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

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**Abstract**

This paper accounts for the role of bailout expectations in shaping the dynamics of banks' credit spreads. I consider a dynamic model of financial intermediation with bank default and time-varying bailout probabilities. In this environment, banks' 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. Tracking their evolution allows me to indirectly infer the relative importance of fundamentals and bailout expectations. Fitting the model to U.S. data, I find that 28 basis points of the 34-basis-point rise in credit spreads after 2010 are due to lower perceived bailout probabilities, with the remainder reflecting weaker fundamentals, partly offset by tighter capital requirements. Finally, I use this decomposition to assess the implications of lower bailout expectations and tighter regulation on banks' risk-taking incentives.

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# 1 Introduction

Since the Global Financial Crisis (GFC), spreads on unsecured bank debt have more than tripled and remained well above pre-crisis levels. This persistence continued despite the post-GFC tightening of regulation, which reduced bank leverage and, all else equal, should have compressed credit spreads by lowering insolvency risk. A plausible driver of higher spreads is the market's reassessment of government support: Title II of the Dodd–Frank Act passed in 2010 sought to curb such expectations by empowering regulators to impose losses on unsecured creditors.[1] However, higher spreads can also be accounted for by weaker fundamentals that raised default risk.

Understanding whether the post-2010 increase in credit spreads reflects higher fundamental risk or a reduction in bailout expectations is crucial to the design of financial regulation. Capital requirements are typically justified as a way to curb the moral-hazard that arises when bank creditors expect to be shielded from losses by the government (Kareken & Wallace 1978, Chari & Kehoe 2016*a*). Yet, evaluating the appropriate stringency of ex-ante regulation requires explicitly accounting for bailout expectations. If reduced bailout expectations drive higher spreads, market discipline already curbs risk-taking, and less tight ex-ante policies may suffice.

The contribution of this paper is to decompose bank credit spreads into a component driven by bailout expectations and another one driven by fundamentals. To do so, I combine a dynamic model of financial intermediation with estimates of 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. Through the lens of the model, the comovement of credit spreads and default probabilities is informative about the relative importance of the two components. The model interprets higher credit spreads together with lower default probabilities as evidence that bailout expectations play an important role. I find that, of the 34-basis-point rise in credit spreads after 2010, about 28 basis points are attributable to lower bailout probabilities. The remainder is driven by fundamentals—about 18 basis points—partly offset by tighter regulation, which lowered default risk and reduced spreads by roughly 12 basis points.

I then use this decomposition to evaluate how Dodd-Frank and the subsequent wave of bank regulation after 2010 changed banks attitudes toward risk. First, my model rationalizes banks' post-crisis retreat from very risky asset markets (e.g. leveraged loans market). Lower bailout expectations increased banks' funding costs, which in turn disproportionately raised risk premia for assets with tail risk exposure, compared to tighter

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

regulatory requirements. Second, a higher cost of capital and greater reliance on expensive equity driven by lower bailout expectations and tighter regulation help explain the reduction in the growth rate of banks' balance sheets post-GFC and the sluggish recovery in asset valuations.

To discipline the model, this paper first proposes a methodology to measure the risk-neutral losses conditional on default for debt holders. I begin with a simple decomposition of credit spreads into a risk-neutral probability of default and an expected loss given default component. When credit spreads stay high even as risk-neutral default probabilities fall, they must be driven by higher losses given default. In this framework, the expected loss given default equals the probability of no bailout times the loss creditors bear without government support. If a bailout with probability $\pi$ makes wholesale creditors whole, while with probability $1 - \pi$ recoveries are tied to the post-default asset value, then a decline in bailout probabilities mechanically raises the expected loss given default and, in turn, spreads, even if default risk itself falls.

Building on this decomposition, I measure expected losses given default in two steps. First, I read the market-implied chance of default from prices of put options on the bank's stock building on the methodology of Carr & Wu (2011). Second, I combine these option-implied default probabilities with Credit Default Swaps (CDS) spreads to recover an estimate of the risk-neutral loss given default. The recovery of the mid-2000s sees projected creditor losses near fifteen percent, but these losses swell to around sixty percent on the eve of the 2007-2009 crisis and remain elevated through the downturn. As sovereign default concerns spike in 2011, expected losses climb again before settling near thirty percent through much of the 2010s and then easing back toward twenty percent by 2020. These countercyclical swings in market-implied losses mirror business-cycle stresses and confirm that creditors' downside exposure is far from constant. I show that a significant portion (around 50%) of the variation in short-term credit spreads can be attributed to changes in expected losses given default and that illiquidity measures in CDS and option markets do not play a major role in explaining the observed variation in expected losses.

However, the post-GFC increase in expected losses—and, consequently, in CDS spreads—could reflect deteriorating fundamentals rather than a change in perceived government support. Observational data alone cannot separate shifts in fundamentals from changes in anticipated government support, because default probabilities are themselves equilibrium outcomes of banks' endogenous decisions and thus depend on 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. Banks hold portfolios of long-term defaultable securities subject to mean-reverting aggregate shocks and disasters. Banks fund those assets by issuing deposits, bank debt, and equity. Deposits trade below market rates and are fully insured by the government. The government bails out debt holders with a time-varying probability $\pi$. When a bailout is granted, the government pays the full shortfall to debt holders, otherwise investors recover the fraction of post-default asset value. Finally, equity issuance is costly: banks face adjustment costs which increase the cost of equity relative to other liabilities.

In this setup, credit spreads on unsecured bank debt vary over time because of fundamental risk—namely, the risk that the bank's assets generate cash flows insufficient to meet debt obligations—and changes in bailout expectations. While these two forces have similar effects on spreads, they have different implications for the bank's insolvency risk.

When the bailout probability is low, the expected loss from default increases dollar-for-dollar, effectively taxing debt issuance by increasing the weight on default costs. This leads to an increase in credit spreads (a drop in the price of debt) and induces intermediaries to take on less leverage. As a result, the default probability is lower ex post. However, when fundamentals deteriorate (e.g., expected asset cash flows fall or risk increases), the expected loss borne by creditors rises. This pushes up credit spreads (debt funding costs) and, even after banks adjust leverage optimally, raises the probability of insolvency, so default rates increase.

Because of these properties, the comovement of credit spreads and default probabilities provides information about the importance of bailout expectations versus fundamentals. All else equal, observing persistently higher credit spreads together with higher default probabilities is interpreted by the model as evidence of a quantitatively sizable role for fundamentals. By contrast, an increase in credit spreads accompanied by a declining default probability indicates that bailout expectations are the underlying source.[2]

In practice, this simple reasoning does not account for the possibility that tighter post-GFC regulation changed how banks manage risk exposure and reduced insolvency risk. However, this argument does not impair my identification strategy. If true risk-neutral default rates were lower than my estimates, that would justify lower post-crisis spreads. Instead, spreads remain persistently higher. Without accounting for changes in regulation, the model would understate the role of bailout expectations. Hence, to discipline the increase in capital requirements and precisely isolate the role of bailout expectations, I exploit the fact that, conditional on fundamentals, the two move credit spreads and the left-tail variance of equity returns in opposite directions in the model. When investors mark down the likelihood of a rescue, spreads rise since creditors expect bigger losses.

[2] Similarly, Bocola & Dovis (2019) use the behavior of the maturity structure of government debt to discipline the component of spreads due to rollover risk versus the role of fundamentals.

Equity tail-volatilities fall because a larger share of downside is already borne by shareholders. Tighter regulation works the other way for credit spreads. By forcing bondholders to share losses ex ante it flattens spreads, yet it reduces downside volatility for equity, whose residual claim becomes less levered.

After fitting the model to U.S. data, I turn to the main quantitative experiment of the paper, which consists of measuring the bailout component of credit spreads. I apply 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 Great Financial Crisis. While doing this, I increase capital requirements from 8% to 10.5%.[3] This matches the increase in correlation between credit spreads and the left-tail variance of equity returns estimated in the data. Because lower bailout odds would have pushed the correlation down (spreads up, volatility down), the observed upward break cleanly identifies—and quantitatively pins down—the dominant role of the post-crisis regulatory regime.

Equipped with this path of structural shocks, I can compute the bailout component of credit spreads. To do so, I construct the counterfactual credit spreads that would have emerged if bailout probabilities were fixed at their pre-crisis level while feeding in the same sequence of fundamental shocks and changes in regulation. The estimated bailout probability allows a decomposition of observed credit spreads into a fundamental component and a bailout component, while controlling for tighter regulation. The bailout component of credit spreads is computed as the difference between actual and counterfactual spreads. The results indicate that diminished bailout odds explain about forty percent of the post-2010 plateau in spreads, with the remainder accounted for by fundamental risk and regulation. The average unsecured spread paid by large U.S. banks increases by 34 basis points between the pre-2008 and the post-2010 periods. In the counterfactual that holds the pre-crisis bailout probability at its high level, the same spread rises by only 6 basis points. Hence, the remaining 28 basis points—almost three quarters of the observed increase—are a pure bailout premium that investors demand once they expect to bear losses. Within the non-bailout component, deteriorating fundamentals account for an 18 basis point increase in unsecured spreads, while tighter post-crisis capital requirements reduced them by about 12 basis points. The intuition is that the increase in capital requirements, by reducing the leverage ratio of the intermediary and forcing it to

[3] I infer time-varying regulatory tightness from market prices by exploiting the model-implied sign reversal in the relationship between CDS spreads and the downside (left-tail) risk-neutral variance of equity returns—estimated from out-of-the-money put options—between the pre-2008 and post-2010 periods. In the model, conditional on fundamentals, changes in regulation and bailout expectations move CDS spreads and left-tail variance with opposite signs; the observed break in their correlation therefore identifies the post-crisis tightening of regulation. To purge fundamentals, I control for right-tail (upside) option-implied moments—constructed from out-of-the-money calls—which, under mild assumptions, load only on fundamentals and are largely insensitive to bailout expectations or capital requirements.

hold more equity, would have pushed down the credit spread by reducing its insolvency risk.

To isolate the importance of the intermediary capital structure in my inference approach, the model is used to construct an additional counterfactual in which banks are forbidden from adjusting leverage, holding it fixed at its ergodic mean. The gap between the counterfactual and the baseline spread measures the strength of the feedback channel through which higher uninsured funding costs lead banks to shrink debt and so mitigate part of the direct bailout-induced repricing. Ignoring this feedback would therefore understate the contribution of the implicit subsidy from government support.

Finally, the model is used to isolate how the post-crisis drop in bailout expectations and tighter regulation reshaped banks' funding costs, risk exposures and the post-crisis path to recovery in bank asset valuations.

While both lower bailout expectations and tighter capital requirements increase banks' cost of capital, they have distinct effects on the compensation that banks require for holding risky assets. When the perceived bailout probability falls, the expected loss borne by creditors rises precisely in default states (state-contingent). Debt financing therefore becomes especially expensive in the very bad states, so banks demand a larger premium to payoffs that are negatively skewed. By contrast, tighter capital requirements mainly operate by reducing leverage and default risk ex-ante and raise required returns through the chance that the constraint binds today or is expected to bind tomorrow. This channel increases average funding costs but it quantitatively loads less on disaster states than the direct increase in loss-given-default induced by lower bailout expectations. Hence, this paper shows that the post-crisis repricing of government guarantees is an important driver of the reallocation of intermediary portfolios away from jump-risk-intensive assets and the subsequent rise of the shadow banking sector.

These higher spreads coincide with a sluggish recovery in asset valuations. Intuitively, when funding becomes more expensive, the required hurdle rate for new investments rises. Risky assets tend to pay off in good times—when financing is easy—and to lose value exactly in bad states—when spreads are high. The higher cost of capital therefore bites where these assets underperform. It lowers the discounted value of their cash flows and reduces banks' willingness to pay for them. I find that this effect persists even though leverage and insolvency risk decline, a force that would otherwise compress spreads and support valuations. The persistent compression in asset valuations reflects slow intermediary recapitalization because equity is costly. Overall, I show that, while more stringent capital regulation successfully reduced bank leverage and default risk, it did not substantially change banks' attitudes toward risk and considerably slowed the recovery in asset valuations.

**Contribution to the literature.** My paper contributes to four strands of the literature. In doing so, it bridges theory and measurement at the intersection of macro-finance, asset pricing, and bank regulation.

My paper quantifies the moral-hazard channel through which anticipated public support distorts banks' leverage and portfolio choices, building on the seminal work of Kareken & Wallace (1978) and more recent contributions including those of Schneider & Tornell (2004), Acharya & Yorulmazer (2007), Diamond & Rajan (2012), Farhi & Tirole (2012), Bianchi (2016), Chari & Kehoe (2016*b*), Nosal & Ordoñez (2016), Bianchi & Mendoza (2018), Dávila & Walther (2020), Dovis & Kirpalani (2022). The core idea in all these papers is that the lack of commitment regarding ex-post optimal policies influences the ex-ante behavior of banks. Building on this insight, I take the bailout process as exogenous—capturing the market's perceived probability of government support—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, the paper offers 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 too-big-to-fail subsidy (Veronesi & Zingales 2010, Schweikhard & Tsesmelidakis 2011, Gandhi & Lustig 2015, Kelly et al. 2016, Hett & Schmidt 2017, Atkeson et al. 2019, Minton et al. 2019, Gandhi et al. 2020, Berndt et al. 2022). 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—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 also derive additional implications about how lower bailout expectations and tighter capital requirements affect banks' choices and macro outcomes.

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, Krishnamurthy & Muir 2017), but innovates by allowing the strength of the government guarantee to feed back into equilibrium leverage, amplifying the cyclicality of expected returns. My paper argues that changes in funding costs driven by state-contingent promises or driven by changes in rules (e.g., capital requirements) have different implications for the *types* of risk intermediaries require compensation for, which has been previously overlooked. 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 resorted to behavioral arguments to replicate the boom–bust pattern in credit valuations (Maxted 2024, Krishnamurthy & Li 2025), in my main estimation I show that the same dynamics can be replicated with movements in the perceived probability of a government bailout together with changes in fundamentals.

Finally, this paper contributes to the quantitative macro-banking literature (Van den Heuvel 2008, Corbae & D'Erasmo 2019, Mendicino et al. 2019, Begenau 2020, Elenev et al. 2021) by using the model to quantify how bailout expectations and fundamentals jointly shape banks' credit spreads and leverage decisions, and to assess the desirability of tighter capital requirements when bailout beliefs are time-varying and influence intermediaries' incentives to take on risk.

This paper is organized as follows. Section 2 lays down 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, risk exposures and the post-crisis path to recovery. 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. 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, ensuring 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 $t$.[4] For ease of notation, we define the risk-free discount factor from $t$ to $\tau$ 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 $\Delta_t$ is the default indicator. If default takes place, the government implements a bailout with probability $\pi_t$, otherwise debtholders recover $\hat{V}_t \leqslant P_t^D D_t$. Hence the payoff per unit of face value is

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

The market value of the debt equals the discounted stream of these payoffs:

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

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

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

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

[4]Formally, the risk-neutral measure is an equivalent martingale measure under which all discounted asset prices are martingales—hence asset prices equal the discounted expectation of future payoffs under this probability measure.

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 and this appears an implicit subsidy to the bank's franchise value.[5]

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

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

In Appendix A.1, I provide the detailed derivations of (1). There, I begin 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 standard CDS conventions: (i) a one-year horizon (rolling multi-maturity quotes to a 1y par spread), (ii) par couponing with unit face value, (iii) a small-spread approximation, and (iv) independence between recovery and the exact timing of default within the year.

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 loss given default (LGD) under the risk-neutral measure.

## 2.2 Recovering Default Probabilities from Option Prices

Following Carr & Wu (2011), the *asset value* process $\{A_t\}_{t\geqslant 0}$ of the bank is modeled as a stochastic process with bounded support, and the face value of debt $D_t$ lies strictly inside those bounds:

$$A_t \in \big[A_l, A_h\big], \qquad 0 < A_l < D_t < A_h.$$

Default occurs the first time the lower threshold is hit:

$$\mathcal{T} = \inf\big\{t \geqslant 0 : A_t \leqslant A_l\big\}.$$

Such an assumption can be justified by the fact that debt covenants and limited li-

[5] Formally, the government guarantee is equivalent 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.

ability drive equity to zero at default yet keep it bounded above in normal times. For large regulated banks, capital requirements and stress tests accelerate the path to insolvency; market capitalization rarely drifts far beyond a plausible recapitalization value, but once losses push assets below a regulatory threshold the stock price collapses. Hence, the equity of major banks often trades within a tight corridor punctuated by crash events, qualitatively matching the setting here.

To understand how the Carr & Wu (2011) framework helps us map out default probabilities from option prices, notice first that it is never optimal to exercise the American put on the bank's equity before default, because the exercise value $D_t - A_t$ is negative when the bank is solvent ($A_t > D_t$). Then, at default ($t = \mathcal{T}$), the equity value $S^E_t = (A_t - D_t)^+$ falls to zero, so immediately exercising the put yields $K$. Before default ($\mathcal{T} > t$), equity is a cancelable call, bounded above by the upper bound of the default region $\mathcal{E} := A_h - D_t > 0$. Choose any strike $K \in (0, \mathcal{E}]$; two cases obtain: (i) if no default occurs before maturity $T$ ($\mathcal{T} > T$), the equity remains above $\mathcal{E}$ and the put expires worthless; (ii) if default happens ($\mathcal{T} \leqslant T$), equity collapses and the put is exercised instantly.

