phi_1 - 1/\bar{g}$. This bound is sufficient (not necessary) and uses only that issuance is costly, which caps $\tilde{e}$.

Finally, I can differentiate (B.14) to get

$$\begin{aligned}
\frac{\partial \mathcal{R}}{\partial A'} &= \left[\frac{\mathbb{F}(\mathbf{S}')\mathcal{P}(\omega^{-,\prime},\mathbf{S}')}{(B')} + RV\frac{\partial \mathbb{F}(\mathbf{S}')}{\partial A'}\right] \\
\frac{\partial \mathcal{R}}{\partial D'} &= \left[-\frac{\mathbb{F}(\mathbf{S}')}{B'} + RV\frac{\partial \mathbb{F}(\mathbf{S}')}{\partial D'}\right] \\
\frac{\partial \mathcal{R}}{\partial B'} &= \left[-\frac{\mathbb{F}(\mathbf{S}')RV}{(B')} + RV\frac{\partial \mathbb{F}(\mathbf{S}')}{\partial B'}\right].
\end{aligned}$$

The derivatives of $q(\mathbf{S})$ are therefore

$$\begin{aligned}
\frac{\partial q(\mathbf{S})}{\partial A'} &= \mathbb{E}\Big\{\mathcal{M}(\mathbf{S}',\mathbf{S})(1-\pi')\left[\frac{\partial \mathcal{R}}{\partial A'} - \frac{\partial \mathbb{F}(\mathbf{S}')}{\partial A'}\right]\Big\} \\
\frac{\partial q(\mathbf{S})}{\partial D'} &= \mathbb{E}\Big\{\mathcal{M}(\mathbf{S}',\mathbf{S})(1-\pi')\left[\frac{\partial \mathcal{R}}{\partial D'} - \frac{\partial \mathbb{F}(\mathbf{S}')}{\partial D'}\right]\Big\} \\
\frac{\partial q(\mathbf{S})}{\partial B'} &= \mathbb{E}\Big\{\mathcal{M}(\mathbf{S}',\mathbf{S})(1-\pi')\left[\frac{\partial \mathcal{R}}{\partial B'} - \frac{\partial \mathbb{F}(\mathbf{S}')}{\partial B'}\right]\Big\}.
\end{aligned}$$

The last piece is the derivative of the loan payoff with respect to ω. Define

$$\bar{z}(\omega) \;=\; \frac{c+1-\delta}{\omega Y},$$

so that

$$\mathcal{P}(\omega,\mathbf{S}) \;=\; \big[c+1-\delta+\delta p(\mathbf{S})\big]\big[1-G(\bar{z})\big] \;+\; \omega Y\int_{-\infty}^{\bar{z}} z\,dG(z).$$

Then,

$$\begin{aligned}
\frac{\partial \mathcal{P}(\omega,\mathbf{S})}{\partial \omega} &= -\big[c+1-\delta+\delta p(\mathbf{S})\big]\,g(\bar{z})\,\frac{d\bar{z}}{d\omega} \;+\; \bar{Y}z\,g(\bar{z})\,\frac{d\bar{z}}{d\omega} \\
&= \big[Y\bar{z}-(c+1-\delta+\delta p(\mathbf{S}))\big]\,g(\bar{z})\,\frac{d\bar{z}}{d\omega},
\end{aligned}$$

with $\dfrac{d\bar{z}}{d\omega} = -\dfrac{c+1-\delta}{\omega^2 Y}$. Substituting and replacing $\bar{z} = c+1-\delta/(Y\omega)$:

$$\frac{\partial \mathcal{P}(\omega,\mathbf{S})}{\partial \omega} = \left[c+1-\delta+\delta p(\mathbf{S}) - \tfrac{c+1-\delta}{Y\omega}\right]\frac{c+1-\delta}{Y\omega^2}\,g\!\left(\frac{c+1-\delta}{\omega Y}\right).$$

C Proofs

C.1 Proof of Proposition 1

Starting from (20),

$$\mathrm{CS}(\mathbf{S}) = \frac{1}{\mathbb{E}_{\mathbf{S}}\big[\mathcal{M}(\mathbf{S}',\mathbf{S})\big]}\mathbb{E}_{\mathbf{S}}\left\{\mathcal{M}(\mathbf{S}',\mathbf{S})\,(1-\pi')\,\mathbb{F}(\mathbf{S}')\big[1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}')\big]\right\}.$$

At date t, $\pi' \equiv \pi_{t+1}$ is not known and enters inside the conditional expectation. The derivative we take is with respect to the t-measurable parameter that shifts the conditional law of π', for concreteness the conditional mean $\mu_{\pi,t} \equiv \mathbb{E}_t[\pi_{t+1}]$. Because the term $(1-\pi')$ enters (20) linearly and $0 \leqslant \pi' \leqslant 1$,

$$\frac{\partial}{\partial \mu_{\pi,t}}\mathbb{E}_t\big[\mathcal{M}(1-\pi')X\big] = \mathbb{E}_t\big[\mathcal{M}(-X)\big],$$

with $X \equiv \mathbb{F}(\mathbf{S}')(1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}'))$ and the interchange of derivative and expectation is justified by dominated convergence since $\mathcal{M}X$ is integrable and bounded in π'. The indirect term depends on $\mu_{\pi,t}$ only via the optimal policy $B'(\mu_{\pi,t})$. Under the standard regularity (unique interior optimum, continuously differentiable primitives), $\partial B'/\partial\mu_{\pi,t}$ exists by the implicit function theorem and the Leibniz rule applies to move the derivative inside the expectation. If one instead considers a pathwise derivative with respect to a specific realization of π', the same expression is obtained because the integrand is affine in π'; the conditions for commutation hold for the same integrability reasons.

Differentiating with respect to the bailout probability (at date t, π' is a random variable realized at $t+1$):

$$\frac{\partial \mathrm{CS}(\mathbf{S})}{\partial \pi'} = \frac{1}{\mathbb{E}_{\mathbf{S}}\big[\mathcal{M}(\mathbf{S}',\mathbf{S})\big]}\mathbb{E}_{\mathbf{S}}\Big\{\mathcal{M}(\mathbf{S}',\mathbf{S})\big[\underbrace{-\mathbb{F}(\mathbf{S}')[1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}')]}_{\text{direct effect}} + \underbrace{(1-\pi')\,\partial_{\pi'}\big(\mathbb{F}(\mathbf{S}')[1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}')]\big)}_{\text{indirect effect}}\big]\Big\}$$

The indirect component operates through intermediaries' optimal choice of next-period debt, B', which affects default losses via the default threshold ω' and recovery RV. By the envelope/implicit-function arguments for the bank's problem, the entire dependence of default losses on π' is through B':

$$\partial_{\pi'}\big(\mathbb{F}(\mathbf{S}')(1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}'))\big) = \frac{\partial B'}{\partial \pi'}\frac{\partial}{\partial B'}\big(\mathbb{F}(\mathbf{S}')(1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}'))\big).$$

Collecting terms and writing the derivative with respect to B' in elasticity form yields

$$\frac{\partial}{\partial B'}\big(\mathbb{F}(\mathbf{S}')(1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}'))\big) = \frac{1}{B'}\,\Omega(\mathbf{S}'),$$

with

$$\Omega(\mathbf{S}') \equiv \big(D' + B' - (1-\chi)\,\mathcal{P}(\omega^*(\mathbf{S}'),\mathbf{S}')\big)\, f(\omega^*(\mathbf{S}'))\,\frac{d\omega^*(\mathbf{S}')}{dB'} + \mathbb{F}(\mathbf{S}')\,\mathrm{RV}(\omega^{-\prime},\mathbf{S}') \geqslant 0,$$

which summarizes: (i) the increase in default probability through a higher threshold $\omega^*(\mathbf{S}')$ when B' rises (first term, using $d\omega^*(\mathbf{S}')/dB' > 0$) and (ii) the dilution of recovery among a larger face value of debt (second term). Substituting back gives the expression in the statement, where the first bracketed term is the indirect effect and the second is the direct effect.

C.2 Proof of Proposition 2

Starting again from (20),

$$\mathrm{CS}\,(\mathbf{S}) = \frac{1}{\mathbb{E}_{\mathbf{S}}\big[\mathcal{M}(\mathbf{S}',\mathbf{S})\big]}\mathbb{E}_{\mathbf{S}}\left\{\mathcal{M}(\mathbf{S}',\mathbf{S})\,(1-\pi')\,\mathbb{F}(\mathbf{S}')\big[1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}')\big]\right\}.$$

Similarly to the proof of Proposition 1, differentiating with respect to the fundamental risk (at date t, Y' is a random variable realized at $t+1$) and interchanging derivative and expectation under the usual integrability conditions gives

$$\frac{\partial \mathrm{CS}\,(\mathbf{S})}{\partial Y'} = \mathbb{E}_{\mathbf{S}}\Big\{\mathcal{M}(\mathbf{S}',\mathbf{S})(1-\pi')\,\partial_{Y'}\big(\mathbb{F}(\mathbf{S}')[1-\mathrm{RV}(\omega^{-\prime},\mathbf{S}')]\big)\Big\}.$$

Holding the stochastic discount factor $\mathcal{M}(\mathbf{S}',\mathbf{S})$ and the loan price $p(\mathbf{S})$ fixed, changes in Y' affect default losses through two channels: (i) a direct cash-flow effect via $\mathcal{P}$ that shifts the default threshold and recoveries even for a fixed B' and (ii) an indirect effect operating through the optimal choice $B'(Y')$. By the chain rule, for any differentiable $h(Y',B')$ we have

$$\frac{d}{dY'}h\big(Y',B'(Y')\big) = \partial_{Y'}h(Y',B')\big|_{B'\,\text{fixed}} + \frac{\partial B'}{\partial Y'}\,\partial_{B'}h(Y',B').$$

Applying this total-derivative decomposition to $h(Y', B') = \mathbb{F}(\mathbf{S}')(1 - RV(\omega^{-\prime}, \mathbf{S}'))$ yields

$$\partial_{Y'}\Big(\mathbb{F}(\mathbf{S}')(1 - RV(\omega^{-\prime}, \mathbf{S}')\Big) = \underbrace{\Big[(1 - RV(\omega^{-\prime}, \mathbf{S}'))\,\partial_{Y'}\mathbb{F}(\mathbf{S}') \; - \mathbb{F}(\mathbf{S}')\,\partial_{Y'}RV(\omega^{-\prime}, \mathbf{S}')\Big]_{\text{holding } B' \text{ fixed}}}_{\text{direct effect}}$$

$$+ \underbrace{\frac{\partial B'}{\partial Y'}\,\frac{\partial}{\partial B'}\Big(\mathbb{F}(\mathbf{S}')(1 - RV(\omega^{-\prime}, \mathbf{S}'))\Big)}_{\text{indirect effect}}.$$

The indirect term can be written as

$$\frac{\partial}{\partial B'}\Big(\mathbb{F}(\mathbf{S}')(1 - RV(\omega^{-\prime}, \mathbf{S}'))\Big) = \frac{1}{B'}\,\Omega(\mathbf{S}'),$$

with

$$\Omega(\mathbf{S}') \equiv \big(D' + B' - (1-\chi)\,\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}')\big)\, f(\omega^*(\mathbf{S}'))\,\frac{d\omega^*(\mathbf{S}')}{dB'} + \mathbb{F}(\mathbf{S}')\,RV(\omega^{-\prime}, \mathbf{S}') \geqslant 0,$$

as defined above.

For the direct cash-flow effect, the default threshold $\omega^*(\mathbf{S}')$ solves

$$\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}') - D' - B' = 0.$$

By the implicit function theorem,

$$\frac{d\omega^*(\mathbf{S}')}{dY'} = -\frac{\partial_Y\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}')}{\partial_\omega\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}')}, \qquad \partial_{Y'}\mathbb{F}(\mathbf{S}') = f(\omega^*(\mathbf{S}'))\,\frac{d\omega^*(\mathbf{S}')}{dY'} = -\,f(\omega^*(\mathbf{S}'))\,\frac{\partial_Y\mathcal{P}}{\partial_\omega\mathcal{P}}(\omega^*(\mathbf{S}'), \mathbf{S}').$$

Within the default region the bond recovery is $RV(\omega^*(\mathbf{S}'), \mathbf{S}') = \big((1-\chi)\,\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}') - D'\big)/B'$, so, holding B' and $\omega^*(\mathbf{S}')$ fixed,

$$\partial_{Y'}RV(\omega^*(\mathbf{S}'), \mathbf{S}') = \frac{(1-\chi)}{B'}\,\partial_Y\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}') \quad \text{(holding } \omega^*(\mathbf{S}') \text{ fixed)}.$$

The shift of the default threshold, $d\omega^*(\mathbf{S}')/dY'$, is already accounted for in $\partial_{Y'}\mathbb{F}(\mathbf{S}')$ above; if included here, the threshold condition $\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}') - D' - B' = 0$ implies the total derivative of $RV(\omega^*(\mathbf{S}'), \mathbf{S}')$ with respect to Y' is zero. Since $\partial_Y\mathcal{P} \geqslant 0$ and $\partial_\omega\mathcal{P} \geqslant 0$ by (6)–(7), we have $\partial_{Y'}\mathbb{F}(\mathbf{S}') \leqslant 0$ and $\partial_{Y'}RV(\omega^*(\mathbf{S}'), \mathbf{S}') \geqslant 0$, so the direct effect is weakly negative.

Collecting terms,

$$\partial_{Y'}\big(\mathbb{F}(\mathbf{S}')(1-RV(\omega^*(\mathbf{S}'),\mathbf{S}'))\big) = \underbrace{\Big[(1-RV(\omega^*(\mathbf{S}'),\mathbf{S}'))\,\partial_{Y'}\mathbb{F}(\mathbf{S}') \;-\; \mathbb{F}(\mathbf{S}')(\mathbf{S}')\,\partial_{Y'}RV(\omega^*(\mathbf{S}'),\mathbf{S}')\Big]}_{\leqslant 0} + \frac{\partial B'}{\partial Y'}\frac{1}{B'}\,\Omega(\mathbf{S}').$$

Under the condition that banks delever when fundamentals weaken, $\partial B'/\partial Y' \geqslant 0$, the indirect term is positive as well and since $\partial_{Y'}(\mathbb{F}(\mathbf{S}')(1-RV(\omega^*(\mathbf{S}'),\mathbf{S}'))) \geqslant 0$, the overall sign is ambiguous.

For completeness, using (6)–(7) and letting $\bar{z}(\omega, Y) = (c+1-\delta)/(\omega Y)$,

$$\frac{\partial \mathcal{P}(\omega,\mathbf{S})}{\partial Y} = \big[c+1-\delta+\delta p(\mathbf{S})\big]\,g(\bar{z})\,\frac{\bar{z}}{Y} + (1-\eta)\,\omega\int_0^{\bar{z}} z\,g(z)\,dz - (1-\eta)\,\omega\,\bar{z}^2\,g(\bar{z}) \quad \geqslant 0.$$

D Computational solution method

This appendix describes the numerical algorithm that solves the dynamic general equilibrium model laid out in Appendix B. The implementation follows the policy iteration framework of Elenev et al. (2021). We first approximate the unknown policy and transition functions by discretizing the state space and employing multivariate linear interpolation. Starting with an initial guess for the policy and transition functions, we iteratively solve the model at each discretized state-space node. At each node, we compute optimal policies by solving the system of nonlinear equilibrium conditions and reformulate Kuhn–Tucker inequalities as equality constraints suitable for standard nonlinear solvers. Given these solutions, we update the transition functions and repeat the procedure until convergence. This iterative process is fully parallelized across state-space points within each iteration. Finally, we simulate the model forward for many periods using the approximated policy and transition functions. We verify that the simulated trajectories remain within the predefined bounds of the discretized state space. To assess computational accuracy, we calculate relative Euler equation errors along the simulated paths. If trajectories breach the grid boundaries or the approximation errors exceed acceptable thresholds, we refine the grid by adjusting bounds or redistributing points and repeat the solution procedure.

The state space consists of three exogenous state variables $[Z_t, d_t, \pi_t]$ and two endogenous state variables $[B_t, D_t]$. We first discretize Z_t into a N^Z-state Markov chain using the Rouwenhurst (1995) method. The procedure chooses the productivity grid points $\{Z_j\}_{j=1}^{N^Z}$ and the $N^Z \times N^Z$ Markov transition matrix $\mathbb{P}_Z$. The same method is used to discretize π_t. The disaster shock d_t can take on two realizations $\{0, 1\}$. The 2×2 Markov transition matrix between these states is given by $\mathbb{P}_d$. Denote the set of the $N^x = 2 \times N^Z \times N^\pi$ values the exogenous state variables can take on as $\mathcal{S}_x = \left\{Z_j\right\}_{j=1}^{N^Z} \times \{0,1\} \times \left\{\pi_j\right\}_{j=1}^{N^\pi}$ and the associated Markov transition matrix $\mathbb{P}_x = \mathbb{P}_Z \otimes \mathbb{P}_d \otimes \mathbb{P}_\pi$.

The solution algorithm requires the approximation of continuous functions defined on the endogenous state variables. Let the true endogenous state space of the model be defined as follows: each endogenous state variable $S_t \in \{B_t, D_t\}$ lies within a continuous and convex subset of real numbers characterized by constant state boundaries $[\bar{S}_l, \bar{S}_u]$. The endogenous state space is therefore given by:

$$\mathcal{S}_n = \left[\bar{B}_l, \bar{B}_u\right] \times \left[\bar{D}_l, \bar{D}_u\right].$$

The total state space is then defined as $\mathcal{S} = \mathcal{S}_x \times \mathcal{S}_n$.

To approximate a general function $f : \mathcal{S} \to \mathbb{R}$, we construct a univariate grid of strictly increasing points (not necessarily equidistant) for each endogenous state variable: $\{B_j\}_{j=1}^{N_B}, \{D_k\}_{k=1}^{N_D}$. These grid points are selected to adequately cover the ergodic distribution of the economy in each dimension and thereby minimize computational errors. We denote the discretized set of endogenous-state grid points by:

$$\hat{\mathcal{S}}_n = \{B_j\}_{j=1}^{N_B} \times \{D_k\}_{k=1}^{N_D},$$

and the total discretized state space as $\hat{\mathcal{S}} = \mathcal{S}_x \times \hat{\mathcal{S}}_n$. This discretized state space contains a total of $N^S = N^x \cdot N^B \cdot N^D$ points, each represented as a 2×1 vector corresponding to the two distinct state variables. Given values $\{f_j\}_{j=1}^{N^S}$ of function f at each grid point $\hat{s}_j \in \hat{\mathcal{S}}$, we can approximate f via multivariate linear interpolation. The solution method approximates three distinct sets of functions defined on the domain of state variables:

- **Policy Functions ($\mathcal{C}_P$):** These functions, $\mathcal{C}_P : \mathcal{S} \to \mathcal{P} \subseteq \mathbb{R}^{N^C}$, determine equilibrium prices, agents' choice variables and Lagrange multipliers on portfolio constraints. Specifically, the 8 policy functions include bond and deposit prices $q^u(\mathcal{S})$, asset prices $p(\mathcal{S})$, consumption $C(\mathcal{S})$, equity issuance for intermediaries $e(\mathcal{S})$, choices of bonds and deposits for intermediaries $B(\mathcal{S}), D(\mathcal{S})$ and multipliers on constraints $\lambda(\mathcal{S}), \lambda^D(\mathcal{S})$.

- **Transition Functions ($\mathcal{C}_T$):** These functions, $\mathcal{C}_T : \mathcal{S} \times \mathcal{S}_x \to \mathcal{S}_n$, specify the next-period endogenous state variables as functions of the current state and next-period exogenous shocks. Each endogenous state variable corresponds to one transition function.

- **Forecasting Functions ($\mathcal{C}_F$):** These functions, $\mathcal{C}_F : \mathcal{S} \to \mathcal{F} \subseteq \mathbb{R}^{N^F}$, are used to compute expectations terms required by the equilibrium conditions. Forecasting functions partially overlap with policy functions but include additional terms. In this model, they consist of bond price $q(\mathcal{S})$, consumption $C(\mathcal{S})$, equity issuance $e(\mathcal{S})$, household value functions $V^H(\mathcal{S})$, intermediary value function $\nu(\mathcal{S})$, and the loan price $p(\mathcal{S})$.

Given an initial guess $\mathcal{C}^0 = \{\mathcal{C}_P^0, \mathcal{C}_T^0, \mathcal{C}_F^0\}$, the equilibrium computation algorithm proceeds through the following steps:

Step A: Initialization. Set the current iterate $\mathcal{C}^m = \{\mathcal{C}_P^m, \mathcal{C}_T^m, \mathcal{C}_F^m\} = \{\mathcal{C}_P^0, \mathcal{C}_T^0, \mathcal{C}_F^0\}$.

Step B: Forecasting Values Computation. For each discretized state-space point $s_j \in \hat{\mathcal{S}}$, $j = 1, \ldots, N^S$, perform the following substeps:

i. Evaluate the transition functions at s_j combined with each possible realization of the exogenous shocks $x_i \in \mathcal{S}_x$, and obtain next-period endogenous state realizations $s_j'(x_i) = \mathcal{C}_T^m(s_j, x_i)$, for $i = 1, \ldots, N^x$.

ii. Evaluate forecasting functions at these future state realizations, obtaining $f_{i,j}^m = \mathcal{C}_F^m(s_j'(x_i), x_i)$.

This produces an $N^x \times N^S$ forecasting matrix $\mathcal{F}^m$, where each entry is a vector given by:

$$f_{i,j}^m = \left[q_{i,j}, C_{i,j}, e_{i,j}, V_{i,j}^H, V_{i,j}, p_{i,j}\right].$$

Step C: Solving the System of Nonlinear Equations. At each discretized state-space point $s_j \in \hat{\mathcal{S}}$, $j = 1, \ldots, N^S$, solve the nonlinear equilibrium conditions for the corresponding set of 8 policy variables. Given the forecasting matrix $\mathcal{F}^m$ from Step B, solve:

$$\hat{P}_j = \left[\hat{q}_j, \hat{p}_j, \hat{C}_j, \hat{e}_j, \hat{B}_j, \hat{D}_j, \hat{\lambda}_j, \hat{\lambda}_j^D\right],$$

where each vector $\hat{P}_j$ satisfies the corresponding equilibrium conditions at s_j. The eight equations are:

$$\hat{q}_j = -\frac{\partial \hat{q}_j}{\partial B_j} B_j + \hat{\lambda}_j + \mathbb{E}_{s'_{i,j}|s_j}\big[\hat{\mathcal{M}}^I_{i,j}\big], \tag{D.1}$$

$$\hat{p}_j = \frac{\partial \hat{q}_j}{\partial A_j} B_j + \hat{\lambda}_j\, \xi \hat{p}_j + \mathbb{E}_{s'_{i,j}|s_j}\big[\hat{\mathcal{M}}^I_{i,j}\, \hat{\mathcal{P}}_{i,j}(\omega^+_{i,j})\big], \tag{D.2}$$

$$(1-\phi_0)\hat{N}_j + \hat{e}_j - \frac{\phi_1}{2}\left(\hat{e}_j\right)^2 = \hat{p}_j\,\hat{A}_j - \hat{q}_j\,\hat{B}_j - (\hat{q}^D_j - \kappa)\,\hat{D}_j, \tag{D.3}$$

$$\left(\xi \hat{p}_j \hat{A}_j - \hat{B}_j - \hat{D}_j\right)\hat{\lambda}_j = 0, \tag{D.4}$$

$$\hat{W}_j - \hat{T}_j \geqslant \hat{C}_j + \hat{q}_j\,\hat{B}_j + \hat{q}^D_j\,\hat{D}_j, \tag{D.5}$$

$$\left(\hat{D}_j - \hat{D}_j\right)\hat{\lambda}^D_j = 0, \tag{D.6}$$

$$\hat{q}^D_j = \kappa - \frac{\partial \hat{q}_j}{\partial D_j} B_j + \hat{\lambda}_j + \hat{\lambda}^D_j + \mathbb{E}_{s'_{i,j}|s_j}\big[\hat{\mathcal{M}}^I_{i,j}\big], \tag{D.7}$$

$$\hat{q}_j = \mathbb{E}_{s'_{i,j}|s_j}\Big[\hat{\mathcal{M}}_{i,j}\left\{1 - \hat{F}_{i,j} + \hat{F}_{i,j}\Big(\pi_{i,j} + (1-\pi_{i,j})\frac{(1-\chi)\hat{\mathcal{P}}_{i,j}(\omega^-_{i,j})\hat{A}_j - \hat{D}_j}{\hat{B}_j}\Big)\right\}\Big], \tag{D.8}$$