We now arrive at a result that is central to the empirical methodology: the condition that allows us to recover default probabilities directly from observed option prices. The put payoff is an indicator of default scaled by $K$. Let $\mathrm{Put}_t(K, T)$ 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 risk-neutral pricing, we obtain that the put option price and the default probability are related as follows:

$$\mathrm{Put}_t(K,T) = \beta_{t,T}\, K\, \mathbb{E}^*_t\big[\mathbf{1}_{\{\mathcal{T}\leqslant T\}}\big] \equiv \beta_{t,T}\, K\, \mathbb{F}^*_{t,T}, \quad \mathbb{F}^*_{t,T} := \mathbb{E}^*_t\big[\mathbf{1}_{\{\mathcal{T}\leqslant T\}}\big], \qquad K \in (0, \mathcal{E}].$$

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 9 September 2008 ($T - t = 494$ 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 re-emerges, reflecting dependence on pre-default equity dynamics.

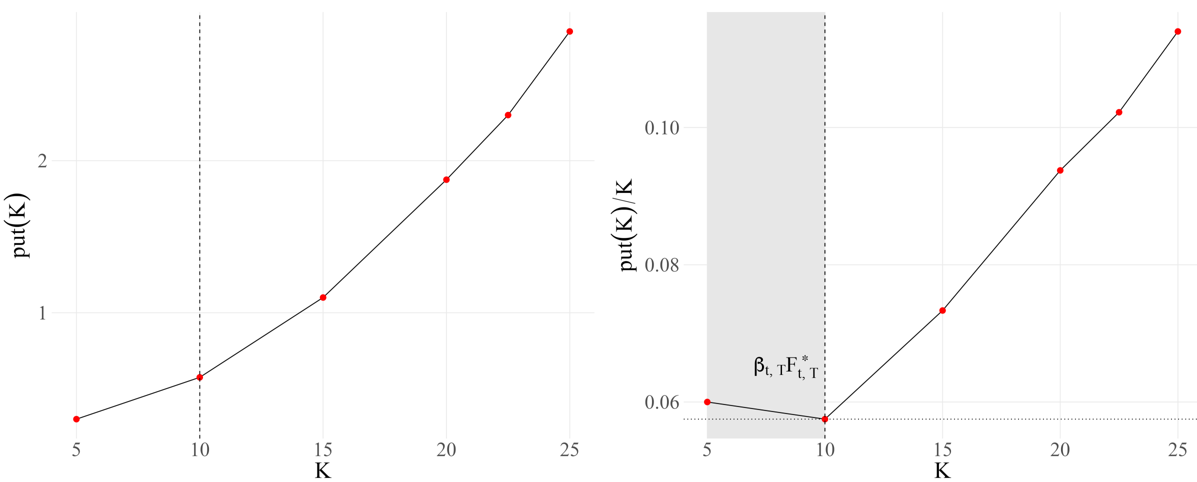
When utilizing a single put option to replicate the intended payoff, the underlying intuition is straightforward. The asset price associated with a deep out-of-the-money put option either remains above the strike price throughout its life or falls below it. Correspondingly, the payoff either yields a fixed amount due to default or expires worthless. There are four possible logical states—asset price above or below the strike price before and after default. We can rule out two. It is exceedingly unlikely for a default to occur while the asset price remains above the deep out-of-the-money put's strike price both before and after the default event. Conversely, we assume that the government never bails out equity holders, i.e. the asset price never declines below the strike price without leading to default.[6]

Finally, I can go back to 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.

**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 09/09/2008, maturity 494 days. The right panel plots the put option scaled price as a function of strike for Morgan Stanley on 09/09/2008, maturity 494 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 $\beta_{t,T}\mathbb{F}^*_{t,T}$.

[6]There is evidence that bailout expectations are priced by equity holders (see Kelly et al. (2016) among others) and, in practice, during the GFC the Paulson plan involved capital injections that supported equity values (Veronesi & Zingales 2010). If interventions prevent default while allowing equity to dip below the strike at some point (i.e., bailouts of equity holders), deep out-of-the-money puts can pay off even without default; interpreting the resulting put slope as a default probability therefore overstates $\mathbb{F}^*$. In the decomposition $\mathrm{CS} \simeq \mathbb{F}^* \times \mathrm{LGD}^*$, this contamination mechanically lowers the inferred $\mathrm{LGD}^*$. Hence any such effect biases against finding higher $\mathrm{LGD}^*$ and cannot explain elevated post-2010 spreads. Moreover, forces that truly reduce $\mathbb{F}^*$ (e.g., post-crisis deleveraging from regulation) compress spreads rather than elevate them. The observed post-2010 combination—normalization of $\mathbb{F}^*$ alongside persistently higher spreads—is therefore conservative for my inference and, if anything, strengthens the identification that diminished bailout protection raised funding costs.

# 3 Empirical Implementation

## 3.1 Data

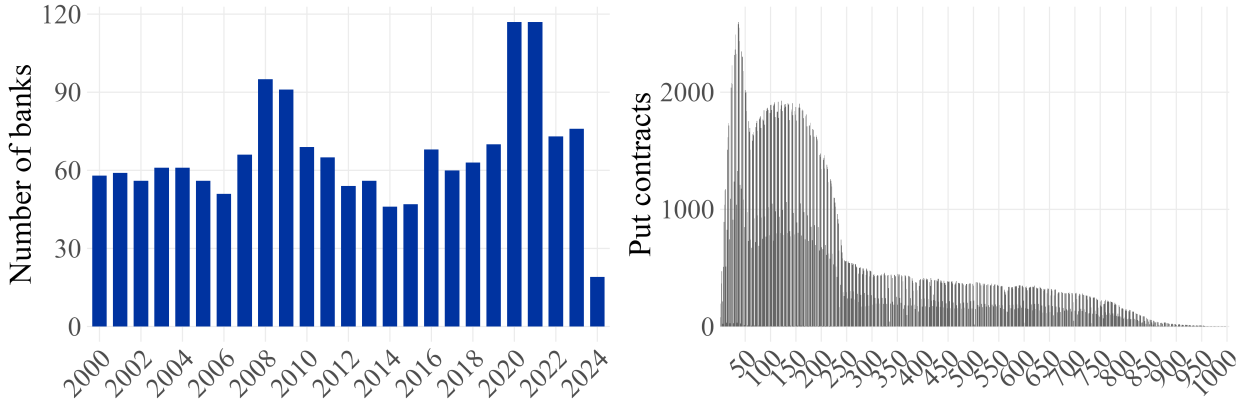
Data on CDS are obtained from IHS Markit. The initial sample consists of daily representative CDS quotes on all entities in the financial sector covered by Markit over the period from January 2000 through December 2022. While the five-year contract is generally thought to be the most liquid, the sample used here includes data on all maturities available for every company. When CDS rates are quoted for primary and non-primary 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". For losses given default, the average recovery is obtained from observed contributed recovery rates, which are sourced from the Markit CDS End of Day curve.

Options data were obtained from OptionMetrics. For each selected date, we 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 highest closing bid and lowest closing ask prices. 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. Whenever I combine data from both CDS contracts and options, to align the two markets, I consider a common one-year horizon. The data from IHS Markit, OptionMetrics, and CRSP are merged based on the *permco* identifier for each bank.

The final sample includes 48 banks from 2000 to 2023. The number of banks at each week ranges from around 30 to 100, with an average of 60 banks. The maturities of the chosen option contracts at the reference date range from 1 to 955 days, with an average of around 150 days. The left panel in 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, coinciding with the start of the financial crisis and again with the COVID-19 crisis. The right panel in Figure 2 plots the number of selected put options contracts across different times to maturity.

**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

**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).

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:

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

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

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

Statistical validity is maintained by continuing window expansion only while $R^2$ remains above a predetermined threshold $\tau = 0.98$. 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 $\{K_1, \ldots, K_{m*}\}$, the parameter $\beta$ is estimated via constrained least squares:

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

This estimator represents the slope of the linear pricing relationship and corresponds to the risk-neutral default probability $\mathbb{F}^*_{t,T}$, as derived from the fundamental pricing equation for default-contingent claims.

For each CDS maturity, the risk-neutral default probability is interpolated to align with the maturity of the CDS contract. Appendix A.2 provides a robustness check for the measure using the Theil–Sen estimator. The Theil–Sen estimator 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, which is to invest in the strike pair $i$ and $j$ that deliver the median risk-neutral default probability. Buying the put of strike $K_j$ and writing the put of strike $K_i$ yields a payoff of $K_j - K_i > 0$ if default happens. Because buying and writing these puts costs a total of $\mathrm{Put}(K_j) - \mathrm{Put}(K_i)$, the normalized spread of this trading strategy earns exactly one dollar if default happens, corresponding to the Theil-Sen estimator.

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 average magnitudes and other statistical behaviors. The estimates from the put options have a larger sample mean, median and a slightly larger standard deviation than the CDS spreads.

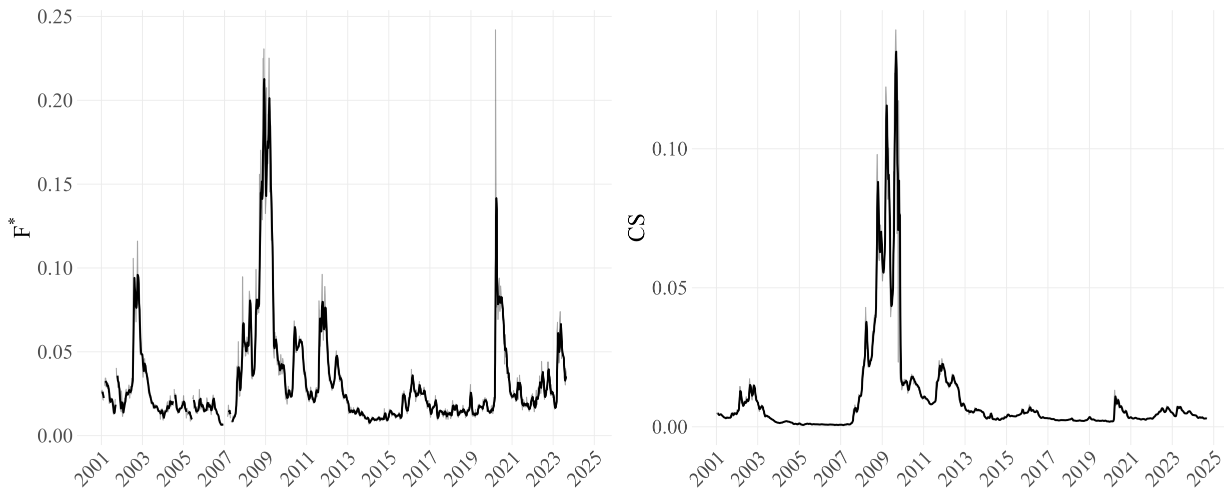
**Table 1: Summary Statistics for** $T = 365$

| | **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.

Figure 3 plots the average 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 Great Financial Crisis. Both series reach their peaks during the GFC but while default probabilities come back 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 if compared to the GFC.

**Figure 3: Average Risk-Neutral Default Probability and CDS Spreads**




**(a) Average $\mathbb{F}^*_t$ for** $T = 365$

**(b) Average $\mathrm{CS}_t$ for** $T = 365$

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

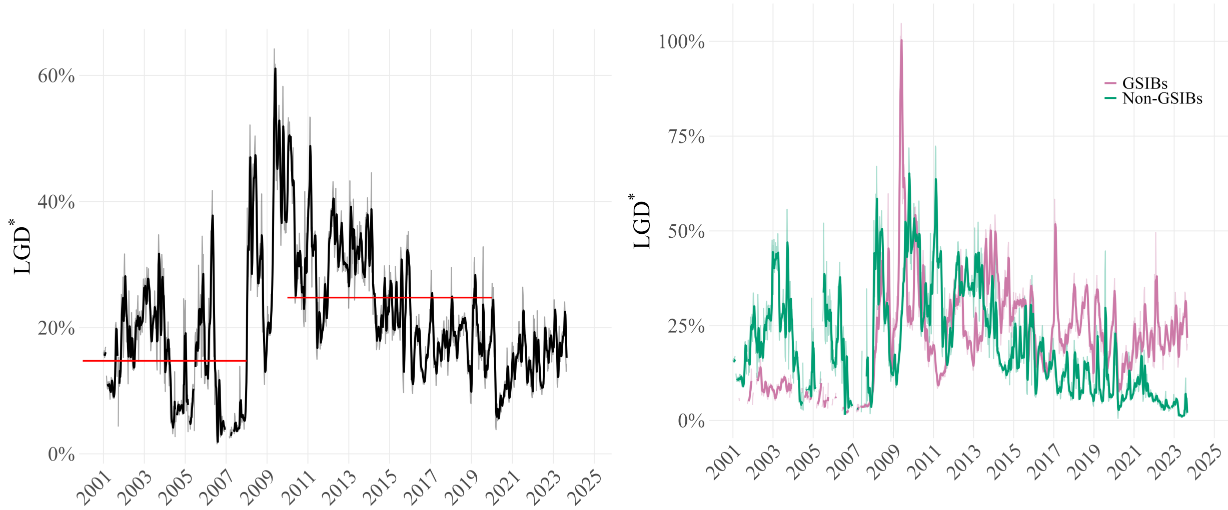
The left panel of Figure 4 plots the time series of the average $\mathrm{LGD}^*_{t,T}$ for $T = 365$ days. $\mathrm{LGD}^*_{t,T}$ varies strongly with business conditions, consistent with the relation between losses-given-default and market fundamentals. In particular, the variation in $\mathrm{LGD}^*_{t,T}$ implies that losses are low at values of approximately 10% during the economic recovery of the mid-2000s. They increase sharply to around 40% with the financial crisis of 2007-2009, and then gradually rise. The secondary increase in 2011 is contemporaneous with the downgrade of U.S. debt. After 2012 the expected losses hover around 30% and then gradually drop to 10% from 2017 onward. In addition, both the risk-neutral default probability $\mathbb{F}^*_{t,T}$ and expected losses $\mathrm{LGD}^*_{t,T}$ are countercyclical. Under the constant-recovery assumption often used to back out default probabilities from CDS, the implied mapping is

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

Because $\mathrm{LGD}^*_{t,T}$ tends to be higher in downturns—when $\mathbb{F}^*_{t,T}$ is also high—the factor $\mathrm{LGD}^*_{t,T}/\bar{\mathrm{LGD}}$ amplifies variation in $\widehat{\mathbb{F}}^{\mathrm{CDS}}_{t,T}$, making it more volatile and right-skewed than the option-implied $\mathbb{F}^*_{t,T}$. The right panel of Figure 4 shows that the average expected losses for Globally Systemically Important Banks (GSIBs) are lower than non-GSIBs pre-GFC but higher post-GFC. This is consistent with the narrative of Berndt et al. (2022) (among others) of a structural shift in expected bailout probability for GSIBs after Dodd-

Frank.

**Figure 4: Expected Losses Given Default**




**(a) Average** $\mathrm{LGD}^*_{t,T}$ **for** $T = 365$

**(b) Average** $\mathrm{LGD}^*_{t,T}$ **for** $T = 365$ **for GSIBs and non-GSIBs**

Notes: the left panel plots the expected losses $\mathrm{LGD}^*_{t,T}$ for a 365-day maturity at weekly frequency (grey line) and 4-weeks moving average (black line). The red horizontal lines represent the averages pre-2008 and post-2010 (excluding the years after 2020). The right panel plots the expected losses for GSIBs (magenta) and non-GSIBs (green) at weekly frequency with 4-weeks moving average.

Consistent with these patterns, Appendix A.3 reports a variance decomposition indicating that expected losses explain approximately 58% of the within-bank time-series variation in CDS spreads.

To assess whether movements in $\mathrm{LGD}^*_{t,T}$ are contaminated by time-varying market liquidity in options and CDS markets, in Appendix A.4 I also construct a liquidity-adjusted series of expected losses. Following Conrad et al. (2020), I regress changes in the logarithm of $\mathrm{LGD}^*_{t,T}$ on changes in security-level and aggregate liquidity proxies (option bid–ask spreads, volume and open interest; CDS depth; TED–SOFR and VIX) and then accumulate the regression residuals to obtain an adjusted series that strips out transitory illiquidity. The goal is to isolate movements in expected losses driven by underlying credit fundamentals rather than by liquidity frictions that can mechanically depress or inflate the raw measure. The adjusted series is notably higher during stress episodes such as 2008–2011, implying that part of the post-crisis decline in unadjusted expected losses reflects improving market liquidity rather than better recoveries, whereas in normal times the adjustment is small. Full regression specification and estimates used to build the adjustment are reported in Appendix A.4.

Taken together, these facts suggest that, after 2010 spreads remained elevated even as risk-neutral default rates normalized. It is, however, difficult to determine from reduced-form evidence alone whether this pattern reflects shifts in underlying credit fundamentals (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 model of financial intermediation with bank default risk, capital regulation and government bailouts. 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 $\nu$ and risk aversion $\gamma$,

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

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

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

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

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 and 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, non-contingent debt and deposit claims and equity claims issued by financial intermediaries. Financial intermediaries, or banks for short, 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. Importanty, intermediaries face equity issuance costs which make their net worth the relevant state variables for asset pricing (He & Krishnamurthy 2013, Brunnermeier & Sannikov 2014) 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.[7]

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 wealth and intermediary net worth. 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 intermediary net worth $N$.[8] Hence I work with the state vector $\mathbf{S} = [N, W, \pi, Z, d]$. 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.

[7] 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 rates that account for the government's equity injections.

[8] 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 $\omega$ are uncorrelated over time. Second, the value function is homogeneous of degree one in 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 $\mathbf{S}$.

## 4.2 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 $\omega$, while $d$ and $b$ are, respectively, deposit and bond repayments due. Intermediaries default when $n < 0$; otherwise they continue operating. The rest of this subsection proceeds in three steps: first, I characterize the asset payoff; second, I describe the problem of solvent intermediaries; third, 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 $p(\mathbf{S})$, amortisation 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 realised 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 $\omega$, 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

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

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 realised tree payoff to debtholders. In our 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. A decline in fundamentals $Y$ depresses the portfolio payoff $\mathcal{P}(\omega, \mathbf{S})$, thereby eroding the intermediary's net worth and raising its default probability.

### 4.2.2 Solvent Intermediaries

If intermediaries are solvent, namely if their individual net worth is positive, $n > 0$, then 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 $q(\mathbf{S}) = \frac{1}{1+r(\mathbf{S})}$ and dividend payouts, $x$. Intermediaries have a payout target that is a fraction $\phi_0$ of net worth, $n$. They can deviate from this target and raise additional equity $e$ that is, 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 intermediairy has at her disposal at the beginning of the period. The second and third term 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 payouts of the bank net of issuance costs. Intermediaries pay deposit insurance fees $\kappa$ 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 are collateralized by the intermediary's portfolio. The parameter $\xi$ 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 of households, their equity holders, and 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 (see, for example, 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 take ownership of these bankrupt intermediaries and liquidate them to recover some of the outstanding debt to be paid to debt holders. 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. Then the aggregate dividend to households is:

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

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, yielding financial wealth $w$. They further pay taxes $T(\mathbf{S})$. Deposit quantities $D$ in the model are demand determined, i.e. 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 inter-temporal 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

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

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 $\chi$ 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 payoff net of debt obligations, 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.[9] 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 $\alpha_D$ captures the average spread between risk-free and deposit rates, while $\beta_D$ 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.[10]

[9] 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 special role of deposits in the banking system and their contribution to banks' cost of capital.

[10] 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 non-pecuniary 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 so they 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 $D' \leqslant \bar{D}'$.

## 4.4 Government

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

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

The first integral captures the expected transfer to bondholders in default states, conditional on a bailout being granted with probability $\pi$, 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

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

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 Clearings 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* $\{C(\mathbf{S}), B'(\mathbf{S})\}$*, 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 $\pi$. 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 intermediary equilibrium capital structure. Having clarified its driving forces, I then study how credit spreads respond to changes in fundamentals and bailout probabilities, and conclude by outlining my proposed indirect inference approach leveraging on these results.

## 5.1 Optimality Conditions

Before discussing the intermediaries' optimality conditions, 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

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

where $\nu(\mathbf{S})$ is the (scaled) value function and $\phi_0$ is the target payout fraction. The first-order condition with respect to equity issuance pins down $\mu$, the shadow price attached to a dollar of equity injections:

$$\mu = \frac{1}{1 - \phi_1 \tilde{e}}$$

Dividing the envelope condition through by $\mu$ gives a compact expression for the "marginal value" of net worth:

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

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 $\mu$ 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 $\mu$) 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:

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

Let $F(\mathbf{S}) \equiv F(\omega^*(\mathbf{S}))$ 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 $\tilde{v}(\mathbf{S}')$, 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 $\pi'$ a bailout prevents losses to creditors, so default losses are borne only with probability $1 - \pi'$. Accordingly, payoffs receive weight $(1 - F(\mathbf{S}'))\tilde{v}(\mathbf{S}')$ in survival states and $(1 - \pi')F(\mathbf{S}')$ in default states, as made explicit in the optimality conditions below.

**Optimal Debt Policy.** The choice of non-contingent 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 non-contingent debt $B'$, the intermediary balances the cheapness of debt financing against the expected cost of default. Formally, by combining the the first-order condition of the intermediary's problem with respect to $B'$ with the one of the household, we obtain[11]

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

$$+\,\mathbb{E}_{\mathbf{S}}\left\{\mathcal{M}\left(\mathbf{S}', \mathbf{S}\right)\underbrace{\left(1 - \pi'\right)\chi\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}')f(\omega^*(\mathbf{S}'))\frac{d\omega^*(\mathbf{S}')}{dB'}}_{\substack{\text{marginal costs} \\ \text{(default costs)}}}\right\}. \tag{18}$$

where $\tilde{\lambda}$ reflects the tightness of the intermediary's leverage constraint (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

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

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 $(1-F(\mathbf{S}'))(1-\tilde{\nu}(\mathbf{S}'))$. The cost is that more debt raises the likelihood of default, which destroys value through expected shortfalls borne by creditors and deadweight losses, captured by $\chi\mathcal{P}(\omega^*(\mathbf{S}'), \mathbf{S}')$ and the sensitivity of default risk to leverage, $\partial F(\mathbf{S}')/\partial B'$.

A higher expected bailout probability $\pi$ tilts this trade-off toward borrowing in two 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 adds a state-contingent subsidy in default states, $F(\mathbf{S}')\,\pi'$, 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 left 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 $\pi$ (medium in black, low in magenta, and high in cyan).[12] In particular, the debt policy is more sensitive to the bailout probability $\pi$ when the intermediary is more levered ($B$ is higher). The right panel of Figure 5 shows the same decision rule $B'$ across three values of fundamentals (baseline in red, low in blue, and high in green). Weaker fundamentals shift the policy downward, limiting issuance at a given $B$, while stronger fundamentals raise desired borrowing; the dispersion across curves is more pronounced at higher leverage.

After having described 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 $B'$.

## 5.2 Credit Spreads, Fundamentals and Bailout Expectations

The credit spread on one-period defaultable debt is determined by the following equilibrium condition derived from the household's problem first-order condition for debt:

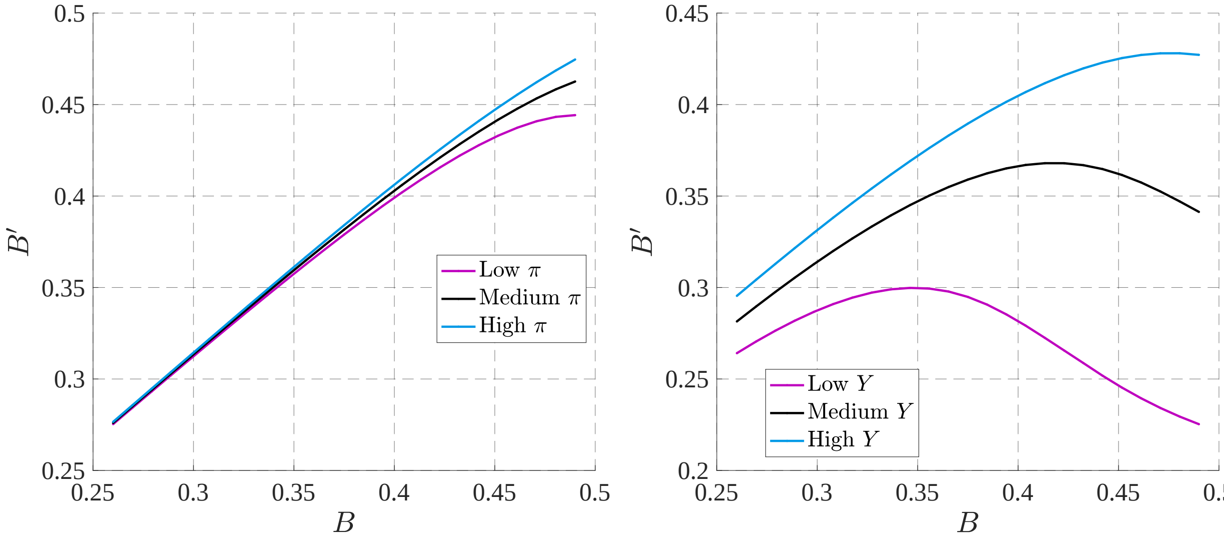
$$\underbrace{r - r^{rf}}_{\text{Credit Spread}} = \underbrace{\mathbb{E}_{\mathbf{S}}\left\{\mathcal{M}\left(\mathbf{S}', \mathbf{S}\right)(1-\pi')F(\mathbf{S}')\left[1 - RV(\omega^{-\prime}, \mathbf{S}')\right]\right\}}_{\text{Expected Default Loss}} \tag{19}$$

Default losses embed three critical elements: the bailout probability $\pi'$ (government intervention likelihood), default probability $F(\mathbf{S}')$, and asset recovery rate $RV(\omega^{-\prime}, \mathbf{S}')$ per unit, conditional on default. The bailout probability $\pi'$ affects the credit spread $r - r^{rf}$ through two distinct channels, as in the following proposition:[13]

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

[13] The analysis abstracts from the effect of changes in the bailout probability $\pi_{t+1}$ 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 much deposits as they can up to the capacity constraint since the cost of issuing deposits is always

**Figure 5: Debt Policy Functions**




**(a) Debt Policy for different $\pi$** **(b) Debt Policy for different $Y$**

Notes: policy functions evaluated at the ergodic means of $D$ and $d = 0$. The left panel plots the debt policy $B'$ as a function of debt $B$ for three values of bailout probability $\pi$ (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 $Y$ (baseline in black, low $Z$ in magenta, and high $Z$ in cyan).

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

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

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

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

*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 $-F(\mathbf{S}')[1 - RV(\omega^{-,\prime}, \mathbf{S}')]$ reflects the *direct* reduction in expected default losses when the bailout probability $\pi'$ increases. Higher $\pi'$ *directly narrows* credit spreads because external intervention is anticipated. On the other hand, an increase in $\pi'$ *widens* spreads, partially offsetting the direct effect through the indirect effect. The intuition is that an

lower then or equal (in the case of no default or full bailout) to the cost of issuing bonds.

increase in $\pi'$ 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 $\pi'$ incentivize banks to adjust their debt levels $B'$. If the semi-elasticity of leverage with respect to the bailout probability $\frac{\partial B'}{\partial \pi'}\frac{1}{B'} > 0$ (i.e., banks take on more debt if $\pi'$ increases), the sign of this effect depends on $\Omega'$. 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:*

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

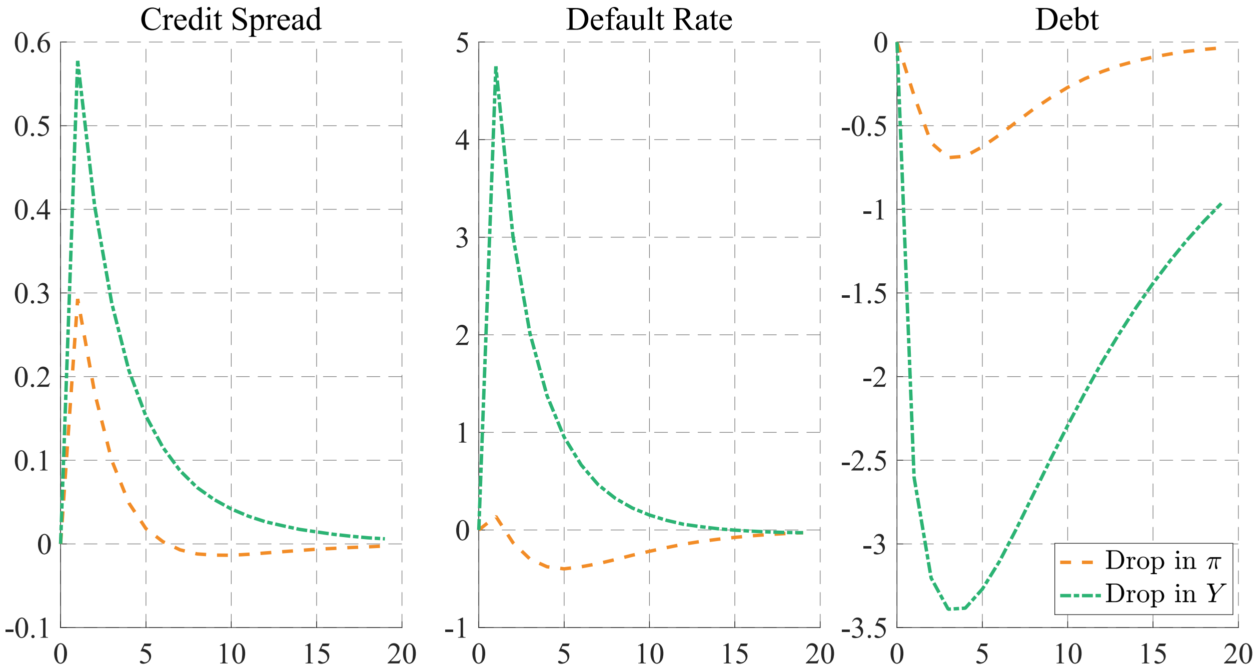
*The sign of the derivative is ambiguous since the direct and indirect effects have opposite signs.*

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

The credit spread is decreasing in fundamentals as long as intermediaries delever when fundamentals worsen—i.e., $\frac{\partial B'}{\partial Y'} < 0$. The *direct* effect captures how $Y'$ shifts the default probability $F(\mathbf{S}')$ and recovery $\mathrm{RV}(\omega^{-,\prime},\mathbf{S}')$. When fundamentals deteriorate, $F(\mathbf{S}')$ increases and recoveries $\mathrm{RV}(\omega^{-,\prime},\mathbf{S}')$ lowers, increasing expected default losses; the opposite holds when fundamentals improve. The *indirect* effect reflects leverage adjustments. To obtain the weakly negative derivative in Proposition 2, it is key that intermediaries delever when fundamentals worsen—i.e., $\frac{\partial B'}{\partial Y'} < 0$—so that, given $\Omega(\mathbf{S}') \geqslant 0$, the indirect term is negative and reinforces the direct channel.

**Inferring the role of bailout expectations.** The logic in Propositions 1 and 2 anticipates distinct joint movements of spreads and default risk under bailout versus fundamental shocks. When $\pi$ moves, the spread reacts through a *direct* change in expected losses and an *indirect* response via the balance-sheet choice $B'$. A lower $\pi$ raises required spreads mechanically but, because intermediaries optimally scale back debt, it also shifts down the default threshold $\omega^*(\mathbf{S}')$, reducing risk-neutral default probabilities. By contrast, when Y worsens, both the default probability and recoveries move adversely *directly*, and—crucially—deleveraging reinforces rather than offsets this deterioration, making spreads and default risk rise together.

**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 $\pi$ by two standard deviations (orange dashed) and a drop in fundamentals Y by two standard deviations (cyan dashed-green). 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 two standard deviations decline in $\pi$ and (ii) a two standard deviations fall in fundamentals Y obtained by a drop in Z. We plot the one-period credit spread, the risk neutral default probability and the debt. Bailout expectations and fundamentals leave distinct joint footprints in spreads and default risk. A decline in $\pi$ 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. By contrast, a fall in Y worsens cash flow prospects and recoveries, increasing 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 co-movements—spread up with default down for $\pi$ 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.

A natural concern is that the post-2010 tightening of capital and liquidity regulation could mechanically force intermediaries to delever, lowering risk-neutral default probabilities, thereby confounding movements attributed to bailout expectations. In theory, changes in regulation do not pose a threat to the identification strategy proposed. The reason is that, even though tightnening regulation could reduce risk-neutral default probabilities, it would then by 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 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.5. In this way, I ensure that any remaining variation is not mechanically attributed to regulation and does not artificially inflate the estimated bailout contribution.

# 6 Quantitative Analysis

The model is calibrated to U.S. bank-level data at the annual frequency from 2000 to 2020. For consistency, the calibration considers the same sample of banks from which risk-neutral default rates and expected losses are constructed in Section 3. Table 2 lists all parameters and organizes them into four sets: fundamental risk, preferences, financial intermediaries balance sheet, 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; 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. Hence, the model is 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.** All parameters governing fundamental risk (aggregate and tree-specific) are calibrated to match moments of the option-implied Bank of America investment grade corporate-bond spreads. In particular, I average the spreads across their rating classes from AAA to BBB. We define a disaster as a period in which the spread is 2.5

**Table 2: Model parameters**

| Parameter | Value | Targets |
|---|---|---|
| **Panel A: Fundamental risk** | | |
| $\pi_d$ | 0.036 | Disaster onsets frequency |
| $\pi_s$ | 0.212 | Disaster spell duration |
| $\eta$ | 0.658 | Bond and loan recovery losses (Elenev et al. 2021) |
| $\delta$ | 0.937 | Corporate debt duration (Elenev et al. 2021) |
| $\zeta$ | 0.15 | Simulated Method of Moments |
| $\rho$ | 0.90 | Simulated Method of Moments |
| $\sigma$ | 0.05 | Simulated Method of Moments |
| $\sigma^z$ | 0.70 | Simulated Method of Moments |
| $\sigma^\omega$ | 0.11 | Simulated Method of Moments |
| **Panel B: Preferences** | | |
| $\beta$ | 0.987 | Simulated Method of Moments |
| $\nu$ | 2 | Simulated Method of Moments |
| $\gamma$ | 7 | Simulated Method of Moments |
| **Panel C: Financial intermediaries** | | |
| $\xi$ | 0.92 | Basel 8% Capital Requirement |
| $\kappa$ | 0.001 72 | Deposit insurance fee (Begenau & Landvoigt 2022) |
| $\alpha_D$ | 0.005 | Deposit spread target (Drechsler et al. 2017) |
| $\beta_D$ | 0.34 | Deposit rate sensitivity (Elenev & Liu 2024) |
| $\chi$ | 0.332 | Bankruptcy cost (Bennett et al. 2015) |
| $\zeta^D$ | −0.4 | Correlation of insured deposits and output |
| $\phi_0$ | 0.02 | Dividend payouts by book equity |
| $\phi_1$ | 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 |
| $\rho^\pi$ | 0.7 | Simulated Method of Moments |
| $\sigma^\pi$ | 0.6 | Simulated Method of Moments |

standard deviations above its mean. The time series of the average spread is shown in the left panel of Figure E.1 in Appendix E.