All expectations are weighted sums over the exogenous-state transitions. Variables carrying a hat (ˆ) are *direct functions* of the policy vector $\hat{P}_j$; they are the choice variables passed to the nonlinear solver at state s_j. In contrast, quantities with subscripts $\{i, j\}$ are pre-computed numbers: they depend only on the forecasting vector $\mathcal{F}^m$ from Step B and therefore remain fixed while solving the local system. To avoid ambiguity, in derivative terms such as $\partial\hat{q}_j/\partial B_j$ and $\partial\hat{q}_j/\partial A_j$, the symbols B_j and A_j denote the *current policy guesses* at node j (entries of $\hat{P}_j$); equivalently, one may write $\partial\hat{q}_j/\partial\hat{B}_j$ and $\partial\hat{q}_j/\partial\hat{A}_j$. With this convention, the price-impact term moved to the right-hand side of the FOC appears with a positive sign, consistent with Appendix B. For example, the stochastic discount factors for households is

$$\hat{\mathcal{M}}_{i,j} \;=\; \beta\left(\frac{V_{i,j}}{CE_j}\right)^{\frac{1}{\nu}-\gamma}\left(\frac{C_{i,j}}{\hat{C}_j}\right)^{-\frac{1}{\nu}},$$

where $V_{i,j}$ and $C_{i,j}$ come from $\mathcal{F}^m$, while $\hat{C}_j$ is part of the current policy vector for which we solve. To compute the expectation at point s_j, we first look up the corresponding column j in the matrix containing the forecasting values that we computed in step B, $\mathcal{F}^m$. This column contains the N^x vectors, one for each possible realization of the exogenous state, of the forecasting values defined in (F). From these vectors, we need consumption $C_{i,j}$ and the value function $V_{i,j}$. Further, we need current consumption $\hat{C}_j$, which is a policy variable chosen by the nonlinear equation solver. Denoting the probability of moving from current exogenous state x_j to state x_i as $\pi_{i,j}$, we compute the certainty equivalent

$$\mathsf{CE}_j = \left[\sum_{x_i | x_j} \pi_{i,j} \left(V_{i,j} \right)^{1-\gamma} \right]^{\frac{1}{1-\gamma}},$$

and then complete expectation as

$$\mathbb{E}_{s'_{i,j}|s_j} \left[\hat{\mathcal{M}}_{i,j} \right] = \sum_{x_i|x_j} \pi_{i,j} \beta \left(\frac{V_{i,j}}{\mathsf{CE}_j} \right)^{1/\nu - \gamma} \left(\frac{C_{i,j}}{\hat{C}_j} \right)^{-1/\nu}.$$

The mapping of solution and forecasting vectors (P) and (F) into the other expressions in the system follows the same principles and is based on the definitions in Model Appendix B. To solve the system in practice, we use a nonlinear equation solver that relies on a variant of Newton's method and use policy functions $\mathcal{C}_P^m$ as initial guess. The final output of this step is an $N^S \times 8$ matrix $\mathcal{P}^{m+1}$, where each row is the solution vector $\hat{P}_j$ that solves the system above at point s_j.

Step D: Updating Forecasting, Policy, and Transition Functions. Given the new policy matrix $\mathcal{P}^{m+1}$ from Step C, set the policy functions to $\mathcal{C}_P^{m+1} \leftarrow \mathcal{P}^{m+1}$. All forecasting functions except the value functions coincide with the policy functions and are updated in the same way. Hats denote current-policy variables, while subscripts (i, j) refer to fixed forecasting quantities from $\mathcal{F}^m$. For value functions, update

$$\hat{V}_j^H = \left\{ (1-\beta)[\hat{C}_j]^{1-1/\nu} + \beta \, \mathbb{E}_{x_i|x_j} \left[(V_{i,j}^H)^{1-\gamma} \right]^{\frac{1-1/\nu}{1-\gamma}} \right\}^{1/(1-1/\nu)},$$

$$\hat{v}_j = \phi_0 N_j - \hat{e}_j + \mathbb{E}_{x_i|x_j} \left[\hat{\mathcal{M}}_{i,j} \tilde{n}(\omega^+, \cdot)(1 - F_{\omega,i,j}) v_{i,j} \right].$$

These updated objects form $\hat{\mathcal{C}}_F^{m+1}$. For transition functions, plug the new policies into each law of motion to obtain $\mathcal{C}_T^{m+1}$.

Step E: Convergence Check. Compute

$$\Delta_F = \left\| \mathcal{C}_F^{m+1} - \mathcal{C}_F^m \right\|, \qquad \Delta_T = \left\| \mathcal{C}_T^{m+1} - \mathcal{C}_T^m \right\|.$$

If $\Delta_F < \mathrm{Tol}_F$ *and* $\Delta_T < \mathrm{Tol}_T$, stop and set $\mathcal{C}^* = \mathcal{C}^{m+1}$. Otherwise apply dampening,

$$\mathcal{C}^{m+1} = D\, \mathcal{C}^m + (1-D)\, \hat{\mathcal{C}}^{m+1}, \qquad 0 < D < 1,$$

reset $\mathcal{P}^m \leftarrow \mathcal{P}^{m+1}$ and return to Step B.

Step F: Simulation. With the converged solution $\mathcal{C}^* = \mathcal{C}^{m+1}$ in hand, we simulate the model for $\bar{T} = T_{ini} + T$ periods.

1. *Exogenous shocks.* The exogenous state x_t follows a Markov chain with transition matrix Π_x. Starting from x_0 and a fixed random seed, we draw $\bar{T} - 1$ uniform random numbers to generate the path $\{x_t\}_{t=1}^{\bar{T}}$ via standard inversion.

2. *Endogenous states.* Given the initial vector $s_0 = [B_0, D_0, Z_0, d_0, \pi_0]$ (so $s_t = [B_t, D_t, Z_t, d_t, \pi_t]$), we update $[B_{t+1}, D_{t+1}] = \mathcal{C}^*_T(s_t, x_{t+1})$, producing the complete sequence $\{s_t\}_{t=1}^{\bar{T}}$.

3. *Burn-in.* We discard the first T_{ini} observations and keep $t = 1, \ldots, T$ to eliminate dependence on initial conditions.

4. *Policy and forecast evaluation.* Along the retained sample we evaluate the policy and forecasting functions; this yields the simulated data set $\{s_t, P_t, f_t\}_{t=1}^{T}$.

D.1 Numerical integration of island shocks

For a given idiosyncratic ("island") shock $\omega_t > 0$, the gross period-t return on the intermediary's loan portfolio aggregated over all surviving intermediaries is

$$\int_{\omega > \omega^*(\mathbf{S})} \mathcal{P}(\omega, \mathbf{S}) f(\omega) d\omega =$$
$$\int_{\omega > \omega^*(\mathbf{S})} \left[\left[c + (1-\delta) + \delta p(\mathbf{S})\right] \int_{\underline{z}(\omega,\mathbf{S})}^{\infty} g(z)\, dz + (1-\eta)\, \omega\, Y \int_0^{\underline{z}(\omega,\mathbf{S})} z\, g(z)\, dz \right] f(\omega) d\omega. \tag{D.9}$$

Define the CDF $G(u) = \int_0^u g(z)\, dz$, its upper tail $\bar{G}(u) = 1 - G(u)$ and the truncated first moment

$$M(u) = \int_0^u z\, g(z)\, dz.$$

Then for any ω we can write

$$\mathcal{P}(\omega, \mathbf{S}) = \left[c + (1-\delta) + \delta p(\mathbf{S})\right] \bar{G}\big(\underline{z}(\omega, \mathbf{S})\big) + (1-\eta)\, \omega\, Y\, M\big(\underline{z}(\omega, \mathbf{S})\big), \tag{D.10}$$

so that the inner integrals over z are evaluated analytically via $G(\cdot)$ and $M(\cdot)$; no discretisation of z is required.

To compute the remaining expectation over ω, let $\{(x_k, w_k)\}_{k=1}^K$ be the K Gauss–Legendre nodes and weights on $[-1, 1]$ and set $u_k = (x_k + 1)/2$. For $\omega \sim \text{Log}\mathcal{N}(1, \sigma_\omega^2)$ with $\log \omega \sim \mathcal{N}(\hat{\mu}, \hat{\sigma}^2)$, where $\hat{\sigma}^2 = \log(1 + \sigma_\omega^2)$ and $\hat{\mu} = -\frac{1}{2}\hat{\sigma}^2$, construct

$$\omega_k = \exp\big(\hat{\mu} + \hat{\sigma}\,\Phi^{-1}(u_k)\big), \qquad k = 1, \ldots, K.$$

Then, for any smooth F, $\mathbb{E}[F(\omega)] \approx \frac{1}{2}\sum_{k=1}^K w_k\, F(\omega_k)$. Applying this to the payoff with the default threshold yields

$$\int_{\omega > \omega^*(\mathbf{S})} \mathcal{P}(\omega, \mathbf{S}) f(\omega)\, d\omega = \mathbb{E}[\mathcal{P}(\omega, \mathbf{S})\, \mathbf{1}\{\omega > \omega^*(\mathbf{S})\}] \approx \frac{1}{2}\sum_{k=1}^K w_k\, \mathbf{1}\{\omega_k > \omega^*(\mathbf{S})\}\, \mathcal{P}(\omega_k, \mathbf{S}). \tag{D.11}$$

Choosing $K = 7$ yields machine-precision accuracy for our calibration with negligible computational cost.

D.2 Evaluating the solution

To evaluate solution quality we perform two checks along the simulated sample path.

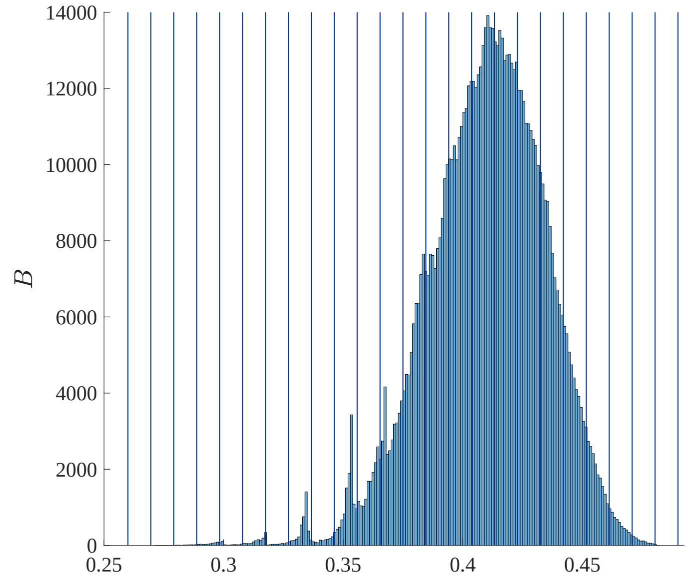
1. *Grid boundary check.* We verify that each simulated state remains inside the grids defined in Step A. Whenever a trajectory exits a bound we enlarge the affected grid range and restart the algorithm from Step A. We also create histogram plots for the endogenous state variables, overlaid with the placement of grid points. These types of plots allow us to check the quality of the grid approximation and that the simulated path of the economy does not violate the state grid boundaries. It further helps us to determine where to place grid points. Histogram plots for the benchmark economy are in Figure D.1.

2. *Relative Euler error check.* For every period t and every equilibrium condition and transition law of motion ℓ, we compute the relative error

$$\varepsilon_t^{(\ell)} = 1 - \frac{\text{RHS}_t^{(\ell)}}{\text{LHS}_t^{(\ell)}},$$

   scaling by a representative endogenous variable taken from the equation. We report the average, median, and tail percentiles of $|\varepsilon_t^{(\ell)}|$. Excessive errors trigger a local grid refinement and a fresh solve–simulate cycle. Table D.1 reports the median error, the 95th percentile of the error distribution, the 99th, and the 100th percentiles during the simulation of the model. Median and 75th percentile errors are small for all equations. Maximum errors are on the order of 0.4% for equations (D.3). It

Figure D.1: Debt Histogram



Notes: histogram plot for the endogenous state variables (debt) from an 80,000-period simulation of the benchmark model. The blue vertical lines represent the grid points.

is possible to reduce these errors by placing more grid points in those areas of the state space but adding points to eliminate the tail errors has little to no effect on any of the results at the cost of increased computation times.

Table D.1: Computational errors

Equation	Avg.	Median	75^{th} pct.	95^{th} pct.	99^{th} pct.	99.5^{th} pct.
(D.1)	5.6748e-05	5.0148e-05	7.8169e-05	1.3691e-04	1.7030e-04	1.7995e-04
(D.2)	4.5492e-05	4.0050e-05	6.2785e-05	1.1316e-04	1.4052e-04	1.4902e-04
(D.3)	0.0011	9.2890e-04	0.0014	0.0026	0.0038	0.0043
(D.4)	8.9997e-05	9.5819e-05	1.2634e-04	1.6539e-04	1.8748e-04	1.9524e-04
(D.5)	7.5519e-05	7.0822e-05	9.7695e-05	1.6551e-04	2.1957e-04	2.4732e-04
(D.6)	2.6146e-18	0	0	0	1.3092e-16	2.6688e-16
(D.7)	5.5286e-05	4.9312e-05	7.6156e-05	1.3377e-04	1.6617e-04	1.7520e-04

Notes: the table reports average, median, 75th percentile, 95th percentile, 99th percentile, and 99.5th percentile absolute errors, evaluated at state space points from a 80,000 period simulation of the benchmark model. Each row corresponds to an equation of the nonlinear system (D.1)–(D.7) listed in step C of the solution procedure.

E Model calibration

Option-implied BofA IG Bond Spread. We measure the investment-grade corporate bond spread using the ICE BofA Option-Adjusted Spread (OAS) indices available from the Federal Reserve Economic Data (FRED). We specifically download the daily OAS for the AAA, AA, A and BBB rating tiers (FRED series IDs: `BAMLC0A1CAAA`, `BAMLC0A2CAA`, `BAMLC0A3CA` and `BAMLC0A4CBBB`). For each business day t, we construct an "IG average OAS" as the simple mean of these four series and handle missing values by averaging the available ratings on that day. The sample runs from January 1, 2000 to December 31, 2020. These OAS series are computed from bond prices and adjust for embedded call options; they are not derived from equity options.