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

$$\ln Z' = \rho \ln Z + (1-\rho)\mu + \sigma\varepsilon, \tag{20}$$

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

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

$$\ln z = \sigma^z \varepsilon, \quad \ln \omega = \sigma^\omega \eta, \tag{21}$$

with $\varepsilon, \eta \overset{\text{i.i.d.}}{\sim} \mathcal{N}(0,1)$. The parameters $\sigma^z$ and $\sigma^\omega$ pin down the cross-sectional dispersion of tree and island shocks, respectively. The standard deviation of tree specific shocks $\sigma^z$ 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, $\sigma^\omega$, 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

$$\mathbb{P}_d = \begin{pmatrix} 1-\pi_d & \pi_d \\ 1-\pi_s & \pi_s \end{pmatrix}, \tag{22}$$

where $\pi_d$ is the probability of a disaster next period conditional on a normal state this period, and $\pi_s$ is the probability of the disaster state next period if there is a disaster in the current period. The disaster-arrival probability, $\pi_d$, and the conditional survival probability, $\pi_s$, are selected to replicate, respectively, the empirical frequency of disaster onsets of 3.6% and the average length of disaster spells of 21.2% as calculated from the data. The disaster-severity coefficient, $\zeta$, is chosen so that the model reproduces the mean spread observed during disaster episodes of 4.8%.

The loss-severity parameter, $\eta = 0.6996$, is calibrated to the bond and loan recovery losses documented by Elenev et al. (2021) of 52%. Similarly I 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 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 unity, $\gamma = 7$ to match the weighted average (by market capitalization) risk neutral variance of equity returns of 7.9% in the data as calculated from equity options data following Martin (2017). The left panel of Figure E.1 in Appendix E shows the time series of the risk neutral variance of equity returns.

**Financial intermediaries.** The intermediary borrowing constraint parameter $\xi$ 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, conforming with the Basel limits. The deposit insurance fee is set to $\kappa = 0.172\%$ following Begenau & Landvoigt (2022) and the convenience yield on deposits $\alpha_D$ 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 $\phi_0$ 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 $\phi_0$. 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 insured deposit limit $\bar{D}$ mean determines the insured deposit share of liabilities. The model generates a value of 50% versus the data counterpart of 64%. 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 is mapped from a latent index via a logit, $\pi = \exp\{\tilde{\pi}\}/(1+\exp\{\tilde{\pi}\})$.[14] The latent index follows an AR(1),

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

The parameters $\bar{\pi}$, $\rho^{\pi}$, and $\sigma^{\pi}$ 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.

## 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, helping sustain observed credit premia while preserving the shape of the empirical distribution.

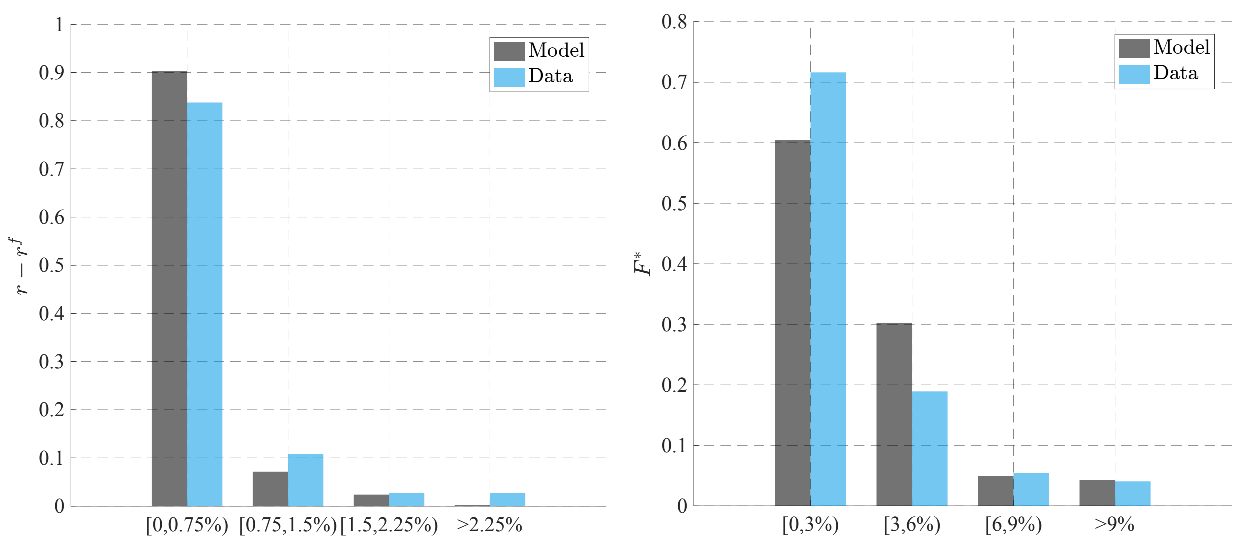
Figure 7 complements these comparisons. The left panel shows that one–year credit spreads are right–skewed in both the data and the model, with similar mass over low-to-moderate spreads and thinner model-implied tails at the highest realizations. The right panel documents that risk–neutral default probabilities 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.

[14] Bailout expectations are kept exogenous and orthogonal to real variables to separate policy from fundamentals. Allowing the bailout probability to depend on intermediary net worth or default risk does not overturn this identification. In the model, deteriorating fundamentals push up credit spreads and risk-neutral default probabilities in the same direction, whereas a decline in bailout probability raises spreads but, via deleveraging, lowers default risk. If anything, making $\pi$ increase when net worth falls (or default risk rises) counteracts the fundamental channel—reducing expected losses and compressing spreads when defaults rise—so it biases against finding a large bailout component. Equivalently, writing $\pi_t = h(N_t) + \varepsilon^{\pi}_t$ with $\varepsilon^{\pi}_t$ orthogonal to fundamentals, the state-dependent part $h(N_t)$ is absorbed by the measurement mapping, and the sign-based separation using the joint behavior of spreads and the option-implied risk-neutral default probabilities remains valid.

**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 rate | 0.0242 | 0.0324 |
| Risk-free rate | 0.0156 | 0.0126 |
| Risk-free rate volatility | 0.0178 | 0.0179 |
| Intermediaries risk neutral variance of equity returns | 0.08 | 0.054 |
| Intermediaries market to book value | 1.4 | 1.2 |
| Intermediaries equity issuance rate | 0.0038 | 0.0050 |
| Insured deposits share of liabilities | 0.64 | 0.60 |
| Credit Default Swap rate | 0.0037 | 0.0038 |
| AR(1) of Credit Default Swap rate | 0.58 | 0.49 |
| Credit Default Swap rate volatility | 0.0040 | 0.0034 |

**Figure 7: Distributions of Credit Spreads and Default Rates**




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

Notes: histograms for model-simulated and empirical distributions, 2000–2020. 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 Great Financial Crisis. In particular, the model is combined with annual data over 2004–2015 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

$$\begin{aligned} \mathbf{Y}_t &= \mathbf{g}\big(\mathbf{S}_t\big) + \boldsymbol{\eta}_t, \\ \mathbf{S}_t &= \mathbf{f}\big(\mathbf{S}_{t-1}, \varepsilon_t\big), \end{aligned} \tag{23}$$

where

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

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

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

namely the credit spread differential $CS_{t,365} \equiv r_{t,365} - r^{rf}_{t,365}$ and the risk neutral default probability $Q^*_{t,365}$ (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 $\varepsilon_t^\pi$—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:

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

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

where the beta parameters $(\alpha_t, \beta_t)$ are calibrated each period to match $g_2(\mathbf{S}_t)$ and a variance set equal to $0.01\,\widehat{\sigma}^2\big(Q^*_{t,365}\big)$. The log-variance $\sigma^2_{CS}$ 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.

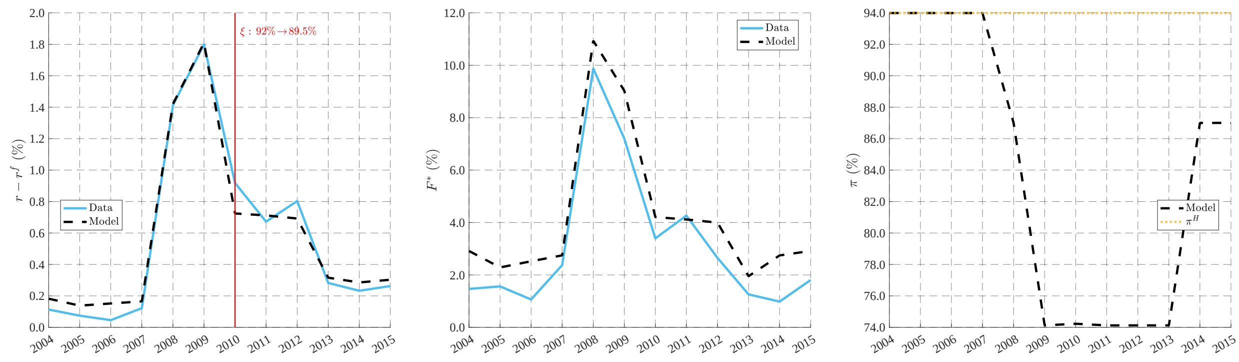
To account for the tightening of regulation after 2010 within the state-space estimation, I impose a deterministic policy break at the start of 2010 and evaluate the model's policy functions under a stricter capital requirement from that date onward. Concretely, for $t < 2010$ the likelihood and the 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), leaving 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 Section A.5 from pre-2008 to post-2010.[15] Economically, this identification exploits that, holding fundamentals 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. Hence, I calibrate post-2010 $\xi$ 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%)—equivalently, a decrease in $\xi$ by 0.025.[16]

Figure 8 compares the model-implied one-year credit spread, default probabilities with their data counterparts, and reports the recovered bailout probability path $\pi$. The model tracks the level and dynamics of credit spreads and default rates closely. The inferred bailout probability is elevated before the crisis and exhibits two distinct drops. A first drop occurs in late 2008 around the Lehman failure—partly tempered by the enactment of the Paulson Plan (TARP)— and a second, more persistent decline begins in 2009 following the 2009Q3 announcement of Dodd–Frank 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 pre-crisis level. This pattern provides the

[15]Section A.5 develops an identification that disentangles 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, instrumenting each interacted tail regressor with its corresponding orthogonalized shifter and clustering by bank and date. The post-2010 downside slope is larger than pre-2008 and the spread–downside slope increases by about 0.20; by the monotonic mapping in Proposition 3, this identifies tighter capital regulation rather than lower bailout expectations.

[16]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.

**Figure 8: The Dynamics of Credit Spreads, Default Rates, and Bailout Probabilities**




**(a) Credit Spreads** **(b) Default Rates** **(c) Bailout Probability**

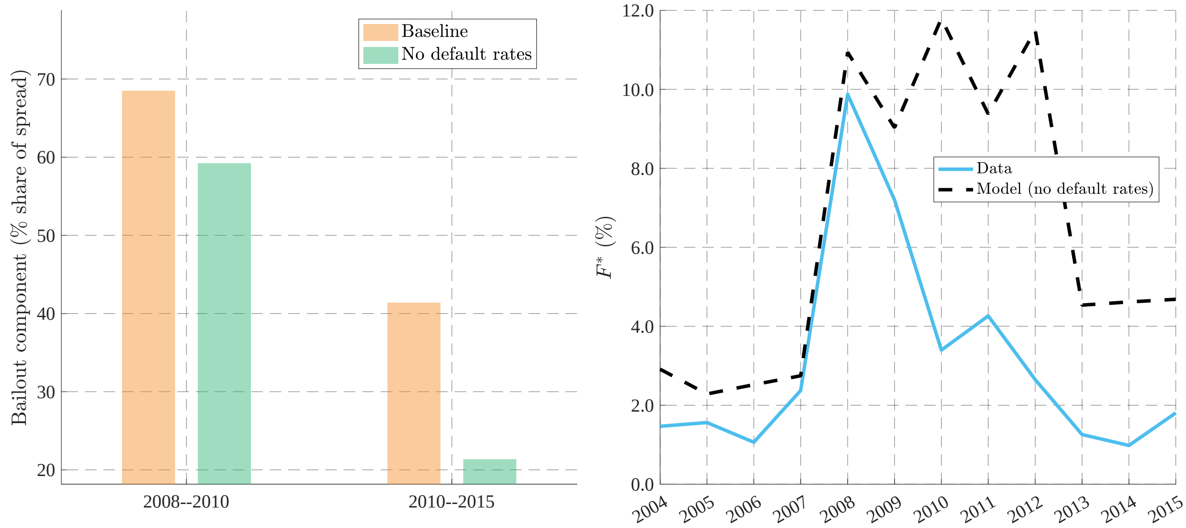
Notes: the left panel plots one-year credit spread, model-implied (black dashed) versus data (cyan solid). The middle panel plots one-year bank default probability, model-implied (black dashed) versus data (cyan solid). The right panel plots recovered bailout probability $\pi$ from the state-space filter (black dashed) and the counterfactual bailout probability (orange dotted). The red vertical line in 2010 represents the increase in capital requirements implied by the model from 8% to 10.5%.

state path used in the counterfactual exercises below and it is consistent with the findings in Berndt et al. (2022).

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 $\pi$ is set to its pre-crisis level which corresponds to the highest state $\pi^H$ for all $t$ in the sample. The difference between the filtered credit spread and the counterfactual one nets out the impact of bailout expectations. This difference is labeled as *the bailout component of credit spreads*. Importantly, the bailout component contributes 67% of the increase in spreads during the GFC as shown in the left panel of Figure 9. During the crisis, the bailout probability dropped from its highest state of 94% to 75% in 2009, remaining low until 2013. The importance of the bailout component is somewhat reduced from 2010 to 2015 accounting for around 43%.

Including observed default rates in the state-space filter is crucial to discipline how much of spreads is attributed to bailout beliefs versus failure risk. Economically, default rates revert toward their pre-crisis levels by 2010–2011, 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, thereby shrinking the portion of spreads assigned to bailout expectations. Consistent with this mechanism, the right panel of Figure 9 shows that, when default rates 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 2009–2010 and only 20% in 2010–2015, compared with 67% and 43%, respectively, in the baseline with default rates included.

**Figure 9: The Information Content of Default Rates**




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

Notes: the left panel plots the bailout component in the baseline economy (orange) and in the case in which default rates 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 pre-crisis level. The right panel plots model default probability when the default rates are excluded from the filter (black dashed) versus the data counterpart (cyan solid).

A behavioural 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 giants nearly followed, creditors suddenly recognised 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 this was not the case. In order to check this, I examine a different counterfactual where the default rates are excluded from the model and compare the model-implied spreads with the data counterpart. The results are presented in Figure 9. The model-implied spreads are close to the data counterpart, but the default probabilities are significantly higher and more persistent than the data counterpart after the GFC. Hence, this evidence is 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 behavioural mechanisms; behavioural frictions generate such dynamics via shifts in beliefs (Maxted 2024, Krishnamurthy & Li 2025). By contrast, in my framework the evolution of bailout expectations helps reproduce the boom–bust pattern while keeping the dynamics of default risk consistent with the data.

Regulatory tightening is a separate concern. Stronger capital and resolution requirements reduce leverage and failure risk and, holding fundamentals fixed, compress unsecured spreads. Thus, even if tighter regulation lowered observed default rates, that force would push spreads down, not up. The persistence of elevated spreads alongside lower default rates 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.

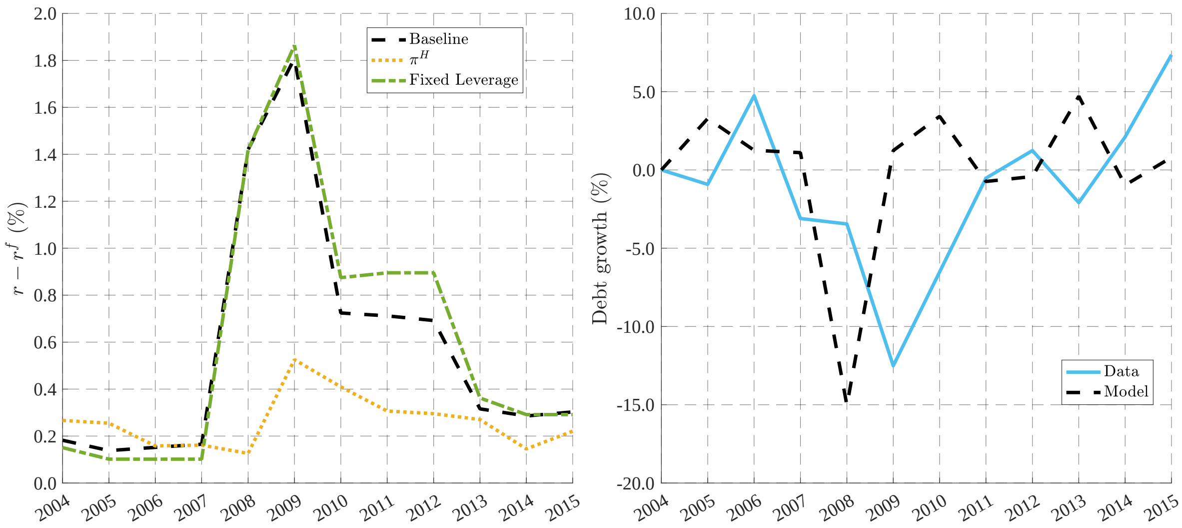
To isolate the role of leverage adjustments, I implement a second counterfactual in which leverage is held fixed at its ergodic mean while allowing bailout expectations and fundamentals to evolve along the estimated state path. The resulting spread (green dash–dot in the left panel of Figure 10) is shown alongside the baseline model-implied spread and the counterfactual with high bailout probability (orange dotted). In 2007–2009, the baseline spread climbs to roughly 180 bp, while the orange series rises only about half as much, revealing a sizable bailout premium when public support appears less certain. By contrast, the green series *overshoots* the baseline, indicating that banks' deleveraging in the data dampens bailout-driven widening. The right panel corroborates this mechanism: model debt growth (black-dashed) exhibits about 15% deleveraging through 2009, followed by a gradual rebuild that closely matches the data (black solid). Because the fixed-leverage series systematically overpredicts spreads relative to the baseline during and after the crisis, any model that ignores banks' balance-sheet adjustment would have to *dial down the estimated bailout probability* to fit the observed path. That mechanical reallocation implies an *underestimation* of the bailout component of credit spreads.

# 8 Reassessing Post-2010 Reforms

In the previous section, I show that the Dodd-Frank Act passed in 2010, helped reduce the perceived probability of government bailouts. In this section, I evaluate how this reform, together with the tightening of regulation, reshaped banks' risk-taking incentives and the pace of the post-crisis recovery. I do so by isolating how lower bailout probabilities and tighter capital requirements, by increasing debt funding costs, affected banks' required compensation for holding risky assets and the post-crisis recovery in aggregate valuations.

While regulating banks' debt-to-equity ratios was successful in bringing down default risk, I argue that alone it did not substantially push away banks from risky asset markets

**Figure 10: The Role of Leverage Adjustments**




**(a) Credit Spreads** **(b) Debt Growth**

Notes: the left panel plots model spread (black dashed), counterfactual with high bailout probability (orange dotted), and counterfactual with leverage fixed at its steady-state level (green dash–dot). The right panel plots model debt growth (black dashed) versus the data counterpart (cyan solid).

and that considerably slowed down the rebound in asset valuations after the crisis.

**Intermediary Risk Pricing.** How does the intermediary price the risks embedded in his asset portfolio? The intermediary faces two systematic shocks: an aggregate productivity innovation $Z$, modeled as a mean-zero AR(1) process, and a rare disaster shock $d$ that raises default losses in extreme states. Let $f = (Z, d)^\top$ collect the two factors. Any return $R(\mathbf{S}', \mathbf{S})$ must satisfy the Euler equation $\mathbb{E}_\mathbf{S}[\mathcal{M}^I(\mathbf{S}', \mathbf{S}) R(\mathbf{S}', \mathbf{S})] = 1$. I define the shadow risk-free gross rate implied by the intermediary as $r^{f,I}(\mathbf{S}) = 1/\mathbb{E}_\mathbf{S}[\mathcal{M}^I(\mathbf{S}', \mathbf{S})]$ where $\mathcal{M}^I(\mathbf{S}', \mathbf{S})$ is the intermediary stochastic discount factor defined as

$$\mathcal{M}^I(\mathbf{S}', \mathbf{S}) \equiv \mathcal{M}(\mathbf{S}', \mathbf{S}) \frac{\tilde{\nu}(\mathbf{S}')}{1 - \xi\tilde{\lambda}}. \tag{24}$$

Recall that as in (16) and that $\tilde{\lambda}$ is the Lagrange multiplier associated with the intermediary's leverage constraint (9). Changes in the cost and composition of funding shift the intermediary SDF and, in turn, the price of risk, as detailed below (Diamond 2020).

For each factor $f \in \{Z, d\}$, the price of risk, defined as the expected excess return on a portfolio with unit beta to $f$ and zero beta to the other factor, is:

$$\lambda_f = -\frac{\mathrm{Cov}\big(\mathcal{M}^I(\mathbf{S}', \mathbf{S}), f'\big)}{\mathbb{E}_\mathbf{S}[\mathcal{M}^I(\mathbf{S}', \mathbf{S})]}.$$

Hence for any traded return $R(\mathbf{S}', \mathbf{S})$ with factor betas $\beta_Z$ and $\beta_d$ the model delivers a two-factor securities–market line

$$\mathbb{E}_{\mathbf{S}}[R(\mathbf{S}', \mathbf{S})] - r^{f,I}(\mathbf{S}) \;=\; \lambda_Z\, \beta_Z + \lambda_d\, \beta_d.$$

Because the units of each $\lambda_x$ are those of an excess gross return per period, changes in these prices can be read as the additional premium investors demand for one extra unit of aggregate or disaster beta.

Tighter capital requirements (lower effective $\xi$) make the leverage constraint bind more often and more severely, raising the Lagrange multiplier $\tilde{\lambda}$. When the constraint binds, intermediaries need to delever to satisfy capital ratios, depressing prices and lowering ex–post returns precisely when the marginal value of intermediary equity $\tilde{v}(\mathbf{S}')$ is high. Moreover, anticipation that the constraint may bind in the future raises required returns today by increasing risk premia (Aiyagari & Gertler 1999, Bocola 2016). Differently, lower perceived bailout probabilities, $\pi$, remove state-contingent transfers to creditors in bad states. Equivalently, they raise the cost of funding exactly in the states where sustaining the balance sheet through new equity is most expensive. This shrinks the intermediary's net worth and increases the marginal value of equity, $\tilde{v}(\mathbf{S}')$, precisely in those states. As a result, the intermediary SDF, $\mathcal{M}^I$, is more *tilted* toward bad states of the world. Hence $\text{Cov}\big(\mathcal{M}^I(\mathbf{S}', \mathbf{S}), f'\big)$ becomes more negative and required excess returns rise.

**Table 4: Pre-2008 vs. post-2010 comparison of baseline and counterfactual economies**

| | **Baseline** | $\pi^H$ | $\xi$ |
|---|---|---|---|
| Credit spread (bp) | 34.3 | 6.35 | 46.0 |
| Intermediary risk-free rate (bp) | 266.0 | 130 | 163.0 |
| Price of *normal* risk (bp) | 1.35 | 0.51 | 1 |
| Price of *disaster* risk (bp) | 12.3 | 6.48 | 9 |
| Leverage (%) | −2.99 | −1.50 | −1.79 |
| Loan price (%) | −4.76 | −1.58 | −3.20 |

Notes: column $\pi^H$ retains the pre-crisis bailout probabilities; column $\xi$ retains the pre-crisis capital requirement.

The first five rows of Table 4 report the contribution of the post-crisis fall in the perceived bailout probability and tighter capital requirements to banks' unsecured funding costs, the pricing of normal and disaster risks and leverage.

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 pre-crisis bailout probability ($\pi^{H}$) 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. Put differently, 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, helping keep spreads about 12 basis points lower.

These changes in funding costs are reflected in the intermediaries' implied risk-free rate and the price of risk embedded in their asset portfolio. Lower bailout probabilities raise the intermediaries' risk-free rate, $r^{f,I}$, substantially. They do so by increasing funding costs, which induce lower leverage and a greater reliance on costlier equity financing. Had pre-crisis bailout beliefs persisted at high levels, $r^{f,I}$ would have increased slightly: intermediaries would have enjoyed pre-crisis default probabilities together with cheaper debt finance. Tighter capital regulation also contributed, accounting for about 1 percentage point of the increase in $r^{f,I}$. Turning to the price of risk, lower bailout probabilities remove state-contingent transfers precisely in disaster states. For intermediaries, this raises the marginal value of equity in those states, sharply increasing $\mathrm{Cov}(\mathcal{M}^{I}(\mathbf{S}', \mathbf{S}), d')$ and hence the price of disaster risk, $\lambda_d$. By contrast, tighter capital requirements have more symmetric effects on the prices of both normal and disaster risk, by their non–state-contingent nature.

Taken together, these findings show that the post-crisis *repricing of government guarantees* is an important driver of higher funding costs and the reallocation of intermediary portfolios away from jump-risk-intensive assets, which the literature typically attributes only to tighter regulation (Buchak et al. 2018, Irani et al. 2021, Buchak et al. 2024).

**Implications for Bank Asset Valuations.** The intermediary's choice of risky asset holdings $A'$ 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

$$p(\mathbf{S}) = \mathbb{E}_{\mathbf{S}}\left\{ \frac{\mathcal{M}(\mathbf{S}', \mathbf{S})}{1 - \tilde{\lambda}\,\xi} \left[ \tilde{v}\left(\mathbf{S}'\right)(1 - F(\mathbf{S}'))\mathcal{P}(\omega^{+\prime}, \mathbf{S}') \right.\right.$$
$$\left.\left. + (1 - \pi')\left[ F(\mathbf{S}')(1 - \chi)\mathcal{P}(\omega^{-\prime}, \mathbf{S}') - \frac{\partial F(\mathbf{S}')}{\partial A'}\chi\mathcal{P}(\omega^{*}(\mathbf{S}'), \mathbf{S}') \right] \right] \right\}. \qquad (25)$$

On the left, $p(\mathbf{S})$ represents the price paid for the risky asset today. On the right, the first term represents the expected marginal benefit of acquiring an additional risky asset in states where the intermediary survives, evaluated at the shadow marginal value of net worth. The second term reflects the value of investment in default and no bailout states: the intermediary internalizes how additional asset exposure influences default likelihood ($\partial F(\mathbf{S}')/\partial A' < 0$) and expected recovery values in default states. This component pushes up the price of the risky asset.

Lower bailout probabilities and tighter capital requirements affect aggregate loan valuations, $p(\mathbf{S})$, through two channels. First, through a change in the composition of the intermediary's funding. A lower perceived bailout probability, $\pi$, removes state-contingent transfers to creditors in bad states, which raises unsecured debt spreads and the intermediaries' marginal cost of funds. In response, intermediaries optimally substitute away from cheap debt toward expensive equity and reduce leverage. Tighter capital requirements, $\xi$, reinforce this substitution mechanically by forcing a higher equity share in funding. Both forces raise the average cost of capital and the hurdle rate at which loans are priced, lowering the willingness to pay for risky cash flows and thus the aggregate loan valuation $p(\mathbf{S})$ even holding expected loan payoffs fixed. Moreover, equity issuance costs make recapitalization of intermediaries' balance sheets more costly, slowing the rebuilding of net worth and thereby delaying the recovery. Second, by reducing leverage, lower bailout expectations and stricter capital requirements lower the frequency and severity of intermediary insolvency. Fewer defaults cut expected deadweight costs and diminish the tail exposure that creditors must be compensated for. All else equal, this channel works in the opposite direction of the previous one and raises $p(\mathbf{S})$ by making the financial sector safer.

In the last row of Table 4, I report how the post-2010 decline in perceived bailout probabilities and the tightening of capital requirements affect loan prices. In the baseline, the loan price is 4.76 percent below its pre-2008 average, whereas under the $\pi^H$ counterfactual it is only 1.58 percent lower. Higher funding costs induced by lower bailout probabilities imply a lower willingness to pay for risky assets, as debt financing becomes more expensive. Similarly, tighter regulation—by tilting banks' capital structures toward equity—also leads to a decline in asset prices. This pattern suggests that, in the new regime, financing-cost effects dominate loan pricing: even after acute default risk recedes, the persistent shift from debt to equity and the removal of state-contingent guarantees keep the marginal cost of funds—and hence required loan returns—durably elevated.[17] Comparing the baseline to the $\xi$ counterfactual suggests that, once lower bailout expectations already induce intermediaries to delever endogenously, the post-2010 tightening of capital requirements pushed funding further toward costly equity and likely slowed the recovery in valuations even more.

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

# 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 remainder due to fundamentals (18 basis points) and partly offset by tighter regulation, which lowered spreads by about 12 basis points.

I then use the model to evaluate how post-crisis lower bailout expectations and tighter regulations affected intermediary risk pricing and the recovery in asset valuations. Lower bailout probabilities raise the price of disaster risk by shifting downside losses to creditors (state-contingent), whereas higher capital requirements lift the cost of capital more uniformly across states with relatively muted effects on disaster premia. This distinction partly explains why removing state-contingent guarantees pushed financial intermediaries out of risky asset markets like the leveraged loan market, over and above the tightening of regulation. At the same time, while both lower bailout expectations and tighter capital requirements reduce leverage and default rates, they also yield a protracted, sluggish recovery in aggregate valuations, as funding shifts toward costlier equity and the rebuilding of intermediaries' net worth slows down.

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 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.[18]

Second, my analysis suggests 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 should account for the bailout component to avoid misinterpreting changes in spreads as purely fundamental risk signals. Regulatory frameworks that condition capital requirements on market-based risk measures may need to adjust for the influence of bailout expectations to ensure accurate risk assessment.

[18] 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 $\mathsf{LGD}^*_{t,T}$

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

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

Hence, the market price of debt is

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

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

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

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

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

The single-period discounted expected loss is

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

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

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

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 annualised spreads of a few hundred basis points,

$$1-(1+\mathrm{CS}_t)^{-1} = \frac{\mathrm{CS}_t}{1+\mathrm{CS}_t} \simeq \mathrm{CS}_t.$$

4. Independence of recovery and timing. Expected recovery $\hat{V}_{t+1}$ is conditionally independent of default timing within the one-year window, consistent with standard CDS pricing conventions.

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

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

## 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). Specifically, I 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

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

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

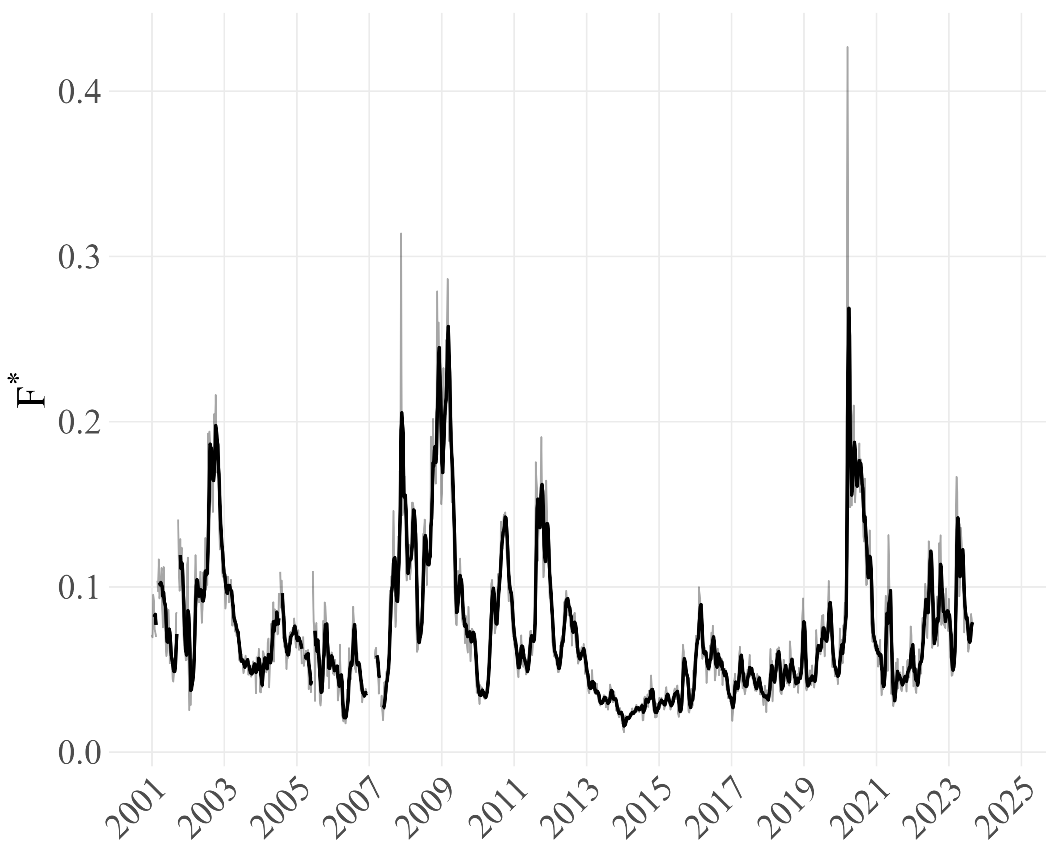
$$R^2 \;=\; 1 \;-\; \frac{\sum_{i=1}^{m}\left(\mathrm{Put}(K_i)-\hat{\beta}_{TS}\,K_i\right)^2}{\sum_{i=1}^{m}\mathrm{Put}(K_i)^2},$$

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 $\tau$. 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 $\{K_1, \ldots, K_{m^*}\}$, 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 35 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: Average $\mathbb{F}^*_{t,T}$ for $T = 365$ using the Theil–Sen estimator**



## A.3 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

$$\log\bigl(\mathrm{CS}_{i,t,365}\bigr) = \beta_0 + \beta_1 \log\bigl(\mathrm{LGD}^*_{i,t,365}\bigr) + \sum_i \beta^i D^i + \sum_t \beta^t D^t + \varepsilon_{i,t}, \tag{A.5}$$

where $\mathrm{CS}_{i,t,365}$ denotes the one-year CDS spread and $\mathrm{LGD}^*_{i,t,365}$ the corresponding risk-neutral expected loss at time $t$ for bank $i$. Equation (A.5) is estimated under four sets of fixed effects. Table A.1 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 $\log(\mathrm{LGD}^*_{t,365})$ equals 0.710 with a clustered standard error of 0.066, so the null hypothesis of unit elasticity is rejected at the one-percent level. Under risk-neutral valuation spreads would move one-for-one with expected losses; a coefficient below unity therefore points to a positive price of default risk, as investors demand an additional premium that attenuates the mechanical pass-through from losses to spreads once bank and date heterogeneity are purged.