From the daily IG average OAS, we build lower-frequency aggregates used in the calibration and diagnostics. A quarterly series is obtained by keeping the end-of-quarter observation (last trading day of each quarter). An annual series is the arithmetic mean of the four quarterly values within each calendar year. On the annual series, we report the mean, standard deviation, and the AR(1) persistence parameter (estimated with an intercept).

For disaster diagnostics, let μ and σ denote the sample mean and standard deviation of the quarterly IG average OAS. We label a quarter as a "disaster quarter" when the spread exceeds the threshold $\mu + 2.5\,\sigma$. We report (i) the mean spread within disaster quarters, (ii) the number of distinct disaster episodes (maximal contiguous runs of disaster quarters), (iii) their average duration in quarters, and (iv) their frequency relative to the full sample.

For visualization we also aggregate the daily series to weekly frequency by averaging within week (Monday–Sunday) and overlay a 4-week moving average. The horizontal dashed line in the right panel of Figure E.1 marks the disaster threshold $\mu + 2.5\,\sigma$ computed from the quarterly series.

3-month US Treasury Yield. We proxy the short risk-free rate with the 3-month Treasury Constant Maturity Rate from the Federal Reserve Economic Data (FRED), series DGS3MO, release H.15 Selected Interest Rates. This series reports the market yield on US Treasury securities at a 3-month constant maturity, quoted on an investment basis at daily frequency. The series runs from January 1, 2000 to December 31, 2020. We construct a quarterly series by taking the end-of-quarter observation, build an annual series as the mean of the quarterly averages and report the mean and standard deviation for the quarterly and annual series.

Intermediary Payouts. We measure equity issuance and payout activity of bank holding companies h in quarter t using FR Y–9C Schedule HC and HI items. The primary equity issuance flow is identified from common stock sales. The relevant item is "Sale of common stock," MDRM BHCK3579. Preferred equity flows are tracked separately, using "Sale of preferred stock," BHCK3577 and "Repurchase of preferred stock," BHCK3578, together with BHCK4596 for earlier preferred stock issues. Treasury stock transactions are included through "Sale of treasury stock," BHCK4782 and "Purchase of treasury stock," BHCK4783. The issuance measure is defined as the net positive inflow from sales of common and preferred stock and treasury stock sales (i.e., $\text{Issuance}_{h,t} = \max\{0, \texttt{BHCK3579} + \texttt{BHCK3580} + \texttt{BHCK3577} + \texttt{BHCK4782}\}$), normalized by beginning-of-quarter equity from Schedule HC, item 27, BHCK3210. This yields the quarterly equity issuance rate $\text{Issuance}_{h,t}/\texttt{BHCK3210}_{h,t-1}$.

Equity payouts are measured from dividends and repurchases. Regular cash dividends are taken from Schedule HI "Cash dividends declared," MDRM BHCK4460 and adjusted to remove cumulative reporting across quarters by differencing within calendar years. Share repurchases are taken from BHCK3578 (repurchase of preferred stock) and BHCK4783 (purchase of treasury stock). We define the gross payout flow as $\text{Payout}_{h,t} = \texttt{BHCK4460} + \texttt{BHCK3578} + \texttt{BHCK4783}$, normalized again by lagged book equity, $\texttt{BHCK3210}_{h,t-1}$.

To harmonize across reporting regimes, we apply the following adjustments: (i) use first differences for dividend flows within a fiscal year to ensure quarterly frequency, (ii) set flows to zero where missing but the equity base is reported, and (iii) winsorize the resulting rates at the 1st and 99th percentiles within quarter to reduce the influence of extreme values. Both issuance and payout rates are thus defined as equity flows scaled by beginning-of-quarter book equity, consistently constructed across time and are expressed at the holding-company level.

Insured Deposits and Uninsured Debt. For each bank holding company h and quarter t we measure uninsured deposits by summing across all depository subsidiaries s controlled by h in quarter t the Call Report Schedule RC–O Memorandum item "Estimated amount of uninsured deposits, including related interest accrued and unpaid", MDRM RCON5597 for domestic offices (or RCFD5597 where reported on a consolidated basis); in other words, $U_{h,t} = \sum_{s \in h} U_{s,t}$ with $U_{s,t} = \texttt{RCON5597}_{s,t}$. We pair this with the holding-company consolidated total deposits from the FR Y–9C balance sheet, Schedule HC "Deposits," item 13, MDRM BHCK2200, denoted $D_{h,t} = \texttt{BHCK2200}_{h,t}$. We then define the insured-deposit measure as the residual $I_{h,t} = D_{h,t} - U_{h,t}$. When RCON/RCFD5597 is not reported for a subsidiary in a given quarter, we construct a conservative fallback proxy from Schedule RC–E size buckets for time deposits: before the March 2010 insurance-limit change, we use "Total time deposits of $100,000 or more," MDRM RCON2604; from March 2010 forward, we use "Total time deposits of more than $250,000," MDRM RCONJ474; where available we also use the split "Total time deposits of $100,000 through \$250,000," RCONJ473 and "Time deposits of less than \$100,000" (\$250,000 after 2017 on Y–9C), RCON6648 (Y–9C successors BHCBHK29 for $<$ \$250,000 and BHCBJ474 for $>$ \$250,000), to verify internal consistency. We aggregate these RC–E quantities to h and use them only when 5597 is missing, and recognize that this proxy can understate uninsured amounts if large non-time transaction or savings balances exceed the insurance limit; when RC–E Memorandum item 1 provides amounts for "deposit accounts (excluding retirement) of more than \$250,000" and for "retirement deposit accounts of more than \$250,000," we reference the corresponding MDRM items RCONF051 and RCONF048 to check plausibility but do not replace 5597-based values. The construction proceeds as follows in a single pass for every h, t: (i) map subsidiary banks to their ultimate parent at t using the regulatory structure as of the report date; (ii) compute $U_{h,t}$ by summing RCON/RCFD5597 across subsidiaries (or the RC–E proxy where needed); (iii) read $D_{h,t}$ = BHCK2200 from FR Y–9C; (iv) set uninsured deposits = $U_{h,t}$ and insured deposits = $\max\{0, D_{h,t} - U_{h,t}\}$.

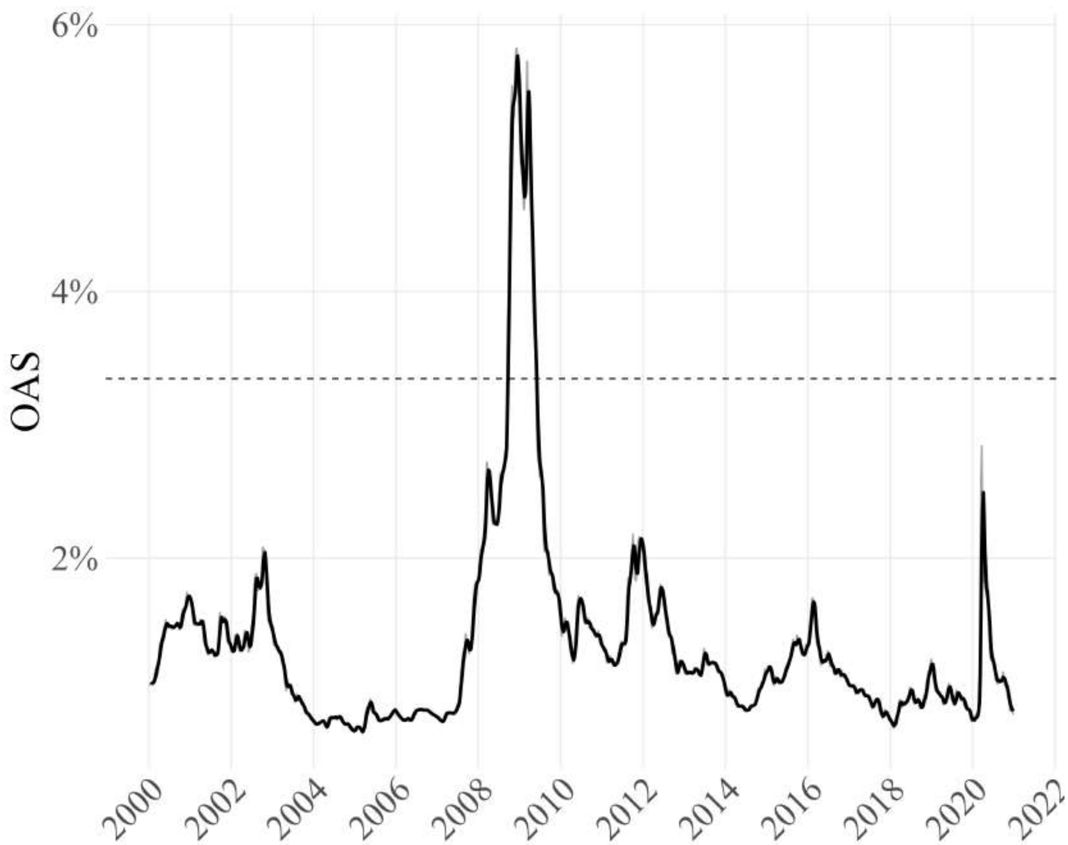
After the variables are formed, we merge them to the FR Y–9C panel by holding-company identifier and quarter and apply deterministic screening and outlier treatment used uniformly across quarters. First, we drop holding-company quarters with zero total deposits ($D_{h,t} = 0$) and we drop quarters with extreme quarter-over-quarter asset growth in levels exceeding 20% in absolute value to remove structural breaks and mismerges. Second, before computing any downstream funding ratios we set the basic deposit components used elsewhere (noninterest-bearing, demand, other savings, time $\leqslant$ limit and time $>$ limit, each split into US and subsidiary-office scopes) to zero when missing and then form the composite "core" and "wholesale" deposit series; these composite deposit series are set to missing prior to 1986:Q2 to align the sample with the availability of the underlying items.

F Details on counterfactual experiments

This section provides details on the counterfactual experiment of Section 7. First, we explain how we use a sequential Monte Carlo particle filter, also called the bootstrap particle filter (Gordon et al. 1995, Chopin et al. 2020, Doucet et al. 2001). Second, we discuss how we generate the decomposition of Figure 8.

Beginning in 2010 (inclusive), we evaluate the policy function under the model with $\xi = 10.5\%$ rather than the baseline value to account for post-crisis regulatory changes; for $t < 2010$ the baseline policy function is used.

Figure E.1: Option-adjusted BofA IG Bond Spread



Notes: the plot shows the Option-adjusted BofA IG bond spread at weekly frequency (black line). The dashed black horizontal line represents the level at 2.5 st.dev above the mean.

For annual data 2004–2015, the nonlinear state–space system is

$$\begin{aligned} \mathbf{Y}_t &= \mathbf{g}(\mathbf{S}_t) + \boldsymbol{\eta}_t, \\ \mathbf{S}_t &= \mathbf{f}(\mathbf{S}_{t-1}, \boldsymbol{\varepsilon}_t), \end{aligned} \tag{F.1}$$

where the state vector and structural innovations are

$$\mathbf{S}_t = \left[\, L_t, W_t, \pi_t,\ Z_t,\ d_t \right]^\top, \qquad \boldsymbol{\varepsilon}_t = \left[\varepsilon_t^d,\ \varepsilon_t^\pi,\ \varepsilon_t^Z\right]^\top.$$

The 2×1 measurement vector contains the one–year credit-spread differential and the risk-neutral default probability constructed in Section 3:

$$\mathbf{Y}_t = \left[CS_{t,365},\ \mathbb{F}^*_{t,365}\right]^\top.$$

To respect the positive support and skewness of observed spreads, we set

$$CS^{\text{data}}_{t,365} = g_1(\mathbf{S}_t)\ \exp(\eta_t^{CS}), \qquad \eta_t^{CS} \sim \mathcal{N}\!\left(-\tfrac{1}{2}\sigma^2_{CS},\ \sigma^2_{CS}\right),$$

while the empirical default probability obeys a shifted beta law,

$$Q^{*\,\text{data}}_{t,365} = g_2(\mathbf{S}_t) + \eta_t^Q, \qquad \eta_t^Q \sim \text{Beta}\big(\alpha_t, \beta_t\big) - \mathbb{E}[\text{Beta}(\alpha_t, \beta_t)].$$

Each quarter the beta parameters

$$\alpha_t = \left[(1 - \mu_t)/\nu_t - 1/\mu_t\right]\mu_t^2, \quad \beta_t = \alpha_t\big(1/\mu_t - 1\big)$$

match the filtered mean $\mu_t = g_2(\mathbf{S}_t)$ and variance $\nu_t = 0.01\,\widehat{\sigma}^2(Q^{*\,\text{data}}_{t,365})$, while $\sigma^2_{CS} = 0.01\,\widehat{\sigma}^2(CS^{\text{data}}_{t,365})$. Both $CS_{t,365}$ and $\mathbb{F}^*_{t,365}$ carry measurement noise.

Let $\mathbf{Y}^t = [\mathbf{Y}_1, \ldots, \mathbf{Y}_t]$ denote the history of observed vectors up to time t and write

$$p(\mathbf{S}_t \mid \mathbf{Y}^t)$$

for the conditional law of the (latent) state vector. No closed-form expression exists for $p(\mathbf{S}_t \mid \mathbf{Y}^t)$ and therefore we approximate it at every t with an auxiliary particle filter that maintains a collection of weighted particles $\{(\mathbf{S}_t^i, \tilde{w}_t^i)\}_{i=1}^N$ such that, for any integrable function f,

$$\frac{1}{N}\sum_{i=1}^{N} f(\mathbf{S}_t^i)\,\tilde{w}_t^i \xrightarrow{\text{a.s.}} \mathbb{E}\left[f(\mathbf{S}_t) \mid \mathbf{Y}^t\right].$$

The mean of the simulated particles then provides a smoothed path for the unobserved state.

Each recursion proceeds as follows:

1. **Initialization ($t = 0$).** Draw an initial cloud $\{\mathbf{S}_0^i\}_{i=1}^N$ from a suitable prior and set the associated (normalized) weights to $\tilde{w}_0^i = 1$ for all i.

2. **Prediction (time t).** For each particle $i = 1, \ldots, N$, simulate a forecast state

$$\mathbf{S}_{t|t-1}^i \sim p(\mathbf{S}_t \mid \mathbf{S}_{t-1}^i)$$

using the state-transition from the model as described in Section D.

3. **Updating of importance weights.** Compute the incremental weight for every forecast particle as

$$w_t^i \;=\; p\big(\mathbf{Y}_t \mid \mathbf{S}_{t|t-1}^i\big)\,\tilde{w}_{t-1}^i.$$

4. **Normalization and resampling.**

   (a) Normalize the normalized weights so they sum to one: $\tilde{w}_t^i = w_t^i \Big/ \sum_{j=1}^N w_t^j$.

   (b) Draw $N = 100000$ particles *with replacement* from $\{\mathbf{S}_{t|t-1}^i, \tilde{w}_t^i\}_{i=1}^N$ and relabel the resampled set as $\{\mathbf{S}_t^i\}_{i=1}^N$.

   (c) Reset all weights to unity, $\tilde{w}_t^i = 1$.

5. **Iterate.** If $t < T$, increase $t \leftarrow t + 1$ and return to Step 2; otherwise terminate.

The next step is to decompose the counterfactual into its components. We now discuss how we use the approximation to $\left\{p\left(\mathbf{S}_t \mid \mathbf{Y}^t\right)\right\}_{t=2004}^{2015}$ along with the structural model to generate the decomposition presented in Figure 8.

Define the model-implied credit spread

$$\widehat{CS}_{t,365} = \sum_{i=1}^N g_1(\mathbf{S}_t^{(i)})\,\tilde{w}_t^{(i)},$$

where $g_1(\mathbf{S}_t)$ is the policy function for the credit spread differential. Starting in 2010 (inclusive), g_1 is evaluated under the model with $\xi = 10.5\%$ rather than the baseline value to reflect regulatory changes. The measurement error is

$$\eta_t^{CS} = CS_{t,365}^{data} - \widehat{CS}_{t,365}.$$

We generate the fundamental component by freezing the bailout probability at its precrisis level and the regulation at its baseline value and backing up the spread

$$\widehat{CS}^{\text{fund}}_{t,365} = \sum_{i=1}^{N} g_1\Big(\mathbf{S}^{(i)}_t \mid \pi_{t+1} = \bar{\pi}^H\Big)\,\tilde{w}^{(i)}_t,$$

The bailout component is then

$$\Delta^{\text{Bailout}}_t = \widehat{CS}_{t,365} - \widehat{CS}^{\text{fund}}_{t,365}.$$

For all evaluations with $t \geqslant 2010$, we likewise use the policy function from the model with $\xi = 10.5\%$.

To construct the model counterpart of the correlation between credit spreads and the downside risk-neutral equity variance across subsamples, we first purge fundamentals using the model's decomposition. For each date t, we first compute the total one-year spread $\widehat{CS}_{t,365}$ and the downside risk-neutral equity variance $\text{Var}^{-}_{t,365}$ under the time-appropriate policy (baseline pre-2008, tighter post-2010). We then obtain their fundamental counterparts by reevaluating the same objects while fixing the bailout probability at its precrisis level, $\pi_{t+1} = \bar{\pi}^H$, holding the filtered fundamentals in $\mathbf{S}_t$ and the regulation regime fixed. The bailout/regulation components are

$$\widetilde{CS}_t \equiv \widehat{CS}_{t,365} - \widehat{CS}^{\text{fund}}_{t,365}, \qquad \widetilde{\text{Var}}^{-}_{t,365} \equiv \text{Var}^{-}_{t,365} - \text{Var}^{-,\text{fund}}_{t,365}.$$

We then estimate the following log–log regression separately in the two subsamples to obtain slope coefficients β^{pre} and β^{post}:

$$\begin{aligned}
\log \widetilde{CS}_t &= \alpha^{\text{pre}} + \beta^{\text{pre}} \log \widetilde{\text{Var}}^{-}_{t,365} + \varepsilon_t, \quad & t \in [2004, 2007],\\
\log \widetilde{CS}_t &= \alpha^{\text{post}} + \beta^{\text{post}} \log \widetilde{\text{Var}}^{-}_{t,365} + \varepsilon_t, \quad & t \in [2010, 2015].
\end{aligned}$$

This procedure removes movements driven by fundamentals and aligns the model with the empirical subsample break; see Section A.7 for data counterparts for tail variances and the identification logic.

G Model extensions

G.1 Equity injections

In this appendix, we extend the baseline environment to allow for bailouts that recapitalize the intermediary itself via equity injections. In this version, the bailout probability π is the probability that an insolvent intermediary is recapitalized as a going concern by the government rather than being liquidated. The government injects just enough equity to restore solvency, takes ownership of the intermediary, and immediately rebates that ownership to households. Existing private shareholders are diluted in those states, which creates an additional wedge for equity valuation but preserves going-concern value relative to outright liquidation.

Insolvency set and shortfall. Let $\mathcal{D}$ denote the set of shock realizations for which an intermediary would be insolvent absent intervention. For asset choices A' and promised repayments $B' + D'$, define the shortfall function

$$J(\omega; \mathbf{S}) = \left[B' + D' - \mathcal{P}(\omega, \mathbf{S}) \, A' \right]_+, \qquad \mathcal{D} = \left\{ \omega : \; J(\omega; \mathbf{S}) > 0 \right\}. \tag{G.1}$$

Bailout technology and ownership. If $\omega \in \mathcal{D}$, then with probability π the government injects $J(\omega; \mathbf{S})$ units of equity to exactly meet promised payments and keep the intermediary operating as a going concern. In exchange, it receives an equity claim on the intermediary that is transferred immediately to households (a rebate of ownership). With probability $1 - \pi$, no intervention occurs and the intermediary is liquidated as in the baseline, with creditors recovering a fraction $\chi \in [0, 1]$ of post-default asset value and the remainder lost as deadweight costs of bankruptcy.

Two implications follow:

1. **Creditor payoffs in insolvency states** remain as in the baseline: they receive $B' + D'$ with probability π and $\chi \, \mathcal{P}(\omega, \mathbf{S}) \, A'$ otherwise. The debt-pricing condition is therefore unchanged conditional on π.

2. **Equityholders are diluted in bailout states.** Preexisting private equity receives no claim in $\omega \in \mathcal{D}_t$, regardless of whether a bailout occurs; in bailout states the government's ownership claim (immediately rebated to households) absorbs the going-concern value that would otherwise not exist under liquidation. This wedge shows up in the equity value function and in the aggregate dividend to households via the government rebate.

Government budget and rebates. Let $T(\mathbf{S})$ be lump-sum taxes on households and $\kappa D'$ the fee revenue collected from intermediaries (as in the baseline). The government's period budget with equity injections is

$$T(\mathbf{S}) + \kappa D' = \pi \, \mathbb{E}_{\mathbf{S}} \Big[J(\omega; \mathbf{S}) \, \mathbb{I}_{\{\omega \in \mathcal{D}\}} \Big] - R^G(\mathbf{S}), \tag{G.2}$$

where $R^G(\mathbf{S})$ is the contemporaneous rebate to households of the ownership the government acquires upon recapitalization. In the baseline results we will keep $R^G(\mathbf{S})$ as an explicit object so as not to impose valuation assumptions on the government's claim. Two convenient normalizations are: (i) *cash-for-ownership*: set $R^G \equiv 0$ so recap injections are financed net by taxes; or (ii) *ownership-as-transfer*: set $R^G(\mathbf{S}) = \theta\, \mathbb{E}_{\mathbf{S}}[\, J(\omega; \mathbf{S})\, \mathbb{I}_{\{\omega \in \mathcal{D}\}}\,]$ for some $\theta \in [0, 1]$ that governs how much of the recap value is immediately rebated.

Household budget and dividends. Let Π^I denote aggregate intermediary dividends as in the baseline. Households receive the additional transfer $R^G(\mathbf{S})$ and pay taxes $T(\mathbf{S})$, so their budget constraint is unchanged except for the replacement $\Pi^I \mapsto \Pi^I + R^G(\mathbf{S}) - T(\mathbf{S})$.

Aggregate resource constraint. Relative to the baseline resource constraint in Equation (15), equity injections remove bankruptcy deadweight losses in the fraction π of insolvency states and replace them with government-financed recapitalizations. Denoting by $\Xi^{liq}(\mathbf{S})$ the baseline resource drain associated with liquidation (the term multiplying χ in (15)), the goods market clearing condition becomes

$$Y = C + \Phi^e\left(\tfrac{e}{N}\right) + (1 - \pi)\, \Xi^{liq}(\mathbf{S}) + (\text{disaster output losses as in baseline}). \tag{G.3}$$

That is, liquidation losses are scaled by $1 - \pi_t$; in bailout states there are no bankruptcy deadweight losses, but public resources are used per (G.2) and redistributed via R^G.

Intermediary problem and pricing. Because creditors' payoffs in insolvency states are unchanged conditional on π, the debt pricing kernel is the same as in the baseline conditional on π. Equityholders' value, however, now embeds an additional dilution wedge: in all $\omega \in \mathcal{D}$, they receive zero regardless of intervention, but with probability π the economy avoids deadweight losses and ownership is transferred to households through R^G. Accordingly, the representative intermediary's value-per-unit-of-net-worth $\nu(\mathbf{S})$ is as in the baseline except that prices and the shadow value of net worth reflect (G.3) and (G.2). The aggregation in Section B carries through with the following adjustment to aggregate dividends:

$$\Pi^I = N\left(\phi_0 - \tfrac{e}{N}\right) - F\, n^0 + R^G(\mathbf{S}), \tag{G.4}$$

where $F \equiv F(\omega^*)$ is the mass of defaulting intermediaries, as in the baseline. The last term is the ownership rebate from government recapitalizations.

This extension nests the baseline as a special case: setting $R^G \equiv 0$ and interpreting π

as the probability of creditor-only bailouts reproduces the original resource and pricing equations. Allowing $R^G > 0$ captures the idea that, in equity bailouts, the government acquires going-concern value and immediately passes it to households and creates dilution for incumbent shareholders while eliminating liquidation losses in those states.

The extension does not materially change the main quantitative mechanisms of the paper: pricing of debt, leverage incentives, and macro propagation remain the same conditional on π. However, equity injections mechanically suppress measured default frequencies because insolvent intermediaries that are recapitalized do not default. This makes the mapping between π and observed default probabilities inconsistent with the data moments we use and can be problematic for identification based on defaults. For this reason, our baseline focuses on creditor-only bailouts.

G.2 Intermediaries' asset choice

In this section we consider an extension of the model in which intermediaries do not hold the entire pool of risky assets. To be the case, we assume that now also households can invest in debt claims as intermediaries $A^{H\prime}$. However, households do not have access to the intermediaries' superior (costless) monitoring technology. They can hold corporate debt that does not require screening and monitoring, such as highly rated corporate bonds, without incurring any monitoring cost. A subset of the total supply of corporate debt $\varphi_0 < 1$ satisfies this requirement. If households want to expand (or shrink) their holdings of corporate debt away from the amount φ_0, they incur costs: $\Phi^H(A^{H\prime}) = \frac{\varphi_1}{2}\left(\frac{A^{H\prime}}{\varphi_0} - 1\right)^2 \varphi_0$ (Brunnermeier & Sannikov 2014, Elenev et al. 2021). In equilibrium, it must be the case that $A^H = 1 - A$ and that the resource constraint is satisfied such that

$$
\begin{aligned}
Y = C + \Phi^e\left(e/N\right) + \chi A \int_{\omega \in \mathcal{D}} \mathcal{P}(\omega, \mathbf{S}) f(\omega) d\omega \\
+ \eta Y \int \int_0^{z(\omega, Y)} \omega z \, g(z) f(\omega) \, dz \, d\omega + \Phi^H(A^{H\prime}).
\end{aligned}
\tag{G.5}
$$

One interpretation is that the household represents other intermediaries who are participants in the same asset markets of the banks (e.g., shadow banks/non-bank financial intermediaries). Another potential interpretation is that they represent a costly securitization technology which allows banks to sell aggregate risk off their balance sheet. The household first-order condition then reads

$$
p(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\left\{\mathcal{M}(\mathbf{S}', \mathbf{S}) \int \mathcal{P}(\omega, \mathbf{S}') f(\omega) d\omega\right\} + \Phi^{H,\prime}(A^{H\prime}). \tag{G.6}
$$

Importantly, the household holds a diversified portfolio of debt claims differently from the intermediaries.