The overall coefficient of determination $R^2$ rises monotonically with the inclusion of fixed effects and reaches 0.936 in the full model, indicating that cross-sectional and temporal dummies absorb nearly all variation in levels. The within-bank $R^2$ climbs from 0.327 when only bank effects are added to 0.700 with date effects alone, then settles at 0.583 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, yet investor risk aversion still drags the elasticity markedly below the theoretical benchmark of one.

## A.4 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 mar-

**Table A.1: Estimates of the panel data regression (A.5)**

| Dependent Variable: | $\log(CS_{t,365})$ | | | |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Constant | -3.813*** | | | |
| | (0.1672) | | | |
| $\log(LGD^*_{t,365})$ | 0.9022*** | 0.7393*** | 0.8514*** | 0.7104*** |
| | (0.0632) | (0.0585) | (0.0721) | (0.0657) |
| *Fixed-effects* | | | | |
| Bank | | Yes | | Yes |
| Date | | | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 33,959 | 33,959 | 33,959 | 33,959 |
| $R^2$ | 0.52604 | 0.61912 | 0.86919 | 0.93560 |
| Within $R^2$ | | 0.32672 | 0.69964 | 0.58284 |

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

Notes: the coefficients $\beta^i$ and $\beta^t$ capture bank and day-fixed effects (FEs). Credit spreads and expected recoveries are measured in decimals.

ket liquidity influences this relationship, I estimate the variation in this difference 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 liquidity measures. Since default probabilities derived from options primarily depend on out-of-the-money options, I compute $\mathsf{SPREAD}^O_t$, the average percentage bid-ask spread for such options. Additionally, $\mathsf{VOL}^O_t$ and $\mathsf{OPEN}^O_t$ represent the sum of volume and open interest for these contracts. For CDS, I measure bank-specific liquidity using five-year depth, $\mathsf{DEPTH}^C_t$, and assume other maturities co-move with it.[19]

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 $\mathsf{FinStress}_t$. 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

[19]Depth is the quantity tradable at prevailing quotes, a liquidity proxy increasing with dealer activity and traded notional. Five-year CDS is 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 $\mathsf{DEPTH}^C_t$ as a curve-wide proxy.

liquidity is proxied using the VIX index, $VIX_t$, 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 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):

$$\begin{aligned}\Delta \log(LGD^*_{t,T}) = a_T + b_1 \Delta \log \mathsf{FinStress}_t + b_2 \Delta \log VIX_t + b_3 \Delta \log \mathsf{SPREAD}^O_{t,T} \\ + b_4 \Delta \log \mathsf{VOL}^O_{t,T} + b_5 \Delta \log \mathsf{OPEN}^O_{t,T} + b_6 \Delta \log \mathsf{DEPTH}^C_{t,T} + e_{t,T}. \quad \text{(A.6)}\end{aligned}$$

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

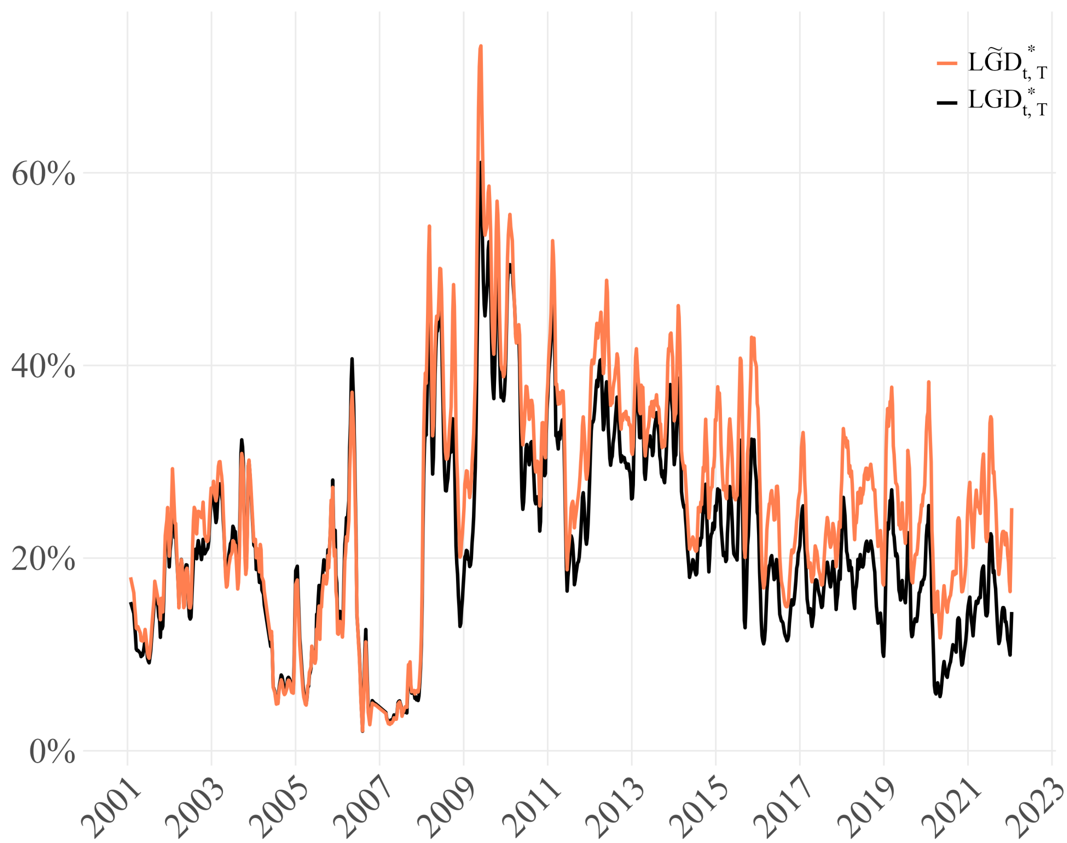
$$L\tilde{G}D^*_{t,T} = \exp\left(\hat{a}_T + \sum_{j=0}^{t} \hat{e}_{t-j,T}\right),$$

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

Figure A.2 plots the time series of $L\tilde{G}D^*_{t,T}$ and $LGD^*_{t,T}$ for $T = 365$ days. $L\tilde{G}D^*_{t,T}$ closely tracks the original $LGD^*_{t,T}$ before the financial crisis, but differs significantly after. $L\tilde{G}D^*_{t,T}$ is higher than $LGD^*_{t,T}$ beginning approximately in 2009. That is, adjusting for liquidity effects results in an estimate of expected losses $L\tilde{G}D^*_{t,T}$ that is meaningfully higher during the financial crisis and in its aftermath. This has two implications. First, it suggests that liquidity effects are not fully reflected in the original expected losses before the crisis. Second, the fact that $L\tilde{G}D^*_{t,T}$ exceeds $LGD^*_{t,T}$ during and after the financial crisis implies that the apparent decline in losses given default from the unadjusted series was largely driven by liquidity distortions. Once these are removed, the higher adjusted losses indicate that the post-GFC increase in volatility and level of expected losses reflects a reduction in perceived bailout support rather than a deterioration in underlying credit fundamentals.

Table A.2 reports the estimates of equation (A.6) 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. In particular, increases in open interest are associated with higher expected losses, while wider bid–ask spreads are associated with lower expected losses, reflecting 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 the interpretation that investors revise downward their expectations of government

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




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

**Table A.2: Estimates of the time–series regression (A.6) for $T = 365$ days**

| Dependent Variable: | $\Delta\log\left(\mathrm{LGD}^{*}_{t,T}\right)$ |
|---|---|
| Model: | (1) |
| *Variables* | |
| Constant ($\alpha_T$) | -0.0001 |
| | (0.0037) |
| $\Delta\log\left(\mathrm{VOL}^{O}_{t,T}\right)$ | -0.0033 |
| | (0.0021) |
| $\Delta\log\left(\mathrm{OPEN}^{O}_{t,T}\right)$ | 0.0363*** |
| | (0.0085) |
| $\Delta\log\left(\mathrm{SPREAD}^{O}_{t,T}\right)$ | -0.0655*** |
| | (0.0157) |
| $\Delta\log(\mathrm{FinStress}_t)$ | -0.0143 |
| | (0.0411) |
| $\Delta\log(\mathrm{VIX}_t)$ | -0.2848*** |
| | (0.0467) |
| $\Delta\log\left(\mathrm{DEPTH}^{C}_{t,T}\right)$ | 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, $\Delta\log(\mathrm{LGD}^{*}_{t,T})$. 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.

support (bailout probability) when volatility spikes. 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.5 Identifying regulatory tightness from market prices

Properly estimating changes in perceived bailout protection requires explicitly accounting for post-GFC regulatory reforms. 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, regulation and bailout expectations move credit spreads and the *downside* variance of equity returns 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 $\xi$ denote the *slackness* of capital regulation (higher $\xi$ means a slacker constraint, i.e., higher permitted leverage) and let $\pi$ denote bailout probability. Around a reference point, the observables admit the local linearization

$$\Delta \log \mathrm{CS}_t = a^\top \Delta\Pi_t + e^\top \Delta Y_t + \varepsilon^S_t, \tag{A.7}$$

$$\Delta \log \mathrm{Var}^{-}_{t,T} = b^\top \Delta\Pi_t + d^\top \Delta Y_t + \varepsilon^-_t, \tag{A.8}$$

$$\Delta \log \mathrm{Var}^{+}_{t,T} = g^\top \Delta\Pi_t + c^\top \Delta Y_t + \varepsilon^+_t, \tag{A.9}$$

where $\Delta\Pi_t = (\Delta\xi_t, \Delta\pi_t)^\top$, $a = (s_\xi, s_\pi)^\top$, $b = (\nu_\xi, \nu_\pi)^\top$, $g = (w_\xi, w_\pi)^\top$, and $e, d, c$ are conformable coefficient vectors on fundamentals $\Delta Y_t$ (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 $\xi$) compresses leverage and reduces both $\mathrm{CS}_t$ 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 $\nu_\xi > 0$.* (ii) Bailouts. *Lower expected bailout support (a fall in $\pi$) increases $\mathrm{CS}_t$ and decreases $\mathrm{Var}^{-}_{t,T}$. In the local linearization this corresponds to $s_\pi < 0$ and $\nu_\pi > 0$.*

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 $\mathrm{Var}^{-}$. 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* $\Delta Y_t$ *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 $\mathrm{Var}^+$ as a proxy for fundamentals when purging $\mathrm{Var}^-$ of non-policy 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 $\Delta Y_t$.

Assumption 2 implies there exists a scalar $\kappa_F$ 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.8)–(A.9) 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 $\Delta Y_t$.[20]

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.

[20] Assumption 2 ensures that the linear combination with slope $\kappa_F$ removes the $\Delta Y_t$-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 $\kappa_F$ by projecting residualized $\log \mathrm{Var}^-_{i,t}$ on residualized $\log \mathrm{Var}^+_{i,t}$ (see §A.5). Consistency requires that tail-specific noises are not systematically co-moving after residualization, e.g., $\mathrm{Cov}(\varepsilon^-_t, \varepsilon^+_t) = 0$ (or small).

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*

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

*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*

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

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

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

*Moreover, letting $\Sigma^{\mathrm{pre}}$ and $\Sigma^{\mathrm{post}}$ 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

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

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 $(\Delta\Pi_t, \Delta Y_t, \varepsilon_t^S, \varepsilon_t^-, \varepsilon_t^+)$. Since $Z_t$ has no $\Delta Y_t$ term, $Z_t$ is orthogonal, in population, to $\Delta Y_t$ by construction.

*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):

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

Hence

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

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

$$\beta^{\mathrm{OP}} = \frac{(b-\kappa_F g)^\top \Sigma\, a}{(b-\kappa_F g)^\top \Sigma\, b}.$$

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

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

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

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

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

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

$$\beta^{\mathrm{OP}} \approx \frac{s_\xi \tilde{v}_\xi \,\mathrm{Var}(\Delta\xi_t) + s_\pi \tilde{v}_\pi \,\mathrm{Var}(\Delta\pi_t)}{v_\xi \tilde{v}_\xi \,\mathrm{Var}(\Delta\xi_t) + v_\pi \tilde{v}_\pi \,\mathrm{Var}(\Delta\pi_t)}, \quad \tilde{v}_j = v_j - \kappa_F w_j,\; j \in \{\xi, \pi\}.$$

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

$$(b-\kappa_F g)^\top \Sigma\, b \;=\; v_\xi \tilde{v}_\xi \,\mathrm{Var}(\Delta\xi_t) + v_\pi \tilde{v}_\pi \,\mathrm{Var}(\Delta\pi_t) \;>\; 0$$

provided at least one of $\mathrm{Var}(\Delta\xi_t), \mathrm{Var}(\Delta\pi_t)$ 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

$$\beta^{OP} = \phi(R) \quad \text{with} \quad \phi(R) \equiv \frac{s_\xi R + s_\pi}{\nu_\xi R + \nu_\pi}.$$

Differentiate:

$$\phi'(R) = \frac{(s_\xi)(\nu_\xi R + \nu_\pi) - (s_\xi R + s_\pi)(\nu_\xi)}{(\nu_\xi R + \nu_\pi)^2} = \frac{s_\xi \nu_\pi - s_\pi \nu_\xi}{(\nu_\xi R + \nu_\pi)^2}.$$

By Assumption 1, $s_\xi > 0$, $\nu_\xi > 0$, $s_\pi < 0$, $\nu_\pi > 0$, hence $s_\xi \nu_\pi - s_\pi \nu_\xi > 0$, so $\phi'(R) > 0$ for all $R \geqslant 0$. Assumption 4(b) states that the adjusted regulation share rises post-2010: $R_{post} > R_{pre}$. Therefore

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

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

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

with $S^E_t$ 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

$$\operatorname{Var}^-_{t,T} \equiv \frac{2}{(T-t)\, R_{f,t}} \left( \frac{1}{(S^E_t)^2} \right) \int_0^{F_{t,T}} \operatorname{put}_t(K,T)\, dK, \tag{A.10}$$

$$\operatorname{Var}^+_{t,T} \equiv \frac{2}{(T-t)\, R_{f,t}} \left( \frac{1}{(S^E_t)^2} \right) \int_{F_{t,T}}^{\infty} \operatorname{call}_t(K,T)\, dK. \tag{A.11}$$

We assemble a panel of banks observed daily, exclude the 2008–2009 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:

$$\begin{aligned} r^-_{i,t} &:= \widehat{\varepsilon}^-_{i,t} \ \text{ from } \ \log \mathrm{Var}^-_{i,t} = \alpha_i + \delta_t + \Gamma_i \log \mathrm{VIX}_t + \varepsilon^-_{i,t}, \\ r^+_{i,t} &:= \widehat{\varepsilon}^+_{i,t} \ \text{ from } \ \log \mathrm{Var}^+_{i,t} = \alpha_i + \delta_t + \Gamma_i \log \mathrm{VIX}_t + \varepsilon^+_{i,t}. \end{aligned} \tag{A.12}$$

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

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

We then form the subsample-specific orthogonalized downside shifters

$$Z^{\text{pre}}_{i,t} \equiv \left(r^-_{i,t} - \kappa^\star_{\text{pre}} r^+_{i,t}\right) \cdot \mathbf{1}\{\text{pre}\}, \qquad Z^{\text{post}}_{i,t} \equiv \left(r^-_{i,t} - \kappa^\star_{\text{post}} r^+_{i,t}\right) \cdot \mathbf{1}\{\text{post}\}. \tag{A.13}$$

In addition—since upside may load on policy—we construct the symmetric orthogonalized upside shifters using the projection of $r^+_{i,t}$ on $r^-_{i,t}$:

$$\Lambda^\star_{\text{pre}} \equiv \arg\min_\lambda \mathbb{E}[(r^+ - \lambda r^-)^2 \mid \text{pre}], \qquad \Lambda^\star_{\text{post}} \equiv \arg\min_\lambda \mathbb{E}[(r^+ - \lambda r^-)^2 \mid \text{post}], \tag{A.14}$$

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

By construction, $(Z^{\text{sub}}_{i,t}, W^{\text{sub}}_{i,t})$ 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

$$\begin{aligned} \log \mathrm{CS}_{i,t} = {} & \beta^{\text{pre}}_- \left(\log \mathrm{Var}^-_{i,t} \cdot \mathbf{1}\{\text{pre}\}\right) + \beta^{\text{post}}_- \left(\log \mathrm{Var}^-_{i,t} \cdot \mathbf{1}\{\text{post}\}\right) \\ & + \beta^{\text{pre}}_+ \left(\log \mathrm{Var}^+_{i,t} \cdot \mathbf{1}\{\text{pre}\}\right) + \beta^{\text{post}}_+ \left(\log \mathrm{Var}^+_{i,t} \cdot \mathbf{1}\{\text{post}\}\right) \\ & + \alpha_i + \delta_t + \Gamma_i \log \mathrm{VIX}_t + \varepsilon_{i,t}, \end{aligned} \tag{A.16}$$

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

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

$$Z_{i,t}^{\text{pre}} \equiv \left(r_{i,t}^{-} - \kappa_{\text{pre}}^{\star} r_{i,t}^{+}\right) \cdot \mathbf{1}\{\text{pre}\}, \qquad Z_{i,t}^{\text{post}} \equiv \left(r_{i,t}^{-} - \kappa_{\text{post}}^{\star} r_{i,t}^{+}\right) \cdot \mathbf{1}\{\text{post}\}$$

load strongly on the endogenous regressors

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

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

$$W_{i,t}^{\text{pre}} \equiv \left(r_{i,t}^{+} - \Lambda_{\text{pre}}^{\star} r_{i,t}^{-}\right) \cdot \mathbf{1}\{\text{pre}\}, \qquad W_{i,t}^{\text{post}} \equiv \left(r_{i,t}^{+} - \Lambda_{\text{post}}^{\star} r_{i,t}^{-}\right) \cdot \mathbf{1}\{\text{post}\}$$

dominate the first stages for

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

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.12)–(A.15) 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:

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

This increase maps monotonically to a rise in the *adjusted regulation share* of the downside policy mixture, hence the post-2010 steepening of the spread-downside relation identifies tighter regulation (a larger regulation-driven share in the adjusted mixture), not a decline in bailout expectations. Tables A.3 and A.4 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 $\mathbf{S} = [N, W, \pi, Z, d]$.