Allowing households to absorb part of the risky debt leaves the core risk-taking margin, leverage, intact. The new element is that intermediaries can directly scale their exposure to fundamental risk by choosing a smaller A (selling/securitizing risk to households), in addition to adjusting leverage. This extra margin does not overturn our main results; it simply offers another channel to attenuate aggregate risk while the key identification lever in the main exercise remains intermediaries' leverage choice.

G.3 Endogenous deposits

This subsection endogenizes deposit creation and pricing by removing the exogenous capacity constraint and letting deposits deliver liquidity services to households. Deposits from different intermediaries are imperfect substitutes in liquidity provision, so a bank's issuance affects the marginal liquidity value of its own deposits through a CES aggregator. As a result, the deposit price q^d embeds a state-contingent liquidity premium and becomes decreasing in the quantity a bank issues; this implies that larger issuance raises the deposit rate. Intermediaries internalize this price impact and choose deposit quantities by trading off the liquidity premium against the dilution in marginal liquidity (market power), with the strength of the price-quantity trade-off governed by the substitutability parameter ρ. In equilibrium, deposits are finite, deposit rates are upward-sloping in issuance, and greater substitutability (higher ρ) compresses spreads and weakens market power. The baseline with effectively perfectly elastic deposits is nested as liquidity services are shut down or as $\rho \to 1$; the extension leaves the core risk-taking margin intact while disciplining how deposit levels and deposit rates move with liquidity demand and competition.

Households. Households derive period utility from consumption and from liquidity services provided by deposits. The recursive problem is

$$V^H(\mathbf{S}) = \max_{C, B', \{D_i'\}_{i\in[0,1]}} \left\{ (1-\beta)\, u^{1-\frac{1}{\nu}} + \beta\, \mathbb{E}_{\mathbf{S}}[\, V^H(\mathbf{S}')]^{\frac{1-\frac{1}{\nu}}{1-\gamma}} \right\}^{\frac{1}{1-\frac{1}{\nu}}},$$

where $u = C^{\vartheta} \mathcal{L}'(\{D_i'\})^{1-\theta}$. subject to the same set of constraints as in the baseline economy. Deposits from different banks are imperfect substitutes in providing liquidity. Let the liquidity aggregator be the CES index

$$\mathcal{L}'(\{D'_i\}) = \left(\int_0^1 (D'_i)^\rho \, di\right)^{1/\rho}, \quad \rho \in (0,1]. \tag{G.7}$$

Households' marginal liquidity value of deposits at bank i is

$$\mathcal{L}'_i \equiv \frac{\partial \mathcal{L}'}{\partial D'_i} = \left(\int_0^1 (D'_j)^\rho dj\right)^{\frac{1}{\rho}-1} (D'_i)^{\rho-1} = \frac{(D'_i)^{\rho-1}}{(\mathcal{L}')^{\rho-1}}. \tag{G.8}$$

Holding aggregate liquidity fixed, its own-elasticity is

$$\frac{\partial \mathcal{L}'_i}{\partial D'_i} = -\frac{1-\rho}{D'_i} \mathcal{L}'_i. \tag{G.9}$$

Optimality with respect to insured deposits yields

$$q^d_{i,t}(\mathbf{S}) = \mathbb{E}_t\Big\{\mathcal{M}(\mathbf{S}', \mathbf{S})\Big(1 + \tfrac{1-\theta}{\vartheta} \tfrac{C'}{\mathcal{L}'} \mathcal{L}'_i\Big)\Big\} \tag{G.10}$$

where the SDF is defined as

$$\mathcal{M}(\mathbf{S}', \mathbf{S}) = \beta\Big(\tfrac{V^H(\mathbf{S}')}{CE(\mathbf{S})}\Big)^{\frac{1}{\nu}-\gamma}\Big(\tfrac{u'}{u}\Big)^{1-\frac{1}{\nu}}\Big(\tfrac{C'}{C}\Big)^{-1}.$$

This representation is equivalent to the standard Epstein–Zin kernel $\mathcal{M} = \beta\big(\frac{V^H(\mathbf{S}')}{CE(\mathbf{S})}\big)^{\frac{1}{\nu}-\gamma}\big(\frac{u'_C}{u_C}\big)^{1-\frac{1}{\nu}}$ with $u_C = \vartheta u/C$.

Financial Intermediaries. The representative intermediary's problem is the same as in the baseline, but now the capacity constraint on deposits is excluded and the first-order condition for deposits is modified to take into account intermediaries market power in deposit markets namely

$$q^d(\mathbf{S}) - \kappa + \frac{\partial q^d(\mathbf{S})}{\partial \tilde{d}'}\tilde{d}' + \frac{\partial q(\mathbf{S})}{\partial \tilde{d}'}\tilde{b}' - \tilde{\lambda}(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\{\mathcal{M}^I(\mathbf{S}', \mathbf{S})(1 - \mathbb{F}(\mathbf{S}'))\}. \tag{G.11}$$

For deposits, intermediaries internalize the effect of their issuance on $q^d(\mathbf{S})$ through households' liquidity services. From (G.8)-(G.10),

$$\frac{\partial q^d(\mathbf{S})}{\partial D'_i} = \mathbb{E}_t\Big\{\mathcal{M}(\mathbf{S}', \mathbf{S}) \tfrac{1-\theta}{\vartheta} \tfrac{C'}{\mathcal{L}'} \frac{\partial \mathcal{L}'_i}{\partial D'_i}\Big\} = -\mathbb{E}_t\Big\{\mathcal{M}(\mathbf{S}', \mathbf{S}) \tfrac{1-\theta}{\vartheta} \tfrac{C'}{\mathcal{L}'} (1-\rho) \frac{\mathcal{L}'_i}{D'_i}\Big\}. \tag{G.12}$$

Under a symmetric equilibrium where all banks choose the same D'_i,

$$\frac{\partial q^d(\mathbf{S})}{\partial D'} = -\mathbb{E}_t\Big\{\mathcal{M}(\mathbf{S}', \mathbf{S})\, \tfrac{1-\theta}{\vartheta}\, \tfrac{C'}{\mathcal{L}'}\, (1-\rho)\, \frac{1}{D'}\Big\}. \tag{G.13}$$

When issuing deposits, intermediaries are now going to trade off the liquidity premium with the reduction in market power.

H Simple economy

H.1 Environment

Agents, preferences and endowments. There are two periods, $t = 1, 2$ and a single consumption good (dollar), which serves as numeraire. The economy is populated by a unit measure of risk-neutral consumers indexed by C and intermediaries indexed by I and a government. There is also a social planner/regulator/government, who sets bailouts and leverage regulation. We denote the possible states of nature at date 1 by $\omega \in [0, \bar{\omega}]$. As described below, ω corresponds to the realization of the returns to intermediaries' technology. Consumers discount the future with a discount factor β and own debt and equity of intermediaries. The endowments of the consumption goods of consumers at date 1 and 2 are $\{n_1^C, n_2^C(\omega)\}$. The budget constraint of intermediaries at date 0 is given by

$$d_1 = q(b, a)b - pa,$$

where p denotes the price of asset, $q(b, a)$ the price of debt, b the face value of debt, a the amount of asset purchased and d_1 is the equity issued if $d_1 < 0$ or the dividend paid if $d_1 > 0$. The budget constraint of intermediaries at date 1 in state ω is given by

$$d_2(\omega) = \max\{\omega a - b, 0\}.$$

The budget constraint of consumers at date 1 and at date 2 in state ω are given by

$$\begin{aligned} c_1 &= n_1^C - q(b, k)b + d_1, \\ c_2(\omega) &= n_2^C(\omega) + d_2(\omega) + b\left(\mathbb{I}_{\{\omega a \geqslant b\}} + \pi \mathbb{I}_{\{\omega a < b\}} + (1-\pi)\chi\frac{\omega a}{b}\mathbb{I}_{\{\omega a < b\}}\right) - T_2. \end{aligned}$$

The budget constraint in period 1 equalizes the consumption of consumers and with the savings in debt $q(b, a)b$ and equity to intermediaries. The budget constraint in period 2 equalizes the consumption of consumers with the face value of debt b for every realization of the state ω and intermediaries dividends net of transfers from government T_2.

Technology and financial contracts. At time 1, intermediaries choose how much asset, a, at price p to buy. By time 2, the intermediaries' assets generate a random return $\omega \geqslant 0$, which follows a distribution $F(\omega) \equiv F$ with $\text{supp}(\omega) = [0, \bar{\omega})$. In the interest of simplicity, we assume that $\int \omega dF(\omega) = 1$. Intermediaries finance their investment by issuing debt with face value b and price $q(b, k)$. We define leverage as the ratio of debt over assets, $\ell = \frac{b}{a}$. It needs to raise the difference in equity. After realization of returns in period 2, intermediaries choose whether to default or not. If the intermediaries default, shareholders receive nothing while financiers are bailed out with probability π by the government, in which case they receive b per unit of capital; otherwise, they receive $\chi\omega$ per unit of investment, where $0 \leqslant \chi \leqslant 1$. The remainder $(1-\chi)\omega$ measures the deadweight loss or costs associated with default. If the intermediaries do not default, financiers are paid b and shareholders receive the residual claim $(1-\phi)(\omega a - b)$ in the form of dividends. ϕ captures the costs of equity issuance or tax advantage of debt. Costs of default and equity issuance costs ensures a nontrivial choice of capital structure. We assume that the costs of bank equity are private and so that $\phi(\omega a - b)$ is reimbursed to the consumers in the form of lump sum transfers. Making the costs of equity social would not impact the results qualitatively.

Regulation. The government finances bailouts by raising lump sum taxes from consumers in period 2. The government balances his budget period by period so that

$$T_2 = \int_0^{\ell} \pi \left(\ell - \chi\omega\right) dF(\omega).$$

The government is also able to impose a leverage cap on intermediaries at date 1. Formally, the government requires that intermediaries set $\ell \leqslant \xi$, where $1-\xi$ is the minimal permitted ratio of equity contribution to risky investment. This constraint imposes a leverage cap, or equivalently, a minimal equity contribution per unit of investment.

Equilibrium definition. An equilibrium is defined as a set of intermediary's capital structure $d_1, b, a, d_2(\omega)$ and default decision, prices for intermediaries debt q and assets p, such that (i) intermediaries maximize their expected net present value while taking into account that any debt issued is valued by consumers, (ii) consumers maximize their utility, and (iii) the capital market clears, $a = 1$.

Our notion of equilibrium, in which intermediaries internalize that their borrowing decisions affect their cost of financing in equilibrium, is standard in models of default.

H.2 Equilibrium characterization

We introduce Lemma 1 which presents a reformulation of the intermediary problem whose solution characterize equilibrium leverage.

Lemma 1 (Intermediaries' problem)**.** *Equilibrium leverage is given by the solution to the following reformulation of the problem faced by intermediaries:*

$$\nu = \max_{\ell} q(\ell)\ell - p + \beta^{I} \int_{\ell}^{\bar{\omega}} (\omega - \ell) dF(\omega) \tag{H.1}$$

where $\beta(1-\phi) = \beta^{I}$*, subject to the leverage constraint and the debt pricing equation*

$$\ell \leqslant \xi, \tag{H.2}$$

$$q(\ell) = \beta \left[\int_{\ell}^{\bar{\omega}} dF(\omega) + \int_{0}^{\ell} \left(\pi + (1-\pi) \frac{\chi\omega}{\ell} \right) dF(\omega) \right]. \tag{H.3}$$

The size decision of the intermediary is then given by

$$\max_{a \geqslant 0} a\nu.$$

Proof of Lemma 1. The problem that intermediary face at date 1, after anticipating their optimal default decision, can be expressed as follows:

$$V = \max_{b,a,d_1,d_2(\omega)} d_1 + \beta(1-\phi) \int d_2(\omega) dF(\omega)$$

subject to budget constraints at date 1 and in each possible state $\{\omega, \pi\}$ at date 1, the capital requirement and the consumers' debt pricing equation

$$d_1 = q(b,a)b - pa, \tag{H.4}$$

$$d_2(\omega) = \max\{\omega a - b, 0\}, \forall \omega \tag{H.5}$$

$$\frac{b}{a} \leqslant \xi, \tag{H.6}$$

$$q(b,a) = \beta \left[\int_{\frac{b}{a}}^{\bar{\omega}} dF(\omega) + \int_{0}^{\frac{b}{a}} \left(\pi + (1-\pi) \frac{\chi\omega a}{b} \right) dF(\omega) \right]. \tag{H.7}$$

Financiers take into account that higher intermediary leverage increases the probability of a default. The intermediary internalizes this effect when making its leverage decision.