## B.1 Stand-in household

The stand-in household solves

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

subject to

$$\begin{aligned} W - T(\mathbf{S}) &\geqslant C + q(\mathbf{S})\, B' + q^d(\mathbf{S})\, D', && \text{(B.1)}\\ W &= \Pi(\mathbf{S}) + \Pi^I(\mathbf{S}) + D' + B'\big[1 - F(\mathbf{S}) + F(\mathbf{S})\big(\pi + (1-\pi) RV(\omega^-, \mathbf{S})\big)\big], && \text{(B.2)}\\ \mathbf{S}' &= \Gamma\big(\mathbf{S}\big). && \text{(B.3)} \end{aligned}$$

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

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

Taking first–order conditions with respect to bonds yields

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

**Table A.3: Projection stage for the subsample-specific tail regressors**

| **Dependent variables** | $\log \mathrm{Var}^{-}_{i,t} \cdot \mathbf{1}\{\text{pre}\}$ | $\log \mathrm{Var}^{-}_{i,t} \cdot \mathbf{1}\{\text{post}\}$ | $\log \mathrm{Var}^{+}_{i,t} \cdot \mathbf{1}\{\text{pre}\}$ | $\log \mathrm{Var}^{+}_{i,t} \cdot \mathbf{1}\{\text{post}\}$ |
|---|---|---|---|---|
| **Model** | (1) | (2) | (3) | (4) |
| *Instruments* | | | | |
| $Z^{pre}_{i,t} \equiv \left(r^{-}_{i,t} - \hat{\kappa}_{pre}\, r^{+}_{i,t}\right) \cdot \mathbf{1}\{\text{pre}\}$ | $1.334^{***}$ | $-0.1405^{***}$ | $0.8198^{***}$ | $-0.1607^{***}$ |
| | (0.0356) | (0.0356) | (0.0324) | (0.0324) |
| $Z^{post}_{i,t} \equiv \left(r^{-}_{i,t} - \hat{\kappa}_{post}\, r^{+}_{i,t}\right) \cdot \mathbf{1}\{\text{post}\}$ | $0.2222^{**}$ | $1.083^{***}$ | $0.2603^{**}$ | $0.5738^{***}$ |
| | (0.0886) | (0.0886) | (0.1075) | (0.1075) |
| $W^{pre}_{i,t} \equiv \left(r^{+}_{i,t} - \hat{\Lambda}_{pre}\, r^{-}_{i,t}\right) \cdot \mathbf{1}\{\text{pre}\}$ | $0.4037^{***}$ | $-0.0539^{***}$ | $1.258^{***}$ | $-0.0650^{***}$ |
| | (0.0176) | (0.0176) | (0.0216) | (0.0216) |
| $W^{post}_{i,t} \equiv \left(r^{+}_{i,t} - \hat{\Lambda}_{post}\, r^{-}_{i,t}\right) \cdot \mathbf{1}\{\text{post}\}$ | $0.1163^{**}$ | $0.3619^{***}$ | $0.1372^{**}$ | $1.168^{***}$ |
| | (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 ($\alpha_i$) | Yes | Yes | Yes | Yes |
| Date ($\delta_t$) | 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 $Z^{pre}_{i,t}$ and $Z^{post}_{i,t}$ for the downside, and $W^{pre}_{i,t}$ and $W^{post}_{i,t}$ for the upside, constructed from residualized tails as in (A.12)–(A.15). Bank and date fixed effects and bank-specific VIX slopes included. Two-way clustered standard errors (bank, date).

**Table A.4: Structural stage estimates for the spread–tail relation by subsample, estimated from (A.16)**

| **Dependent variable** | $\log CS_{i,t}$ |
|---|---|
| $\log \text{Var}^{-}_{i,t} \cdot \mathbf{1}\{\text{pre}\}$ | 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 ($\alpha_i$) | Yes |
| Date ($\delta_t$) | 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 $(Z^{pre}_{i,t}, Z^{post}_{i,t}, W^{pre}_{i,t}, W^{post}_{i,t})$. Bank and date fixed effects and bank-specific VIX slopes included. Two-way clustered standard errors (bank, date).

where

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

## B.2 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 $\omega$ 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

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

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 $\omega$ 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 $\mu$, the Lagrange multiplier on the leverage constraint by $\lambda$, and the Lagrange multiplier on the deposit constraint by $\lambda^d$. The FOC with respect to $\tilde{e}$ is

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

The FOC with respect to $a'$ is given by

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

The FOC for $d'$ is

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

Finally, the FOC for $b'$ yields

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

The envelope condition is

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

We can divide by $\mu$ and re-write more compactly

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

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

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

where we define the SDF of the intermediaries $\mathcal{M}^I(\mathbf{S}', \mathbf{S})$ as

$$\mathcal{M}^I(\mathbf{S}', \mathbf{S}) = \mathcal{M}(\mathbf{S}', \mathbf{S})\,(1 - \phi_1 \tilde{e}) \left( \phi_0 + \frac{1 - \phi_0}{1 - \phi_1 \tilde{e}'} \right), \tag{B.14}$$

and $\tilde{\lambda} = \frac{\lambda}{\mu}$ is the scaled Lagrange multiplier on the leverage constraint and $\tilde{\lambda}^d = \frac{\lambda^d}{\mu}$ 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. Then all intermediaries, including newly started ones, 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. Then the average net worth of surviving intermediaries in $t+1$ is recursively defined as

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

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

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

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.[21]

[21] A simple sufficient lower bound on payouts that rules out unbounded equity accumulation follows 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 $N = (1 - F(\mathbf{S}))N^+ + F(\mathbf{S})n^0$ in the cross-section. The first-order condition $\mu = 1/(1 - \phi_1\tilde{e})$ 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 $\tilde{e}$.

## B.3 Derivatives of debt price

To obtain the partial derivatives we need to differentiate equation (B.4). Let's first rewrite it as

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

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

$$\mathcal{R}(\omega, \mathbf{S}) \equiv F(\mathbf{S}')\frac{(1-\chi)\mathcal{P}(\omega^{-,\prime}, \mathbf{S}')A' - D'}{B'} = F(\mathbf{S}')RV^{B}, \tag{B.15}$$

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

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

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

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

Finally, we can differentiate (B.15) to get

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

Hence the derivatives of $q(\mathbf{S})$ are

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

The last piece is the derivative of the loan payoff with respect to $\omega$. 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 (19),

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

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 $\pi'$, for concreteness the conditional mean $\mu_{\pi,t} \equiv \mathbb{E}_t[\pi_{t+1}]$. Because the term

$(1-\pi')$ enters (19) 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 $X \equiv F(\mathbf{S}')(1 - RV(\omega^{-\prime}, \mathbf{S}'))$, and the interchange of derivative and expectation is justified by dominated convergence since $\mathcal{M}X$ is integrable and bounded in $\pi'$. 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 $\pi'$, the same expression is obtained because the integrand is affine in $\pi'$; the conditions for commutation hold for the same integrability reasons.

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

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

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

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

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

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

with

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

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 (19),

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

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

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

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 $h(Y', B') = F(\mathbf{S}')(1 - RV(\omega^{-\prime}, \mathbf{S}'))$ yields

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

The indirect term can be written as

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

with

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

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,

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

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 $B'$ fixed,

$$\partial_{Y'} RV(\omega^*(\mathbf{S}'),\mathbf{S}') = \frac{(1-\chi)}{B'}\Big(\partial_Y \mathcal{P}(\omega^*(\mathbf{S}'),\mathbf{S}') \;+\; \partial_\omega \mathcal{P}(\omega^*(\mathbf{S}'),\mathbf{S}')\,\frac{d\omega^*(\mathbf{S}')}{dY'}\Big).$$

Since $\partial_Y \mathcal{P} \geqslant 0$ and $\partial_\omega \mathcal{P} \geqslant 0$ by (6)–(7), we have $\partial_{Y'} F(\mathbf{S}') \leqslant 0$ and $\partial_{Y'} RV(\omega^*(\mathbf{S}'),\mathbf{S}') \geqslant 0$, so the direct effect is weakly negative.

Collecting terms,

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

Under the condition that banks delever when fundamentals weaken, $\partial B'/\partial Y' \geqslant 0$, the indirect term is positive as well, and since $\partial_{Y'}(F(\mathbf{S}')(1-RV(\omega^*(\mathbf{S}'),\mathbf{S}'))) \geqslant 0$, 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, reformulating 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 pre-defined 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 four 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 $D_t$ and $\pi_t$. The disaster shock $d_t$ can take on two realizations $\{0, 1\}$. The $2 \times 2$ 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 $\mathcal{S}_x = \{Z_j\}_{j=1}^{N^Z} \times \{0, 1\} \times \{\pi_j\}_{j=1}^{N^\pi}$, and the associated Markov transition matrix $\mathbb{P}_x = \mathbb{P}_Z \otimes \mathbb{P}_d \otimes \mathbb{P}_\pi \otimes \mathbb{P}_D$.

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 $[\bar{S}_l, \bar{S}_u]$. Thus, the endogenous state space is 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, thereby minimizing 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 $2 \times 1$ 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 $s_j \in \hat{\mathcal{S}}$, $j = 1, \dots, N^S$, perform the following sub-steps:

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

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 $s_j \in \hat{\mathcal{S}}$, $j = 1, \dots, N^S$, 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:

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

$$\hat{p}_j = \frac{\partial \hat{q}_j}{\partial A_j} B_j + \hat{\lambda}_j\, \xi \hat{p}_j + \mathbb{E}_{s'_{i,j}|s_j}\big[\hat{\mathcal{M}}^I_{i,j}(1-\hat{F}_{i,j})\, \hat{\mathcal{P}}_{i,j}(\omega^+_{i,j})\big], \tag{D.2}$$

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

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

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

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

$$\hat{q}^D_j = \kappa - \frac{\partial \hat{q}_j}{\partial D_j} B_j + \hat{\lambda}_j + \hat{\lambda}^D_j + \mathbb{E}_{s'_{i,j}|s_j}\big[\hat{\mathcal{M}}^I_{i,j}(1-\hat{F}_{i,j})\big], \tag{D.7}$$

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

All expectations are weighted sums over the exogenous-state transitions. Variables carrying a hat ($\hat{}$) 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. 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 being solved for. sumption. 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

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

and then complete expectation as

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

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, using 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

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

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

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 $\bar{T} = T_{\text{ini}} + T$ periods.

1. *Exogenous shocks.* The exogenous state $x_t$ follows a Markov chain with transition matrix $\Pi_x$. 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 $s_0 = [B_0, D_0, Z_0, D_0, d_0, \pi_0]$, 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 $T_{\text{ini}}$ 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, yielding 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 is

$$\mathcal{P}_t(\omega_t) = \left[c + (1-\delta) + \delta p_t\right] \int_{\underline{z}(\omega_t, Z_t, d_t)}^{\infty} g(z)\, dz + (1-\eta)\, \omega_t\, Z_t\, e^{-\zeta d_t} \int_0^{\underline{z}(\omega_t, Z_t, d_t)} z\, g(z)\, dz, \tag{D.9}$$

where the default boundary solving $y_t = c + (1-\delta)$ is

$$\underline{z}(\omega_t, Z_t, d_t) = \frac{c + (1-\delta)}{\omega_t\, Z_t\, e^{-\zeta d_t}}. \tag{D.10}$$

Let $\{(x_k, w_k)\}_{k=1}^{K}$ be the K Gauss–Legendre nodes and weights on $[-1, 1]$; transforming them by $z_k = \frac{\bar{z}}{2}(x_k + 1)$ for any upper limit $\bar{z} > 0$ gives

$$\int_0^{\bar{z}} g(z)\, dz \approx \frac{\bar{z}}{2} \sum_{k=1}^{K} w_k\, g(z_k), \qquad \int_0^{\bar{z}} z\, g(z)\, dz \approx \frac{\bar{z}}{2} \sum_{k=1}^{K} w_k\, z_k\, g(z_k). \tag{D.11}$$

Because $\int_{\underline{z}}^{\infty} g(z)\, dz = 1 - \int_0^{\underline{z}} g(z)\, dz$, substituting $\bar{z} = \underline{z}(\omega_t, Z_t, d_t)$ from (7) into (D.11) delivers the quadrature approximation

$$\widehat{\mathcal{P}}_t(\omega_t) = \left[c + (1-\delta) + \delta p_t\right] \left[1 - \frac{\underline{z}}{2} \sum_{k=1}^{K} w_k\, g(z_k)\right] + (1-\eta)\, \omega_t\, Z_t\, e^{-\zeta d_t} \frac{\underline{z}}{2} \sum_{k=1}^{K} w_k\, z_k\, g(z_k), \tag{D.12}$$

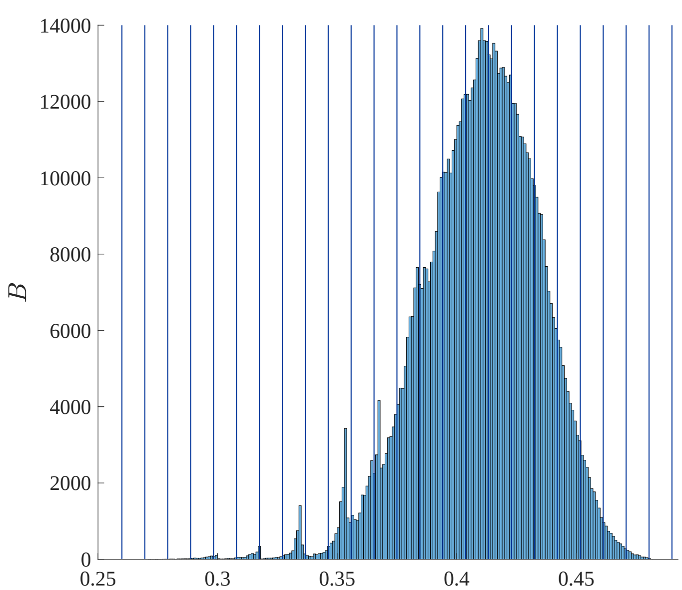
where $z_k = \frac{\bar{z}}{2}(x_k + 1)$. The same Gauss–Legendre grid also discretises the shock itself: for $\omega \sim \text{Log}\mathcal{N}(1, \sigma_\omega^2)$ with $\log \omega \sim \mathcal{N}(\hat{\mu}, \hat{\sigma}^2)$, where $\hat{\sigma}^2 = \log(1 + \sigma_\omega^2)$ and $\hat{\mu} = -\frac{1}{2}\hat{\sigma}^2$, each node gives $\omega_k = \exp\big(\hat{\mu} + \hat{\sigma}\,\Phi^{-1}(\frac{x_k+1}{2})\big)$ and any smooth $F(\omega)$ satisfies $\mathbb{E}[F(\omega)] \approx \frac{1}{2}\sum_{k=1}^{K} w_k F(\omega_k)$. Choosing $K = 7$ yields machine-precision accuracy 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.

**Figure D.1: Debt Histogram**




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.

2. *Relative Euler error check.* For every period t and every equilibrium condition and transition law of motion $\ell$, 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 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.

Computational errors

| Equation | Avg. | Median | $75^{\text{th}}$ pct. | $95^{\text{th}}$ pct. | $99^{\text{th}}$ pct. | $99.5^{\text{th}}$ 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 |

**Table D.1: 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 (E1)–(E15) listed in step 2 of the solution procedure and to the transition equations for the state variables (T1)–(T4). The first column lists the corresponding equation references in Appendix D.**

# 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) indexes available from the Federal Reserve Economic Data (FRED). Specifically, we 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, handling missing values by averaging the available ratings on that day. The sample runs from 2000-01-01 to 2020-12-31. 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 $\mu$ and $\sigma$ 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 U.S. 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 U.S. Treasury securities at a 3-month constant maturity, quoted on an investment basis at daily frequency. The series goes from 2000-01-01 to 2020-12-31. 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 $\text{Issuance}_{h,t}/\texttt{BHCK3210}_{h,t-1}$.

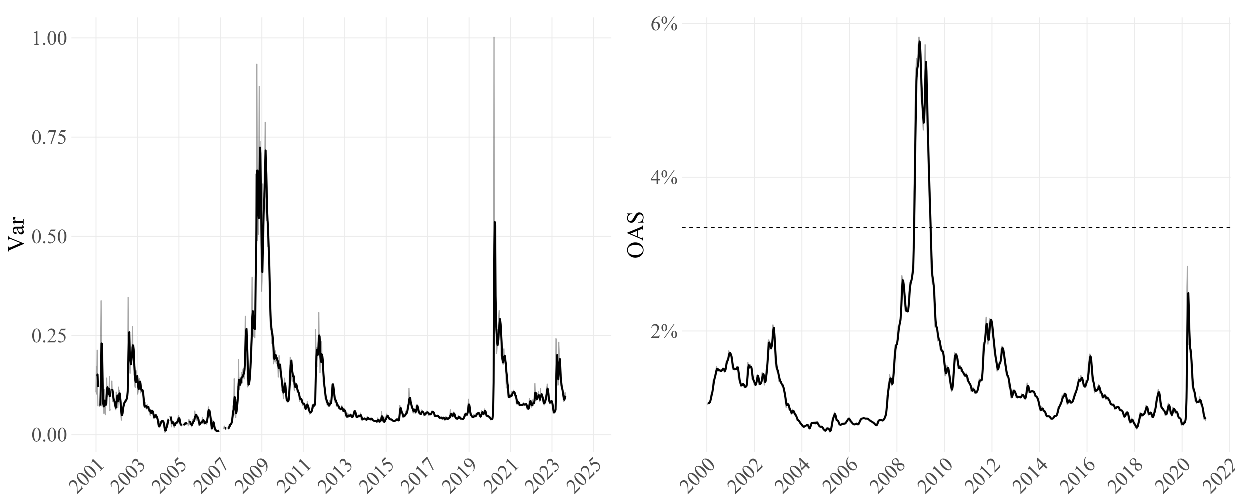
Equity payouts are measured from dividends and repurchases. Regular cash dividends are taken from Schedule HI "Cash dividends declared", MDRM BHCK4460, and adjusted to remove cumulative reporting across quarters by differencing within calendar years. Share repurchases are taken from BHCK3578 (repurchase 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), i.e., $U_{h,t} = \sum_{s \in h} U_{s,t}$ 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, recognizing 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 U.S. 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.

**Figure E.1: Risk-neutral variance of equity returns and Option-adjusted BofA IG bond spread**




Notes: the left panel shows the risk-neutral variance of equity returns for 365-day maturity contracts at weekly frequency (grey line) and 4-weeks moving average (black line). The right panel 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.

# F Details on counterfactual experiments

This section provides details on the counterfactual experiment of Section 7. First, we explain how we use the particle filter to extract information on the sequence of $\{\pi_t\}$. 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.

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 $4 \times 1$ state vector and structural innovations are

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

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

$$\mathbf{Y}_t = \left[CS_{t,365},\ Q^*_{t,365}\right]^\top, \quad CS_{t,365} \equiv r_{t,365} - r^{rf}_{t,365}.$$

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

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

while the empirical default probability obeys a shifted beta law,

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

Each quarter the beta parameters

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

match the filtered mean $\mu_t = g_2(\mathbf{S}_t)$ and variance $\nu_t = 0.01\,\hat{\sigma}^2(Q^{*\,data}_{t,365})$, while $\sigma^2_{CS} = 0.01\,\hat{\sigma}^2(CS^{data}_{t,365})$. Only $CS_{t,365}$ and $Q^*_{t,365}$ 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 $f$,

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

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

Each recursion proceeds as follows:

1. **Initialisation ($t = 0$).** Draw an initial cloud $\{\mathbf{S}_0^i\}_{i=1}^N$ from a suitable prior and set the associated (unnormalised) 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. **Normalisation and resampling.**
   (a) Normalise the unnormalised 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 re-label 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

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

We generate the fundamental component by freezing the bailout probability at its pre-crisis level and backing up the spread

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

The bailout component is then

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

The same procedure is applied for the counterfactual with fixed $B_{t+1} = \bar{B}$ and $D_{t+1} = \bar{D}$ where $\bar{B}$ and $\bar{D}$ are the ergodic means of the uninsured debt and insured deposits, respectively. 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-2010, tighter post-2010). We then obtain their fundamental counterparts by re-evaluating the same objects while fixing the bailout probability at its pre-crisis 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

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

We then compute Pearson correlations within the two subsamples using these purged series:

$$\rho^{\text{pre}} = \text{corr}\big(\log \widetilde{CS}_t,\, \log \widetilde{\text{Var}}_{t,365}^{-}\big)_{t \in [2004,2007]}, \qquad \rho^{\text{post}} = \text{corr}\big(\log \widetilde{CS}_t,\, \log \widetilde{\text{Var}}_{t,365}^{-}\big)_{t \in [2010,2015]}.$$

This procedure removes movements driven by fundamentals and aligns the model with the empirical subsample break; see Section A.5 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 $\pi$ is the probability that an insolvent intermediary is recapitalized as a going concern by the government rather than 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 $\pi$ 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 $\pi$ and $\chi\, \mathcal{P}(\omega, \mathbf{S})\, A'$ otherwise. Hence the debt-pricing condition is unchanged conditional on $\pi$.

2. **Equity-holders are diluted in bailout states.** Pre-existing 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 $\mathsf{T}(\mathbf{S})$ 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

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

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

**Aggregate resource constraint.** Relative to the baseline resource constraint in Equation (15), equity injections remove bankruptcy deadweight losses in the fraction $\pi$ 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 $\chi$ 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 $\pi$, the debt pricing kernel is the same as in the baseline conditional on $\pi$. Equityholders' value, however, now embeds an additional dilution wedge: in all $\omega \in \mathcal{D}$, they receive zero regardless of intervention, but with probability $\pi$ 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 $\pi$ 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, creating 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 $\pi$. However, equity injections mechanically suppress measured default frequencies because insolvent intermediaries that are recapitalized do not default. This makes the mapping between $\pi$ and observed default rates 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 $\varphi_0$, 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

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

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, implying 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 $\rho$. In equilibrium, deposits are finite, deposit rates are upward-sloping in issuance, and greater substitutability (higher $\rho$) 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

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

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

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

**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

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

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, $\omega$ corresponds to the realization of the returns to intermediaries' technology. Consumers discount the future with a discount factor $\beta$ 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 $\omega$ 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 $\omega$ 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 $\omega$ 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 $supp(\omega) = [0, \bar{\omega})$. For 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. Post-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 $\pi$ 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. $\phi$ captures the costs of equity issuance or tax advantage of debt. Costs of default and equity issuance costs ensures a non-trivial 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 governme 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

$$
\begin{aligned}
d_1 &= q(b,a)b - pa, && \text{(H.4)}\\
d_2(\omega) &= \max\{\omega a - b, 0\}, \forall \omega && \text{(H.5)}\\
\frac{b}{a} &\leqslant \xi, && \text{(H.6)}\\
q(b,a) &= \beta\left[\int_{\frac{b}{a}}^{\bar{\omega}} dF(\omega) + \int_0^{\frac{b}{a}}\left(\pi + (1-\pi)\frac{\chi\omega a}{b}\right)dF(\omega)\right]. && \text{(H.7)}
\end{aligned}
$$

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

$$
\begin{aligned}
d_1 &= q(\ell)\ell - p && \text{(H.8)}\\
\ell &\leqslant \xi, && \text{(H.9)}\\
q(\ell) &= \beta\left[\int_{\ell}^{\bar{\omega}} dF(\omega) + \int_0^{\ell}\left(\pi + (1-\pi)\frac{\chi\omega}{\ell}\right)dF(\omega)\right]. && \text{(H.10)}
\end{aligned}
$$

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 non-default 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 $\xi$. 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*

$$\frac{d\nu\left(\ell^\star\right)}{d\ell} = \underbrace{\beta\int_0^{\ell}\pi dF(\omega) + (\beta-\beta^I)\int_{\ell}^{\bar{\omega}} dF(\omega)}_{\substack{\textit{marginal benefits} \\ \textit{(subsidy + valuation difference)}}} - \underbrace{\beta(1-\pi)(1-\chi)\ell f(\ell)}_{\substack{\textit{marginal costs} \\ \textit{(distress)}}} = \lambda. \tag{H.11}$$

*where $\lambda$ 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 $\ell$, 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 $\xi$, 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 $\xi$ 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 $\pi$ and the leverage constraint $\xi$.

**Lemma 2.** *The intermediaries willingnes to pay for a dollar of risky assets* $p$ *is increasing in the bailout probability* $\pi$ *and in the leverage constraint* $\xi$*. The debt price* $q$ *is increasing in the bailout probability* $\pi$ *and decreasing in the leverage constraint* $\xi$*.*

*Proof of Lemma 2.* We start with studying changes in $\xi$. 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 $\xi$:

$$\frac{\partial p}{\partial \xi} = q(\xi) + \xi \frac{\partial q}{\partial \xi} - \beta^{I}(1 - F(\xi)).$$

By using the first-order condition for leverage evaluated at $\ell = \xi$, we can express the derivative as exactly the marginal value of leverage, $\lambda$, which is positive. Therefore, the asset price is increasing in $\xi$. Secondly, the asset price is increasing in $\pi$ 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 $\pi$ since

$$\frac{\partial q}{\partial \pi} = \beta \int_{0}^{\xi} (\xi - \chi\omega) \, dF(\omega) > 0,$$

and decreasing in $\xi$ since

$$\frac{\partial q}{\partial \pi} = -\beta(1-\pi)\Big\{f(\xi)\big[1-\tfrac{\chi\omega}{\xi}\big] \;+\; \tfrac{\chi\omega}{\xi^2}\,F(\xi)\Big\} < 0.$$

□

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 wanto 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 sensitives 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 $\omega$, 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 $\omega$ 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 $\varepsilon$. In particular, we 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 $\omega$. 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 $\omega$ (Dávila & Walther 2023).

**Lemma 3.** *The sensitivity of the asset price* $p$ *to the bailout probability* $\pi$ *and the leverage constraint* $\xi$ *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* $\pi$.

*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 $\varepsilon$ 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

$$\begin{aligned}
\lim_{\varepsilon\to 0} \frac{dh(\omega)}{d\varepsilon} &= \frac{g(\omega)}{1-F(\omega)} + \frac{f(\omega)}{1-F(\omega)}\frac{G(\omega)}{1-F(\omega)} < 0 \\
&\iff g(\omega) + \frac{f(\omega)}{1-F(\omega)}G(\omega) < 0 \\
&\iff \frac{g(\omega)}{G(\omega)} + \frac{f(\omega)}{1-F(\omega)} > 0 \\
&\iff \frac{f(\omega)}{1-F(\omega)} > -\frac{g(\omega)}{G(\omega)}
\end{aligned}$$

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:

$$\begin{aligned}
\frac{\delta \frac{dp}{d\pi}}{\delta F} \cdot G &= \lim_{\varepsilon\to 0} \frac{\left(\beta \int_0^{\xi} (\xi - \chi\omega)\, d\,(F+\varepsilon G)\right) - \left(\beta \int_0^{\chi} (\xi - \chi\omega)\, dF\right)}{\varepsilon} \\
&= \beta \left(\int_0^{\xi} (\xi - \chi\omega)\, dG(\omega)\right) = \beta G(\xi)\xi - \beta\chi \int_0^{\xi} \omega dG(\omega) \\
&= \beta G(\xi)\xi(1-\chi) + \beta\chi \int_0^{\xi} G(\omega) d\omega,
\end{aligned}$$

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:

$$\begin{aligned}
\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G &= \beta\pi G(\xi) + (\beta - \beta^I)(1 - G(\xi)) - \beta(1-\pi)(1-\chi)\xi g(\xi) \\
&= -G(\xi)\left(-\beta\pi + (\beta - \beta^I) + \beta(1-\pi)(1-\chi)\xi\frac{g(\xi)}{G(\xi)}\right).
\end{aligned}$$

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, in particular, it depends on the extent to which creditors are bailed out. In particular, in the limit as $\pi$ approaches 0, the term is positive, and so the sign of the derivative is positive. But as $\pi$ 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 ($\pi x$) 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-$\omega$ 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 $\pi$. 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:

$$(\beta - \beta^I) + \beta(1-\chi)\xi \frac{g(\xi)}{G(\xi)} > 0,$$

implying $\frac{\delta \frac{dp}{d\xi}}{\delta F} \cdot G > 0$. 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 non-monotonicity 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

$$\tilde{e}(\omega) = \big(1-\phi\big)\,(\omega - \xi)\,\mathbf{1}_{\{\omega \geq \xi\}}, \quad E_0 = \beta^I \underbrace{\int_{\xi}^{\bar{\omega}} (\omega - \xi)\, dF(\omega)}_{=A(\xi)},$$

so the gross equity return per dollar of initial equity is

$$R_E(\omega) = \frac{\tilde{e}(\omega)}{E_0} = \frac{(\omega-\xi)\mathbf{1}_{\{\omega \geq \xi\}}}{A(\xi)}, \qquad \mathbb{E}[R_E] = 1.$$

Define[22]

$$\sigma_L^2(\xi) := F(\xi), \qquad \sigma_R^2(\xi) := \int_{\xi}^{\bar{\omega}} \big(R_E(\omega) - 1\big)^2\, dF(\omega),$$

so that total variance satisfies

$$\sigma_E^2(\xi) = \sigma_L^2(\xi) + \sigma_R^2(\xi) \;=\; \frac{B(\xi)}{A(\xi)^2} - 1,$$

[22] $A(\xi)$ and $B(\xi)$ are standard "truncated moment" objects: $A(\xi) = \int_{\xi}^{\bar{\omega}} (\omega - \xi)\, dF$, $B(\xi) = \int_{\xi}^{\bar{\omega}} (\omega - \xi)^2\, dF$.

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 $\sigma_R^2$ relies on Cauchy–Schwarz: $B(\xi)(1 - F(\xi)) \geqslant A(\xi)^2$ with equality only for degenerate payoffs.

Increasing the cap (higher $\xi$) raises both left-tail mass and right-tail dispersion; conversely, **tightening capital regulation** (lower $\xi$) *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 $\pi$:

$$\frac{\partial \xi}{\partial \pi} = 0.$$

Equity pay-offs themselves never contain the bailout transfer, hence

$$\boxed{\frac{\partial \sigma_L^2}{\partial \pi} = 0}, \qquad \boxed{\frac{\partial \sigma_R^2}{\partial \pi} = 0}.$$

A change in the bailout probability $\pi$ leaves both tails *unchanged* when leverage is already capped. Bailout policy 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

$$\boxed{\frac{d\sigma_L^2}{d\pi} = f(\ell^\star)\, \frac{d\ell^\star}{d\pi} \; > \; 0} \qquad \Longrightarrow \qquad \pi \uparrow \; \Rightarrow \; \text{default probability rises.}$$

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

$$\boxed{\frac{d\sigma_R^2}{d\pi} = \frac{\partial \sigma_R^2}{\partial \ell}\, \frac{d\ell^\star}{d\pi} \; > \; 0} \qquad \Longrightarrow \qquad \pi \uparrow \; \Rightarrow \; \text{right-tail dispersion rises.}$$

Hence, bailouts affect equity variance only through the leverage choice. If the cap is slack, higher $\pi$ pushes $\ell^\star$ up, thereby raising both the frequency of default (left tail) and the dispersion of surviving returns (right tail). Lower $\pi$ does the opposite. Tightening $\xi$ that becomes binding compresses leverage directly and symmetrically trims both tails, independent of $\pi$.

## H.5 Social-planner problem

The planner internalises all real resource costs—dead-weight default losses and equity-issuance costs—while treating bail-out transfers and lump-sum taxes as pure redistribution. Normalising 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 $\lambda^{SP}$ for the cap constraint:

$$\boxed{\beta\phi\big[1 - F(\ell)\big] - \beta(1-\chi)\,\ell f(\ell) = \lambda^{SP}} \tag{FOC$_{\text{SP}}$}$$

with complementary-slackness $\lambda^{SP}(\ell - \xi) = 0$, $\lambda^{SP} \geqslant 0$. Comparing the FOC$_{\text{SP}}$ with the FOC$_{\text{Priv}}$ in (H.11), we see that the planner internalizes the bailout subsidy as a transfer. Therefore in distress, the planner percived 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 $\ell^{SP} < \ell^{Priv}$ wheneve $\pi > 0$.. Hence the planner faces a classic regulation trade-off: choose $\xi$ 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 $\pi$ and cap $\xi$. 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 $\phi$ captures equity issuance costs and $\chi$ 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 $\xi$ 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. □