First, notice that intermediaries optimally default at date 1 whenever $\omega < \ell$ and repay when $\omega \geqslant \ell$. To solve the intermediary problem, divide the intermediary objective by a

to get

$$\nu = \max_{\ell} d_1 + \beta(1-\phi)\int_{\ell}^{\bar{\omega}} (\omega - \ell)dF(\omega)$$

subject to the budget constraint at date 0 and the debt pricing equation

$$d_1 = q(\ell)\ell - p \tag{H.8}$$

$$\ell \leqslant \xi, \tag{H.9}$$

$$q(\ell) = \beta\left[\int_{\ell}^{\bar{\omega}} dF(\omega) + \int_0^{\ell}\left(\pi + (1-\pi)\frac{\chi\omega}{\ell}\right)dF(\omega)\right]. \tag{H.10}$$

Substituting period 1 budget constraint into the objective function, we can rewrite the problem as in the statement of the lemma. The size decision of the intermediary is then given by

$$\max_{a \geqslant 0} a\nu.$$

□

It is possible to fully characterize the equilibrium of the model by incorporating the default decision of intermediaries at date 1 and the pricing of debt by consumers into the intermediaries' date 0 problem. First, notice that intermediaries optimally default at date 1 whenever $\omega < \ell$ and repay when $\omega \geqslant \ell$. The first component of the objective function represents the equity issued/dividends paid by the intermediary in period 0 to the consumers. The second component in equation (H.1) corresponds to the present value of the equity payoffs. Since consumers are only paid in the nondefault states, this integral is over states in which $\omega \geqslant \ell$. The first constraint is the leverage constraint, which states that the ratio of debt over assets cannot exceed ξ. The second constraint corresponds to the present value of the debt payoffs in default states (per unit), as perceived by consumers. When intermediaries default ($\omega < \ell$), consumers receive $\chi\omega$ per unit of investment, which accounts for the deadweight losses of default. Intermediaries do not directly benefit from government bailouts and their objective function simply corresponds to their market value at date 2. Nevertheless, markets generate implicit incentives to capture government bailouts, because the implicit subsidy is accounted for in security prices.

We are now ready to characterize the optimal solution to the intermediary problem in the following proposition.

Proposition 4 (Equilibrium leverage)**.** *Equilibrium leverage $\ell^\star$ is given by the solution to*

$$\frac{d\nu\left(\ell^\star\right)}{d\ell} = \underbrace{\beta\int_0^\ell \pi dF(\omega) + \left(\beta-\beta^I\right)\int_\ell^{\bar{\omega}} dF(\omega)}_{\substack{\textit{marginal benefits} \\ \textit{(subsidy + valuation difference)}}} - \underbrace{\beta(1-\pi)(1-\chi)\ell f(\ell)}_{\substack{\textit{marginal costs} \\ \textit{(distress)}}} = \lambda. \tag{H.11}$$

where λ is the Lagrange multiplier associated with the leverage constraint.

Three forces determine the marginal value of leverage, characterized in Equation (H.11). The first force corresponds to the additional leverage an intermediary is able to raise because of the bailout subsidy in present value terms. The second force arises due to the differences in valuation between intermediaries and consumers. By increasing the leverage ratio ℓ, an intermediary is able to raise in present value terms $\beta(1-F(\ell))$ dollars per unit invested, whose repayment cost in present value terms corresponds to $\beta(1-\phi)(1-F(\ell))$. This second force is proportional to the difference in discount factors $\beta-\beta^I>0$. The third force corresponds to the marginal increase in deadweight losses associated with defaulting more frequently after increasing leverage. These three forces guarantee that equilibrium leverage is strictly positive.

Notice that

$$\frac{d\nu\left(\ell\right)}{d\ell}\,|_{\ell=0}= \beta-\beta^I>0,$$

so that the intermediary find it optimal to choose non-negative leverage in equilibrium. Therefore, for a given leverage constraint ξ, our problem always features a solution for leverage in $[0,\xi]$. The presence of bailout subsidies imply that intermediary would lever up to the maximum leverage constraint ξ given the linearity of their problem so that $\ell=\xi$.

Note that a positive amount of bank investment $a>0$ in equilibrium requires that the expected profit per unit is zero, $\nu=0$, which, when combined with equation (H.1), gives intermediaries willingness to pay for a dollar of risky assets as

$$p = q(\xi)\xi + \beta^I\int_\xi^{\bar{\omega}}(\omega-\xi)dF(\omega). \tag{H.12}$$

which corresponds the present value of the expected payoffs of the intermediary's assets. The first term corresponds to the present value of the expected payoffs of the debt issued by the intermediary, while the second term corresponds to the present value of the expected payoffs of the equity issued by the intermediary.

H.3 Comparative statics

First, we show how the equilibrium asset price p changes with the bailout probability π and the leverage constraint ξ.

Lemma 2. *The intermediaries willingnes to pay for a dollar of risky assets* p *is increasing in the bailout probability* π *and in the leverage constraint* ξ*. The debt price* q *is increasing in the bailout probability* π *and decreasing in the leverage constraint* ξ*.*

Proof of Lemma 2. We start with studying changes in ξ. Given the expression for the asset price,

$$\begin{aligned} p &= \beta\left[\int_{\xi}^{\bar{\omega}} \xi dF(\omega) + \int_{0}^{\xi} (\pi\xi + (1-\pi)\chi\omega)\, dF(\omega)\right] + \beta^{I} \int_{\xi}^{\bar{\omega}} (\omega - \xi) dF(\omega), \\ &= \beta \int_{0}^{\xi} (\pi\xi + (1-\pi)\chi\omega)\, dF(\omega) + \int_{\xi}^{\bar{\omega}} (\beta^{I}\omega + (\beta - \beta^{I})\xi) dF(\omega), \end{aligned}$$

We can differentiate the asset price with respect to ξ:

$$\frac{\partial p}{\partial \xi} = q(\xi) + \xi \frac{\partial q}{\partial \xi} - \beta^{I}(1 - F(\xi)).$$

By using the first-order condition for leverage evaluated at $\ell = \xi$, we can express the derivative as exactly the marginal value of leverage, λ, which is positive. Therefore, the asset price is increasing in ξ. Secondly, the asset price is increasing in π since

$$\frac{\partial p}{\partial \pi} = \xi \frac{\partial q}{\partial \pi} = \beta \int_{0}^{\xi} (\xi - \chi\omega)\, dF(\omega) > 0.$$

Finally, the debt price is increasing in π since

$$\frac{\partial q}{\partial \pi} = \beta \int_{0}^{\xi} (\xi - \chi\omega)\, dF(\omega) > 0,$$

and decreasing in ξ since

$$\frac{\partial q}{\partial \xi} = -\beta(1-\pi)\left\{ f(\xi)\left[1 - \tfrac{\chi\omega}{\xi}\right] + \tfrac{\chi\omega}{\xi^2} F(\xi) \right\} < 0.$$

□

Second, we are interested in understanding how the sensitivity of asset prices to bailout probabilities and leverage constraints changes with riskiness of the asset. To do so, we want to compare the derivatives characterized in Lemma 2 under perturbations of the distribution of the asset returns. Since we have specified flexible distributions of asset returns, we will characterize how the asset price sensitivities to bailout probability and leverage change with changes in the risky asset payoff distribution using variational (Gateaux) derivatives. Formally, we consider perturbations of the form

$$F(\omega) + \varepsilon G(\omega),$$

where $F(\omega)$ denotes the original cumulative distribution function of ω, the variation $G(\omega)$ represents the direction of the perturbation and $\varepsilon \geqslant 0$ is a scalar. When $G(\omega) < 0$, it is natural to say that for the perturbed distribution the probability assigned to states equal or lower than ω is now higher. We consider variations $G(\omega)$ that are continuously differentiable and satisfy $G(0) = G(\bar{\omega}) = 0$. These conditions ensure that perturbed beliefs are still valid cumulative distribution functions for small enough values of ε. We particularly analyze perturbations $G(\omega)$ that induce lower risk in the sense of hazard-rate dominance. Formally, an absolutely continuous distribution $F(\omega)$ becomes less risky in the sense of hazard-rate dominance if the hazard rate $h(\omega) \equiv \frac{f(\omega)}{1-F(\omega)}$ decreases for all ω. This is a stronger requirement than first-order stochastic dominance, but a weaker requirement than the monotone likelihood ratio property. Therefore, in terms of variational derivatives, a perturbation $G(\omega)$ induces optimism in a hazard-rate sense if $\frac{\delta h(\omega)}{\delta F} \cdot G \leqslant 0$ for all ω (Dávila & Walther 2023).

Lemma 3. *The sensitivity of the asset price* p *to the bailout probability* π *and the leverage constraint* ξ *in response to changes in the distribution of the asset payoffs is given by the following variational derivatives:*

$$\frac{\delta \frac{dp}{d\pi}}{\delta F} \cdot G = \beta G(\xi)\xi(1-\chi) + \beta\chi \int_0^{\xi} G(\omega) d\omega,$$
$$\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G = -G(\xi) \left(-\beta\pi + (\beta - \beta^I) + \beta(1-\pi)(1-\chi)\xi \frac{g(\xi)}{G(\xi)} \right).$$

If we consider hazard-rate-dominant perturbations such that $G(\omega) < 0$*, then the first derivative is negative and the second derivative is ambiguous and inversely related to* π*.*

Proof of Lemma 3. Before proving the results, we prove the property of hazard rate perturbations that we will use to show the main results of the lemma. The hazard rate after an arbitrary perturbation is given by $h(\omega) = \frac{f(\omega)+\varepsilon g(\omega)}{1-(F(\omega)+\varepsilon G(\omega))}$. Its derivative with respect to ε takes the form

$$\frac{dh(\omega)}{d\varepsilon} = \frac{g(\omega)}{1-(F(\omega)+\varepsilon G(\omega))} + \frac{(f(\omega)+\varepsilon g(\omega))G(\omega)}{(1-(F(\omega)+\varepsilon G(\omega)))^2}.$$

In the limit in which $\varepsilon \to 0$, for hazard-rate dominance to hold, it must be the case that $\lim_{\varepsilon \to 0} \frac{dh(\omega)}{d\varepsilon} < 0$; therefore

$$\lim_{\varepsilon \to 0} \frac{dh(\omega)}{d\varepsilon} = \frac{g(\omega)}{1 - F(\omega)} + \frac{f(\omega)}{1 - F(\omega)} \frac{G(\omega)}{1 - F(\omega)} < 0$$
$$\iff g(\omega) + \frac{f(\omega)}{1 - F(\omega)} G(\omega) < 0$$
$$\iff \frac{g(\omega)}{G(\omega)} + \frac{f(\omega)}{1 - F(\omega)} > 0$$
$$\iff \frac{f(\omega)}{1 - F(\omega)} > -\frac{g(\omega)}{G(\omega)}$$

where in the second-to-last line the sign of the inequality flips because $G(\omega)$ is negative, since hazard-rate dominance implies first-order stochastic dominance. We compute $\frac{\delta \frac{dp}{d\pi}}{\delta F} \cdot G$ as follows:

$$\frac{\delta \frac{dp}{d\pi}}{\delta F} \cdot G = \lim_{\varepsilon \to 0} \frac{\left(\beta \int_0^{\xi} (\xi - \chi\omega)\, d\,(F + \varepsilon G)\right) - \left(\beta \int_0^{\chi} (\xi - \chi\omega)\, dF\right)}{\varepsilon}$$
$$= \beta \left(\int_0^{\xi} (\xi - \chi\omega)\, dG(\omega) \right) = \beta G(\xi)\xi - \beta\chi \int_0^{\xi} \omega dG(\omega)$$
$$= \beta G(\xi)\xi(1 - \chi) + \beta\chi \int_0^{\xi} G(\omega) d\omega,$$

where the last equality follows after integrating by parts. If we consider a distribution G that dominates F in a hazard-rate sense, $G(\omega) < 0$, then it is clear that the derivative is negative. In the same way, we can compute $\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G$ as follows:

$$\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G = \beta\pi G(\xi) + (\beta - \beta^I)(1 - G(\xi)) - \beta(1 - \pi)(1 - \chi)\xi g(\xi)$$
$$= -G(\xi) \left(-\beta\pi + (\beta - \beta^I) + \beta(1 - \pi)(1 - \chi)\xi \frac{g(\xi)}{G(\xi)} \right).$$

If we consider a distribution G that dominates F in a hazard-rate sense, $G(\omega) < 0$, then it is sufficient to study the sign of the term in the parentheses:

$$-\beta\pi + (\beta - \beta^I) + \beta(1 - \pi)(1 - \chi)\xi \frac{g(\xi)}{G(\xi)}.$$

At an interior optimum, Equation (H.11) implies that

$$\frac{dp}{d\xi} = \frac{\beta\pi}{1 - F(\xi)} - \beta\pi + \beta - \beta^I - \beta(1 - \chi)(1 - \pi)\xi \frac{f(\xi)}{1 - F(\xi)} = \lambda \geqslant 0$$

or, equivalently,

$$\beta(1-\pi)-\beta^{I} \geqslant \beta(1-\chi)(1-\pi)\xi\frac{f(\xi)}{1-F(\xi)}-\frac{\beta\pi}{1-F(\xi)}.$$

Hazard-rate dominance implies that $\frac{f(\omega)}{1-F(\omega)} \geqslant -\frac{g(\omega)}{G(\omega)}$, so the following relation holds:

$$\beta(1-\pi)-\beta^{I} \geqslant -\beta(1-\pi)(1-\chi)\xi\frac{g(\xi)}{G(\xi)}+\frac{\beta\pi g(\xi)}{f(\xi)G(\xi)}$$

The sign of the expression is ambiguous and, it particularly depends on the extent to which creditors are bailed out. In the limit as π approaches 0, the term is positive and so the sign of the derivative is positive, but as π approaches 1, the term can turn into negative as the bailout likelihood decreases the distress costs arising from default. This can make the derivative negative. □

The first derivative is negative under hazard-rate dominance ($G(\omega) \leqslant 0$). A less risky distribution dampens the effect of bailouts (πx) on asset prices. Bailouts become more impactful in riskier environments because higher default risk (more mass at $\omega < \xi$) increases the value of bailout guarantees; greater exposure to low-ω states ($\int_0^{\xi} G(\omega)d\omega \geqslant 0$) raises the implicit subsidy from bailouts. If the payoff distribution has less mass in the left tail (lower default likelihood), the bailout subsidy becomes less valuable. When F shifts toward safer states ($G(\omega) < 0$), intermediaries and consumers anticipate lower bailout transfers, which deflate asset prices. This makes bailout policies less potent in propping up prices when assets are safer.

On the other hand, the sign of the variational derivative $\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G$ depends critically on the bailout probability π. The net effect is determined by the balance of three components:

$$\underbrace{-\beta\pi}_{\substack{\text{Reduced marginal benefit}\\ \text{from bailouts}}} + \underbrace{(\beta-\beta^{I})}_{\substack{\text{Valuation difference}\\ \text{(debt vs. equity)}}} + \underbrace{\beta(1-\pi)(1-\chi)\xi\frac{g(\xi)}{G(\xi)}}_{\substack{\text{Marginal default cost}\\ \text{amplified by risk}}}.$$

When $\pi \approx 0$, the net effect simplifies to:

$$(\beta-\beta^{I})+\beta(1-\chi)\xi\frac{g(\xi)}{G(\xi)} > 0,$$

which implies $\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G > 0$. A safer distribution ($G(\xi) < 0$) increases the price sensitivity to leverage constraints, as default costs are less important. Conversely, when $\pi \approx 1$, the net effect becomes:

$$-\beta + (\beta - \beta^I) < 0,$$

yielding $\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G < 0$. With full bailouts, safer distributions decreases price sensitivity to leverage constraints, as bailouts subsidize default risk. This nonmonotonicity reflects the interplay between bailout subsidies, valuation differences, and default costs. Policymakers must account for both asset riskiness and bailout expectations when designing leverage constraints: higher capital requirements depress intermediaries willingness to pay for risky assets, but the effect is more pronounced when more bailouts are expected.

H.4 Variance of equity returns, bailouts and regulation

With a binding leverage cap $\ell = \xi$, per-unit-asset equity pays

$$\tilde{e}(\omega) = \big(1 - \phi\big)\,(\omega - \xi)\,\mathbf{1}_{\{\omega \geqslant \xi\}}, \quad E_0 = \beta^I \underbrace{\int_{\xi}^{\bar{\omega}} (\omega - \xi)\,dF(\omega)}_{=A(\xi)},$$

so the gross equity return per dollar of initial equity is

$$R_E(\omega) = \frac{\tilde{e}(\omega)}{E_0} = \frac{(\omega - \xi)\mathbf{1}_{\{\omega \geqslant \xi\}}}{A(\xi)}, \qquad \mathbb{E}[R_E] = 1.$$

Define[33]

$$\sigma_L^2(\xi) := F(\xi), \qquad \sigma_R^2(\xi) := \int_{\xi}^{\bar{\omega}} \big(R_E(\omega) - 1\big)^2\,dF(\omega),$$

so that total variance satisfies

$$\sigma_E^2(\xi) = \sigma_L^2(\xi) + \sigma_R^2(\xi) \;=\; \frac{B(\xi)}{A(\xi)^2} - 1,$$

because $\sigma_L^2 = F(\xi)$ and $\sigma_R^2 = (B/A^2) - 1 - F(\xi)$. Using $A'(\xi) = -(1 - F(\xi))$, $B'(\xi) = -2A(\xi)$, one obtains

$$\boxed{\frac{\partial \sigma_L^2}{\partial \xi} = f(\xi) > 0} \qquad \text{and} \qquad \boxed{\frac{\partial \sigma_R^2}{\partial \xi} = \frac{2\big[(1 - F(\xi))\,B(\xi) - A(\xi)^2\big]}{A(\xi)^3} > 0},$$

where the strict inequality for σ_R^2 relies on Cauchy–Schwarz: $B(\xi)(1 - F(\xi)) \geqslant A(\xi)^2$ with equality only for degenerate payoffs.

Increasing the cap (higher ξ) raises both left-tail mass and right-tail dispersion; con-

[33] $A(\xi)$ and $B(\xi)$ are standard "truncated moment" objects: $A(\xi) = \int_{\xi}^{\bar{\omega}} (\omega - \xi)\,dF$, $B(\xi) = \int_{\xi}^{\bar{\omega}} (\omega - \xi)^2\,dF$.

versely, **tightening capital regulation** (lower ξ) *reduces both contributions in the same direction*. Thus the variance-cutting effect of stricter capital is "tail-symmetric."

On the other hand, because the cap binds, $\ell = \xi$ is fixed by regulation and does not respond to π:

$$\frac{\partial \xi}{\partial \pi} = 0.$$

Equity pay-offs themselves never contain the bailout transfer; therefore

$$\boxed{\frac{\partial \sigma_L^2}{\partial \pi} = 0}, \qquad \boxed{\frac{\partial \sigma_R^2}{\partial \pi} = 0}.$$

A change in the bailout probability π leaves both tails *unchanged* when leverage is already capped. Bailout expectations can affect equity-return variance only indirectly, by altering the chosen leverage, once the cap ceases to bind; in that interior region, the impact operates through the left tail first and then transmits to the right via the leverage channel.

When the regulatory cap is loose enough that the intermediary's optimal leverage is determined by the first-order condition (H.11), with $\sigma_L^2 = F(\ell^\star)$ we have

$$\boxed{\frac{d\sigma_L^2}{d\pi} = f(\ell^\star)\,\frac{d\ell^\star}{d\pi} > 0} \quad \Longrightarrow \quad \pi \uparrow \;\Rightarrow\; \text{default probability rises.}$$

Using the earlier derivative $\dfrac{\partial \sigma_R^2}{\partial \ell} = \dfrac{2\big[(1-F)\,B - A^2\big]}{A^3} > 0$, the chain rule gives

$$\boxed{\frac{d\sigma_R^2}{d\pi} = \frac{\partial \sigma_R^2}{\partial \ell}\,\frac{d\ell^\star}{d\pi} > 0} \quad \Longrightarrow \quad \pi \uparrow \;\Rightarrow\; \text{right-tail dispersion rises.}$$

Hence, bailouts affect equity variance only through the leverage choice. If the cap is slack, higher π pushes $\ell^\star$ up, thereby raising both the frequency of default (left tail) and the dispersion of surviving returns (right tail). Lower π does the opposite. Tightening ξ that becomes binding compresses leverage directly and symmetrically trims both tails, independent of π.

H.5 Social-planner problem

The planner internalizes all real resource costs, deadweight default losses and equity-issuance costs, while treating bailout transfers and lump-sum taxes as pure redistribution. Normalizing the investment scale to $a = 1$ (linearity), the planner solves

$$\max_{\ell \leqslant \xi} \mathcal{W}(\ell) := \beta \Big[-\underbrace{\phi \int_{\ell}^{\bar{\omega}} (\omega - \ell)\, dF(\omega)}_{\text{equity-issuance cost}} - \underbrace{(1-\chi) \int_{0}^{\ell} \omega\, dF(\omega)}_{\text{default dead-weight loss}} \Big]. \tag{SP}$$

First-order condition. Denote the pdf by $f(\omega) = F'(\omega)$. Differentiating $\mathcal{W}$ and imposing the Kuhn–Tucker multiplier λ^{SP} for the cap constraint:

$$\boxed{\beta\phi\big[1 - F(\ell)\big] - \beta(1-\chi)\,\ell f(\ell) = \lambda^{SP}} \tag{FOC$_{SP}$}$$

with complementary-slackness $\lambda^{SP}(\ell - \xi) = 0,\ \lambda^{SP} \geqslant 0$. Comparing the FOC_{SP} with the FOC_{Priv} in (H.11), we see that the planner internalizes the bailout subsidy as a transfer. Therefore, in distress, the planner perceived that the default costs are higher than the private agent. Because both the marginal benefit is higher and the marginal cost is lower for the intermediary, we have $\ell^{SP} < \ell^{Priv}$ whenever $\pi > 0$. The planner therefore faces a classic regulation trade-off: choose ξ low enough to curb excessive leverage (and its dead-weight default losses) yet not so low that it foregoes the efficiency gains from substituting cheaper debt for costly equity. Formally, the optimal capital requirement satisfies

$$\xi^{\star} = \ell^{SP}.$$

H.6 Optimal bailout policy

The social planner maximizes total welfare $\mathcal{W}$, which equals the sum of consumer and intermediary utilities. Under risk neutrality, this reduces to minimizing deadweight losses from default and equity costs. We derive the planner's optimal bailout policy in three steps.

Let $\ell(\pi, \xi)$ denote equilibrium leverage under bailout probability π and cap ξ. Welfare per unit asset is:

$$\mathcal{W}(\pi, \xi) = \underbrace{-\beta\phi \int_{\ell}^{\bar{\omega}} (\omega - \ell) dF(\omega)}_{\text{Equity costs}} \underbrace{-\beta(1-\chi) \int_{0}^{\ell} \omega dF(\omega)}_{\text{Default losses}} \tag{H.13}$$

where ϕ captures equity issuance costs and χ recovery rates.

The private FOC for leverage (eq. H.11) equates marginal benefits (subsidy + valuation gap) to marginal costs (default). The social planner internalizes externalities:

$$\ell^{SP} = \arg\max_{\ell} \mathcal{W}(\ell)$$
$$\Rightarrow \beta[\phi(1 - F(\ell)) - (1 - \chi)\ell f(\ell)] = 0 \tag{H.14}$$

Comparing (H.11) and (H.14) reveals $\ell^*_{\text{Priv}} > \ell^{SP}$: private leverage exceeds the social optimum due to bailout subsidies. When the cap is slack ($\ell^*_{\text{Priv}} < \xi$), total derivative:

$$\frac{d\mathcal{W}}{d\pi} = \underbrace{\frac{\partial \mathcal{W}}{\partial \ell}\frac{d\ell^*_{\text{Priv}}}{d\pi}}_{\text{Indirect effect via leverage}}$$
$$\text{where } \frac{\partial \mathcal{W}}{\partial \ell} = \beta[\phi(1 - F(\ell)) - (1 - \chi)\ell f(\ell))] < 0 \tag{H.15}$$
$$\frac{d\ell^*_{\text{Priv}}}{d\pi} = \frac{\beta \int_0^{\ell^*} dF + \beta(1 - \chi)\ell^* f(\ell^*)}{(\beta - \beta^I)f(\ell^*) + \beta(1 - \pi)(1 - \chi)f(\ell^*)} > 0 \tag{H.16}$$

The negative indirect effect dominates, implying $\frac{d\mathcal{W}}{d\pi} < 0$. Thus:

Proposition 5 (Optimal bailout policy)**.** *The welfare-maximizing bailout probability is:*

$$\pi^\star = 0 \quad \textit{(strictly optimal if cap is slack, weakly if binding)}$$

Proof. When ξ binds ($\ell = \xi$), $\frac{d\ell}{d\pi} = 0 \Rightarrow \frac{d\mathcal{W}}{d\pi} = 0$. However, setting $\pi = 0$ remains weakly optimal as bailouts only redistribute without affecting real allocations. For slack caps, the negative leverage effect makes $\pi = 0$ strictly optimal. □